DOI:10.13648/j.cnki.issn1674-0629.2013.05.007

文章编号: 1674-0629(2013)05-0001-08 中图分类号: TM406; TM402 文献标志码: A

风电并网关键技术: 风电的直接概率预测

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摘要: 风电是一种重要的可再生能源，但风电具有的高波动性和随机性使其大规模并网运行面临各种困难和挑战。准确的风电功率预测是减少风电并网风险的关键技术之一。由于风电功率时间序列的高度波动性，传统的基于点预测方法无法提供可靠的风电功率预测结果。基于概率区间的风力发电预测技术能够同时量化预测误差和相关概率，从而降低由于预测误差带来的各种风险，可以更有效地支持电力系统应对各种不确定性和风险。首先总结风电功率预测技术的最新发展，然后提出了一个基于超级学习机和进化计算的方法直接生成风电预测区间。相较于已有的方法，所提出的算法优点在于能够直接通过一次性优化过程产生预测区间，从而在保证高有效性的前提下简化了模型和计算量，避免了传统方法中包含的误差数据分析等高计算量的步骤。通过丹麦实际风电场数据对所提出的方进行了各种测试，结果表明该方法能够高效和准确地提供风电功率概率预测区间。
关键词: 风电; 概率区间预测; 超级学习机; 进化计算

The Key Technology for Grid Integration of Wind Power: Direct Probabilistic Interval Forecasts of Wind Power

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Abstract: The wind power is an important renewable energy, but it has features of high volatility and uncertainty, therefore a large scale integration of wind power into power system will impose significant challenges in system operation. Accurate wind power prediction is one of the key technologies to reduce the risk of its grid integration. Because of the nonstationarities and nonlinearities of wind power series, traditional point prediction methods cannot provide satisfactory prediction results. In contrast, probabilistic interval based wind power forecasting techniques can simultaneously quantify the prediction error and the associated probability, thereby can more effectively support power system operation to cope with various uncertainties and risks. This paper firstly summarizes the latest developments in wind power forecasting techniques, then proposes an Extreme Learning Machine (ELM) and evolutionary computation based method to directly generate wind power prediction intervals. Compared to the existing methods, the advantage of the proposed method is able to directly generate prediction intervals through one optimization process, thus to largely simplify the model construction and avoid prediction errors analysis. The proposed method has been tested with practical wind farm data in Denmark, and the results demonstrate that it can efficiently and accurately provide probabilistic prediction intervals of wind power.
Key words: wind power; probabilistic interval forecast; extreme learning machine; evolutionary computation

The critical challenge of wind power [1-2] lies in its high intermittency and uncertainty. In countries like Denmark, where the penetration hits already a fairly high record close to 30%, the management of the wind production is a more critical challenge for power system operators in many aspects. Conventional power generation technologies, apart from occasional failures, are flexibly dispatchable in the sense that future production can be precisely planned in advance to meet the demand. This is not the case with wind or solar power, which solely depends on the weather conditions that are full of uncertainties. Consequently, accurate forecasts of the power productions of wind farms for next few hours or days ahead become essential for their optimal integration into power systems.

Currently, power systems in most countries have the obligations to accept wind power completely. Thus system operators have to, empirically without specific analysis, entrust large amount of idle resources of high costs to counterbalance the wind power variations and ensure the system security. Therefore improvements of wind forecasts have both technical and economic significances to power system operators and electricity consumers. Wind forecasts with poor accuracies lead to highly risky operation situations. There have been incidents happened in practice, where poor forecasts led to serious security events. As illustrated in Fig 1, a case in point happened in January 2005, Denmark, where a power imbalance of over 2 000 MW occurred between the actual and forecasted wind generation due to an extremely high wind speed that was not properly forecasted beforehand [3-4].

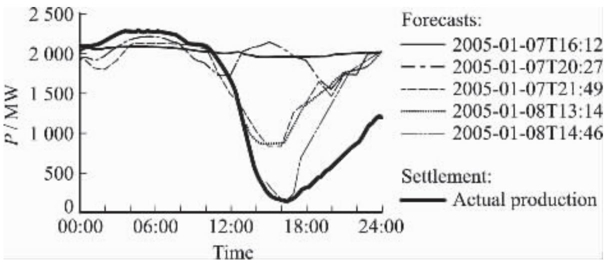

Fig. 1 Daily Production Curve

The curves in Fig. 1 show the short-term point-wise forecasts (up to 21. 5 h) for the severe storm at western Denmark on the 8th January, 2005. The first forecasts show production capacity of about 2 000 MW wind power was expected in the period between noon and 6 pm. The actual production around 4 pm reached no more than 200 MW, only a tenth of the estimate, because most wind turbines shut down due to high wind speed (>20 m/s). The system operator Energinet. dk had struggled to activate all available reserves to balance the system during the event [3].

The state-of-the-arts wind forecast methods fall into several categories as follows [5]:

(i) Physical models i. e. the NWP (numerical weather prediction) methods;

(ii) Time series analysis models;

(iii) Advanced methods based on data mining and machine learning techniques.

The NWP method relies on physical models commonly used in meteorological weather forecasts [5], and performs forecasts by numerically solving a set of conservation equations considering global air system parameters such as mass, momentum, and heat at given locations. The NWP model usually involves a spatial grid containing local latitude, longitude and elevation information with reasonable horizontal resolutions to ensure the NWP accuracy. The method is less effective for the complex nonlinear systems such as the forecast of wind speed, due to the fact that they need detailed system identification and data analysis at very high computational costs. E. g. the Hong Kong Observatory provides NWP based weather forecast using Operational Regional Spectral Model (ORSM) on a spatial grid of 20 km for inner domain and 60 km for outer domain to provide 42-hour and 72-hour forecasts respectively [6]. The NWP method also suffers from the insufficient details between the grid nodes. In contrast, forecast methods in categories ii & iii, which are based on mainly a database of past wind and other meteorological data and no detailed system identification data, are expected to be more effective for the forecast of wind fluctuations.

Short term wind prediction based on time series models and statistical methods has been reported in [7-8]. Autoregressive Models (AR), Moving Average (MA) and Autoregressive Moving Averages (ARMA) models are frequently used to model linear dynamic structures, to depict linear relationships among lagged variables and to serve as vehicles for linear wind forecasting. The linear regression models can be computationally efficient with however poor performances due to the high volatility of wind power time series and cannot fulfill the operation needs of power systems. Different Neural Network (NN) based methods are also proposed for short term wind speed forecasts, including e. g. fuzzy-neural network, radial basis function and recurrent neural networks [5,9-11]. The NN based methods have shown somewhat good performances for short term wind speed forecasting. However, the NN models commonly suffer from a number of deficiencies especially with respect to generalization, local minima, overtraining, and applicability to large scale systems. Nevertheless, most existing methods provide only a single point-wise estimation of wind speed or power into future scope. Accordingly using the forecasted results for power system operation planning can imply a high risk due to the high uncertainties involved in the actual wind variations as evidenced by practical experiences [3].

Recognizing the importance and limitation of existing forecast methods, this paper develops an innovative probabilistic forecasting tool that can provide both robust wind forecasts and quantified uncertainties simultaneously. Compared to existing methods in the field, the new method distinguishes itself in an integral optimization approach to directly construct optimal PIs without the prior knowledge, statistical inference or distribution assumption of forecasting errors required in most traditional approaches.

The paper is organized as follows, Section 1 introduces the-state-of-the-arts probabilistic interval forecasting methods and formulation of the prediction intervals for wind power. Section 2 focuses on the evaluation criteria of probabilistic prediction intervals. Section 3 presents the proposed formulation of the optimal PI construction, followed by case studies in Section 4. Section 5 concludes the paper with several conclusions and future scope.

1 Probabilistic Prediction Intervals for Wind Power

1.1 State-of-the-arts Probabilistic Forecasting Methods for Wind Power

Traditional point forecasts of e. g. a wind farm power production Y_{t+h} at time t for h hours ahead involves finding a function f_h such that

$$Y_{t+h} = f_h(Y^{\Delta}_{t,h}; X_{t,h}) + \varepsilon_{t+h}, \tag{1}$$

where $Y^{\Delta}_{t,h} = (Y_t, Y_{t-1}, \cdots, Y_{t-l})$ is a vector of lagged values of the wind power series to be predicted and $X_{t,h}$ can be a vector of lagged exogenous variables informing about the instantaneous weather conditions around the measurement location e. g. ambient temperatures.

For $\alpha \in [0, 1]$ and an integer $h \geqslant 1$, predicting the α - quantile $q_{t+h|t}(\alpha)$ (or confidence interval) of wind power Y_{t+h} given the information at time t is defined as finding the smallest value $q_{t+h|t}(\alpha)$ such that

$$P(Y_{t+h} \leqslant q_{t+h|t}(\alpha) \mid X_{t,h}) \geqslant \alpha. \tag{2}$$

If given $X_{t,h}$, the cumulative distribution function F of Y_{t+h} is increasing and known beforehand, then $q_{t+h|tt}(\alpha) = F^{-1}(\alpha)$. The quantile forecast at time t for horizon h is therefore the forecast of $q_{t+h|t}(\alpha)$, denoted as $\hat{q}_{t+h|tt}(\alpha)$, termed as Prediction Interval (PI) [7,2-13]. Eq. (2) defines the upper bound of PI and the lower bound can be defined in a similar way.

Compared to the traditional point forecast, the probabilistic forecast methods generate a pair of prediction intervals (PIs) with associated confidence levels that can effectively quantify the uncertainties of future wind production, thus enabling all power system players to do e. g. beforehand preparation for possible scenarios. This can significantly reduce the risks due to high wind penetration in various operation and planning activities, such as the wind farm control, reserve setting, energy storage sizing, unit commitment, wind power trading, and so forth [4-15].

Quite a few methods can be applied for probabilistic wind power forecast. [16] and [17] proposed a quantile regression based method to estimate different forecasting quantiles. Based on the point forecast results by well recognized systems such as AWPPS (armines wind power prediction system) and WPPT (wind power prediction tool), PIs are constructed through a combined nonparametric probabilistic forecasting and adaptive resampling approach in [7]. Meteorological ensembles are adopted to generate predictive distribution and PIs. The uncertainty of wind power forecast is analyzed through the nonlinear power curve and statistical analysis of wind speed prediction errors in [18]. The conditional kernel density estimation is applied to approximate the probability distribution of wind power series [19].

Most existing methods of probabilistic forecast rely on statistical analysis of point forecast errors to develop PIs. Therefore, these methods require several major steps to construct the forecasting model (including to construct the point forecast models), to analyze the point forecast errors, and to finally estimate and test the PIs. In addition, prior assumption of forecast error distribution is usually involved in these methods. In view of these deficiencies, this paper proposes a new direct approach for PI forecast of wind power based on ELM (extreme learning machine) [20] and particle swarm optimization (PSO) [21], simplifying the PI construction as one optimization step. Because of ELM, the new approach overcomes many drawbacks of the traditional NNs based methods such as local minima, overtraining, and high commuting costs etc.

1.2 Extreme Learning Machine

ELM is a novel learning algorithm dedicated for single-hidden layer feedforward neural networks (SLFNs) with extremely fast learning and superior generalization. Different from traditional gradient-based training algorithms such as the Back-propagation (BP) [20], ELM randomly chooses the input weights and hidden biases, which are not needed to be tuned in the training process, thus dramatically saving the training time. Given a dataset with N arbitrary distinct samples $\{(x_i, t_i)\}_{i=1}^{N}$, where $x_i \in \mathbb{R}^n$ and $t_i \in \mathbb{R}^m$ are inputs and targets respectively, ELM with K hidden neurons and activation function $\psi(\cdot)$ can approximate the N samples with zero error as follows:

$$f(x_j)p = \sum_{i=1}^{K} \beta_i \psi(a_i \cdot x_j + b_i) = t_j (j = 1, \cdots, N), \quad (3)$$

where $a_i = [a_{i1}, a_{i2}, \cdots, a_{in}]^{\mathrm{T}}$ is the weight vector connecting the i^{th} hidden neuron and the input neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^{\mathrm{T}}$ is the weight vector connecting the i^{th} hidden neuron and the output neurons, b_i denotes the threshold of the i^{th} hidden neuron, and $\psi(a_i \cdot x_j + b_i)$ is the output of the i^{th} hidden neuron with respect to the input x_j. Eq. (3) can be simplified as

$$H\beta = T, \quad (4)$$

where H is the hidden layer output matrix of the modeled ELM, and

$$H = \begin{bmatrix} \psi(a_1 \cdot x_1 + b_1) & \cdots & \psi(a_K \cdot x_1 + b_K) \\ \vdots & & \vdots \\ \psi(a_1 \cdot x_N + b_1) & \cdots & \psi(a_K \cdot x_N + b_K) \end{bmatrix}_{N \times K} \quad (5)$$

The i^{th} column of H denotes the output vector of the i^{th} hidden neuron with respect to the inputs $x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^{\mathrm{T}}$. In addition, β is the matrix of output weights and T is the matrix of targets.

With the weights a_i and the hidden layer biases b_i randomly determined, the hidden layer output matrix H can be uniquely determined, and consequently the estimated parameters a_i^*, b_i^* and β_i^* can be obtained by

$$\|H(a_1^*, \cdots, a_k^*, b_1^*, \cdots, b_k^*)\beta^* - T\| = \min_{\beta} \|H(a_1, \cdots, a_k, b_1, \cdots, b_k)\beta - T\|, \quad (6)$$

which is equivalent to minimizing the cost function of the traditional gradient-based learning algorithms used in e. g. BP algorithm.

Training an SLFN using ELM is simply equivalent to finding a unique smallest norm least-square solution of the linear system in (4), i. e.

$$\beta^* = H^+ T, \quad (7)$$

where H^+ is the Moore-Penrose generalized inverse of the hidden layer output matrix H, which can be obtained through singular value decomposition (SVD) method.

The advantages of the ELM algorithm are significant. The traditional gradient based NNs learning algorithms like BP always involve iterative training that is time consuming. The ELM training features extremely fast speed because of the simple matrix computation according to (7), and can always guarantee the optimal performance. In addition, it has many advantages such as avoiding overtraining and local minima etc [20].

1.3 Formation of PIs

Given a dataset $\{(x_i, t_i)\}_{i=1}^{N}$, where x_i and t_i are relevant input variables and future target to forecast, PI with nominal confidence $(1-\alpha)$ of the future target t_i, represented as $I_t^{\alpha}(x_i)$, is defined as

$$I_t^{\alpha}(x_i) = [L_t^{\alpha}(x_i), U_t^{\alpha}(x_i)], \quad (8)$$

where $L_t^{\alpha}(x_i)$ and $U_t^{\alpha}(x_i)$ denote the lower and upper bounds of $I_t^{\alpha}(x_i)$ respectively, such that the future target t_i is expected to be covered by $I_t^{\alpha}(x_i)$ with the probability $(1-\alpha)$.

2 Evaluation Criteria for Prediction Intervals

Different from the traditional point forecast methods, the performance evaluation of probabilistic forecast model cannot employ traditional indices like NMAE (normalized mean average error) etc. Instead, the indices of reliability and sharpness are specially defined and applied [22].

2.1 Reliability

Reliability refers to the ability of probabilistic forecasts to fulfill the nominal probabilities. Under a large number of, e. g. 20% forecasted quantiles, ideally 20% of the power output should be observed. The reliability herein is measured by the deviation of observed proportion from the theoretical one.

In principle, the future targets t_i are expected to be enclosed by the constructed PIs with the nominal coverage probability $(1-\alpha)$, termed as PI nominal confidence (PINC, noted quantitatively as C_{PINC}). PI coverage probability measured by PICP (noted quantitatively as P_{PICP}), is a key indicator of the reliability for the constructed PIs [13,22], defined as

$$P_{\text{PICP}} = \frac{1}{N_t} \sum_{i=1}^{N_t} c_i^{\alpha}, \quad (9)$$

where N_t is the number of test samples, and $c_i^{(\alpha)}$ is the indicator of PICP, which is equal to 1 if the future target is enclosed by the produced PI, otherwise 0. The PICP of derived PIs is expected close to the nominal confidence. Then, average coverage error (ACE, noted quantitatively as E_{ACE}) can be calculated to assess the reliability of PIs, defined by

$$E_{ACE} = P_{PICP} - C_{PINC}. \tag{10}$$

Ideally the E_{ACE} should be zero or as close to zero as possible. The smaller the absolute E_{ACE} is, the higher reliability of the constructed PIs will be resulted.

2.2 Sharpness

Sharpness refers to the ability of a probabilistic forecast to concentrate the probability of a future outcome, and can be calculated as the width of PIs, i.e.

$$\delta_t^\alpha(x_i) = U_t^\alpha(x_i) - L_t^\alpha(x_i). \tag{11}$$

In the study, we are interested in PIs with two quantiles defined as (2), the interval score is used to assess the overall skill of constructed PIs to take into account the sharpness perspective [13,22]. The interval score of PI $I_t^\alpha(x_i)$ for a single prediction point, denoted as $Sc_t^\alpha(x_i)$, can be defined as

$$Sc_t^\alpha(x_i) = \begin{cases} -2\alpha\delta_t^\alpha(x_i) - 4[L_t^\alpha(x_i) - t_i], & \text{if } t_i < L_t^\alpha(x_i) \\ -2\alpha\delta_t^\alpha(x_i), & \text{if } t_i \in I_t^\alpha(x_i) \\ -2\alpha\delta_t^\alpha(x_i) - 4[t_i - U_t^\alpha(x_i)], & \text{if } t_i > U_t^\alpha(x_i) \end{cases} . \tag{12}$$

The $Sc_t^\alpha(x_i)$ is for each prediction point and the overall score value $\overline{Sc_t^\alpha}$ is the average of $Sc_t^\alpha(x_i)$ over the entire test data,

$$\overline{Sc_t^\alpha} = \frac{1}{N_t}\sum_{i=1}^{N_t} Sc_t^\alpha(x_i). \tag{13}$$

The score awards narrow PIs provided the future target is enclosed. Otherwise, penalties should be applied. Including all properties of PIs, the interval score could assess the overall skill of forecasted PIs, but cannot quantitatively distinguish the contributions of the two aspects. Nevertheless, given PIs with similar reliability, the smaller the absolute score $\overline{Sc_t^\alpha}$ indicates the higher sharpness and consequently the higher quality of PIs.

3 Direct Construction of PIs

3.1 Objective

The core idea of the proposed method is to formulate the PI construction as a multi-objective model, where the objectives addressing reliability and sharpness of PIs are included. Although the interval score accounts for reliability and sharpness, it cannot quantitatively distinguish the contributions of the two aspects specifically. Moreover, the score is not a dedicated index for reliability assessment anyhow. Therefore to emphasize the reliability aspect, which should be prioritized in forecasts, ELM output weights β are optimized with respect to the objective F combining E_{ACE} and overall score $\overline{Sc_t^\alpha}$ (or noted quantitatively as S_{core}) to optimize both reliability and sharpness of PIs at particular confidence levels $100(1-\alpha_i)\%$, $i = 1, 2, \cdots, n$,

$$\min_\beta F = \chi|E_{ACE}| + \lambda|\overline{Sc_t^\alpha}|, \tag{14}$$

where $|\cdot|$ is the absolute value function, and χ and λ are importance weights of the reliability and overall skill respectively. The weights χ and λ are simply set as unit values in our study, indicating that equal importance is assigned to both objectives, and this is not unreasonable.

3.2 Particle Swarm Optimization

The objective function of the proposed approach is non-differentiable and therefore solved by Particle Swarm Optimization (PSO) in our study, which is a heuristic optimization method and has been proved to be an efficient, robust and gradient-free optimization algorithm [21]. PSO also distinguishes itself from other heuristic optimization methods by its strong searching capability and fast convergence speed.

If the search space of PSO is D-dimensional and the size of the particles population is S, the i^{th} particle of the swarm can be represented by X_i and the best particle in the swarm, i.e. the particle generating the smallest objective function value, is denoted as P_g. The previous best position, i.e. the position with the smallest objective function value of the i^{th} particle is denoted as P_i^b, and the position velocity of the i^{th} particle is represented as V_i. In each iteration, the velocity of each particle is computed, and all the particles are updated accordingly,

$$V_i = V_i + R_1(P_i^b - X_i) + R_2(P_g - X_i), \tag{15}$$

$$X_i = X_i + V_i, \tag{16}$$

where $i = 1, 2, \cdots, S$; R_1 and R_2 are random numbers within $[0, c_1]$ and $[0, c_2]$ respectively. The velocity of the i^{th} particle is a function of three components, namely the particle's previous velocity, the distance between the particle's previous best position and current position, and the distance between the swarm's best success and the particle's current location. After the updating, the velocity are kept in the range $[-V_{max}, +V_{max}]$. The performance of each particle is evaluated through the formulated objective function (14).

3.3 The Training Procedure

The proposed method is actually a MOOP based regression procedure to construct the optimal PIs. The first step of implementation is to collect datasets for training and test, including historical wind power data and wind speed and NWP information, etc. With the obtained training datasets, the parameters of ELM including the network structure, input weights a_i and biases b_i are determined. As the decision variables in PSO, a population array of particles for the output weights of ELM β_{int} are prepared for evolution process. Velocities V in the search space are initialized as well. Then it goes into the PSO iteration to optimize the formulated forecaster. Finally, the resultant forecaster is evaluated based on the test data.

Because of the superb mapping capability of ELM, the proposed algorithm is highly flexible to include various input information or output forecasts at various lookahead steps. The proposed approach is indeed performance-oriented, and the quality of constructed PIs with respect to reliability and sharpness is ensured.

4 Case Studies

The highly chaotic climate systems are responsible for the high level of uncertainties in wind power generation. To comprehensively validate the effectiveness of the proposed approach, it is tested by the wind farm on Bornholm Island in Denmark, with a total installed capacity P_c of 30 MW approximately. Wind power generation data with one-hour resolution of the wind farm is used in the study covering the period from February to December 2012.

When the look-ahead time is shorter than a few hours, the statistical approach can usually outperform the NWP-based technique. Without loss of generality, in the case study we just focus on one-hour and two-hour ahead wind power forecasting, which provide essential information in dispatching generation and ancillary services in practice, e. g. in the Nord Pool market in Scandinavia, the hourly market plays a key role in maintaining the system balance[23]. Notably, the wind power series is used as the inputs alone to the proposed approach to conduct the prediction. For longer look-ahead time, other relevant data such as the NWP information can be incorporated as the input easily to enhance the accuracy.

To evaluate the performance of the proposed probabilistic interval forecasting approach, there PI forecasting techniques including the climatology method, the normal forecast method, and the persistence method are used to estimate PIs using the same datasets for benchmarking. The climatology is regarded as the most widely applied benchmark for probabilistic interval forecasting of weather-related processes, e. g. wind power forecasting herein. It is actually based on the unconditional predictive distribution obtained from all historical wind power data. In the normal approach, the normal distribution is used to estimate PIs, and its mean and variance can computed from the observed data. Both the climatology and normal approaches are unconditional predictions and cannot properly address the heteroscedasticity of wind power series. The two approaches are easy to outperform for short look-ahead time forecasting. For point forecasting, the persistence forecast method is a widely used benchmark and is known to be difficult to outperform for short look-ahead time. The persistence based probabilistic forecast model is used as benchmark herein, which can be a fair and popular benchmark for short-term forecasting[7,10]. The forecast error by this method is assumed to be random and normally distributed. Its mean is given by the last available power measurement, and the variance is computed using the latest observations.

In the case study, we focus on high confidence PI forecast. This is because decision makers in power systems prefer information of high confidence levels in their daily operation. Specially, PIs with 90% and 99% confidence levels are studied in this study. The wind power data from February to September 2012 is used for training the proposed and the benchmark models. The rest data are used for testing purpose.

Tab. 1 and Tab. 2 compare the performances of PIs generated by different methods in terms of ACE, PICP and overall score.

Tab. 1　Evaluation of Constructed PIs with One-Hour Horizon

C_{PINC} /%	Methods	P_{PICP} /%	E_{ACE} /%	S_{core} /%
90	Proposed Method	90.60	0.60	-5.12
	Climatology	88.84	-1.16	-16.35
	Normal	87.70	-2.30	-19.59
	Persistence	88.83	-1.17	-5.79
99	Proposed Method	98.86	-0.14	-0.99
	Climatology	97.27	-1.73	-1.84
	Normal	97.95	-1.05	-2.09
	Persistence	96.18	-2.82	-1.37

Tab. 2　Evaluation of Constructed PIs with Two-Hour Horizon

C_{PINC} /%	Methods	P_{PICP} /%	E_{ACE} /%	S_{core} /%
90	Proposed Method	90.24	0.24	-7.62
	Climatology	88.84	-1.16	-16.35
	Normal	87.70	-2.30	-19.59
	Persistence	88.55	-1.45	-9.27
99	Proposed Method	97.72	-1.28	-1.24
	Climatology	97.27	-1.73	-1.84
	Normal	97.95	-1.05	-2.09
	Persistence	96.18	-2.82	-1.98

The proposed method outperforms all other methods for both one and two hour ahead forecasts. It presents the best reliability with smaller average absolute ACE. It also provides the best overall score. E.g. for $C_{PINC}=90\%$., the P_{PICP}, E_{ACE} and S_{core} of the proposed method are 90.60%, 0.60% and -5.12% respectively for one hour ahead forecast. The persistence method generally presents the second best performance, while the other two methods perform very poorly. The P_{PICP}, E_{ACE} and S_{core} generated by the persistence method are 88.83%, -1.17 and -5.79% respectively for one hour ahead forecast.

Fig. 2 and Fig. 3 present the PIs generated by the proposed method for one and two hour ahead forecasts at $C_{PINC}=90\%$. The effectiveness of the proposed approach is well demonstrated in the figures, where the actual wind productions are well enclosed by the constructed PIs. Obviously PIs with two-hour look-ahead time are wider than that of one-hour look-ahead time, which can be understood that the longer time prediction would have higher uncertainty.

Among the benchmarks, the climatology and normal ones are based unconditional predictive distribution of the historical data, therefore cannot reflect the actual properties of the wind production. The persistence model adopts relatively advanced modeling of the uncertainties involved in the time series, and therefore can provide much better forecasts. Still the proposed method exhibits the best forecasting performance due to the optimization and ELM based approach, which possesses strengthened generalization and flexibility. The method can also be extended to different prediction horizons by incorporating different external information such as NWP. With the unique advantages and outstanding performance, the proposed method can provide accurate and meaningful information to support various decision making problems in power systems, such as unit commitment and system dispatch.

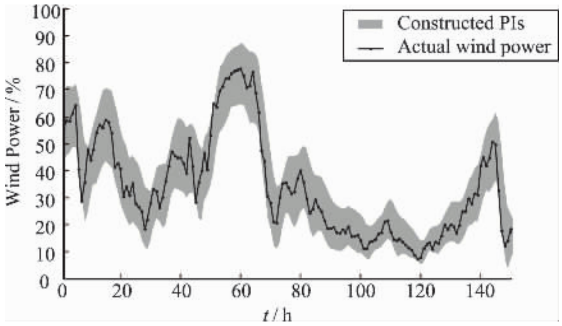

Fig. 2　PIs with Nominal Confidence 90% and One-Hour Look-ahead Time Obtained by the Proposed Approach in October 2012.

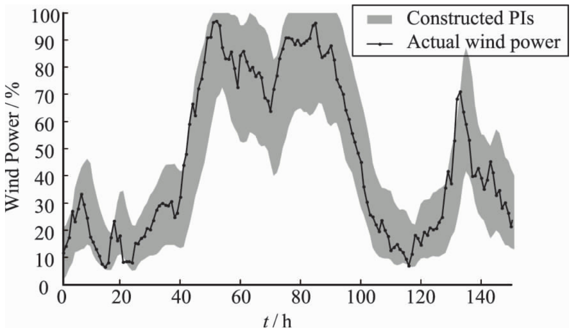

Fig. 3　PIs with Nominal Confidence 90% and Two-Hour Look-ahead Time Obtained by the Proposed Approach in November 2012.

5　Conclusions

Wind power forecast is critical challenging yet due to its nonstationarites and nonlinearities. Traditional point prediction cannot provide satisfactory performance, and probabilistic interval forecast presents a new and effective way to quantify the uncertainties involved in wind power forecast. Without the need of prior analysis or assumptions about forecasting errors, this paper proposes a novel direct approach to construct prediction intervals of wind power. Based on extreme learning machine and particle swarm optimization, the proposed method produces PIs of high quality in one single optimization step, which can not only guarantee the optimal performance, but also greatly reduce the computing efforts, distinguishing the method from most existing methods. The method presents an excellent generalized framework of probabilistic wind power forecasting with high flexibility and extendibility. Future work is underway to extend the method for multiple-step forward forecasting.

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Received date: 2013-09-30

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收稿日期: 2013-09-30

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