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Review of Evaluation Criteria and Main Methods of Wind Power Forecasting

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Abstract

Wind power has characteristics of randomness and uncontrollability. China needs to learn from the successful experience of wind power prediction in European. Wind power forecasting (WPF) will be an important part of the power system construction in the future. Firstly, the classification of WPF is discussed according to the different classified methods. Secondly, the evaluation criteria about the uncertainty of WPF are summarized. Thirdly, we give a survey on the main methods of WPF. Finally, the development direction of WPF is proposed.

Keywords: Wind power forecasting; Error evaluation; Current situation; Development direction.

1. Introduction

Currently, countries in the world increasing emphasis on the development of clean energy and improve energy efficiency in order to countering the climate changes and committing energy security. The developing trend of the world energy is clean energy, low carbon, and high efficiency. As the basis and premise of the low-carbon electricity, in recent years, smart grid technology rapidly develops in many countries. Smart grid has become the development trend of the future grid [1].

China State Grid Corporation has proposed the strong smart grid strategy. In addition to significantly reducing the energy losses in the electricity transmission and distribution, the smart grid also has an important role in power structural optimization and acceptance of clean energy [2].

As a kind of non-pollution renewable energy, wind power has been growing rapidly in many areas, especially in Europe countries and America. Research shows that China has great potential for wind energy utilization, and its wind energy in land and sea can be developed to achieve the total installed capacity of about 7 to 1.2 billion kW. Other latest assessment reports the data even up to 2.5 billion kW or

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more [3]. Therefore, China has enough capacity to support wind power to become an important part of the energy structure in the future.

Wind power has characteristics of randomness and uncontrollability. China needs to learn from the successful experience of wind power prediction in European and America. Wind power forecasting (WPF) will be an important part of the power system construction in the future. WPF is identified as an important method to operate power systems with large wind power penetrations [3].

2. Classification of WPF

2.1. Classification according to time horizons

The forecasting system is divided into 4 categories according to time horizons- very short term, short term, medium term, or long term. The time span is different in various literature descriptions. The specific classification is listed in Table 1 by summarizing the reference [4] and [5]. Various time horizon has different range and application purpose.

Table 1: Classification of different time horizons

Time Horizon	Range	Application Purpose
Very short term (in minutes)	Few seconds to 30 minutes ahead	•Electricity Market Clearing •Wind Turbine Control
Short term (in hours)	30 minutes to 48(or 72) hours ahead	•Economic Load Dispatch Planning •Load Increment/Decrement Decisions
Medium term (in days)	48(or 72) hours to 1 week ahead	•Generator Online/Offline Decisions (Arrangements for Maintenance) • Unit Commitment Decisions
Long term (in years)	1 week to 1 year or more ahead	• Maintenance Scheduling to Obtain Optimal Operating Cost • The Feasibility Study for Design of the Wind Farm

2.2. Classification according to methods and principles

The forecasting system is divided into 2 categories according to methods and principles.

- Physical Approach

Physical methods [6], [7] are to increase the real resolution of numerical weather prediction model in order to achieving accurate prediction of the weather.

The main disadvantage with the physical approach is that it needs measured data (on-line or off-line), as well as data of good quality.

- Statistical Approach

The statistical approach can transform the input variables into wind generation in a single step. The statistical approach includes several statistical linear and nonlinear models.

The artificial intelligence approach belongs to statistical approach. The essence of artificial intelligence approach is to establish the relationship between input and output by artificial intelligence methods, rather than the form of analytical method. The model described in this way is usually non-linear model. Many artificial intelligence methods are more excellent than the conventional methods and have good development prospect [8].

2.3. Classification according to predict object

The forecasting system is divided into 3 categories according to predict object- point forecasting (or spot forecasting), wind farm forecasting, or regional forecasting.

Miguel G. Lobo [9] described a method to make aggregated wind power predictions for a region with several wind farms distributed. As the number of wind farms in a region increased, the use of aggregated wind power prediction methods became faster than making predictions for each of the wind farms in the region and add them.

2.4. Classification according to input data

- Using Data of Numerical Weather Prediction
- Not Using Data of Numerical Weather Prediction

2.5. Classification according to forecasting data

- Wind Speed Forecasting(Indirect Method)

  Values of wind power are estimated by applying the appropriate transformations to values of wind speed.
- Wind Power Forecasting(Direct Method)

  This method forecast wind generation directly, without a previous step in which the wind speed is forecasted.

2.6. Evaluation criteria about the uncertainty of WPF

Wind power forecasting has a character of the inherent uncertainty, which means that WPF cannot ever be exact. Therefore, it is essential that wind power forecasting is properly evaluated. It is very important to evaluate the error measures on data that have not been used to build the prediction model or to tune the method's parameters.

The evaluation methods on the uncertainty of wind power forecasting are listed as follows [10] [11].

- The Mean Error(ME)

$$ME_k = \overline{e}_k = \frac{1}{N}\sum_{t=1}^{N} e_{t+k|t} \tag{1}$$

where:

$e_{t+k|t} = P_{t+k} - \hat{P}_{t+k|t}$ Is the error corresponding to time $t+k$ for the prediction made at time t;

P_{t+k} is the measured power at time $t+k$;

$\hat{P}_{t+k|t}$ is the power forecast for time $t+k$ made at time t;

N is the number of prediction errors used for method evaluation.

- The Mean Square Error(MSE)

$$MSE_k = \overline{e_k^2} = \frac{1}{N}\sum_{t=1}^{N} e_{t+k|t}^2 \tag{2}$$

- The Root Mean Square Error(RMSE)

$$RMSE_k = \sqrt{MSE_k} = \sqrt{\frac{\sum_{t=1}^{N} e_{t+k|t}^2}{N}} \tag{3}$$

Both systematic and random errors affect the RMSE.

- The Mean Absolute Error(MAE)

$$MAE_k = \frac{1}{N}\sum_{t=1}^{N}\left|e_{t+k|t}\right| \tag{4}$$

Both systematic and random errors affect the MAE.

- The Standard Deviation of the Error(SDE)

$$SDE_k = \sqrt{\frac{\sum_{t=1}^{N}[e_{t+k|t} - \overline{e}_k]^2}{N-1}} \tag{5}$$

Only the random errors contribute to the SDE.

- The Normalized Root Mean Square Error(NRMSE)

$$NRMSE_k = \frac{RMSE_k}{P_{inst}} = \frac{1}{P_{inst}}\sqrt{\frac{\sum_{t=1}^{N} e_{t+k|t}^2}{N}} \tag{6}$$

where: P_{inst} is the wind farm installed capacity.

- The Normalized Mean Absolute Error(NMAE)

$$NMAE_k = \frac{MAE_k}{P_{inst}} = \frac{1}{P_{inst}} \cdot \frac{1}{N}\sum_{t=1}^{N}\left|e_{t+k|t}\right| \tag{7}$$

- The Mean Absolute Percentage Error (MAPE)

$$MAPE_k = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{e_{t+k|t}}{P_{t+k}}\right| = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{P_{t+k} - \hat{P}_{t+k|t}}{P_{t+k}}\right| \tag{8}$$

The MAE has unit, but MAPE is the percentage of the forecast error and the measured error.

The main evaluation methods refer to "(1)-(8)." Different evaluation methods have different effects depending on the characteristic of WPF system. For example, the RMSE is more sensitive to the presence of erroneous data when compared to the MAE. Therefore, if there is doubt about the quality of the evaluation set, the MAE should be preferred as a main evaluation criterion since it presents greater robustness when confronted with large prediction errors. It is essential to establish a more accurate and universal error evaluation system.

3. Main Methods of WPF

We summarize the existing wind power prediction methods as follows.

- Persistence

Persistence wind or power forecasting assumes that the wind (speed and direction) or power at a certain future time will be the same as it is when the forecast is made, which can be formulated as

$$v'_{t+k|t} = v_t \qquad (k = 1,2,3,4...)$$

$$P'_{t+k|t} = P_t \qquad (k = 1,2,3,4...)\ .$$

Persistence is obviously a very simple method and is mentioned here since it is used as a reference to evaluate the performance of advanced methods. An advanced method is worth implementing if it outperforms persistence. Wind, however, is somehow persistent in nature. Persistence is a difficult method to beat, especially on the short-term (1–6 hr) [12].

- Random Time Series

Reference [13] reported a method named as vectorization of univariate hourly wind speed time series. This method had been presented for eliminating diurnal nonstationary, and vectorized hourly wind speed was expressed as a vector auto regression (VAR) model. The results showed that the presented VAR model can yield satisfactory hourly wind speed forecast as long as 72 h ahead under normal weather conditions.

Andrew Boone [14] simulated the short-term wind speed forecast errors using a multi-variate ARMA (1, 1) time-series model. L. Torres [15] used the ARMA (autoregressive moving average process) and persistence models to predict the hourly average wind speed up to 10 h in advance.

Erasmo Cadenas [16] developed Hybrid models consisting of Autoregressive Integrated Moving Average (ARIMA) models and Artificial Neural Network (ANN) models.

R.G. Kavasseri [17] examined the use of fractional-ARIMA or f-ARIMA models, and forecast wind speeds on the day-ahead (24 h) and two-day-ahead (48 h) horizons.

- Neural Networks(NN)

Sideratos G [18] described two wind power forecasting methodologies based on radial basis neural networks and fuzzy logic techniques to estimate the quality of the numerical weather predictions. The effectiveness of both tools was shown by comparing their performance with the performance of the persistence method.

S.Li [19] gave a method to do time series prediction forecast of wind power generation using recurrent multilayer perceptron (RMLP) neural networks. The paper presented a four layer RMLP network and the extended Kalman filter based backpropagation through time algorithm was used to train the RMLP networks.

Luis Vargas [20] presented the focus time-delay neural network (FTD NN) to forecast wind power. One remarkable feature of the FTD NN was that it did not require dynamic backpropagation to compute the network gradient. It trained faster than other dynamic networks.

- Adaptive Neural Fuzzy Inference System (ANFIS)

Cameron Potter [21] introduced a novel approach -application of an Adaptive Neural Fuzzy Inference System (ANFIS) to forecasting a wind time series. It concluded that ANFIS was a promising forecasting technique. Reference [22] introduced the rules of integrity check and reasonableness check. It proposed an adaptive neuro-fuzzy inference system (ANFIS) model, in which fuzzy inference algorithm was used to interpolate the missing and invalid wind data.

- Grey Predictor

T.H.M. El-Fouly [23] presented a novel technique for wind speed forecasting and wind power prediction based on using the Grey predictor model GM (1, 1). The effectiveness of the proposed predictor was revealed using simulation results. T.H.M. El-Fouly [24] investigated a modified version for the Grey predictor model referred to the adaptive alpha GM (1, 1) model. It showed that using the averaged Grey rolling model disclosed an improvement in the prediction accuracy, compared with the persistent model, of wind power prediction up to 36.31% for the MAE, 25.83% for the RMSE and 36.34% for the average percentage error.

- Markov-Switching Autoregressive(MSAR) Model

P. Pinson [25] [26] presented a methodology based on a Markov-switching autoregressive model with time-varying coefficients. The quality of this methodology was demonstrated from the test case of two large offshore wind farms in Denmark. An advantage of the method was that one can easily derive full predictive densities along with the usually generated point forecasts.

- Random Forests

Lionel Fugon [27] examined models include neural networks, support vector machines, and random forests. The comparison had revealed that Random Forest outperformed the rest of the models.

- Nearest Neighbor Search(NNS)

Andrew Kusiak [28] showed that the k-nearest neighbor model, combined with the principal component analysis approach, outperformed other models studied. Data mining and evolutionary computation were integrated for building the models for prediction and monitoring.

- Wavelet Transform

J.P.S. Catalão [29] proposed artificial neural networks in combination with wavelet transform (NNWT) for short-term wind power forecasting in Portugal. The application of the proposed NNWT approach to wind power forecasting in Portugal was both novel and effective. The MAPE had an average value of 6.97%, outperforming persistence, ARIMA and NN approaches. Hui Liu [30] proposed a new short-term forecasting method based on the methods of wavelet and classical time series analysis.

- Evolutionary Algorithms(EA)

René Jursa [31] introduced a new short-term prediction method based on neural networks and the nearest neighbour search. In comparison to the manually specified neural network model, the new method gets a reduction of the prediction error for the most wind farms.

- Support Vector Machines (SVM)

Sancho Salcedo-Sanz [32] discussed the application of two different evolutionary computation techniques to tackle the hyper-parameters estimation problem in SVMrs. Specifically he tested an Evolutionary Programming algorithm (EP) and a Particle Swarm Optimization approach (PSO). Junyi Zhou [33] presented a systematic study on fine tuning of Least-squares support vector machines (LS-SVM) model parameters for one-step ahead wind speed forecasting for the first time. Three SVM kernels, namely linear, Gaussian, and polynomial kernels, were implemented. LS-SVMs were compared against the persistence approach, and it was found that they can outperform the persistence model in the majority of cases.

- Particle Swarm Optimization (PSO)

N. Amjady [34] presented a new forecasting engine including a new enhanced particle swarm optimization component and a hybrid neural network. The proposed wind power forecasting strategy was applied to real-life data from wind power producers in Alberta, Canada, and Oklahoma, USA. The presented numerical results demonstrated the efficiency of the proposed strategy.

- Chaos Optimization

Reference [35] reported that the time series of wind power generation capacity had chaos characteristic by analyzing modeling with low dimension nonlinear dynamics. Dong Lei [36] examined the time series of wind power generating capacity by nonlinear dynamical methods in order to identify chaos characteristic from its random-like waveform. The analysis of modeling with low dimensions nonlinear dynamics indicated that time series of wind power generating capacity had chaos characteristic.

We have analyzed many methods. Different methods have their own advantages and disadvantages. For example, neural networks perform well for raw data input and have strong learning and training abilities. Fuzzy logic models outperform others when dealing with reasoning problems, while the learning and adjusting abilities are mediocre. The accurate comparison of all the methods is quite difficult because these methods depend on different situations, and the data collection is a formidable task.

4. Development direction of WPF

In recent years, many scholars have done a lot of research on wind power prediction. They have made a lot of improvements, so that the prediction accuracy continues to increase. But the prediction method is not perfect, we need to do further research in the following areas:

4.1. Do further study on artificial intelligence approach and improve the training algorithm in order to achieving more accurate results

Taking into account the available literature, novel methodologies are still required in order to improve forecasting accuracy and reduce the uncertainty in wind power predictions, while maintaining an acceptable computation time. In addition, new approaches on complex terrain are the focus of future research.

4.2. Combine different physical and statistical models to achieve good results both in long term and short term forecasting

We should build up a combined approach taking advantage from the higher accuracy of time series based models in shorter horizons and advantage from the wider forecast horizons of physical/meteorological models. The combined approach integrates mathematical/statistical and physical/meteorological models.

4.3. Do further research on the practical application of the methods, not only in theoretical

The existing prediction model should put into use in actual wind farm. Minimize the increment peaking demand of the power capacity because of the access of wind power, thereby improving the economics of grid operation and the acceptance of wind power capacity.

4.4. Do further research on the adaptive parameter estimation

The models may automatically adopt to changes in the farm and in the surroundings.

4.5. Establish a more accurate and universal error evaluation system

Establish a standard for measurement of performance of models.

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