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Ensemble methods for wind and solar power forecasting—A state-of-the-art review

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ABSTRACT

This paper reviews state-of-the-art on wind speed/power forecasting and solar irradiance forecasting with ensemble methods. The ensemble forecasting methods are grouped into two main categories: competitive ensemble forecasting and cooperative ensemble forecasting. The competitive ensemble forecasting is further categorized based on data diversity and parameter diversity. The cooperative ensemble forecasting is divided according to pre-processing and post-processing. Typical articles are discussed according to each category and their characteristics are highlighted. We also conduct comparisons based on reported results and comparisons based on simulations conducted by us. Suggestions for future research include ensemble of different paradigms and inter-category ensemble methods among others.

Contents

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Nomenclature

Abbreviations

AdaBoost	adaptive boosting
ANN	artificial neural network
ANFIS	adaptive neuro-fuzzy inference system
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
ARTMAP	predictive adaptive resonance theory
BP	backpropagation
CI	computational intelligence
CSP	concentrated solar power
CVNN	complex-valued neural network
DWT	discrete wavelet transform
ECMWF	European Center for Medium-Range Weather Forecasting
EMD	empirical mode decomposition
EnKF	ensemble Kalman filter
FNN	fuzzy neural network
GARCH	generalized autoregressive conditional heteroscedasticity
GHI	global horizontal irradiation
kNN	k-nearest neighbors
MLP	multi-layer perceptron
NWP	numerical weather prediction
NECP	National center for environmental prediction
NDBC	National data buoy center
NSRDB	National solar radiation data base
PR	pattern recognition
PRNN	pipelined recurrent neural network
PV	photo-voltaic
RNN	recurrent neural network
RBPN	recurrent backpropagation network
RVNN	real-valued neural network
SMA	seasonal moving average
SVM	support vector machine
SVC	support vector classification
SVR	support vector regression
TSI	total satellite image

Error measures

NMSE	normalized mean square error
NMAE	normalized mean absolute error
RMSE	root mean square error
MRE	mean relative error
MAE	mean absolute error
MSE	mean square error
MAPE	mean absolute percentage error
MASE	mean absolute scaled error

1. Introduction

Renewable/sustainable energy sources, such as wind energy, solar energy, wave energy and tidal energy, draw increasing attention of researchers due to the shortage and their adverse impacts on the environment of fossil fuel. Renewable energy is abundant and environmentally-friendly. However, the cost of using renewable energy is still high because it is difficult to be integrated into the power grid either temporally or spatially. Among various renewable energy sources, wind and solar are two most commonly used sources. This paper focuses on these two types of renewable energy sources.

Consumable electricity has a unique feature: consuming while producing with little or no storage. Conventional electricity power is generated according to the demand from residential, industrial and commercial customers. The primary problem of introducing renewable energy into the power grid is the unpredictability such as intermittent nature of wind speed, and furthermore for a wind farm, different wind turbines generate different amount of power based on the wind direction and location within the wind farm [1]. Solar irradiance is affected by cloud cover, haze effect and solar elevation angle. Although the solar elevation angle is analytically determinant, the cloud cover and haze effect are stochastic [2].

The unpredictability causes a large fluctuation in the power outputs and in order to smooth the fluctuation, large amount of battery storage or power reserve capacity is required, which is costly. By improving the forecasting accuracy, these reserves can be reduced. In addition, accurate wind speed/power forecasting and solar irradiance forecasting can improve the energy conversion efficiency, reduce the risk caused by system overloading and extreme weather conditions, and can improve the unit commitment optimization [3–5].

The objective of this paper is to review some of the recently published articles on ensemble wind speed/power and solar irradiance forecasting with a clear categorization. The details of the ensemble forecasting methods with examples will be discussed in the paper as well. The strengths and weaknesses of each approach are also identified. The comparisons of the results presented in the literature and the experimental comparisons based on our own simulations are discussed. In addition, promising future research directions are also recommended.

The remaining of this paper is organized as follows: Section 2 discusses the ensemble forecasting methodologies on wind speed/power and solar irradiance forecasting; Section 3 reviews state-of-the-art ensemble forecasting methods; Section 4 compares the reviewed ensemble forecasting methods with numerical examples and Section 5 concludes the paper and proposes some future research directions.

2. Ensemble forecasting methodologies

This section gives a brief introduction on wind speed/power forecasting and solar irradiance forecasting followed by the introduction of ensemble forecasting methodologies.

2.1. Wind speed/power forecasting

Wind is bulk, directed movement of air. Wind power is generated by propelling a turbine to rotate, which converts the mechanical power to electrical power. The conversion from wind speed to wind power is shown as [3]

$$P = \frac{1}{2}\rho A C_p(\lambda, \beta) v^3 \tag{1}$$

where ρ is the air density, A is the area of the turbine when rotating, $C_p(\lambda, \beta)$ is the efficiency which is affected by two parameters: tip speed ratio λ and blade pitch β, and v is the up-wind speed. If the wind turbine is placed in a wind farm, wake effect should also be considered.

In the literature [6,7], wind power forecasting and wind speed forecasting are considered equivalent if a proper wind speed to wind power conversion equation such as (1) is available. Therefore, wind speed and wind power forecasting is equivalently discussed in the paper.

Several wind speed/power forecasting review/survey papers are presented in the literature [8–10,6,11,3]. In the reported literature, wind speed/power forecasting can be categorized according to (i) approaches and (ii) forecasting time horizons. There are mainly three approaches for wind speed/power forecasting: physical approach, statistical approach and hybrid approach. There are mainly four forecasting time horizons: very-short term, short term, medium term and long term. The definitions of these two different categorizing schemes are summarized in Tables 1 and 2. However, to the best of authors knowledge, there is no survey and experimental comparison paper of ensemble methods for renewable energy forecasting.

2.2. Solar irradiance forecasting

Solar power, is emitted from the sun and received by the earth. In a broad sense, solar power creates everything on the earth including both renewable and fossil energy sources. In a narrow sense, solar power is the one that can be converted into electrical power. There are mainly two kinds of conversions: photovoltaic (PV) that converts solar power directly to electricity, and concentrated solar power (CSP) that first converts solar power into heat and then converts into electricity by a heat engine. Despite the variations of conversion, solar irradiance index G is critical for solar power. Solar irradiance is the amount of solar energy received on a surface per unit time per unit area on the earth. It is affected by the location, time and cloud/haze cover. An analytical formula is shown as [12]

$$G=\alpha G_0\left(1+0.033\cos\frac{360d}{365}\right)\sin\theta_s$$
$$\sin\theta_s=\cos h\cos\delta\cos\phi+\sin\delta\sin\phi \tag{2}$$

where θ_s is the solar elevation angle, h is the solar hour angle, δ is the sun declination, ϕ is the local latitude, d is the date sequence of a year, α is the cloud/haze cover index and G_0 is solar irradiance constant which is recorded as 1367 W/m^2 by World Meteorological Organization [12].

Solar irradiance can be divided into three categories: direct, diffuse and global. Direct irradiance is the solar radiance that pans through directly to the earth's surface. Diffuse irradiance is the scattered solar radiance out of the direct beam. Global irradiance is the sum of the above two [13]. Eq. (2) is for the global irradiance or global horizontal irradiance (GHI) [14].

Similar to wind speed/power forecasting, solar irradiance forecasting can also be categorized according to the approaches [14,15] as shown in Table 3.

In [16], solar irradiance was categorized based on the forecasting time horizon and the authors also proposed suitable approaches for different time horizons. The categories and the proposed approaches are presented in Table 4.

2.3. Ensemble forecasting

The above-mentioned papers focused on reviewing state-of-the-art wind speed/power and solar irradiance forecasting based on a single predictor. In this paper, we focus on reviewing ensemble predictors and categorizing them according to their characteristics. The details will be discussed in Sections 3.1 and 3.2.

An ensemble method is popular in statistics and machine learning. It uses multiple predictors to obtain an aggregated decision which is better than any of the base predictors [17]. According to Opitz and Maclin [17], there are two kinds of ensemble methods: competitive and cooperative for ensemble classification. Similar to classification, ensemble forecasting can be categorized into competitive and cooperative ensemble forecasting. Competitive ensemble forecast is to train different predictors individually with different datasets or the same dataset but with different parameters and then the prediction is obtained by averaging (or other equivalence) the decisions of all individual predictors (base predictors). On the other hand, cooperative ensemble forecast is to divide the prediction task into several sub-tasks and select appropriate predictors for each sub-task based on the characteristics of the sub-tasks, and the final decision is a sum of all the outputs of the base predictors.

Table 2
Wind speed/power forecasting categorization based on forecasting time horizon [3].

Time horizon	Interval
Very short term	<30–min
Short term	0.5–6-h
Medium term	6–24-h
Long term	1–7-day

Table 3
Solar irradiance forecasting categorization based on approach [14,15].

Approach	Input	Examples
Physical	Meteorological data	NWP, TSI
Statistical	Historical data	ANN, MLP, ARIMA, RNN

Table 4
Solar irradiance forecasting categorization based on forecasting time horizon [16].

Time horizon	Interval	Approach
Very short term	0.5–6 h	TSI
Medium term	6–48 h	NWP with Mesoscale

Table 1
Wind speed/power forecasting categorization based on approach.

Approach	Input	Examples
Physical [3,6,10,8]	Meteorological data	NWP, ECMWF, NCEP
Statistical [3,6,10,8]	Historical data	ARIMA, Kalman filter
CI-based [6]	Historical data	ANN, FNN, SVM
Hybrid [3,8]	Historical data	ARIMA-ANN, ARIMA-SVM
Spatial correlation [10]	Historical and geographical data	ANN, FNN, NWP

3. Literature review

This section reviews some state-of-the-art ensemble forecasting methods according to two categories: competitive ensemble forecasting and cooperative ensemble forecasting.

3.1. Competitive ensemble forecasting

Competitive ensemble forecasting approach uses multiple predictors constructed with slightly different initial conditions or different parameters that are able to construct individual forecast models to form an ensemble forecast model (multi-model ensemble). The forecasting results from all models or selected models after pruning are aggregated by averaging. The confidence level can be measured by the variations of the spread of individual results which are used during the averaging process [30].

Diversity is a key feature in competitive ensemble forecasting. If the base predictors return similar decisions, then there will be less improvement. In competitive forecasting, if the sub-tasks are similar, the outputs of base predictors will be similar and the performance improvement of the ensemble predictor will be marginal. For classification, diversity can be further categorized as data diversity, parameter diversity and kernel diversity [17,31,32]. Similar to classification, we categorize diversity into data diversity and parameter diversity for forecasting. Kernel diversity used in ensemble classification is not reported in the forecasting literature and it will be discussed as a future research direction.

A block diagram of competitive ensemble forecasting is shown in Fig. 1. There are two variations based on data diversity and parameter diversity. Some example competitive ensemble forecasting models are also listed in the figure and they are discussed in detail in the following subsections.

3.1.1. Data diversity

For data diversity-based competitive ensemble forecasting, more than one input datasets are fed into the forecasting system. There are two variations as shown in Eqs. (3) and (4). Eq. (3) represents a forecasting approach that applies N predictors $f_1(\cdot)\dots f_N(\cdot)$ for N input datasets $\mathbf{x}_1\dots\mathbf{x}_N$ and the final prediction is a weighted average of them all. Eq. (4) represents another forecasting approach that only employs a single predictor $f(\cdot)$ for N input datasets. The example competitive ensemble forecasting approaches are discussed in the following paragraphs:

$$\hat{y}(t+h)=\frac{1}{n}\sum_{i=1}^{N} w_i f_i(\mathbf{x}_i(t)) \tag{3}$$

$$\hat{y}(t+h)=f(\mathbf{x}_1(t),\dots,\mathbf{x}_N(t)) \tag{4}$$

where $\hat{y}$ is the predicted value and h is the forecast horizon.

A study on *solar* irradiance forecasting at Fontana, California during 2009–2010 was reported in [18]. A two-model competitive ensemble forecasting method was proposed: the first model predicted the solar irradiance using non-linear regression on meteorological data and the second model predicted the solar irradiance based on daily pattern recognition. The outputs of these two models were weighted and combined for 1-h and 3-h ahead forecasting. The authors compared their results with previously reported results and stated that the two-model competitive ensemble forecasting method had a smaller error than the errors of previously reported methods. The authors also proposed to use an adaptive learning method to update the models on a daily basis.

$$\text{Competitive Ensemble Forecasting}\begin{cases}\text{Data Diversity}\begin{cases}\text{Two-Model Competitive [18]}\\ \text{Bagging [19]}\\ \text{AdaBoost [20, 21]}\\ \text{Spatial Correlation [22, 23, 24]}\end{cases}\\ \text{Parameter Diversity}\begin{cases}\text{Ensemble Predictor [25, 26, 27]}\\ \text{Multi-Scheme [28]}\\ \text{Ensemble Kalman Filter [29]}\end{cases}\end{cases}$$

Fig. 1. Block diagram of competitive ensemble forecasting methods.

Bootstrap aggregation (Bagging) is a popular method for data diversity [33]. Bagging has two phases: the bootstrap phase to sample the original dataset with replacement to obtain N datasets and the aggregating phase to combine the outputs of N base predictors trained by each dataset by averaging. In [19], a bagging ANN model was introduced for short-term *solar* irradiance forecasting. The bagging ANN model consists of three different types of ANNs: MLP, radial basis function ANN (RBFNN) and recurrent neural network (RNN) with historical data after bootstrapping. The data used were from Japan Meteorological Agency during 2007–2008. The results showed that the error measures of the bagging ANN models were smaller than those of single MLP, RBFNN and RNN.

Adaptive boosting (AdaBoost) is an extension of bagging [34]. It first applies bagging to create a collection of datasets, introducing data diversity. Then it sequentially trains the predictor with the datasets, and at each iteration, AdaBoost assigns higher weights to the data points with larger error and smaller weights to the data points with smaller error. AdaBoost can boost the prediction accuracy of weak predictors. Some AdaBoost based ensemble methods are AdaBoost-ANN [20] and EMD-AdaBoost-ANN [21] for short-term wind speed forecasting.

The above-mentioned forecasting approaches follow Eq. (3) because there are multiple predictors associated with multiple datasets. In the following paragraphs, approaches reflecting Eq. (4) are discussed.

To forecast the *wind* speed of a certain location, historical wind speed data of the location and the neighborhood locations are required for spatial correlation based forecasting. Compared with single location forecasting, spatial correlation based forecasting improves the accuracy with different input data and the corresponding location information, i.e. the data are diversified spatially. Therefore, spatial correlation based forecasting achieves competitive ensemble prediction by data diversity. Spatial correlation based forecasting is advantageous over single location based forecasting because it takes terrain and other geographical variations into account and reduces the error of prediction, which is known as the spatial smoothing effect [10].

For *solar* irradiance forecasting, spatial correlation is widely used. A spatial correlation-based method called total satellite image (TSI) is usually used [16] in short-term forecasting. The images of sky are taken by satellites with different spatial and temporal coordinates. In [22], an ANN based spatial correlation solar irradiance predictor was implemented with 17 geographical and meteorological datasets in Turkey from 2000 to 2002. The purpose is to determine the solar energy potential of Turkey. The authors selected 11 stations to train the ANNs and the remaining 6 stations were used for testing the performance of the trained ANNs. Finally, the predicted data from each station formed a monthly solar potential map. A spatial correlation-based fuzzy expert system was reported in [23] for *wind* speed forecasting. The forecasting time horizon was up to several hours. The authors employed two genetic algorithms for selecting the optimal parameters. The authors expanded the research to a spatial correlation Takagi–Sugeno–Kang (TSK) fuzzy model [35] with wind speed and direction as the inputs to the model. The wind speed and direction data were collected within 30 km of the wind parks for analysis. Two wind parks in Greece were used for evaluation: Thessaloniki Gulf and Crete. 30, 60, 120 and 240-min ahead forecasting was implemented and the performance of the spatial correlation fuzzy model was found to be better than the persistent model.

A local RNN with three *wind* speed measuring stations in Gulf of Thessaloniki, Greece was presented in [24]. A recurrent infinite impulse response MLP (IIR-MLP) was the forecasting model and the inputs were the wind speeds at the three stations. Compared with finite impulse response MLP (FIR-MLP), diagonal RNN (DRNN) and ARMA, IIR-MLP had superior performances with either global recursive prediction error (GRPE) or decoupled recursive prediction error (DRPE) training algorithm.

3.1.2. Parameter diversity

Parameter diversity approach varies the parameters $\boldsymbol{\theta}_1 \ldots \boldsymbol{\theta}_N$ of a predictor to produce N predictors $f_1(\cdot)\ldots f_N(\cdot)$ and each predictor will learn from the same dataset $\mathbf{x}$. The predicted value $\hat{y}$ is obtained by averaging the outputs of all predictors as shown in Eq. (5).

$$\hat{y}(t+h) = \frac{1}{N}\sum_{i=1}^{N} f_i(\mathbf{x}(t), \boldsymbol{\theta}_i) \tag{5}$$

where $\hat{y}$ is the predicted value and h is the forecast horizon.

Two centers, namely European Center for Medium-Range Weather Forecasts (ECMWF) and National Centers for Environmental Prediction (NCEP), used competitive ensemble forecasting methods since 1990s for long-term and long-range weather forecasting [25,36]. Their ensemble forecasting methods are widely used for *wind* speed/power forecasting. The ensemble forecasting methods comprise several numerical predictions integrated from different initial conditions. The initial conditions represent different initial uncertainties of the meteorological analysis. Both ECMWF and NCEP use perturbation theory for creating the initial conditions. ECMWF uses singular vectors to construct initial perturbations for maximum perturbation growth rate during the first two days [26] whereas for NCEP, breeding vectors are used to construct initial perturbations because breeding perturbation can compensate the accumulated growing errors [26,36,27]. Detailed information on singular vector perturbation and breeding vector perturbation is reported in [26,37].

Pinson and Hagedorn [38] verified the ECMWF ensemble predictor with 2010 Europe *wind* speed data for 6-day ahead forecasting. The forecasting results were compared with the observations from stations over the European continent and the authors concluded that in order to obtain a good forecast, horizontal resolution of the wind speed data is critical, and the reliability and skill of the ensemble predictor should be further improved.

A multi-scheme ensemble forecasting method was reported in [28]. Multiple predictors were constructed from numerical weather prediction (NWP) model with modified physical parameters. The reported multi-scheme ensemble forecasting method was tested on *wind* speed data obtained from the UK and Ireland for 48 h ahead forecasting. The results showed that the reported method has smaller MAE and RMSE than single forecasting and forecasting with simpler training methods [28].

Kalman filter is a sequential data assimilation algorithm for solving non-linear problems. Kalman filter is suitable for noisy data and data with inaccuracies [39]. Kalman filter estimates the data in a recursive manner: prediction and updating. In the prediction stage, Kalman filter estimates a current state vector containing one or more state variables with their probabilities and in the updating stage, it updates the state vector with a weighted average and proceeds to the next time step. Due to its recursive nature, Kalman filter can run in real time without additional past information.

Ensemble Kalman filter (EnKF) [29] is an ensemble version of Kalman filter. Each ensemble member ϕ (state vector) is a vector of computed wind speed, parameters and historical wind speed. Kalman filter then updates the state vector recursively until a certain termination condition is fulfilled. In [29], the authors introduced a two-stage ARIMA–EnKF for *wind* speed forecasting. Firstly, ARIMA(3, 1, 0) was employed to model the wind speed time series (January 2008, NDBC site 41002). Secondly, a state vector was formed by concatenating the coefficients of the ARIMA model, the current wind speed and the historical wind speed. Finally, EnKF used the ensemble state vectors with slightly varying parameters for forecasting. The result showed that ARIMA–EnKF had smaller RMSE and MAE than ARIMA alone.

Other variations of EnKF were also reported for wind speed/power forecasting such as reduced-rank extended Kalman filter, bred mode EnKF [39].

3.2. Cooperative ensemble forecasting

Cooperative ensemble forecasting divides a prediction task into several sub-tasks and solves each sub-task individually. The overall forecasting results are obtained by aggregating the forecast values of all predictors. A block diagram of cooperative ensemble forecasting is shown in Fig. 2. There are two variations: one is pre-processing and the other is post-processing. Typical approaches are listed in the figure. These two variations are discussed in the following subsections.

3.2.1. Pre-processing

Pre-processing is to divide the input dataset into several sub-datasets and each sub-dataset is modelled and predicted by a predictor. Usually the predictor is the same for all sub-datasets. The final prediction is a summation of all the outputs of the predictors.

A popular time series decomposition method called wavelet decomposition was reported in several literature [40,41]. Wavelet theory is to study the time series in frequency domain as well as time domain. Wavelet decomposition is to decompose the time series into a set of sub-series based on a mother wavelet that can be predicted more accurately [41]. There are two kinds of decompositions: continuous and discrete. For practical applications, discrete wavelet transform (DWT) is usually used for decomposition. The key equations of wavelet decomposition based forecasting are shown in (6).

$$\begin{aligned}
&\{\mathbf{x}_{D_i}(t), \mathbf{x}_{A_n}(t)\} = \mathrm{DWT}(\mathbf{x}(t))\\
&\hat{y}_{D_i}(t+h) = f(\mathbf{x}_{D_i}(t))\\
&\hat{y}_{A_j}(t+h) = f(\mathbf{x}_{A_j}(t))\\
&\hat{y}(t+h) = \sum_{i=1}^{n} \hat{y}_{D_i}(t+h) + \hat{y}_{A_j}(t+h)
\end{aligned} \tag{6}$$

where $\mathbf{x}$ is the original dataset, $\mathbf{x}_{D_i}$ is the ith detailed component, $\mathbf{x}_{D_i}$ is the ith detailed component, $\mathbf{x}_{A_j}$ is the jth abstract component, h is the forecast horizon, $\hat{y}$ is the predicted value and $f(\cdot)$ is the predictor.

In [40], a number six Daubechies wavelet was used for the discrete wavelet decomposition. After decomposition, there were three detailed decompositions ($\mathbf{x}_{D_i}(t),\ i=1,2,3$) and one approximated decomposition ($\mathbf{x}_{A_3}(t)$). ARIMA was selected to be the

$$\text{Cooperative Ensemble Forecasting}\begin{cases}\text{Pre-processing}\begin{cases}\text{Wavelet Decomposition [40, 41, 42, 5]}\\ \text{EMD [43, 44, 45]}\\ \text{Complex Value [46, 47]}\end{cases}\\[2ex] \text{Post-processing}\begin{cases}\text{ARIMA-CI [48, 49]}\\ \text{SVR-SVC [50]}\\ \text{Multi-Stage [51]}\end{cases}\end{cases}$$

Fig. 2. Block diagram of cooperative ensemble forecasting methods.

predictor for each sub-series. Finally the forecast results were aggregated to obtain the final result. The reported wavelet-ARIMA model was evaluated with 3, 5, and 10-h ahead *wind* speed forecast, and the performance was better than the conventional ARIMA method.

A Wavelet-Particle Swarm Optimization (PSO)-ANFIS approach was introduced in [41]. The authors also used Daubechies wavelet to decompose the *wind* speed time series into 4 layers (sub-series) and the authors used ANFIS as the predictor for forecasting. In addition, the authors also proposed to use PSO to find the optimal parameters of ANFIS. The reported forecasting model was tested on a Portugal wind power time series, 2007–2008 for a 3-h ahead forecasting. Compared with seven other models, the result of the wavelet-PSO-ANFIS was the best.

Haque et al. [42] reported a wavelet-fuzzy predictive adaptive resonance theory (ARTMAP) network for *wind* power forecasting. Fuzzy ARTMAP can be a supervised or unsupervised learning model. It is able to learn without forgetting. Compared with conventional fuzzy neural network (FNN), fuzzy ARTMAP has adaptive learning ability, dynamic neuron updating for long term memory, fast and stable learning. The authors employed Mallat's multi-resolution analysis to decompose the input dataset into 3 level sub-datasets. The results showed daily, weekly and monthly forecasts for Kent Hill wind farm, New Brunswick Canada. Compared with eight algorithms, the error measures of the wavelet-fuzzy ARTMAP showed a great improvement.

Cao and Cao [5] presented a wavelet recurrent backpropagation network (RBPN) for *solar* irradiance forecasting. The RBPN is a dynamic ANN that has the option to feedback the outputs totally or partially. The dataset used was from Baoshan Meteorological Station, Shanghai during 1995–2000. The wavelet used was number seven Daubechies wavelets. The authors used cut-and-trial method [5] to determine the number of hidden neurons of a 3-layer RBPN. The results showed that for one-day ahead forecasting, the proposed wavelet RBPN outperformed the RBPN without wavelet decomposition.

Empirical mode decomposition (EMD) is another time series decomposition method [52]. Unlike wavelet decomposition, it decomposes a time series based on the time domain only without a deterministic function (as mother wavelet in wavelet decomposition). The decomposed time series then undergoes the similar procedures as in wavelet decomposition.

In [43,44], the authors proposed to firstly decompose the wind speed time series followed by extracting and forming feature sets from the decomposed data. Then the feature sets were used to train a k-nearest neighbor (kNN) and SVR, respectively. In [45], the authors proposed to use an ensemble version of EMD called complete ensemble EMD with adaptive noise to decompose the wind speed time series data and train ANN and SVR with the decomposed data. The EMD based forecasting methods outperformed the forecasting methods without decomposition.

If wind speed and wind direction are considered as complex numbers, it is possible to convert complex valued wind speed time series from polar form ($|\text{speed}|\angle\text{direction}$) to Cartesian form ($Re+jIm$). The key equations of complex value transformation based forecasting are shown below:

$$\mathbf{a}(\mathbf{t})+j\mathbf{b}(\mathbf{t})=\mathbf{x}(\mathbf{t})\angle\boldsymbol{\theta}(\mathbf{t})$$

$$\hat{y}(t+h)\angle\hat{\theta}(t+h)=f_{Re}(\mathbf{a}(t))+jf_{Im}(\mathbf{b}(t)) \tag{7}$$

where $\mathbf{x}$ is the wind speed magnitude, θ is the wind direction, $\mathbf{a}$ and $\mathbf{b}$ are the real and imaginary part of the wind vector, $f_{Re}(\cdot)$ and $f_{Im}(\cdot)$ are the prediction functions for real and imaginary parts, respectively, $j=\sqrt{-1}$, h is the forecast horizon, $\hat{y}$ and $\hat{\theta}$ are the predicted magnitude and direction, respectively.

Goh et al. [46] presented a complex-valued estimation of *wind* power with a complex-valued real-time recurrent learning algorithm and a pipelined RNN (PRNN). The learning algorithm used a gradient search technique for both real part and imaginary part to update the parameters of the PRNN. The authors claimed that since wind speed and wind direction are highly correlated, complex-valued estimation is advantageous over wind speed-only estimation. In addition, RNN was claimed to be suitable for non-linear and non-stationary signals due to its nonlinear dynamical feature. The PRNN was used to model a wind speed/direction time series from Iowa with 1-min average. However, in this paper, no forecast is done other than model estimation.

In [47], a complex valued neural network (CVNN) was employed for *wind* speed forecasting. CVNN is similar to real valued neural network (RVNN) but it can handle complex valued data without introducing two RVNNs for real part and imaginary part separately. The authors used CVNN for 24-h ahead forecasting of a wind speed/direction data from Japan Meteorological Agency during 2009 and compared with RVNN, the MAPE was smaller for every month.

3.2.2. Post-processing

A time series data may have more than one characteristics and each characteristic is suitable for one particular method. For example, ARIMA model is suitable for modelling linear time series and ANN is more preferred for modelling non-linear time series. Forecasting the time series consecutively by two or more predictors is considered as cooperative ensemble forecasting based on post-processing.

There are several cooperative ensemble forecasting models based on post-processing reported in the literature, such as ARIMA–GARCH [48], ARIMA–ANN, ARIMA–SVM [49] and SVR–SVC [50].

ARIMA is a linear time series model that models and forecasts general time series. Generalized auto-regressive conditional heteroscedasticity (GARCH) is a non-linear model that models the dynamic variance of the residuals after linear regression. As shown in Eq. (8), ARIMA firstly models the linear portion of the time series and then the residual ϵ is modelled by a GARCH function.

$$\hat{y}(t+1)=\text{ARIMA}(x(t),\ldots,x(t-p+1))+\epsilon(t)$$

$$\epsilon(t)=z(t)\delta(t),\quad z(t)\sim\mathcal{N}(0,1)$$

$$\delta(t)^2=\text{GARCH}(\delta^2(t-1),\ldots,\delta^2(t-a),\\ \epsilon^2(t-1),\ldots,\epsilon^2(t-b)) \tag{8}$$

where $\hat{y}$ is the predicted value, ϵ is the residual, δ is the standard deviation, p is the order of the AR term in the ARIMA model, a and b are the orders of the δ^2 and ϵ^2 terms, respectively.

In [48], an ARIMA–GARCH model was presented. However, before applying the model, the *wind* speed time series was converted into stationary and normally distributed by one step differencing and Weibull cumulative distribution function (CDF) fitting. Two wind speed time series prediction models namely ARIMA(1,1,4)–GARCH(1,1) and ARIMA(1,0,1)–GARCH(1,1) were used. Although the objective of this paper was to find a proper model for wind speed modelling, extension on forecasting is possible by applying the models to the testing data.

Several ARIMA–ANN and ARIMA–SVM models were reviewed in [49] which focused on reviewing the hybrid forecasting approaches. As stated in the paper, ARIMA is a robust and the most widely used model for linear time series whereas ANN and SVM are the typical CI tools for non-linear time series regression.

A *wind* speed/power time series y_t can be decomposed into two parts: a linear part l_t and a non-linear part n_t. Firstly, the linear part can be modelled by ARIMA. Secondly, a CI model $f(\cdot)$ is applied to the residuals after ARIMA fitting to model the non-linear part. Finally, the two modelled parts are added together to obtain the final predicted result $\hat{y}_t$.

$$\hat{l}(t) = \text{ARIMA}(\mathbf{x}(t))$$

$$e(t) = x(t) - \hat{l}(t)$$

$$\hat{n}(t) = f(\mathbf{e}(t))$$

$$\hat{y}_t = \hat{l}_t + \hat{n}_t \tag{9}$$

where e is the residual from the linear prediction and $\hat{n}$ is the predicted value from the CI predictor on the residual.

In [49], a 2-year hourly *wind* speed dataset from an observation site in Colorado, US during 2005–2007, was used to evaluate ARIMA–ANN and ARIMA–SVM against ARIMA, ANN and SVM models with 1, 3, 5, 7 and 9 step ahead forecasting. However, there is no significant improvement from ARIMA to ARIMA–ANN/ ARIMA–SVM for wind speed forecasting.

In [53], an ARMA–time delay neural network (TDNN) model was reported. The authors firstly used several statistical de-trending methods to generate a stationary *solar* irradiance time series and then they used ARMA to predict the linear part of the time series and TDNN to predict the non-linear part. Finally they combined the two predicted results for the final prediction. The author compared the hybrid ARMA–TDNN model with single ARMA and TDNN models and the results showed a smaller normalized RMSE (NRMSE) due to the hybrid model.

A *wind* speed forecasting tool based on SVM regression (SVR) and SVM classification (SVC) was reported in [50]. It is a two-stage forecasting with SVR as the main predictor and SVC as the post-processing tool. A time series was firstly modelled by an SVR to obtain the predicted output $\hat{s}_t$ as well as the residuals e_t. Then the residuals e_t are classified by an SVC into one of three possible classes: $(-\infty, -\epsilon]$, $(-\epsilon, +\epsilon)$, and $[+\epsilon, +\infty)$ based on a user defined threshold ϵ. Thirdly, a compensation mapping from the residuals e_t to an offset ω is established such that

$$\hat{y}(t+h) = \begin{cases} \hat{s}(t) + \omega & e(t) \le -\epsilon \\ \hat{s}(t) & -\epsilon < e(t) < +\epsilon \\ \hat{s}(t) - \omega & e(t) \ge +\epsilon \end{cases} \tag{10}$$

The authors used a three-year hourly wind speed dataset to test the model against SVR [50]. The reported model had smaller MSE and MAPE than the SVR model. However, the user defined threshold ϵ and the offset ω were not clearly defined and it is dataset dependent.

For *solar* irradiance forecasting, a multi-stage ANN was reported in [51]. There were three stages: (i) first stage forecasts the average atmospheric pressure based on the historical average atmospheric pressure data, (ii) second stage forecasts the irradiance level based on the output of the first stage and (iii) third stage forecasts the solar irradiance based on the output of the second stage as well as the historical meteorological data. This multi-stage ANN was applied to forecast the heat pump water supply system rather than a PV system. The results showed a reasonable improvement compared with a single-stage ANN.

4. Results and discussion

In this section, selected ensemble forecasting methods are evaluated with wind speed/power and solar irradiance time series data. Firstly the results reported from selected literature are summarized and compared and secondly three selected ensemble forecasting methods are evaluated with four wind speed time series datasets and four solar irradiance time series datasets and their performance is compared and discussed.

4.1. Metrics to assess forecast error

The performance of the predictors is measured by various error measures, they are summarized in Table 5. The smaller the error measures, the better the performance of the predictor.

4.2. Performance comparison based on results in the literature

Various ensemble forecasting methods are reviewed in the above sections. The applications of the methods are on wind speed/power forecasting and solar irradiance forecasting. Although the methods can be categorized into competitive ensemble forecasting and cooperative ensemble forecasting, the performance cannot be clearly differentiated due to the unique characteristics of the datasets. Tables 6 and 7 show the detailed results of some selected ensemble methods.

As shown in Table 6, the forecasting horizons for wind speed/ power of the selected reviewed methods fall into the short-term to mid-term categories according to Table 2 except for the Multi-scheme model [28] which is a long-term forecasting model. The forecasting horizons for solar irradiation in Table 7 of the selected reviewed methods are all 1 day ahead which is mid-term forecasting according to Table 4.

The selected competitive ensemble wind speed/power forecasting methods for review are from [35,28,29]. The remaining selected methods [41,47,49,50] belong to cooperative ensemble wind speed/power forecasting category. The selected solar irradiance forecasting methods also have both competitive ensemble forecasting methods such as [18,19] and cooperative ensemble forecasting methods such as [5,51].

The ensemble forecasting methods generally outperformed the best alternative methods. The only exception is that the ARIMA–ANN/SVR for wind speed/power forecasting [49] did not outperform the ARIMA model.

Competitive ensemble forecasting methods usually require a larger number of datasets or a larger collection of parameters for the predictor. Therefore, competitive ensemble forecasting requires superior computing power and computation time. In addition for competitive ensemble forecasting methods based on physical approaches, a large investment on meteorological stations is expected. However, competitive ensemble forecasting improves the forecasting accuracy by diversity. Competitive ensemble forecasting is usually used in mid-term and long-term forecasting.

Cooperative ensemble forecasting methods usually have lower computing power requirements than competitive ensemble forecasting methods because they do not need to model a large number of datasets from different stations or model one dataset using several parameter sets. However, the forecasting time horizon of cooperative ensemble forecasting methods is usually

Table 5
Error measures table, y is the observed value, $\hat{y}$ is the predicted value and n is total number of samples.

Measure	Formula
NMSE	$\frac{1}{n}\sum_{i=1}^{n}\frac{\hat{y}_i - y_i}{y_i - \bar{y}}$
NMAE	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert\hat{y}_i - y_i\rvert}{\max(y_i)}$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
MRE	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert\hat{y}_i - y_i\rvert}{y_i}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
MSE	$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\lvert\frac{y_i - \hat{y}_i}{y_i}\rvert \times 100\%$
MASE	$\frac{\sum_{i=1}^{n}\lvert\hat{y}_i - y_i\rvert}{\frac{n}{n-1}\sum_{i=2}^{n}\lvert y_i - y_{i-1}\rvert}$

Table 6
Results summary of reviewed models forecasting on wind speed/power forecasting.

Methodology	Resolution	Horizon	Benchmark methods	Improvement[a]
Spatial correlation, fuzzy [35]	20, 10, 5 min	0.5, 1, 2, 4 h	Single site	3.02% (RMSE)
Multi-scheme [28]	1 h	48 h	Single-scheme	17.07% (MAE), 16.96% (RMSE)
EnKF [29]	10 min	10 min	ARIMA	9.49% (RMSE), 27.64% (MAE), 21.54% (MRE)
Wavelet-PSO-ANFIS [41]	15 min	3 h	ARIMA, wavelet-ANN, wavelet-fuzzy	15.67% (MAPE), 15.75% (NMAE)
CVNN [47]	1 h	24 h	RVNN, physical	36.96% (MAPE), 10% (MAE)
ARIMA-ANN/SVR [49]	1 h	1, 3, 5, 7, 9 h	ANN, SVR	0.1%–5.5% (RMSE, MAE)
SVR-SVC [50]	1 h	1 h	SVR	32.9% (MAPE), 33.3% (MSE)

[a] The improvement is based on the comparison between the reported method E_p and the best performed benchmark method E_b. Improvement $= \frac{E_b - E_p}{E_b} \times 100\%$.

Table 7
Results summary of reviewed forecasting models on solar irradiance forecasting.

Methodology	Resolution	Horizon	Benchmark methods	Improvement[a]
Non-linear regression and PR [18]	1 h	1, 3 h	Regression, ARIMA, ANN	40% (MRE, 1 h), 33.3% (MRE, 3 h)
Bagging ANN [19]	1 h	1 day	MLP, RBFNN, RNN	17.4% (MAE), 2.3% (MAPE)
Wavelet-RBPNN [5]	1 day	1 day	RBPNN	74.5% (MAE), 77.61% (MRE)
Multi-stage ANN [51]	1 day	1 day	ANN	17.43% (MAE)

[a] The improvement is based on the comparison between the reported method E_p and the best performed benchmark method E_b. Improvement $= \frac{E_b - E_p}{E_b} \times 100\%$.

shorter than competitive ensemble forecasting methods. Therefore, cooperative ensemble forecasting is mainly used for very-short-term or short-term forecasting.

4.3. Comparisons based on real wind and solar time series

We selected three ensemble methods to compare their performance based on two wind speed time series and solar irradiance time series datasets. The three ensemble methods are ARIMA-BP, Wavelet Transform-BP (WT-BP) and Bagging-BP. The wind speed time series dataset is obtained from National Data Buoy Center (NDBC) site 42,020 [54] during year 2011 which is averaged in 1 h interval. The dataset is rescaled to $[0, 1]$ interval. The evaluation datasets W1–W4 are sub-sampled from the original time series. For each evaluation dataset, the first 70% are used for training and the remaining 30% are used for testing. The forecasting horizons are 1, 3 and 5 h ahead. For wind speed forecasting, the three ensemble based forecasting methods were compared with two non-ensemble methods: ARIMA and BP. The parameters of ARIMA are shown in Table 8. The performance based on RMSE and MASE is tabulated in Table 9.

The solar irradiance time series dataset is obtained from National Solar Radiation Data Base (NSRDB) site 723,815 [55] during year 2008–2009 and it is averaged in 1 h interval. The dataset is rescaled to $[0, 1]$ interval. The evaluation datasets S1–S4 are sub-sampled from the original time series. For each evaluation dataset, the first 70% are used for training and the remaining 30% are used for testing. The forecasting horizons are 12, 18 and 24 h ahead. For solar irradiance forecasting, the three ensemble based forecasting methods were compared with two non-ensemble methods: seasonal moving average (SMA) and BP. The parameters of SMA are shown in Table 10. The performance based on RMSE and MASE is tabulated in Table 11.

As shown in Table 9, the ARIMA-BP outperformed ARIMA for 1, 3 and 5 h ahead forecasting. However, the ARIMA-BP did not outperform BP for 1 and 3 h ahead forecasting and only have a better performance on W3 dataset for 5 h ahead forecasting. Comparing WT-BP against BP, we can see that WT-BP had better performance than BP for 1 h ahead forecasting but equally good performance for 3 and 5 h ahead forecasting. Comparing Bagging-BP against BP, we can see that Bagging-BP outperformed BP for 1, 3 and 5 ahead forecasting on 3 out of 4 datasets in terms of RMSE

Table 8
Parameters of ARIMA model for wind speed forecasting, p is the order of AR term, d is the order of differencing, q is the order of MA term, ϕ is the coefficient of the AR term and θ is the coefficient of the MA term.

Dataset	p	d	q	ϕ	θ
W1	0	0	1	–	0.0129
W2	1	1	0	0.1324	–
W3	1	1	0	0.0272	–
W4	1	1	1	−0.997	0.989

Table 9
Comparison of five forecasting methods on wind speed forecasting.

Dataset	Horizon (h)	ARIMA	BP	ARIMA-BP	WT-BP	Bagging-BP
RMSE						
W1	1	0.256	0.072	0.107	0.051	0.062
3	0.250	0.095	0.131	0.081	0.103	
5	0.250	0.119	0.152	0.111	0.135	
W2	1	0.274	0.081	0.124	0.068	0.083
3	0.256	0.163	0.175	0.163	0.159	
5	0.257	0.192	0.231	0.208	0.187	
W3	1	0.193	0.069	0.077	0.064	0.061
3	0.187	0.109	0.116	0.074	0.097	
5	0.177	0.153	0.143	0.100	0.130	
W4	1	0.249	0.077	0.116	0.061	0.060
3	0.252	0.109	0.115	0.159	0.098	
5	0.250	0.128	0.167	0.152	0.122	
MASE						
W1	1	5.587	1.343	2.130	0.821	1.092
3	5.245	1.793	2.597	1.508	1.926	
5	5.032	2.203	2.925	2.108	2.489	
W2	1	4.161	1.171	1.921	0.915	1.209
3	4.118	2.438	2.893	2.500	2.463	
5	4.055	2.882	3.599	3.004	2.863	
W3	1	3.374	1.069	1.304	0.833	0.953
3	3.320	1.782	1.925	1.159	1.680	
5	3.105	2.673	2.478	1.597	2.333	
W4	1	4.660	1.341	2.113	0.957	1.031
3	4.826	1.867	2.075	2.501	1.630	
5	4.738	2.214	2.968	2.611	2.030	

Table 10
Parameters of SMA model for solar irradiance forecasting, q is the order of MA term, Q is the seasonality (SMA term), θ is the coefficient of the MA term and Θ is the coefficient of the SMA term.

Dataset	q	Q	θ	Θ
S1	1	24	0.482	−0.944
S2	1	24	0.510	−0.961
S3	1	24	0.322	−0.853
S4	1	24	0.598	−0.923

Table 11
Comparison of five forecasting methods on solar irradiance forecasting.

Dataset	Horizon (h)	SMA	BP	ARIMA-BP	WT-BP	Bagging-BP
RMSE						
S1	12	0.070	0.057	0.073	0.058	0.064
18	0.073	0.060	0.080	0.064	0.064	
24	0.071	0.076	0.077	0.099	0.068	
S2	12	0.061	0.040	0.069	0.032	0.045
18	0.052	0.047	0.066	0.042	0.045	
24	0.060	0.047	0.067	0.051	0.046	
S3	12	0.052	0.017	0.067	0.020	0.021
18	0.061	0.021	0.060	0.015	0.017	
24	0.056	0.022	0.056	0.027	0.018	
S4	12	0.036	0.030	0.045	0.025	0.028
18	0.035	0.030	0.039	0.032	0.032	
24	0.039	0.034	0.039	0.038	0.038	
MASE						
S1	12	1.666	1.339	1.782	1.247	1.461
18	1.626	1.319	2.044	1.505	1.531	
24	1.562	1.751	1.871	2.407	1.510	
S2	12	1.794	1.158	2.048	0.856	1.217
18	1.498	1.337	2.061	1.186	1.221	
24	1.674	1.330	1.949	1.470	1.329	
S3	12	2.624	1.081	3.969	1.240	1.200
18	3.606	1.387	3.566	1.056	1.138	
24	3.044	1.439	3.196	1.781	1.175	
S4	12	1.211	0.965	1.684	0.781	0.893
18	1.295	1.007	1.443	1.080	1.048	
24	1.356	1.151	1.420	1.262	1.103	

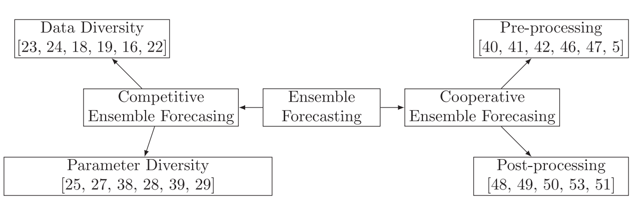

Fig. 3. Block diagram of ensemble methods for wind and solar power forecasting.

and MASE except that for 3 h ahead forecasting, bagging-BP had equally good performance as BP according to MASE.

For wind speed forecasting, the cooperative ensemble method ARIMA-BP significantly outperformed ARIMA which is different from the conclusion drawn in [49]. The competitive ensemble method bagging-BP outperformed BP for all forecasting horizons tested. The cooperative ensemble method WT-BP had better performance for shorter forecasting horizon than BP but a significantly drop in performance when the forecasting horizon increases.

As shown in Table 11, ARIMA-BP underperformed SMA for 12, 18 and 24 h ahead solar irradiance forecasting and ARIMA-BP also underperformed BP for all forecasting horizons. WT-BP had better performance for 12 h ahead forecasting than BP but equally good performance for 18 h ahead forecasting yet worse performance than BP for 24 h ahead forecasting. We can infer that WT-BP is more suitable than BP for shorter horizon forecasting. Bagging-BP outperformed BP for 24 h ahead forecasting on all 4 datasets but underperformed BP for 12 h ahead forecasting on 3 out of 4 datasets and had similar error measures as BP for 18 h ahead forecasting. It showed that bagging-BP has better performance than BP for longer horizon forecasting.

For solar irradiance forecasting, the cooperative ensemble method ARIMA-BP did not outperform ARIMA as in [49]. The competitive ensemble method bagging-BP outperformed BP for longer forecasting horizon. The cooperative ensemble method WT-BP had better performance for shorter forecasting horizon than BP.

5. Conclusion and future work

This paper reviewed recently published articles on wind speed/power forecasting and solar irradiance forecasting by using ensemble methods. The ensemble forecasting methods are categorized into two main categories: competitive ensemble forecasting and cooperative ensemble forecasting. The competitive ensemble forecasting has been further categorized based on data diversity and parameter diversity. The cooperative ensemble forecasting has been divided according to pre-processing and post-processing. A block diagram of ensemble methods for wind and solar power forecasting is shown in Fig. 3. Typical articles have been discussed according to each category. The performance of the ensemble forecasting methods has been summarized and the results have shown that the ensemble forecasting methods in general have outperformed the non-ensemble methods.

The authors have also evaluated three ensemble forecasting methods with real wind speed and solar irradiance datasets and concluded that the competitive ensemble forecasting method (Bagging-BackPropagation as evaluated) had better performance on longer forecasting horizon and the cooperative ensemble forecasting method (Wavelet Transform-BackPropagation as evaluated) had better performance on shorter forecasting horizon for both wind speed and solar irradiance forecasting.

5.1. Future work

As mentioned in Section 3.1, there are three diversities for ensemble classification. But, only data diversity and parameter diversity are found to have been used in the literature. Kernel diversity is a possible future research topic which can be applied to ensemble SVR. For kernel-based predictors such as SVR, different kernel functions will result in different performances and thus diversity will be created.

Bagging is a popular method to create data diversity. However, it is challenging to aggregate the results from the predictors to interpret the final result. Therefore, possible future work on Bagging ensemble forecasting is to investigate on better aggregation methods and unbiased and efficient pruning of base predictors.

Another possible future work is on ensemble forecasting across different paradigms. The correlation across different renewable sources should be studied and when modelling one renewable source, the other correlated renewable sources can be imported as exogenous inputs.

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References

[1] Bremnes JB. A comparison of a few statistical models for making quantile wind power forecasts. Wind Energy 2006;9:3–11.
[2] Mellit A, Kalogirou SA. Artificial intelligence techniques for photovoltaic applications: a review. Prog Energy Combust Sci 2008;34:574–632.
[3] Soman S, 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 (NAPS2010), Arlington, TX; 2010. p. 1–8.
[4] Kalogirou SA. Artificial neural networks in renewable energy systems applications: a review. Renew Sustain Energy Rev 2001;5:373–401.
[5] Cao JC, Cao SH. Study of forecasting solar irradiance using neural networks with preprocessing sample data by wavelet analysis. Energy 2006;31(15):3435–45.
[6] Lydia M, Kumar S. A comprehensive overview on wind power forecasting. In: International power and energy conference (IPEC2010), Singapore; 2010. p. 268–73.
[7] Hill DC, McMillan D, Bell KRW, Infield D. Application of auto-regressive models to U.K. wind speed data for power system impact studies. IEEE Trans Sustain Energy 2012;3(1):134–41.
[8] Wu Y-K, Hong J-S. A literature review of wind forecasting technology in the world. In: IEEE Power Tech, Lausanne, Switzerland; 2007. p. 504–9.
[9] Costa A, Crespo A, Navarro J, Lizcano G, Madsen H, Feitosa E. A review on the young history of the wind power short-term prediction. Renew Sustain Energy Rev 2008;12:1725–44.
[10] Lei M, Shiyan L, Chuanwen J, Hongling L, Yan Z. A review on the forecasting of wind speed and generated power. Renew Sustain Energy Rev 2009;13 (4):915–20.
[11] Foley AM, Leahy P, McKeogh E. Wind power forecasting and prediction methods. In: International conference on environment and electrical engineering (EEEIC2010), Prague, Czech Republic; 2010. p. 61–4.
[12] Wang F, Mi Z, Su S, Zhao H. Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters. Energies 2012;5:1355–70.
[13] Mellit A, Eleuch H, Benghanem M, Elaoun C, Pavan AM. An adaptive model for predicting of global, direct and diffuse hourly solar irradiance. Energy Convers Manag 2010;51:771–82.
[14] Diagne HM, David M, Boland J. Solar irradiation forecasting: state-of-the-art and proposition for future developments for small-scale insular grids. In: American solar energy society national solar conference (SOLAR2012), Denver, CO; 2012.
[15] Kleissl J. Current state of the art in solar forecasting. In: California renewable energy forecasting, resource data and mapping. California Institute for Energy and Environment; 2010. p. A1–26.
[16] Heinemann D, Lorenz E, Girodo M. Forecasting of solar radiation. In: Dunlop E, Wald L, Suri M, editors. Solar resource management for electricity generation from local level to global scale. NY: Nova Science Publishers; 2006. p. 83–94.
[17] Opitz D, Maclin R. Popular ensemble methods: an empirical study. J Artif Intell Res 1999;11:169–96.
[18] Hall J, Hall J. Forecasting solar radiation for the Los Angeles basin—phase II report. In: American solar energy society national solar conference (SOLAR2011), Raleigh, NC; 2011.
[19] Chaouachi A, Kamel RM, Ichikawa R, Hayashi H, Nagasaka K. Neural network ensemble-based solar power generation short-term forecasting. World Acad Sci Eng Technol 2009;54:54–9.
[20] Wu J, Zhang B, Wang K. Application of adaboost-based bp neural network for short-term wind speed forecast. Power Syst Technol 2012;36(9):221–5.
[21] Ren Y, Qiu X, Suganthan PN. EMD based adaboost-BPNN method for wind speed forecasting. In: Proceedings of IEEE symposium on computational intelligence and ensemble learning (CIEL2014), Orlando, US; 2014.
[22] Sozen A, Arcaklýogcblu E, Ozalp M. Estimation of solar potential in Turkey by artificial neural networks using meteorological and geographical data. Energy Convers Manag 2004;45:18–9.
[23] Damousis I, Dokopoulos P. A fuzzy expert system for the forecasting of wind speed and power generation in wind farms. In: IEEE Power engineering society international conference on power industry computer applications (PICA2001); 2001. p. 63–9.
[24] Barbounis T, Theocharis J. Locally recurrent neural networks for wind speed prediction using spatial correlation. Inf Sci 2007;177(24):5775–97.
[25] Nielsen H, Nielsen T, Madsen H, Badger J, Giebel G, Landberg L, et al. Wind power ensemble forecasting. In: Proceedings of the 2004 global windpower conference, Chicago, Illinois; 2004.
[26] Magnusson L, Leutbecher M, Källén E. Comparison between singular vectors and breeding vectors as initial perturbations for the ECMWF ensemble prediction system. Mon Weather Rev 2007;136(11):4092–104.
[27] Kalnay E. Atmospheric modeling, data assimilation and predictability. UK: Cambridge University Press; 2007.
[28] Lang S. Wind energy forecasting in the Irish power system using a multi-scheme ensemble prediction system. Technical Report, University College Cork; 2007.
[29] Wei Z, Weimin W. Wind speed forecasting via ensemble Kalman filter. In: International conference on advanced computer control (ICACC2010), vol. 2, Shenyang, China; 2010. p. 73–7.
[30] Manousos P. Ensemble prediction systems. Technical Report, Hydrometeorological Prediction Center; July 2006.
[31] Ren Y, Suganthan PN. A kernel-ensemble bagging support vector machine. In: 12th international conference on intelligent systems design and applications (ISDA2012), Brunei; 2012.
[32] Ren Y, Suganthan PN. Empirical comparison of bagging-based ensemble classifiers. In: 15th international conference on information fusion (Fusion2012), Singapore; 2012. p. 917–24.
[33] Breiman L. Bagging predictors. Mach Learn 1996;24:123–40.
[34] Shrestha DL, Solomatine DP. Experiments with AdaBoost.RT, an improved boosting scheme for regression. Neural Comput 2006;18(7):1678–710.
[35] Damousis I, Alexiadis M, Theocharis J, Dokopoulos P. A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Trans Energy Convers 2004;19(2):352–61.
[36] Nielsen H, Madsen H, Nielsen T, Badger J, Giebel G, Landberg L, et al. Wind power ensemble forecasting using wind speed and direction ensembles from ECMWF or NCEP. Technical Report, Denmark Project PSO; 2005.
[37] Magnusson L, Källén E, Nycander J. Initial perturbations for ensemble forecasting. Nonlinear Process Geophys 2008;15:751–9.
[38] Pinson P, Hagedorn R. Verification of the ECMWF ensemble forecasts of wind speed against analyses and observations. Meteorol Appl 2012;19(4):484–500.
[39] Thomas M, Hamill TM, Steven L, Mullen, Chris Snyder, David P. Baumhefner, Zoltan Toth. Ensemble forecasting in the short to medium range: report from a workshop. Bull Amer Meteor Soc 2000;81:2653–2664, http://dx.doi.org/10.1175/1520-0477(2000)081 < 2653:efitst > 2.3.CO;2.
[40] Liu H, Tian H-Q, Chen C, Li Y-F. A hybrid statistical method to predict wind speed and wind power. Renew Energy 2010;35:1857–61.
[41] Catalão J, Pousinho H, Mendes V. Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in portugal. IEEE Trans Sustain Energy 2011;2(1):50–9.
[42] Haque AU, Mandal P, Meng J, Srivastava AK, Tseng T-L, Senjyu T. A novel hybrid approach based on wavelet transform and fuzzy ARTMAP network for predicting wind farm power production. In: IEEE industry applications society annual meeting (IAS2012), Las Vegas, NV, 2012. p. 1–8.
[43] Ren Y, Suganthan PN. EMD-kNN models for wind speed forecasting. J Power Energy Eng 2014;2(4):176–85.
[44] Ren Y, Suganthan PN, Srikanth N. A novel empirical mode decomposition with support vector regression for wind speed forecasting. IEEE Trans Neural Netw Learn Syst 2015;PP(99):1.
[45] Ren Y, Suganthan PN, Srikanth N. A comparative study of empirical mode decomposition-based short-term wind speed forecasting methods. IEEE Trans Sustain Energy 2015;6(1):236–44.
[46] Goh SL, Popovic D, Mandic D. Complex-valued estimation of wind profile and wind power. In: IEEE mediterranean electrotechnical conference (MELECON2004), vol. 3, Dubrovnik, Croatia; 2004. p. 1037–40.
[47] Kitajima T, Yasuno T. Output prediction of wind power generation system using complex-valued neural network. In: SICE annual conference (SICE2010), Taipei, Taiwan; 2010. p. 3610–3.
[48] Lojowska A, Kurowicka D, Papaefthymiou G, van der Sluis L. Advantages of ARMA-GARCH wind speed time series modeling. In: IEEE international conference on probabilistic methods applied to power systems (PMAPS2010), Singapore; 2010. p. 83–8.
[49] Shi J, Guo J, Zheng S. Evaluation of hybrid forecasting approaches for wind speed and power generation time series. Renew Sustain Energy Rev 2012;16:3471–80.
[50] Ji G-R, Han P, Zhai Y-J. Wind speed forecasting based on Support Vector Machine with forecasting error estimation. In: International conference on machine learning and cybernetics (ICMLC2007), vol. 5, Hong Kong; 2007. p. 2735–9.
[51] Kemmoku Y, Orita S, Nakagawa S, Sakakibara T. Daily insolation forecasting using a multi-stage neural network. Solar Energy 1999;66(3):193–9.
[52] Huang N, Shen Z, Long S, Wu M, Shih H, Zheng Q, et al. The empirical mode decomposition and Hilbert spectrum for nonlinear and nonstationary time series analysis. Proc R Soc Lond A 1998;454:903–95.
[53] Wu J, Keong CC. Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN. Solar Energy 2011;85(5):808–17.
[54] National data buoy center historical data, URL: 〈http://www.ndbc.noaa.gov/historical_data.shtmlhttp://www.ndbc.noaa.gov/historical_data.shtml〉; July 2012.
[55] National solar radiation data base. URL: 〈http://rredc.nrel.gov/solar/old_data/nsrdb/http://rredc.nrel.gov/solar/old_data/nsrdb/〉; February 2014.