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Interval forecasts of a novelty hybrid model for wind speeds

Shanshan Qin [a,b], Feng Liu [b,*], Jianzhou Wang [c], Yiliao Song [b]

[a] *MOE Key Laboratory of Western China's Environmental Systems, Research School of Arid Environment & Climate Change, Lanzhou University, Lanzhou 730000, China*

[b] *School of Mathematics and Statistics, Lanzhou University, Lanzhou 730000, China*

[c] *School of Statistics, Dongbei University of Finance and Economics, Dalian 116025, China*

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ABSTRACT

The utilization of wind energy, as a booming technology in the field of renewable energies, has been highly regarded around the world. Quantification of uncertainties associated with accurate wind speed forecasts is essential for regulating wind power generation and integration. However, it remains difficult work primarily due to the stochastic and nonlinear characteristics of wind speed series. Traditional models for wind speed forecasting mostly focus on generating certain predictive values, which cannot properly handle uncertainties. For quantifying potential uncertainties, a hybrid model constructed by the Cuckoo Search Optimization (CSO)-based Back Propagation Neural Network (BPNN) is proposed to establish wind speed interval forecasts (IFs) by estimating the lower and upper bounds. The quality of IFs is assessed quantitatively using IFs coverage probability (IFCP) and IFs normalized average width (IFNAW). Moreover, to assess the overall quality of IFs comprehensively, a tradeoff between informativeness (IFNAW) and validity (IFCP) of IFs is examined by coverage width-based criteria (CWC). As an applicative study, wind speeds from the Xinjiang Region in China are used to validate the proposed hybrid model. The results demonstrate that the proposed model can construct higher quality IFs for short-term wind speed forecasts.

1. Introduction

Wind energy, as a promising source of renewable and green energy, has received increasing attention due to its inexhaustibility, sustainability, ecological awareness and the substantial contribution to energy security. However, high penetration of wind power also makes a number of challenges in power system operations and planning, turbine maintenance scheduling and power grid integration, mainly stemming from uncertain and intermittent nature of wind speed (Jung and Broadwater, 2014; Song et al., 2014). Thereby, reliable wind speed forecasting and coping with wind uncertainty have been recognized as a crucial factor for the optimal distribution of wind energy, for the efficient and safe operation of wind turbines, for shipping, aviation, agriculture and environmental planning and for scheduling, maintenance, control and resource planning (Abdel-Aal et al., 2009; Mandic et al., 2009).

Up to now, abundant research has been directed toward wind speed and wind power forecasting by organizations and institutes with considerable experience in the field. The models reported in the literature can be classified into three categories: (a) physical models, (b) statistical models and (c) hybrid or combination models (Jung and Broadwater, 2014; Song et al., 2014; Soman et al., 2010). Physical models are based on the lower atmosphere or numerical weather prediction (NWP) utilizing weather prediction data such as pressure, temperature, obstacles and surface roughness (Salcedo-Sanz et al., 2009; Lei et al., 2009; Costa et al., 2008; Landberg et al., 2003). Statistical methods draw on vast historical data without considering meteorological conditions, which usually are representative of conventional time series models (Liu et al., 2010; Erdem and Shi, 2011), the Artificial Neural Network (ANN) approach (Li and Shi, 2010; Blonbou, 2011; Haque et al., 2012), the support vector machine (Liu et al., 2014; Zhou et al., 2011) and the ANN-Fuzzy approach (Catalao et al., 2011; Hong et al., 2010). As for hybrid or combination model, the basic idea of this method is to combine different approaches retaining strengths of each method to improve the model's forecasting performance (Guo et al., 2011; Wang et al., 2014; Su et al., 2014; Haque et al., 2013, 2014).

According to the above literature, research on wind speed forecasting is primarily driven by an individual or hybrid model and

* Corresponding author.
E-mail address: liuf13@lzu.edu.cn (F. Liu).

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then applied for decision-making. Those methods for wind speed forecasting mostly focus on generating deterministic forecasts while few of them handle the uncertainty of wind speeds properly. Bremnes (Kani and Riahy, 2008) noted that the purpose of most approaches is to make a deterministic forecast, but knowledge about uncertainty is not directly provided. However, the accuracy of deterministic forecasts is highly variable and usually low on average (El-Fouly et al., 2006). Actually, the predictive errors always exist regardless of forecasting model type, model training methods and explanatory variables. From a practical view, an inherent and irreducible uncertainty exists in every forecast generated by different models inducing decision-making problematic or even prone to mistakes (El-Fouly et al., 2006). As for the decision maker, missing the uncertainty of wind speeds may lead to some degree of risk in the power system management. Therefore, quantification of uncertainties associated with wind speed forecasts is essential for optimal management of wind farms and their successful integration into power systems.

Although the interval forecasts instead of deterministic forecasts has drawn attention, relatively little research refers to wind speeds. Song et al. (2014) performed both of the point and interval forecasting of the future wind speed by the Markov switching model and the Bayesian approach. Pinson and Kariniotakis (2004) estimated the confidence interval through the wind speed prediction errors. Jiang et al. (2013) proposed a Bayesian structural break model to forecast the future wind speed and its intervals. Methods based on ANN were examined by incorporating the uncertainty into the deterministic forecasts to improve the credibility and reliability of wind power forecasting (Quan et al., 2014).

The above methods have been utilized for IFs construction in the literature. In traditional IFs construction approaches, the major strategy is to minimize the predictive error rather than to improve the quality of IFs being optimal in their key factors such as width and coverage probability. While in the comparative case studies for IFs construction, the coverage probability is taken as the only measure to evaluate the IFs quality (Papadopoulos et al., 2001), which cannot completely describe the characteristics of constructed IFs. Uncertainties of prediction can be properly quantified and represented using IFs and confidence intervals (CIs), which describe the uncertainty in the prediction of a future realization of a random variable and an unknown but fixed value respectively (Meade and Islam, 1995). According to their definitions, IFs account for more sources of uncertainty and is wider than the corresponding CIs (Heskes, 1997).

In the present work, a hybrid interval forecasting model using Wavelet de-noising (WD), CSO and BPNN is developed to estimate the IFs associated with short-term wind speeds. The major contributions of this study are as follows:

- A hybrid model is initially developed to quantify uncertainties associated with wind speed forecasts.
- CSO algorithm, with a strong searching ability, is integrated into BPNN.
- Different levels of prediction tasks are implemented and compared together.
- The test results from sixteen cases are evaluated by coverage probability, width of intervals and coverage width-based criterion CWC.

The rest of this paper is organized as follows: Section 2 presents the methods related to this research. Section 3 illustrates the detained information of the developed model. And the case study and analysis are given in Section 4. Followed that conclusions are presented.

2. Methodology

In this section, the main methods related in this study will be described briefly, including WD technique, BPNN and CSO algorithm.

2.1. Wavelet de-noising (WD) technique

The WD technique is an effective tool for noise removal, which has been widely utilized in the fields of signal processing, image processing and time series analysis (Wei-Chang, 2013). WD technique is based on the wavelet transform (WT) that is divided into two categories: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) upon which the wavelets are sampled continuously or discretely (Hong et al., 2010). The CWT is defined as the convolution of a time series $x(t)$ with a mother wavelet function $w(t)$ (Wei-Chang, 2013; Mandal et al., 2014):

$$\mathrm{CWT}_x^w(b,a)=\phi_x^w(b,a)=\frac{1}{\sqrt{|a|}}\int x(t)\cdot w*\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

where $*$ denotes the complex conjugate of $w(t)$, b is a translation coefficient and a is a scale parameter. Let $b=k/2^s$ and $a=1/2^s$, then the DWT can be defined as follows:

$$\mathrm{DWT}_x^w(k,s)=\phi_x^w\left(\frac{k}{2^s},\frac{1}{2^s}\right)=\int x(t)\cdot w*\left(\frac{t-k/2^s}{1/2^s}\right)\mathrm{d}t \tag{2}$$

where s and k are the scale and translation coefficient respectively. Discrete in nature s and k belong to the integer set.

Considering the discrete wind speed series, DWT is taken for data analysis prior to modeling. Details of this method can be seen in Mandal et al. (2014), Zhang et al. (2013).

2.2. Back Propagation Neural Network (BPNN)

BPNN, which was developed by Rumelhart et al. (1988) as a solution to the problem of training multi-layer perceptron and was identified as the most common type of Artificial Neural Network (ANN) model, has been widely used in many fields due to its ability of classification and linear or nonlinear mapping (Liu et al., 2012). The basic structure of a BPNN with two outputs is shown in Fig. 1(e). Details of BPNN can be found in Liu et al. (2012), Wang et al. (2014).

2.3. Cuckoo Search Optimization (CSO) algorithm

The CSO algorithm, inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds, is a recently developed metaheuristic algorithm by Yang and Deb (2009). For CSO algorithm, two behaviors are adapted and combined from nature that fulfill the criteria of a metaheuristic algorithm, which are described as follows Wang et al. (2015):

• Breeding behavior

Many species of cuckoos lay their eggs in communal nests, but to increase the hatching probability of their own eggs, they always remove other's eggs. Once a host cuckoo discovers an alien egg (does not belong to itself), then it will either throw the egg away or discard the current nest and build another nest elsewhere. Whereas in the CSO algorithm, in each step, with the new solutions generated, the poorer solutions are abandoned.

• Lévy flight

Generally, the flight path of many birds is effectively a random walk that is representative of Lévy flights with step length drawn

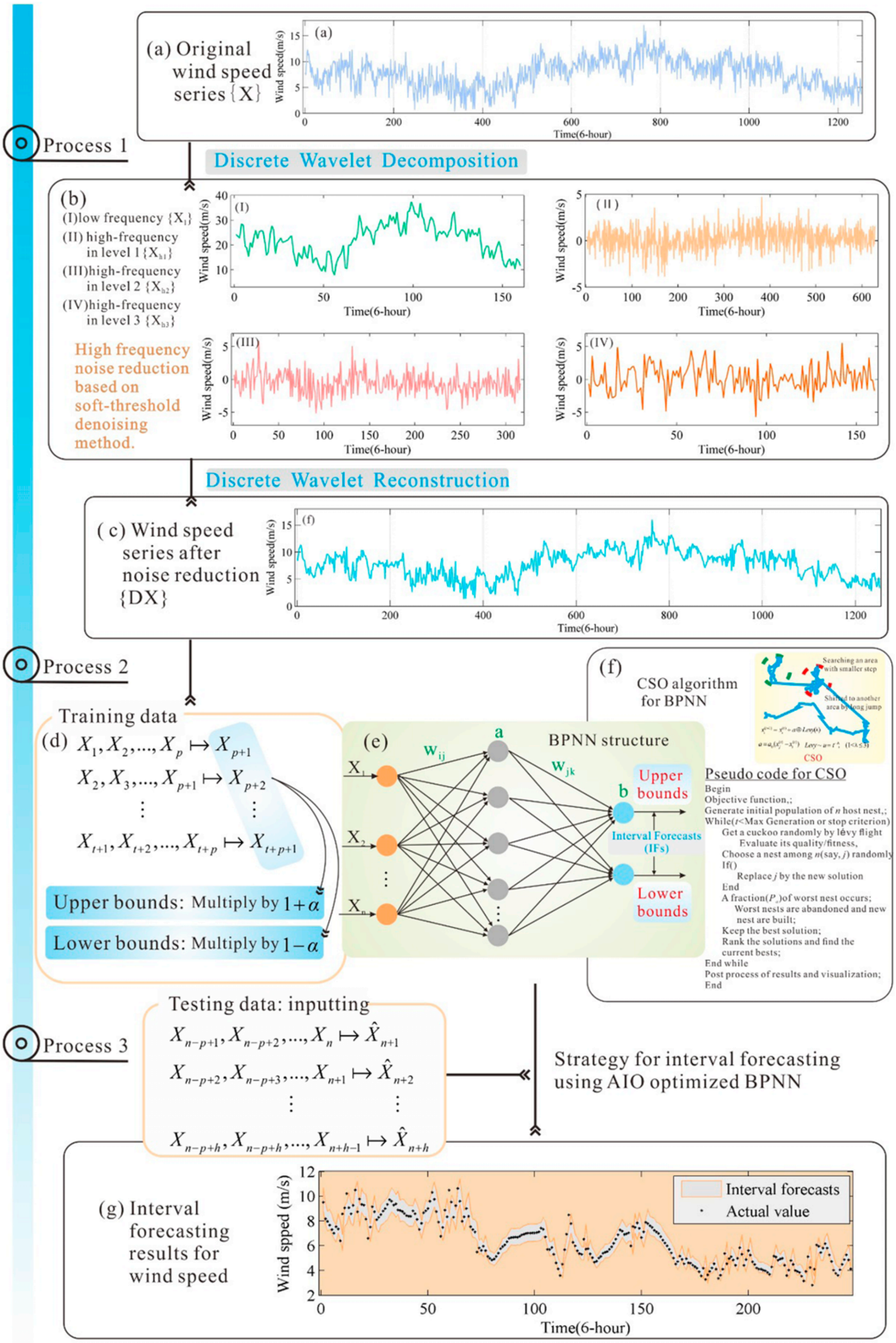


Fig. 1. The main procedure of the proposed hybrid model. Process 1: WD; Process 2: model training; and Process 3: forecasting and testing.

from the Lévy distribution. In CSO-based algorithm for producing a new solution $x^{(t+1)}$ for a cuckoo, a Lévy flight is defined as the following expression:

$$x_i^{t+1} = x_i^t + \alpha \oplus \mathrm{Levy}(\lambda) \tag{3}$$

$$\alpha = \alpha_0 (x_j^{(t)} - x_i^{(t)}) \tag{4}$$

$$\mathrm{Levy}(\lambda) \sim l^{-\lambda}, \quad (1 < \lambda < 3) \tag{5}$$

where x_i^t is the eggs (samples), i is the sample size, t is the iterations and α is the step size, mostly utilized in Eq. (4). The symbol $\oplus$ denotes entry-wise multiplication while the Lévy (λ) values can be found in the Lévy distribution defined in Eq. (5).

Based on such behavior, it is therefore highly probable that CSO can outperform other metaheuristic algorithms in nonlinear optimization problems. The more information about CSO method can be found in the literature Wang et al. (2015).

3. Proposed interval forecasts (IFs) model

In this section, a novel model for IFs will be developed. The first part illustrates evaluation indices of IFs, and the second one introduces the procedures of the new model in this work.

3.1. Evaluation indices of IFs

The quality of IFs needs to be assessed quantitatively by evaluation indices. In this paper, IFs coverage probability (IFCP), IFs normalized average width (IFNAW) and a combinational index, and named coverage width-based criterion (CWC) are selected to evaluate the quality of developed IFs. The detailed description of evaluation indices can be referenced in the Appendix.

3.2. Construction of wind speed interval forecasts model: WD–CSO–BPNN

In this paper, the proposed model, which incorporates the WD technique into a BPNN model based on CSO optimization, is adopted for wind speed interval forecasts. The original wind speed series unavoidably includes some noisy information, herein the WD technique is applied to filter out the noise and extract the essential features from the original wind speed series. Additionally, in BPNN, unstable neutral networks are often challenged due to the randomly generated initial weights and thresholds that leave a potentially vital impression on the learning process (Qin et al., 2014). To make the BPNN structure more stable, thereby, the CSO algorithm is used to initialize and determine these parameters. Details of this novel model are expressed as follows (Wei-Chang, 2013), and the main procedures are illustrated in Fig. 1.

Step 1: WD. The original wind speed series are decomposed into a high-frequency component and low-frequency component, which represents the noise signal and main features of the wind speed series (see Fig. 1(a–c)).

Step 2: Data splitting and normalization. The available wind speed series after noise reduction are split into the training set and test set, which are denoted as D_{train} including input sets and output sets for training parameters of BPNN and D_{test} which consists of inputs and outputs for the testing model's forecasting effectiveness, respectively. For establishing the model, the training data sets and the input test sets are normalized with the same setting (see Fig. 1(d)).

Step 3: Initialization. A BPNN with two outputs is shown in Fig. 1(e). The number of connection weights of BPNN is the size of a cuckoo egg in CSO algorithm, namely the dimension of optimized parameters. These initial weights can be randomly assigned while the parameter (p_a) of CSO algorithm is set to be 0.25 an optimal value that has been verified by Yang and Deb (2010).

Step 4: Optimization. The objective function of CSO algorithm is given as follows:

$$f_{objective} = \frac{1}{n}\sum_{i=1}^{n}[(U_i - U_i^{train})^2 + (L_i - L_i^{train})^2] \quad (6)$$

where n is sample size of D_{train}. The output training sets, U_i and L_i denote the upper and lower bounds of the training sets, as for U_i^{train} and L_i^{train}, the corresponding fitting results of U_i and L_i. The optimized algorithm terminates if it reaches the maximum iterations.

Step 5: BPNN construction. The best solution obtained by CSO algorithm is set to be the final connection weights of BPNN training and construction. The terminal condition of network training is set as the reach of maximum iterations or no further improvement (see Fig. 1(d–f)).

Step 6: IFs construction for test data set. The IFs of output test sets are generated by importing input test sets based on the established optimal BPNN (see Fig. 1(g)).

Step 7: Evaluation. The quality of IFs is assessed by the indices IFCP and IFNAW, which present the validity and informativeness of IFs, respectively. With the aim of comprehensive evaluation, CWC is calculated as well.

4. Case study and analysis

4.1. Data sets

The Xinjiang region, accounting for more than one-sixth of China's total territory, possesses abundant wind resources due to its geographical characteristics. Nine major wind zones are located in the Xinjiang region (see Fig. 2(I)): Dabancheng, Alataw Mountain Pass, Junggar Basin, Erqisi River, Western Turpan, Baili, Lop Nur, and the north and south Gobi of Hami wind regions. To investigate the potential of wind power, it is highly worthwhile to conduct interval forecasts of wind speeds in this region.

In this paper, the six hourly mean wind speed data observed in four representative sites of nine major wind zones are selected as illustrative examples to construct and evaluate the proposed model. To facilitate the following modeling, we record the original wind speed series in study site A, B, C and D as $\{X_A\}$, $\{X_B\}$, $\{X_C\}$ and $\{X_D\}$, respectively. The original wind speed series together with their statistical measures, i.e., minimum, maximum and mean and the standard deviations, are shown in Fig. 2(II–III). As shown in Fig. 2(III), the standard deviations are all above 2.5, which implies the original wind speed series fluctuates significantly with the minimum/maximum of $\{X_A\}$, $\{X_B\}$, $\{X_C\}$ and $\{X_D\}$ are 0.30/17.13 m/s, 0.28/13.95 m/s, 0.14/14.10 m/s and 0.28/13.45 m/s, respectively. This can be intuitively observed from the amplitude and frequency of the series fluctuation, which can quickly change from very high to low values and vice versa.

4.2. Process of WD

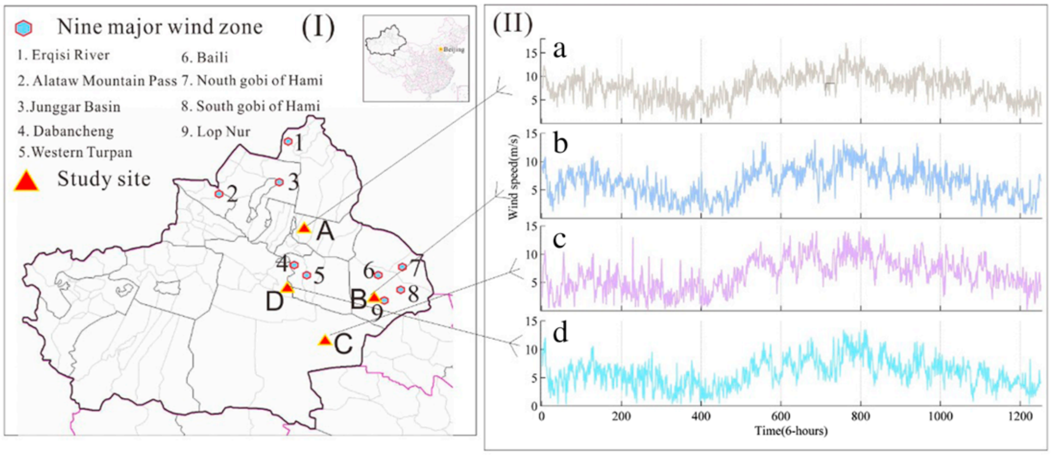
Because the selection of mother wavelet functions is not the core information to illustrate, Daubechies of order 3 (db3) is used to decompose the original series into three levels, which is based upon the similar work in Zhang et al. (2013), with the WD process and results displayed in Fig. 1(a–c). Herein, $\{X_A\}$ is selected as an example.

4.3. Data splitting and parameters selection

The wind speed IFs problem tries to obtain the estimates $\hat{U}(t+k)$ and $\hat{L}(t+k)$, upper and lower bounds of wind speed $X(t+k)$, based upon the previous p observations $X(t), X(t-1), \ldots, X(t-p+1)$. For each case study, we split the wind speeds into a training set (80%) and a test set (20%). Furthermore, the training set is further divided into input-training set and output-training set. Because the CSO–BPNN structure has two output layers, representing the lower and upper bounds of the corresponding output-training set, the output-training set needs to be redefined as LU_output-training set, which is given by Eq. (7).

$$\text{LU\_output-training}(i) = [\text{output-training}(i) \times (1-\alpha)\ \text{output-training}(i)\cdot(1+\alpha)] \quad (i = 1, 2, \ldots, n) \quad (7)$$

where n is the number of the output training set. α, the determining factor of the widths of the LU_output-training set, is predesigned before model training, i.e., 10%, 15%, 20% and 30%. On the



(III) Statistical measures of original wind speed series

Area	Mean(m/s)	Std.[a](m/s)	Min(m/s)	Max(m/s)
Site A	7.75	2.76	0.30	17.13
Site B	6.23	2.70	0.28	13.95
Site C	6.40	2.90	0.14	14.10
Site D	5.77	2.53	0.28	13.45

Std.[a]: Standard deviation.

Fig. 2. Original wind speeds: (I) specific location for four study sites; (II) original wind speed series; (III) the statistical measures for wind speeds.

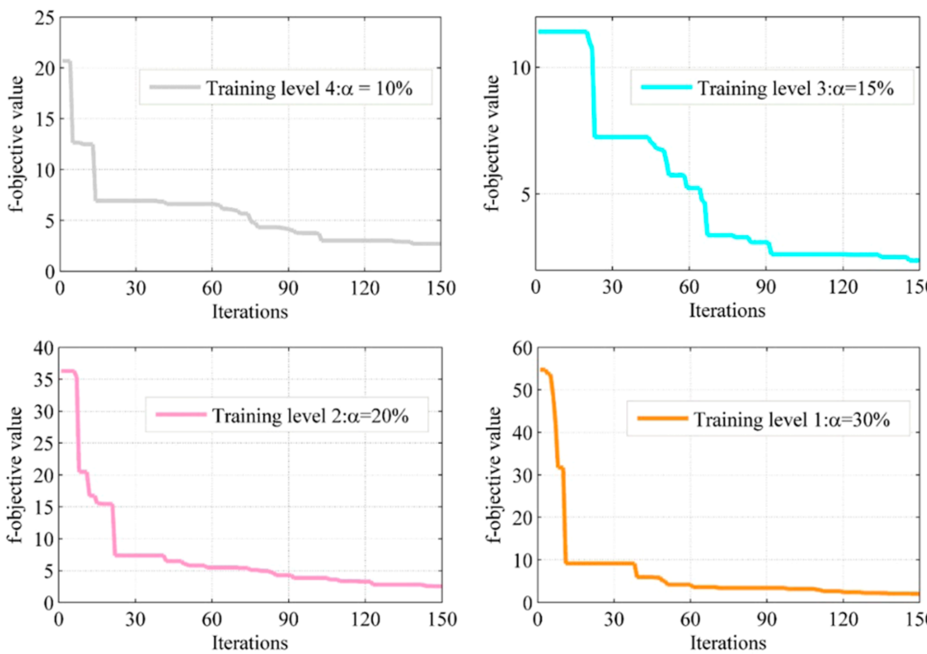


Fig. 3. The convergence behavior of CSO algorithm ($\{X_A\}$).

basis of the above four α values, the model training process is divided into 4 levels, which are level 1, level 2, level 3 and level 4, respectively. Herein we also take $\{X_A\}$ as an example to clearly illustrate the formation of training sets, which can be seen in Fig. 1(d).

According to the four different training levels, the nominal confidence level μ in Eq. (A.3) (see Appendix) is set to be 80%, 85%, 90% and 95%, respectively. Furthermore, η is chosen to be 50 as to highly penalize wind speed IFs with a coverage probability less than the corresponding nominal confidence level. IFCP, IFNAW and CWC measure are selected to examine the quality of constructed IFs.

4.4. Optimization and determination for parameters of BPNN structure

In the CSO algorithm, each egg in a nest represents a solution, which are the connection weights and thresholds of BPNN structure. In this sub-section, we also take $\{X_A\}$ as an example to illustrate the convergence behavior of the CSO algorithm, and the results can be observed in Fig. 3. It shows that the objective function monotonically decreases with respect to iteration. The initial values of objective function are very large, but they all decreased gradually as the iteration increased.

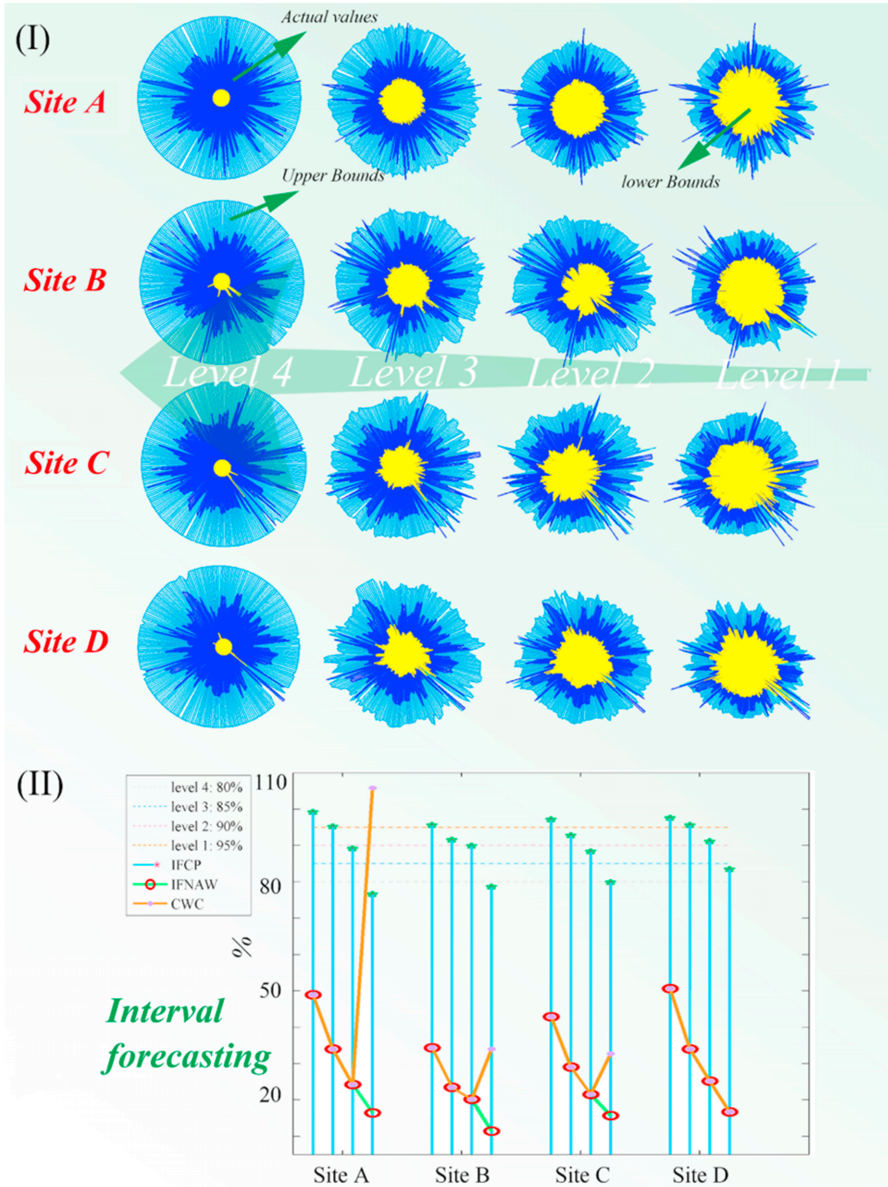


Fig. 4. Results comparison of wind speed IFs for study sites.

4.5. Wind speed IFs results

The results for wind speed IFs consist of three parts: training procedure, test results and quality evaluation of IFs. The key factor for BPNN is connection weights and thresholds, the controller of BPNN structure, which are determined by the CSO algorithm in the above subsection. Considering different types of prediction problems, the training process is conducted at four levels on the basis of four different LU_output-training sets defined by Eq. (7). The final performance of the proposed model is examined by test set. For each case study, the corresponding test results can be obtained upon the optimal CSO–BPNN structure. Test results for four case studies are demonstrated in Fig. 4.

In Fig. 4, part (I) shows results of four sites including actual wind speeds indicated by the green arrow in the first circle of Site A, upper bounds pointed in Site B and lower bounds, yellow area in this figure. A relative brief consequence can be seen in part (II). It is obvious that level 4 has the best performance when forecasting interval of wind speeds in Fig. 4(I). As the nominal level decreases, the effectiveness of this new method is also decreasing for each study. From the view of Sites, the proposed model performs best in Site D than others because the interval between upper bounds and lower bounds cover the actual wind speeds better than bounds of Site A, Site B and Site C do. This figure also illustrates a fact that lower bounds have higher rates of success when obtaining the wind data's bounds than upper bounds do.

To quantitatively evaluate the quality of wind speed IFs constructed by the proposed model, the numerical test results of all of the cases are shown in Table 1. Not only the IFCP and IFNAW but also CWC are calculated and listed in Table 1. It is assumed that the constructed IFs are theoretically valid if their coverage probability is larger than or equal to the corresponding nominal confidence level (Khosravi et al., 2013). That is to say, violation of this condition leads to invalid IFs and destroys their credibility. According to the results in Table 1 and Fig. 4(II), the IFCP is larger than the corresponding nominal confidence level in the majority of conducted experiments, and therefore the IFs are valid. Furthermore, a positive gap between IFCP and the corresponding nominal confidence

Table 1
Wind speed IFs evaluation indices.

Nominal Confidence level	Level	Site A IFCP (%)	Site A IFNAW (%)	Site A CWC (%)	Site B IFCP (%)	Site B IFNAW (%)	Site B CWC (%)	Site C IFCP (%)	Site C IFNAW (%)	Site C CWC (%)	Site D IFCP (%)	Site D IFNAW (%)	Site D CWC (%)
95%	4	99.19	48.93	48.93	95.56	34.33	34.33	97.18	42.91	42.91	97.58	50.62	50.62
90%	3	95.16	34.03	34.03	91.53	23.47	23.47	92.74	29.03	29.03	95.56	33.97	33.97
85%	2	89.11	24.21	24.21	89.92	20.15	20.15	88.31	21.51	21.51	91.13	25.2	25.2
80%	1	76.61	16.42	105.85	78.63	11.39	33.98	79.84	15.69	32.69	83.47	16.68	16.68

Table 2
Comparisons of Adaptive Neuron-Fuzzy Inference System (ANFIS), WD–GA–BPNN and WD–PSO–BPNN.

Nominal Confidence level	Level	Site A IFCP (%)	Site A IFNAW (%)	Site A CWC (%)	Site B IFCP (%)	Site B IFNAW (%)	Site B CWC (%)	Site C IFCP (%)	Site C IFNAW (%)	Site C CWC (%)	Site D IFCP (%)	Site D IFNAW (%)	Site D CWC (%)
ANFIS													
95%	4	99.6	49.82	49.82	93.15	34.33	34.33	95.97	43.92	43.92	97.58	50.69	50.69
90%	3	94.35	33.21	33.21	89.92	23	23	90.32	29.33	29.33	95.56	33.8	33.8
85%	2	87.9	24.91	24.91	81.45	17.26	17.26	86.29	21.97	21.97	89.11	25.35	25.35
80%	1	71.37	16.63	1258.4	67.74	11.54	5310	74.6	14.62	232.5	76.61	16.89	108.78
WD-GA-BPNN													
95%	4	97.98	48.91	48.91	93.95	34.47	34.47	97.18	42.94	42.94	96.37	50.79	50.79
90%	3	93.95	33.98	33.98	91.94	23.45	23.45	93.15	28.97	28.97	94.76	33.91	33.91
85%	2	87.1	24.37	24.37	89.52	20.22	20.22	87.5	21.57	21.57	91.13	25.14	25.14
80%	1	75	16.58	218.51	78.63	11.48	34.25	79.03	15.7	41.16	82.26	16.73	16.73
WD-PSO-BPNN													
95%	4	97.58	48.95	48.95	93.55	34.25	34.25	97.58	42.88	42.88	95.56	50.56	50.56
90%	3	93.95	33.99	33.99	91.94	23.44	23.44	92.74	29.06	29.06	94.76	33.88	33.88
85%	2	87.1	24.38	24.38	87.9	20.33	20.33	88.71	21.56	21.56	89.11	25.25	25.25
80%	1	74.6	16.42	261.16	77.82	11.56	45.9	78.23	15.7	53.82	83.87	16.61	16.61

level highlights the capability of the proposed model for generating reliable IFs. While there are some empirical cases that IFCP is not satisfactory, such as the IFCP at training level 4 in sites A, B and C. However, it is worth noting that there are only 3 out of 16 unsatisfactory cases in which the difference between the IFCP and its corresponding nominal confidence level (80%) is less than 4% with the maximum 3.39% and minimum 0.16%. This finding implies that the proposed model construct valid IFs in the presence of a high level and robustness.

It is significant to note that the coverage probability has a direct relationship with the training levels. As the training level goes from level 1 to level 4, both the coverage probability and the width of IFs increase. High coverage probability of IFs indicates that the IFCP measure for the test sample sets are very satisfactory applying the proposed model. On the other hand, much wider of the constructed wind speed intervals implies less informative. Therefore, both the conflicting indices are balanced by a comprehensive measure CWC.

As seen from Table 1, on the condition that the IFCP satisfy the corresponding confidence level for different training levels, the CWC is equal to the INFAW. Otherwise, it is enlarged by a penalty term defined in Eq. (A.3). As some empirical case of site A at training level 4, CWC is very large, over 100%. While for cases of site B and C at training level 4, CWC is greater than their corresponding IFNAW value due to their unsatisfactory IFCP. Overall, CWC values are mostly less than 100 (15 over 16 cases), which indicates that constructed IFs are valid and sufficiently narrow (Khosravi et al., 2011a), and the proposed approach can effectively establish a tradeoff between validity and informativeness.

Table 2 shows the forecasting results of ANFIS, WD–GA–BPNN and WD–PSO–BPNN. Comparing results of Table 1 with those of Table 2 indicates that the proposed model, WD–CSO–BPNN, outperforms ANFIS, and CSO is more effective than GA and PSO to optimize the parameters of BPNN especially when the level is 1 and the nominal confidence is 80%.

5. Conclusions

Wind energy, a renewable and clean energy source, has become increasingly significant for sustainable energy development and environmental protection. Reliable and accurate wind speed forecasts are vital for wind power generation. However, the complexities of wind speed series pose great challenges to precise wind speed forecasting. Considerable research effort has been devoted to generating deterministic wind speed forecasting values. However, few studies have been conducted to handle the uncertainty of wind speeds properly, which may exert a certain degree of risk in the operation of energy system.

To overcome the deficiencies of the deterministic forecast to handle uncertainties, a newly proposed model called WD–CSO–BPNN is adopted and developed to construct wind speed IFs. Considering the high fluctuation and volatility of original wind speed series, WD technique is applied to reduce the high-frequency item. The series after noise elimination with the main feature of original wind speed series are utilized for model construction. Additionally, CSO algorithm with a strong searching capability for parameter adjustment is incorporated into BPNN for connection weights optimization, upon which the BPNN structure can be determined to forecast wind speed intervals, lower and upper bounds of each point. Finally, the quality of wind speed IFs is comprehensively examined by quantitative evaluation measures, which shows that the proposed WD–CSO–BPNN model can construct higher quality IFs in a short time at different training levels with different forecasting tasks or purposes.

This paper addresses the problem of uncertainty quantification for wind speed forecasts. While from a practical view, constructed wind speed IFs, a complementary source of information on wind forecasts, can be efficiently utilized along with predictive values by end users for decision-making due that uncertainties associated with wind speed forecasts are quantified, and decision-makers can assess the probability of risk they bear when applying deterministic wind forecasts.

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Appendix

IFCP, a significant characteristic of IFs, shows the probability of target values covered by the lower and upper bounds. That is defined as follows (Quan et al., 2014; Khosravi et al., 2013, 2011a):

$$\mathrm{IFCP} = \frac{1}{n}\sum_{i=1}^{n} c_i \tag{A.1}$$

where n is the number of samples and $c_i = 1$ if the target value $v_i \in [L_i, U_i]$, otherwise $c_i = 0$. L_i and U_i are the lower and upper bounds of the ith IF, separately.

Another quantitative measure, IFs normalized average width (IFNAW), evaluates IFs from this aspect and is defined as follow (Khosravi et al., 2013, 2011b):

$$\mathrm{IFNAW} = \frac{1}{nR}\sum_{i=1}^{n}(U_i - L_i) \tag{A.2}$$

where R is the range of underlying targets defined as the difference between their maximum and minimum values.

A combinational index, named coverage width-based criterion (CWC), is introduced by Quan et al. (2014), Khosravi et al. (2013, 2011a).

$$\mathrm{CWC} = \mathrm{IFNAW}(1 + \gamma(\mathrm{IFCP})e^{-\eta(\mathrm{IFCP}-\mu)}) \tag{A.3}$$

where μ and η are two hyper-parameters. The role of μ, denoting the pre-assigned IFCP that must be met, corresponds to the nominal confidence level associated with IFs. As for η, it is usually set to a large value to magnify the difference between μ and IFCP, which can highly penalize the unsatisfied IFs. $\gamma(\mathrm{IFCP})$ is defined by the following step function:

$$\gamma(\mathrm{IFCP}) = \begin{cases} 0 & \mathrm{IFCP} \geq \mu \\ 1 & \mathrm{IFCP} < \mu. \end{cases} \tag{A.4}$$

According to the step function, the exponential term in Eq. (A.3) can be eliminated whenever IFCP $\geq \mu$ thereby CWC equals IFNAW. Otherwise, the corresponding penalty will be accounted by CWC. Actually, the CWC measure tries to find a tradeoff between validity (IFCP) and informativeness (IFNAW) of IFs.

References

Abdel-Aal, R.E., Elhadidy, M.A., Shaahid, S.M., 2009. Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks. Renew. Energy 34 (7), 1686–1699.
Blonbou, R., 2011. Very short-term wind power forecasting with neural networks and adaptive Bayesian learning. Renew. Energy 36 (3), 1118–1124.
Catalao, J.P.S., Pousinho, H.M.I., Mendes, V.M.F., 2011. Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal. IEEE Trans. Sustain. Energy 2 (1), 50–59.
Costa, A., Crespo, A., Navarro, J., Lizcano, G., Madsen, H., Feitosa, E., 2008. A review on the young history of the wind power short-term prediction. Renew. Sustain. Energy Rev. 12 (6), 1725–1744.
El-Fouly, T.H.M., El-Saadany, E.F., Salama, M.M.A., 2006. One day ahead prediction of wind speed using annual trends. In: Power Engineering Society General Meeting, 2006. IEEE, p. 7.
Erdem, E., Shi, J., 2011. ARMA based approaches for forecasting the tuple of wind speed and direction. Appl. Energy 88 (4), 1405–1414.
Guo, Z., Zhao, J., Zhang, W., Wang, J., 2011. A corrected hybrid approach for wind speed prediction in Hexi Corridor of China. Energy 36 (3), 1668–1679.
Haque, A.U., Mandal, P., Kaye, M.E., Meng, J., Chang, L., Senjyu, T., 2012. A new strategy for predicting short-term wind speed using soft computing models. Renew. Sustain. Energy Rev. 16 (7), 4563–4573.
Haque, A.U., Mandal, P., Meng, J., Negnevitsky, M., 2013. Wind speed forecast model for wind farm based on a hybrid machine learning algorithm. Int. J. Sustain. Energy 1–14 (ahead-of-print).
Haque, A., Nehrir, M.H., Mandal, P., 2014. A hybrid intelligent model for deterministic and quantile regression approach for probabilistic wind power forecasting. IEEE Trans. Power Syst. 29 (4), 1663–1672.
Heskes, T., 1997. Practical confidence and prediction intervals. Adv. Neural Inf. Process. Syst. 176–182.
Hong, Y.Y., Chang, H.L., Chiu, C.S., 2010. Hour-ahead wind power and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs. Energy 35 (9), 3870–3876.
Jiang, Y., Song, Z., Kusiak, A., 2013. Very short-term wind speed forecasting with Bayesian structural break model. Renew. Energy 50, 637–647.
Jung, J., Broadwater, R.P., 2014. Current status and future advances for wind speed and power forecasting. Renew. Sustain. Energy Rev. 31, 762–777.
Kani, S.P., Riahy, G.H., 2008. A new ANN-based methodology for very short-term wind speed prediction using Markov chain approach. In: Electric Power Conference, 2008. EPEC 2008. IEEE Canada. IEEE, pp. 1–6.
Khosravi, A., Nahavandi, S., Creighton, D., 2013. Prediction intervals for short-term wind farm power generation forecasts. IEEE Trans. Sustain. Energy 4 (3), 602–610.
Khosravi, A., Nahavandi, S., Creighton, D., Atiya, A.F., 2011a. Lower upper bound estimation method for construction of neural network-based prediction intervals. IEEE Trans. Neural Netw. 22 (3), 337–346.
Khosravi, A., Nahavandi, S., Creighton, D., Atiya, A.F., 2011b. Comprehensive review of neural network-based prediction intervals and new advances. IEEE Trans. Neural Netw. 22 (9), 1341–1356.
Landberg, L., Giebel, G., Nielsen, H.A., Nielsen, T., Madsen, H., 2003. Short-term prediction—An overview. Wind Energy 6 (3), 273–280.
Lei, M., Shiyan, L., Chuanwen, J., Hongling, L., Yan, Z., 2009. A review on the forecasting of wind speed and generated power. Renew. Sustain. Energy Rev. 13 (4), 915–920.
Li, G., Shi, J., 2010. On comparing three artificial neural networks for wind speed forecasting. Appl. Energy 87 (7), 2313–2320.
Liu, S.Q., Lu, X.F., Liu, R.M., Zeng, W.H., He, M.C., 2012. The application of the Bp neutral network in the estimation of non-point source pollution. Procedia Environ. Sci. 13, 263–273.
Liu, D., Niu, D., Wang, H., Fan, L., 2014. Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. Renew. Energy 62, 592–597.
Liu, H., Shi, J., Erdem, E., 2010. Prediction of wind speed time series using modified Taylor Kriging method. Energy 35 (12), 4870–4879.

Mandal, P., Zareipour, H., Rosehart, W.D., 2014. Forecasting aggregated wind power production of multiple wind farms using hybrid wavelet-PSO-NNs. Int. J. Energy Res.
Mandic, D.P., Javidi, S., Goh, S.L., Kuh, A., Aihara, K., 2009. Complex-valued prediction of wind profile using augmented complex statistics. Renew. Energy 34 (1), 196–201.
Meade, N., Islam, T., 1995. Prediction intervals for growth curve forecasts. J. Forecasting 14 (5), 413–430.
Papadopoulos, G., Edwards, P.J., Murray, A.F., 2001. Confidence estimation methods for neural networks: A practical comparison. IEEE Trans. Neural Netw. 12 (6), 1278–1287.
Pinson, P., Kariniotakis, G., 2004. On-line assessment of prediction risk for wind power production forecasts. Wind Energy 7 (2), 119–132.
Qin, S., Liu, F., Wang, J., Sun, B., 2014. Analysis and forecasting of the particulate matter (PM) concentration levels over four major cities of China using hybrid models. Atmos. Environ. 98, 665–675.
Quan, H., Srinivasan, D., Khosravi, A., 2014. Short-term load and wind power forecasting using neural network-based prediction intervals.
Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1988. Learning representations by back-propagating errors. Cogn. Model.
Salcedo-Sanz, S., Pérez-Bellido, Á.M., Ortiz-García, E.G., Portilla-Figueras, A., Prieto, L., Paredes, D., 2009. Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction. Renew. Energy 34 (6), 1451–1457.
Soman, S.S., Zareipour, H., Malik, O., Mandal, P., 2010. A review of wind power and wind speed forecasting methods with different time horizons. In: North American Power Symposium (NAPS), 2010. IEEE, pp. 1–8.
Song, Z., Jiang, Y., Zhang, Z., 2014. Short-term wind speed forecasting with Markov-switching model. Appl. Energy 130, 103–112.
Su, Z., Wang, J., Lu, H., Zhao, G., 2014. A new hybrid model optimized by an intelligent optimization algorithm for wind speed forecasting. Energy Convers. Manage. 85, 443–452.
Wang, Z., Liu, F., Wu, J., Wang, J., 2014. A hybrid forecasting model based on bivariate division and a back propagation artificial neural network optimized by chaos particle swarm optimization for day-ahead electricity price. Abst. Appl. Anal. 2014, 31 pages, Article ID 249208, http://dx.doi.org/10.1155/2014/249208.
Wang, J., Qin, S., Jin, S., Wu, J., 2015. Estimation methods review and analysis of offshore extreme wind speeds and wind energy resources. Renew. Sustain. Energy Rev. 42, 26–42.
Wang, J., Zhang, W., Li, Y., Wang, J., Dang, Z., 2014. Forecasting wind speed using empirical mode decomposition and Elman neural network. Appl. Soft Comput. 23, 452–459.
Wei-Chang, Y., 2013. New parameter-free simplified swarm optimization for artificial neural network training and its application in the prediction of time series. IEEE Trans. Neural Netw. Learn. Syst. 24 (4), 661–665.
Yang, X.S., Deb, S., 2009. Cuckoo search via Lévy flights. In: Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on. IEEE, pp. 210–214.
Yang, X.S., Deb, S., 2010. Engineering optimisation by cuckoo search. Int. J. Math. Model. Numer. Optim. 1 (4), 330–343.
Zhang, W., Wang, J., Wang, J., Zhao, Z., Tian, M., 2013. Short-term wind speed forecasting based on a hybrid model. Appl. Soft Comput. 13 (7), 3225–3233.
Zhou, J., Shi, J., Li, G., 2011. Fine tuning support vector machines for short-term wind speed forecasting. Energy Convers. Manage. 52 (4), 1990–1998.