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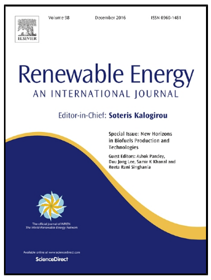

A Novel Hybrid Methodology for Short-term Wind Power Forecasting Based on Adaptive Neuro-fuzzy Inference System

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- Three individual intelligence models are used for short-term wind forecasting.
- A new data preprocess method based on Pearson correlation coefficients is proposed.
- A hybrid methodology based on adaptive neuro-fuzzy inference system is proposed.
- The proposed data preprocess method is prove to be effective.
- The proposed hybrid methodology presents a significant improvement in accuracy.

A Novel Hybrid Methodology for Short-term Wind Power Forecasting Based on Adaptive Neuro-fuzzy Inference System

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Abstract

With the increased penetration of wind power into the electric grid of China, many challenges emerge due to its fluctuation and intermittence. In this context, it is crucial to achieve higher accuracy of the short-term wind power forecasting for safe and economical operation of the power system. Hence, this paper proposes a novel hybrid methodology for short-term wind power forecasting, successfully combining three individual forecasting models using the adaptive neuro-fuzzy inference system (ANFIS). The backpropagation neural network (BPNN), radial basis function neural network (RBFNN), and least squares support vector machine (LSSVM) are selected as the individual forecasting models. A new data preprocessing method based on Pearson correlation coefficient (PCC) is also applied for selecting proper inputs for three individual models. Results obtained show the advancement of the PCC based data preprocessing method. Also, the comparison studies demonstrate that the proposed hybrid methodology presents a significant improvement in accuracy with respect to three individual models.

Keywords:
Short-term wind power forecasting, Pearson correlation coefficient, Neural network, Least squares support vector machine, Adaptive neuro-fuzzy inference system, Hybrid methodology.

1. Introduction

Wind power generation has experienced a rapid growth in recent years, with the global cumulative installed wind power capacity increasing from initial 6.1 GW in 1996 to 318.105 GW in 2013 [1]. As wind is inherently intermittent and stochastic, wind power is consequently fluctuating source of electric grids. The penetration of a large share of wind power in an electric grid presents some important challenges to electricity supply industry both technically and economically [2]. However, accurate wind power forecasting is considered as one of the most efficient ways to tackling these challenges [3, 4].

With the fast growth of Chinese wind sector in recent years, China has become the country with the most cumulative and new installed wind power capacity [5]. However, the giant wind power capacity outstrips the ability of the power grid and system operators to manage it effectively [1]. Due to the continuous growth of the installed wind power capacity in China, there is an increasing demand to develop new forecasting tools with enhanced accuracy.

Wind power forecasting approaches can be classified by time-scales and input variables. The prediction ranging from millisecond to seconds is intended for wind turbines control [6-8]. Time scales from minutes to several hours or even weeks are beneficial to improving the absorbing ability for increasing wind power penetration [9-13].

There are two schools for short-term prediction, i.e., physical method and statistical method. Physical method aims at estimating the wind power output by utilizing some physical variables such as local terrain, environmental temperature and numerical weather prediction (NWP), which provides the weather forecasts by solving complex mathematical models of atmosphere [14-18]. Statistical method tries to find the relationship between the wind power forecasts and historical time series of measured data. Traditional statistical models are persistence model, ARMA models, and Kalman Filter [19-21]. Also, artificial intelligence models e.g., backpropagation neural network (BPNN), radial basis function neural network (RBFNN), least squares support vector machine (LSSVM), adaptive neuro-fuzzy inference system (ANFIS) [22-26] have been widely applied based on the historical power series.

Basically, the statistical method can provide a better prediction accuracy for very short-term forecasting, whereas physical method outperforms the statistical method when the forecasting horizon increases to several hours even days [10, 17]. However, the process of obtaining the meteorological forecasts in physical method can act as the first step to forecast the wind power, i.e., the forecasted meteorological information is supplied as input to the statistical models [13, 21, 27].

A hybrid strategy based on the physical technique and statistical artificial neural network (ANN) model was proposed in [27] for short-term wind power prediction. In [27], artificial neural model (ANN) model was applied to forecast the output power of each wind generator with the inputs of the wind speed, wind direction, and temperature at the wind turbine hub height. Similarly, in this paper, these meteorological variables are also used as the basic input data for statistical artificial intelligence model to forecast the power of each wind generator, and the power of the whole wind farm can be summed. Compared with the prior advanced work in [27], two innovative contributions are included in this paper at the stage of statistical artificial intelligence model to improve the accuracy. Firstly, a new data preprocessing method based on Pearson correlation coefficient (PCC) is proposed to select the proper feature inputs for statistical artificial intelligence models from the basic input data, enhancing the mapping accuracy of these models. Three popular artificial intelligent models, i.e., BPNN, RBFNN, and LSSVM are employed as the individual statistical prediction models, respectively. It is shown that the RBFNN model has the highest accuracy in both the spring and summer seasons, whereas the BPNN model and LSSVM model perform best in the fall and winter seasons, respectively. In this context, to obtain the highest prediction accuracy for all seasons and further improve the accuracy, a novel hybrid methodology based on ANFIS is proposed in this paper. The forecasted power values of three individual models are combined by ANFIS, which could take advantages of each forecasts and output the final wind power forecast.

The proposed hybrid methodology is tested on a case study using real data from a wind farm located in Sichuan province, China. Considering the numerical weather prediction system is still under construction, the available actual meteorological data is used in replace of the forecasted meteorological data. To prove its improvement of forecasting accuracy, a through comparison study will take into account BPNN, RBFNN, LSSVM and the proposed hybrid methodology.

The rest of this paper is organized as follows. Section 2 presents the proposed methodology, followed by forecasting accuracy evaluation in Section 3. A practical case study is implemented in Section 4. Section 5 draws the final conclusions.

2. Proposed Methodology

The proposed novel hybrid methodology results from the innovative combination of the intelligent models. In this paper, BPNN, RBFNN, LSSVM are considered as individual statistical wind power forecasting models for each wind generator. The PCC based preprocessing method is embodied in the hybrid methodology as a part of input selection for individual models. The ANFIS model combines the forecasted wind power from these three individual forecasting models and outputs the final forecasted wind power for each wind generator, developing a mapping relationship of three individual forecasted power values to the final forecasted power. Historical dataset of three individual forecasted power values and real power is utilized to train the ANFIS model to make the final forecasted power more approximate to the real power.

2.1 Data preprocessing

The performance of the artificial intelligence models depends on their inputs and parameters. Correlation based methods have been applied to selecting the inputs for wind power forecasting models [28, 29]. In this paper, a new data preprocessing method based on Pearson correlation coefficient (PCC) is employed to select the proper types of inputs with fixed number of inputs. PCC is a statistical metric that evaluates the direction and strength of a linear relationship between two variables, which has been widely used in many fields of science [30-32]. PCC between two variables x and y is defined as

$$\rho(x,y) = \frac{E[xy]}{\sigma_x \sigma_y} \tag{1}$$

where $E[xy]$ is the cross-correlation between x and y, σ_x^2 and $\sigma_x^2$are the variances of the signals x and y, respectively.

Pearson correlation analysis is implemented for each wind generator to analyze the linear correlation between the weather variables and wind power output. Table 1 shows the PCC between each type of weather variable and wind power output WP_t for one selected wind generator, in 2012, where WS, WD, and T refer to wind speed, wind direction, and temperature at the wind turbine hub height, respectively.

Table 1
Pearson correlation analysis results.

Variable Type	WS	WD	T
X_t	0.869	-0.170	0.162
X_t^2	0.883	-0.171	0.161
X_t^3	0.901	-0.171	0.161

X_t: value at single time node *t*; $X_t^p = \sum_{i=1}^{p} \beta_i X_{t-i+1}$, $p = 2, 3$.

It can be seen from Table 1 that wind speed has high linear correlation with wind power output, while the correlation coefficients between wind direction, temperature and wind power output are very small, respectively. In addition, it is demonstrated that the correlation coefficient between the weighted mean value of wind speed data at more time nodes WS_t^p (p=2, 3) and the output power WP_t is greater than it between WS_t and WP_t. Note that the weighting factor β_i is determined by maximizing the correlation coefficient of X_t^p to the target power WP_t. On the other hand, there is no similar phenomenon for wind direction and temperature.

Under the above analysis, the inputs for three statistical individual models are selected as the weighted mean wind speed at three time nodes $\lambda_1 WS_t^3$, weighted wind direction $\lambda_2 WD_t$, and weighted temperature $\lambda_3 T_t$, where λ_i is defined by the PCC of the selected type of weather variable to the wind power output for each wind generator.

Table 2

Values of β for 8 wind turbines

Wind turbine	β_1	β_2	β_3
1	0.42	0.40	0.18
2	0.43	0.38	0.19
3	0.44	0.42	0.14
4	0.41	0.40	0.19
5	0.43	0.39	0.18
6	0.42	0.41	0.17
7	0.42	0.39	0.19
8	0.42	0.41	0.17

Table 3

Values of λ for 8 wind turbines

Wind turbine	λ_1	λ_2	λ_3
1	0.886	-0.127	-0.067
2	0.901	-0.170	0.162
3	0.831	-0.087	-0.038
4	0.896	-0.125	-0.085
5	0.887	-0.055	-0.030
6	0.861	0.201	-0.110
7	0.893	0.244	-0.102
8	0.784	-0.123	0.055

2.2 Back propagation neural network

The back propagation neural network (BPNN) has been a popular wind power forecasting model in recent years due to its recognized nonlinear mapping ability and strong self-learning ability [4]. The architecture of the BP network is shown in Fig. 1. The typical BP neural network consists of one input layer, one or more hidden layers and one output layer. The network's parameters i.e., the weights and biases, play a critical role in forecasting performance of the network [22]. The mapping relationship between the inputs and output is developed with the training dataset.

A three-layer BP neural network is selected in this paper. As shown in Fig. 1, the weighted mean wind speed $\lambda_1 WS_t^3$, wind direction $\lambda_2 WD_t$, and temperature $\lambda_3 T_t$ obtained from PCC based data preprocessing are considered as inputs. The forecast results of BP neural networks are 48-hour-ahead forecasted wind power series for each wind generator. The time resolution of the inputs and power is 15 minutes.

The BPNN based forecasting model is described in the following steps:

Step 1: Create a database with a set of historical meteorological variables and the corresponding wind power at the same time.

Step 2: Existing traditional data preprocessing method is first employed. The primitive data is processed in the same way described in [27], including deleting improper data and data normalization.

Step 3: Apply the proposed PCC based data preprocessing method, obtaining the input-output pairs divided into training set and testing set for individual models.

Step 4: Establish and train the BP neural network model using the NNET toolbox in Matlab.

Step 5: Obtain the forecasted wind power series output WP_t^b from the input data of testing set using the trained network.

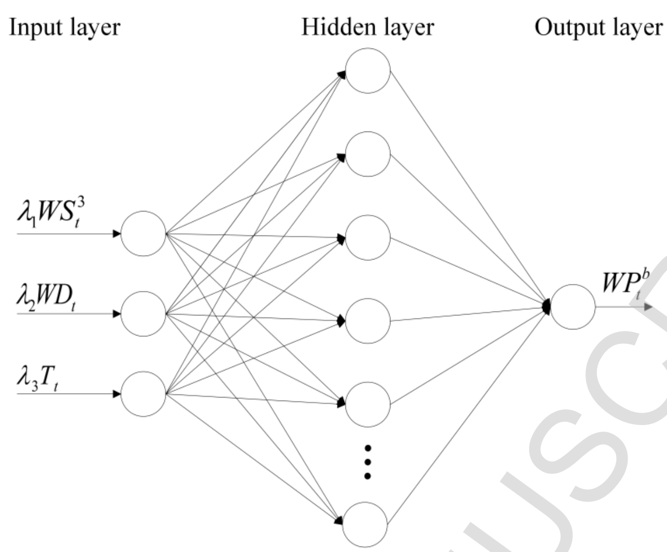

Fig. 1. Architecture of the BP neural network model.

2.3 Radial basis function neural network

The architecture of the RBF neural network (RBFNN) model is shown in Fig. 2. The hidden layer neurons of RBFNN use radial basis functions as activation functions, which differ RBFNN from other ANNs, and Gaussian function is selected as the radial basis function in this paper [22, 23]. The output of the hidden neurons H_j is computed according to the following equation:

$$H_j(x) = \exp\left(-\|x - c_j\|^2/\sigma_j^2\right) \tag{2}$$

where c_j and σ_j are the center and the width of the Gaussian potential function for the *j*-th neuron in the hidden layer, *x* refers to the input of the RBFNN model. Each output neuron of RBFNN computes the final output as the weighted summation of the hidden layer's outputs:

$$O_i = \sum_{j=1}^{N} \omega_{ij} H_j(x) + b_i \tag{3}$$

where O_i is the output of the i-th neuron in the output layer; ω_{ij} refers to the weight between the *j*-th neuron in the hidden layer and the *i*-th neuron in the output layer; $H_j(x)$ is the output of the *j*-th neuron in the hidden layer; and b_i is the bias of the *i*-th neuron in the output layer.

The procedures of the RBFNN based forecasting model are almost the same as BPNN except for the training step. Table 4 presents the training parameters of BPNN and RBFNN. The forecasted wind power series output WP_t^r are obtained from the RBFNN model.

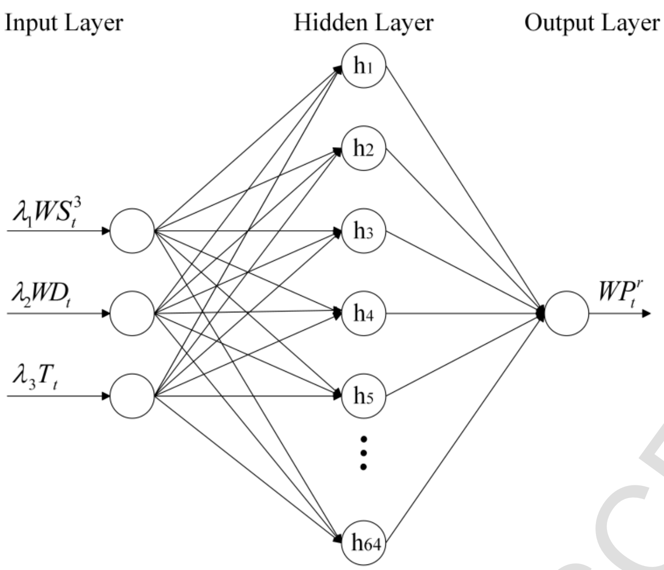

Fig. 2. Architecture of the RBFNN model.

Table 4

Training parameters selection for BPNN and RBFNN.

Model	Training parameters
BPNN	Backpropagation training function='trainlm', Number of neurons in hidden layer=9, Maximum epochs=500, Maximum validation failures=50, Learning rate=0.005, Training goal=0.0005
RBFNN	Training goal=0.0005, Spread of the radial basis function=1.0, Maximum number of neuros=64, training function='newrb', Maximum epochs=500

2.4 Least square support vector machines

SVM has been recognized as an efficient method for coping with problems of nonlinear classification, function estimation and regression [26]. Similar to other artificial intelligence models, the performance of SVM is influenced by the SVM configuration, including the inputs and parameters [33].

Least squares support vector machines (LSSVM) is used in this work due to its low computation complexity and high generalization capability [26]. The formulated quadratic programming problem is simplified into a linear problem without loss of its advantages in LSSVM, which distinguishes it from the standard SVM. It has been demonstrated by many benchmark datasets that the generalization performance of LSSVM is comparable to that of the standard SVM [34]. However, the computational expense of training LSSVM reduces significantly.

SVM converts a nonlinear regression (or classification) problem in the sample space into a linear regression (or classification) problem in the Hilbert space.

$$y = w^{\mathrm{T}}\varphi(x) + b \tag{4}$$

where *w* and *b* refer to the weight vector and bias term respectively. Given a set of training dataset $\{(\boldsymbol{x_i}, y_i)\}_{i=1}^{N}$, the optimal weight and bias term of the LSSVM can be determined by minimizing the cost function, which is defined by

$$\min R(\mathrm{w,e}) = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma\|e\|^2 \tag{5}$$

subject to

$$y_i = w^T\varphi(x_i) + b + e_i \quad i = 1,2,\ldots,N \tag{6}$$

The formulation of LSSVM model consists of equality rather than inequality constraints and takes into account a squared error loss function with regularization term similar to ridge regression.

Construct the Lagrangian

$$L(\boldsymbol{w},b,\boldsymbol{e},\alpha) = R\ (\boldsymbol{w},\boldsymbol{e}) - \sum_{i=1}^{N}\alpha_i(\boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + b + e_i - y_i) \tag{7}$$

where α_i are the Lagrange multipliers. According to the Karush-Kuhn-Tucker Theorem, the conditions of optimality are described as

$$\frac{\partial L}{\partial \boldsymbol{w}} = 0 \rightarrow \boldsymbol{w} = \sum_{i=1}^{N}\alpha_i\varphi(\boldsymbol{x}_i)$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{N}\alpha_i = 0$$

$$\frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma e_i$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + b + e_i - y_i = 0$$

After combining the above four equations, b and α can be solved by

$$\begin{bmatrix} 0 & 1_v \\ 1_v^{\mathrm{T}} & \boldsymbol{K} + \gamma^{-1}\boldsymbol{I} \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \tag{8}$$

where $1_v = (1,1,\ldots,1)$, $\boldsymbol{I}$ is the identity matrix, $\boldsymbol{y} = (y_1,y_2,\ldots,y_N)^{\mathrm{T}}$, $\boldsymbol{K} = (k(\boldsymbol{x}_i,\boldsymbol{x}_j))_{i,j=1}^{N}$ is the kernel matrix, and the kernel function is $k(\boldsymbol{x}_i,\boldsymbol{x}_j) = \varphi^{\mathrm{T}}(\boldsymbol{x}_i)\varphi(\boldsymbol{x}_j)$. Consequently, in terms of vectors $\boldsymbol{x}$ and $\boldsymbol{x}_i$, the output's estimation formula of LSSVM regression model becomes

$$y = \sum_{i=1}^{N}\alpha_i k(\boldsymbol{x},\boldsymbol{x}_i) + b \tag{9}$$

Also, typical Gaussian kernels is used in this work, which is defined as

$$k(\boldsymbol{x},\boldsymbol{x}_i) = \exp\ (-\|\boldsymbol{x}-\boldsymbol{x}_i\|^2/\sigma^2) \tag{10}$$

where $\|.\|$ means the 2-norm, and σ is a constant controlling the width of Gaussian kernel.

The input data of LSSVM is the same as BPNN and RBFNN. Therefore the procedures of data creation and process will not be described repeatedly. The procedures of implementing the LSSVM model are briefly described below.

Step 1: Configure the LSSVM model. The regularization parameter, γ, is selected as 16. Also, σ^2 of the Gaussian kernel function is determined as 0.01.

Step 2: Train the LSSVM model with the training dataset. The values of α_i and b in LSSVM are obtained directly via solving the linear equation (8).

Step 3: Extract the output of the LSSVM based on the input data of testing sample using the parameters trained from the previous steps, obtaining the forecasted wind power series WP_t^s.

2.5 Adaptive neuro-fuzzy inference system

ANFIS is a hybrid system combining neural network and fuzzy logics: NN has the capability of self-learning, which enables the fuzzy system auto-adjust accordingly with the proposed problem [24].

The architecture of five-layer ANFIS is shown in Fig. 3. Note that the inputs of the ANFIS model are the output forecasted power series from the individual models, i.e., BP neural network, RBF neural network and LSSVM model. The function of each layer of the ANFIS is briefly depicted as:

Layer 1 fuzzifies the inputs with the membership functions. Two membership functions are used for each input, and the membership functions for A, B, and C are chosen to be bell-shaped [25].

$$O_i^1 = \mu_{A_i}(x),\ i = 1, 2 \tag{11}$$

$$\mu_{A_i} = \frac{1}{1 + \left|\frac{x - r_i}{p_i}\right|^{2q_i}} \tag{12}$$

where x is the input of the ANFIS, O_i^j denotes the output of ith node in layer j, and $\{p_i, q_i, r_i\}$ are referred to as premise parameters.

Layer 2 is a rule layer and each node of which multiplies all the incoming signals and send the product out. Each node output represents the firing strength of a rule.

Layer 3 is the normalization layer. Each node computes the normalized firing strength based on the received inputs from all nodes of layer 2, i.e. calculating the ratio of a given rule's firing strength to the sum of all rules' firing strength [22].

In layer 4, each node is connected to the output of layer3 and all inputs of the ANFIS model. The output of each node in this layer represents the contribution of a given rule to the overall output.

$$O_i^4 = O_i^3\left(a_i WP_t^b + b_i WP_t^r + c_i WP_t^s + d_i\right) \tag{13}$$

where $\{a_i, b_i, c_i, d_i\}$ are referred to as consequent parameters.

Layer 5 is the output layer. The single node $\sum$ in this layer computes the overall output by summing all signals from layer 4 and therefore yield final wind power forecasts

$$WP_t^{final} = \sum_i O_i^4 \tag{14}$$

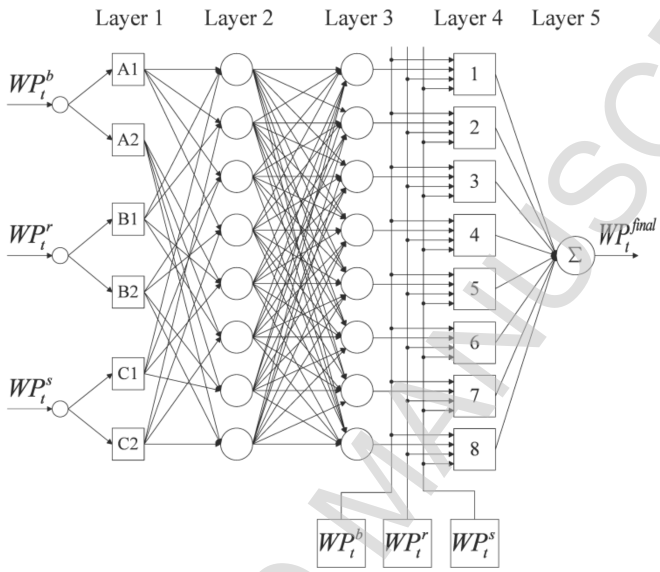

Fig. 3. Architecture of the ANFIS model

2.6 Hybrid methodology

The structure of the proposed hybrid methodology is illustrated in Fig. 4.

Theoretically, the hybrid methodology should embody the physical method that deduces the forecasted wind speed, wind direction and temperature at each wind turbine's hub height from the NWP data. However, considering the numerical weather prediction system is still under construction, the available real measured meteorological data at each wind turbine's hub height is employed to simulate the output forecasted meteorological information of the physical method.

The detailed procedure used to implement the hybrid methodology is described as in successive steps.

Step-1: Create a matrix with a set of real WS, WD, T, and WP data for each wind generator with the same time interval of 15 mins. The measured data was collected from the real wind farm dating from January to December of 2012.

Step-2: Select 48-hour-ahead prediction (192 power values).

Step-3: Delete improper data and normalize data.

Step-4: Implement the PCC based data preprocessing to select the inputs for the individual forecasting models. Then divide the input-output pairs into training set and testing set for the individual models.

Step-5: Train the individual forecasting models respectively using training data according to the corresponding procedures introduced in section 2.3-2.5. The training procedures of individual models are repeated every 30 days, which means their network parameters are updated based on new training dataset every 30 days.

Step-6: Obtain three forecasted wind power series of each wind generator respectively from the trained BP neural network, RBF neural network, and LSSVM model based on the input data in testing set.

Step-7: Divide the power dataset into training set and testing set for the ANFIS model, which consists of three forecasting wind power series from the individual models and the measured real wind power series. Train the ANFIS model using the training set. The least-squares method is applied to determine the consequent parameters in layer 4, and the backpropagation gradient descent method is employed to learn the premise parameters in layer 1. During the self-adaptive learning process, the ANFIS is allowed to adjust its parameters according to the input-output pairs submitted. It is essential for the ANFIS to generalize well when applied to new data. Thus very considerable training set should not be used during the learning process to avoid the overtraining, and it will be retrained every 120 hours considering its small computation cost of training process.

Step-8: Save all parameters of the trained ANFIS model. Obtain the final forecasted power series of each wind generator from the trained ANFIS model based on the input data in the testing set.

Step-9: The forecasted power series of the whole wind farm is given by adding up the final forecasted power series of all wind generators.

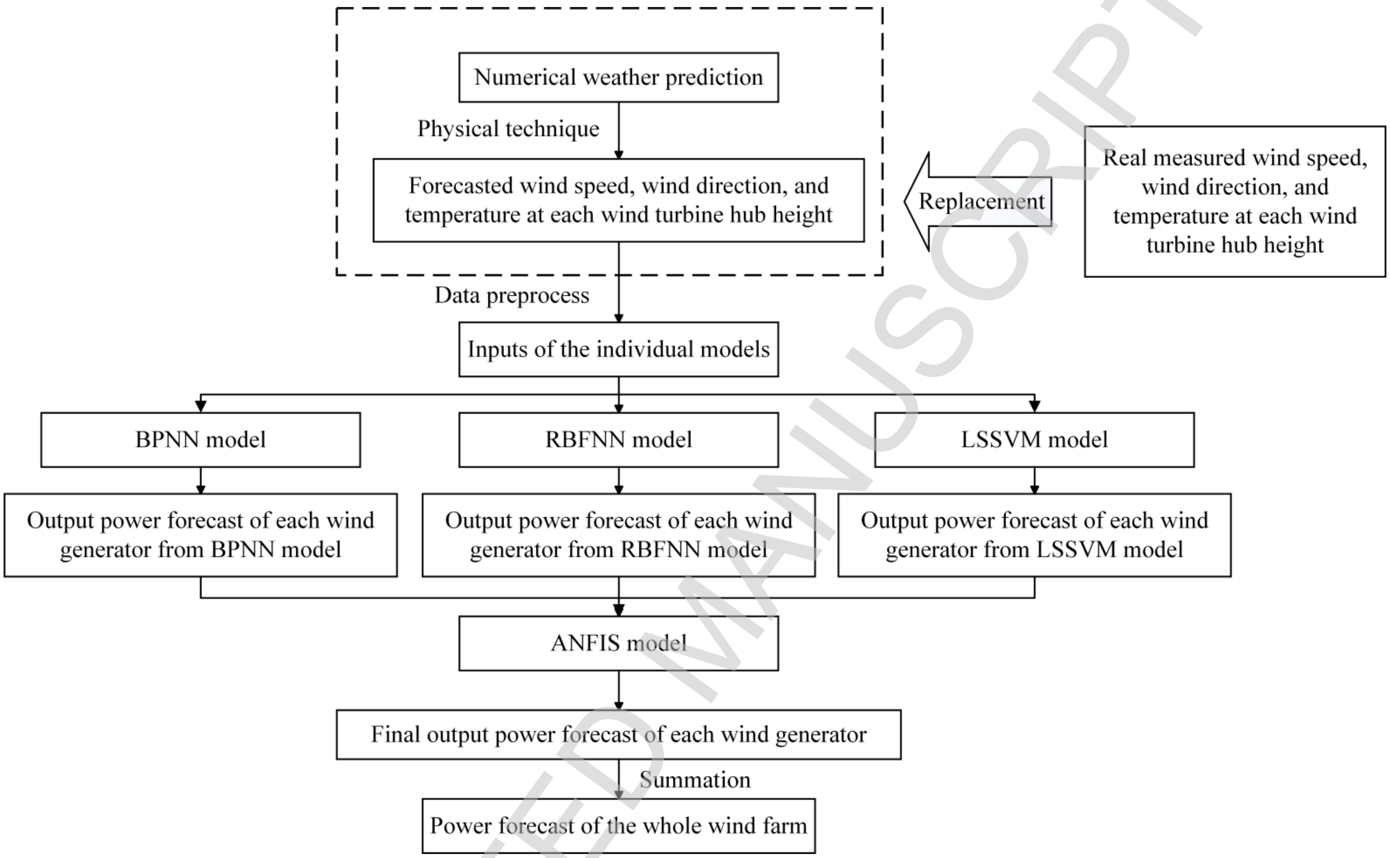

Fig. 4. Structure of the proposed hybrid methodology

3. Forecasting accuracy evaluation

To evaluate the accuracy of the forecasting models, three types of accuracy measures are computed.

The mean absolute percentage error (MAPE) criterion is given by

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{\left|WP_h - WP_h^{forecast}\right|}{\overline{WP}} \tag{15}$$

$$\overline{WP} = \frac{1}{N}\sum_{h=1}^{N} WP_h \tag{16}$$

where WP_h and $WP_h^{forecast}$ are the actual and forecasted wind power at period *h*, respectively; $\overline{WP}$ is the mean value for the forecast horizon; *N* is the number of forecasted periods.

Additionally, the normalized mean absolute error (*NMAE*) criterion is considered, defined as follows:

$$NMAE = \frac{100}{N}\sum_{h=1}^{N}\frac{\left|WP_h - WP_h^{forecast}\right|}{WP_{ins}} \tag{17}$$

where WP_{ins} refers to the installed wind power capacity.

Furthermore, the normalized root mean square error (*NRMSE*) is also taken into account, computed as

$$NRMSE = \frac{100\sqrt{\sum_{h=1}^{N}\left(WP_h - WP_h^{forecast}\right)^2}}{\sqrt{N}\cdot WP_{ins}} \tag{18}$$

4. Case study

The proposed hybrid methodology has been tested using the real data from a practical wind farm located in Sichuan province of China. There are 8 wind turbine generators in the wind farm. The rated installed capacity of an individual generator is 2 MW and the total installed capacity of the wind farm is 16 MW.

The BPNN, RBFNN, and LSSVM models predict 48-hour-ahead wind power values, taking into account the previous 60 days dataset consisting of wind speed, wind direction, temperature at each wind turbine hub height and the measured output power of the corresponding wind generator with a time interval of 15 mins. The PCC based data preprocessing is implemented for each wind turbine generator based on the training dataset to select the proper input for the individual models, which are retrained to update their parameters until the next 30 days actual wind power values are obtained.

The proposed hybrid methodology, combing the above three individual prediction models with ANFIS, therefore is also applied to predict the 48-hour-ahead wind power output. Power dataset $\{WP_t^b, WP_t^r, WP_t^s, WP_t\}$ of previous 240 hours with a time interval of 15 mins is considered as the training set of ANFIS. The training procedure of the ANFIS is repeated until the next 120 hours actual wind power values are obtained.

Firstly, in order to validate the effectiveness of the proposed data preprocessing method, a detailed accuracy comparison is implemented between individual models with the PCC based data preprocessing and the models without it, in which the wind speed WS_t, sine of wind direction $sin\,(WD_t)$, cosine of wind direction $cos\,(WD_t)$, and temperature T_t at each wind turbine hub height are used as the inputs.

It is concluded from Table 5-Table 7 that the PCC based data preprocessing presents a significant improvement in forecasting accuracy in four seasons for all individual models. With the introduction of the PCC based data preprocessing, the annual average MAPE values of BPNN, RBFNN, and LSSVM models decrease by 26.78%, 31.49%, and 21.67%, respectively. The annual average NMAE values of BPNN, RBFNN, and LSSVM models decrease by 25.98%, 28.00%, and 21.71%, respectively. Also, the annual average NRMSE values of BPNN, RBFNN, and LSSVM models decrease by 22.50%, 27.07%, and 14.20%, respectively.

Table 5
MAPE evaluation for the year of 2012

Season	PCC based data preprocessing	BPNN	RBFNN	LSSVM
Spring	Y	14.83	14.21	17.68
	N	18.23	18.88	22.44
Summer	Y	21.70	13.64	27.40
	N	28.53	25.01	33.38
Fall	Y	8.72	10.24	14.12
	N	13.38	13.94	19.66
Winter	Y	9.18	10.22	9.16
	N	14.20	12.69	11.73

Y: with PCC based data preprocessing; N: without PCC based data preprocessing.

Table 6
NMAE evaluation for the year of 2012

Season	PCC based data preprocessing	BPNN	RBFNN	LSSVM
Spring	Y	5.33	5.11	6.35
	N	6.55	6.79	8.07
Summer	Y	2.86	1.80	3.61
	N	3.76	3.29	4.40
Fall	Y	1.31	1.54	2.12

	N	2.01	2.09	2.95
Winter	Y	2.64	2.94	2.63
	N	4.08	3.65	3.37

An accuracy comparison is then implemented between the proposed hybrid methodology, (BRSA), and three individual forecasting models for the data of 2012, which is presented in Table 8.

For the sake of a fair comparison, the proposed PCC based data preprocessing is applied when carrying out all the forecasting models, i.e., BPNN, RBFNN, LSSVM, and BRSA. As is shown in Table 8, the accuracy comparison in all seasons between BPNN, RBFNN and LSSVM models shows inconsistent results. RBFNN model outperforms BPNN and LSSVM models in both spring and summer seasons, whereas BPNN model and LSSVM model perform best in the fall and winter seasons, respectively. In this context, it is difficult to select the optimal wind power forecasting model from these three popular artificial intelligence models. The proposed hybrid methodology in this paper is proved to be a good solution of this difficult problem, presenting a significant accuracy improvement in all seasons with respect to each individual model, which can be observed in Table 4. Regarding the MAPE criterion, the average MAPE value of the proposed hybrid methodology decreases by 33.05%, 24.57% and 46.69% with respect to BPNN, RBFNN, and LSSVM models, which is illustrated visually in Fig. 5 for four seasons.

Table 7

NRMAE evaluation for the year of 2012

Season	PCC based data preprocessing	BPNN	RBFNN	LSSVM
Spring	Y	7.84	7.24	9.45
	N	8.93	9.60	11.26
Summer	Y	6.07	3.51	7.75
	N	7.81	6.21	8.85
Fall	Y	2.53	2.95	4.89
	N	3.67	3.74	5.32
Winter	Y	3.78	4.22	3.71
	N	5.68	5.02	4.64

Table 8

Accuracy comparison results

Season	Forecasting model	MAPE	NMAE	NRMSE
Spring	BPNN	14.83	5.33	7.84
	RBFNN	14.21	5.11	7.24
	LSSVM	17.68	6.35	9.45
	BRSA	11.76	4.23	6.24
Summer	BPNN	21.70	2.86	6.07
	RBFNN	13.64	1.80	3.51
	LSSVM	27.40	3.61	7.75
	BRSA	10.35	1.36	2.79
Fall	BPNN	8.72	1.31	2.53
	RBFNN	10.24	1.54	2.95
	LSSVM	14.12	2.12	4.89
	BRSA	6.70	1.01	2.37
Winter	BPNN	9.18	2.64	3.78
	RBFNN	10.22	2.94	4.22
	LSSVM	9.16	2.63	3.71
	BRSA	7.63	2.19	2.70

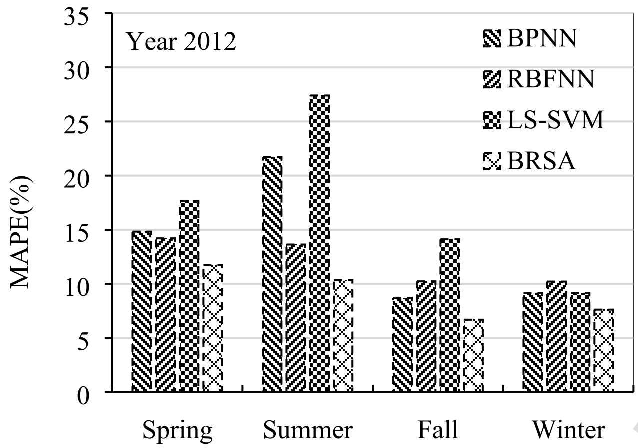

Fig. 5. Histogram of MAPE results for 2012.

Due to the small proportion of real wind power generation to the installed wind power capacity, it is noticeable that the NMAE value of each forecasting model in every season is dramatically smaller than the MAPE value, respectively. It experiences an average NAME 2.20 %, which is superior to three individual models. Additionally, improvement in the average NRMSE of the hybrid methodology with respect to three individual models is 30.27%, 21.32% and 45.35%, respectively.

The following days are randomly chosen from each season: March 1, July 7, September 27, and December 14, 2012. The forecasted wind power curves of different models and actual wind power curves are shown in Fig. 6-Fig. 9.

The hybrid methodology is also efficient in terms of computation cost. The BPNN, RBFNN, and LSSVM are trained and tested simultaneously. The time cost of training ANFIS model is also very short due to the small iteration times and small training set. The average computation time of the hybrid methodology is less than 5 minutes, working with Matlab on a PC with 2 GB of RAM and 2.67GHz processor.

Hence, the hybrid methodology not only presents a large improvement of forecasting accuracy, but also works with an acceptable computation cost.

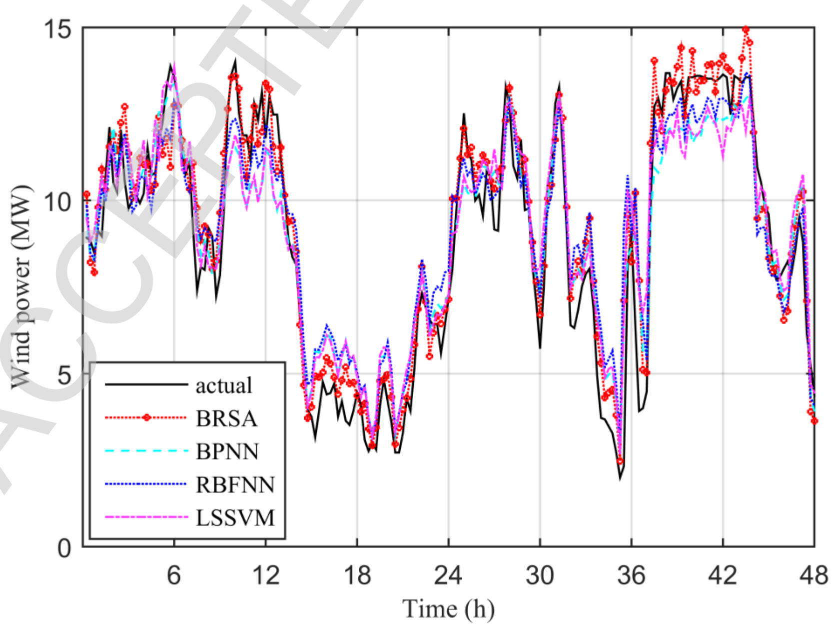

Fig. 6 Actual wind power and forecasted wind power for the selected spring day.

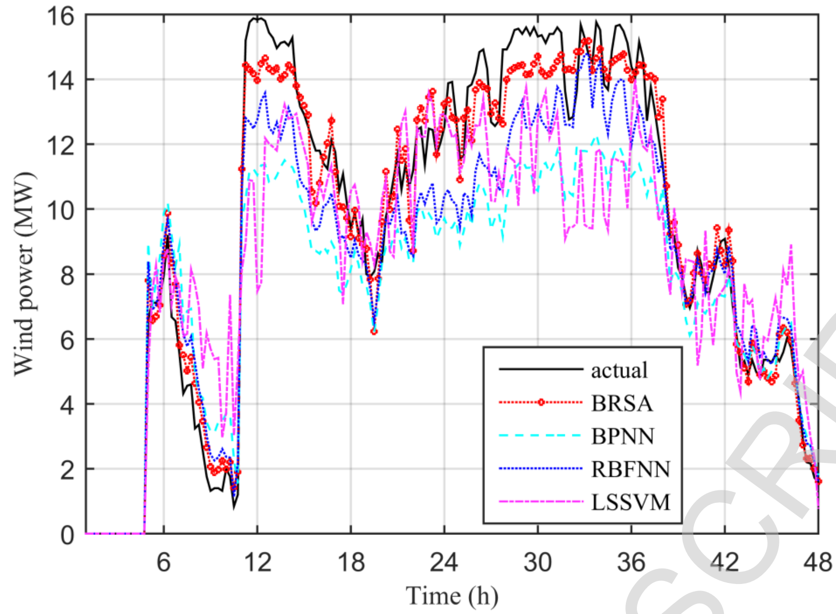

Fig. 7. Actual wind power and forecasted wind power for the selected summer day.

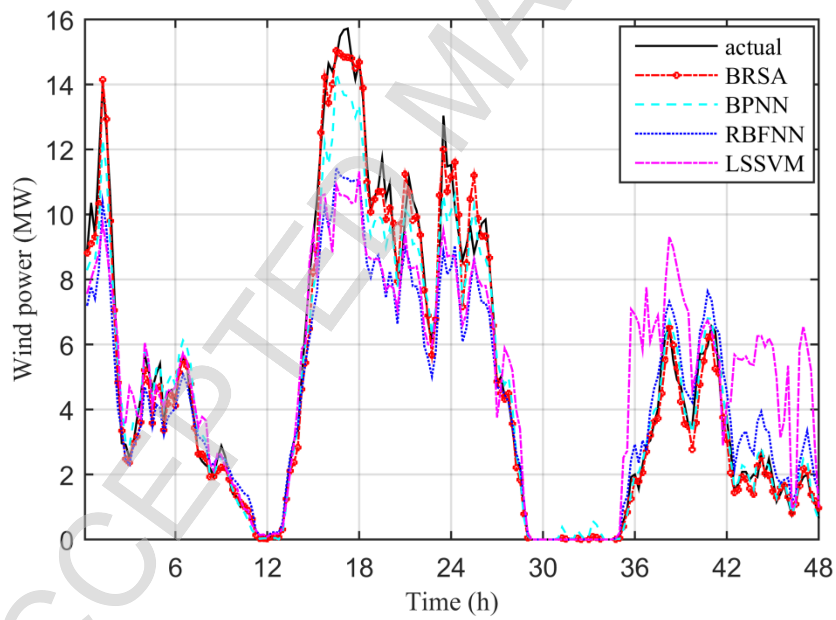

Fig. 8. Actual wind power and forecasted wind power for the selected fall day.

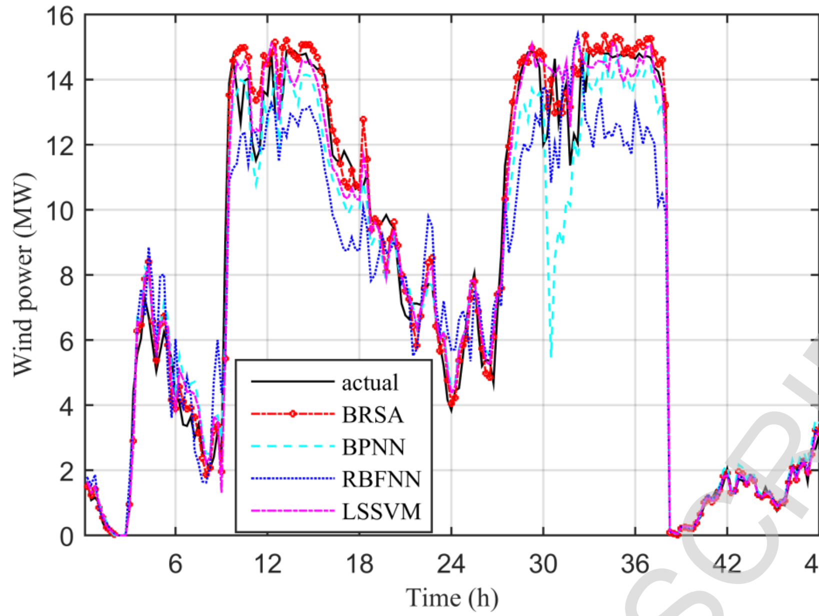

Fig. 9. Actual wind power and forecasted wind power for the selected winter day.

5. Conclusion

A novel hybrid methodology for 48-hour-ahead short-term wind power forecasting is proposed in this paper. Firstly, the proposed methodology takes into account a new data preprocessing method based on Pearson correlation coefficient (PCC) to enhance the mapping accuracy of the artificial intelligence forecasting models. Simulation results demonstrate that the forecasting accuracy is improved by using the PCC based preprocessing method. Secondly, results from real wind farm show that RBFNN model outperforms BPNN and LSSVM models in both spring and summer seasons, whereas the BPNN model and LSSVM model perform best in the fall and winter seasons, respectively. In this context, ANFIS model is employed to combine the forecasted power of three individual models and output the final forecasted power in this paper. Detailed accuracy comparisons have been implemented proving that the proposed hybrid methodology outperforms three individual forecasting models in each season and presents a significant improvement in accuracy.

It is essential to state that the results in this paper do not represent the models' actual performance in a real case scenario where the forecasted meteorological data instead of measured meteorological data will be used as input. The error of meteorological data will has an additional impact on the models' performances, which may lead to higher error metrics and increasing forecasting error with the forecast horizon unlike figures 6-9 suggest. Our further work is to obtain numerical weather prediction data and refine it with advanced data preprocessing method in order to reduce its error and associated impact on wind power forecasting models' performance.

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References

[1] Global Wind 2013 Report, Global Wind Energy Council. Brussels, Belgium, 2013.

[2] Kabouris, J.; F.D. Kanellos, "Impacts of large-scale wind penetration on designing and operation of electric power systems," *Sustainable Energy, IEEE Transactions on*, vol. 1, no. 2, pp. 107,114, July 2010.

[3] Sideratos, G.; Hatziargyriou, N. D., "An advanced statistical method for wind power forecasting," Power Systems, IEEE Transactions on, vol. 22, no. 1, pp. 258,265, Feb 2007.

[4] Wen-Yeau Chang., "Short-Term wind power forecasting using the enhanced particle swarm optimization based hybrid method," energies, vol. 6, no. 9, pp. 4879,4896, Sep 2013.

[5] Lingo Xiao.; Jianzhou Wang; Yao Dong.; Jie Wu, "Combined forecasting models for wind energy forecasting: A case study in China," Renewable and Sustainable Energy Reviews, vol. 44, pp. 271,288, April 2015.

[6] Potter, C.W.; Negnevitsky, M., "Very short-term wind forecasting for tasmanian power generation," Power Systems, IEEE Transactions on, vol. 21, no. 2, pp. 965,972, May 2006.

[7] Shu Fan.; Liao, J.R.; Yokoyama, R.; Luonan Chen.; Wei-Jen Lee, "Forecasting the Wind Generation Using a Two-Stage Network Based on Meteorological

Information," Energy Conversion, IEEE Transactions on , vol.24, no.2, pp.474,482, June 2009.
[8] Barbounis, T.G.; Theocharis, J.B.; Alexiadis, M.C.; Dokopoulos, P.S., "Long-term wind speed and power forecasting using local recurrent neural network models," Energy Conversion, IEEE Transactions on , vol.21, no.1, pp.273,284, March 2006.
[9] Kariniotakis, G.N.; Stavrakakis, G.S.; Nogaret, E.F., “Wind power forecasting using advanced neural networks models,” Energy Conversion, IEEE Transactions on, vol. 11, no. 4, pp. 762,767, Dec 1996.
[10] Giebel G.; Kariniotakis, G.; Brownsword. R. (2003). The state of the art in short-term prediction of wind power—A literature overview, Position paper for the ANEMOS project [Online]. Available http://www.anemos-project.eu
[11] Alexiadis, M.C.; Dokopoulos, P.S.; Sahsamanoglou, H.S., "Wind speed and power forecasting based on spatial correlation models," Energy Conversion, IEEE Transactions on , vol.14, no.3, pp.836,842, Sep 1999.
[12] Barbounis, T.G.; Theocharis, J.B.; Alexiadis, M.C.; Dokopoulos, P.S., “Long-term wind speed and power forecasting using local recurrent neural network models,” Energy Conversion, IEEE Transactions on, vol. 21, no. 1, pp. 273,284, March 2006.
[13] 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,” Renewable and Sustainable Energy Reviews, vol. 12, no. 6, pp. 1725,1744, Aug 2008.
[14] Osório, G.J.; Matias, J.C.O.; Catalão, J.P.S., “Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information,” Renewable Energy, vol. 75, pp. 301,307, March 2015.
[15] Ramirez-Rosado, I.J.; Fernandez-Jimenez, L.A.; Monteiro, C.; Sousa, J.; Bessa, R., “Comparison of two new short-term wind-power forecasting systems,” Renewable Energy, vol. 34, no. 7, pp. 1848,1854, July 2009.
[16] Landberg, L., “Short-term prediction of the power production from wind farms,” Journal of Wind Engineering and Industrial Aerodynamics, vol. 80, pp. 207,220, March 1999.
[17] Tascikaraoglu, A.; Uzunoglu, M., “A review of combined approaches for prediction of short-term wind speed and power,” Renewable and Sustainable Energy Reviews, vol. 34, pp. 243,254, June 2014.
[18] Cassola, F.; Burlando, M., “Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output,” Applied Energy, vol. 99, pp. 154,166, Nov 2012.
[19] Torres, J.L.; García, A.; De Blas, M.; De Francisco, A., “Forecast of hourly average wind speed with ARMA models in Navarre (Spain),” Solar Energy, vol. 79, no. 1, pp. 65,77, July 2005.
[20] Zhongyue Su; Jianzhou Wang; Haiyan Lu; Ge Zhao, “A new hybrid model optimized by an intelligent optimization algorithm for wind speed forecasting,” *Energy Conversion and Management*, vol. 85, pp. 443,452, Sep 2014.
[21] Ma Lei, Luan Shiyan; Jiang Chuanwen; Liu Hongling; Zhang Yan, “A review on the forecasting of wind speed and generated power,” Renewable and Sustainable Energy Reviews, vol. 13, no.4, pp. 915,920, May 2009.
[22] Haque, A.U.; Mandal, P. ; Kaye, M.E.; Meng, J.; Liuchen Chang; Senjyu, T., “A new strategy for predicting short-term wind speed using soft computing models,” Renewable and Sustainable Energy Reviews, vol. 16, no. 7, pp. 4563,4573, Sep 2012.
[23] Sideratos, G.; Hatziargyriou, N.D., "Probabilistic Wind Power Forecasting Using Radial Basis Function Neural Networks," Power Systems, IEEE Transactions on , vol.27, no.4, pp.1788,1796, Nov. 2012
[24] Johnson, P.; Negnevitsky, M.; Muttaqi, K.M., "Short term wind power forecasting using adaptive neuro-fuzzy inference systems," Power Engineering Conference, 2007. AUPEC 2007. Australasian Universities , vol., no., pp.1,6, 9-12 Dec. 2007
[25] Catalão, J.P.S.; Pousinho H.M.I.; Mendes V.M.F., “Hybrid Wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal,” IEEE Trans Sustain Energy vol. 2, no.1 pp. 50-59 Jan 2011.
[26] Junyi Zhou; Jing Shi; Gong Li, “Fine tuning support vector machines for short-term wind speed forecasting,” Energy Conversion and Management, vol.52, no. 4, pp. 1990,1998, Apr 2011.
[27] Huaiwu Peng; Fangrui Liu; Xiaofeng Yang, “A hybrid strategy of short term wind power prediction,” Renewable Energy, vol. 50, pp. 590,595, Feb 2013.
[28] Bhaskar K; Singh S N, “AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network,” IEEE Transactions on Sustainable Energy, vol. 3, no. 2, pp. 306,315, 2012.
[29] Bilgili M; Sahin B; Yasar A, “Application of artificial neural networks for the wind speed prediction of target station using reference stations data,”Renewable Energy, vol. 32, no. 14, pp. 2350,2360, 2007.
[30] Benesty, J.; Jingdong Chen; Yiteng Huang, "On the Importance of the Pearson Correlation Coefficient in Noise Reduction," Audio, Speech, and Language Processing, IEEE Transactions on , vol.16, no.4, pp.757,765, May 2008
[31] Dunn, O.J.; Clark, V.A., Applied Statistics: Analysis of Variance n and Regression. New York: Wiley, 1974.
[32] Feifei Bai; Yong Liu; Yilu Liu; Kai Sun; Bhatt N.; Rosso, A.D.; Farantatos, E.; Xiaoru Wang, “Measurement-Based Correlation Approach for Power System Dynamic Response Estimation,” Accepted by IET Generation, Transmission & Distribution, April 2015.
[33] Da Liu; Dongxiao Niu; Hui Wang; Leilei Fan, “Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm,” Renewable Energy, vol. 62, pp. 592,597, Feb 2014.
[34] Gestel, T.V.; Suykens, J.A.K.; Baesens, B.; Viaene, S.; Vanthienen, J.; Dedene, G.; et al., “Benchmarking least squares support vector machine classifiers,” Machine Learning , vol. 54, pp. 5,32, 2004.