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# A Literature Review of Wind Forecasting Methods

**Wen-Yeau Chang**

Department of Electrical Engineering, St. John's University, New Taipei City, Taiwan
Email: changwy@mail.sju.edu.tw

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## Abstract

**In this paper, an overview of new and current developments in wind forecasting is given where the focus lies upon principles and practical implementations. High penetration of wind power in the electricity system provides many challenges to the power system operators, mainly due to the unpredictability and variability of wind power generation. Although wind energy may not be dispatched, an accurate forecasting method of wind speed and power generation can help the power system operators reduce the risk of unreliability of electricity supply. This paper gives a literature survey on the categories and major methods of wind forecasting. Based on the assessment of wind speed and power forecasting methods, the future development direction of wind forecasting is proposed.**

## Keywords

**Literature Survey; Wind Forecasting Categories; Wind Speed and Power Forecasting Methods**

## 1. Introduction

Rising crude oil prices highlights the exploitation of renewable energy applications. The wind power is one of the most attractive renewable energy technologies because of its high efficiency and low pollution [1]. However, since the power produced by the wind energy conversion systems (WECS) is varied with the atmosphere meteorology and wind speed [2-3], unexpected variations of the WECS power generation may increase operating costs for the electricity system because the requirements of primary reserves will be increased, and place potential risks to the reliability of electricity supply [4].

The power system operators have to predict changes of the wind power production in order to schedule the spinning reserve capacity and to manage the grid operations [4]. To reduce the reserve capacity and increase the wind power penetration, the accurate forecasting of wind speed is needed [5]. In addition, wind power forecasting plays an important role in the allocation of balancing power. Besides, wind power forecasting is used for the day-ahead scheduling of conventional power plants and trading of electricity on the spot market [6].

Although the prediction accuracy of wind power forecasting is lower than the prediction accuracy of load forecasting. Wind power forecasts still play a key role to address the operation challenges in electricity supply. Recently, several methods have been employed for the wind power forecasting. Many literatures have been devoted to the improvements of wind power forecasting approaches by researchers with wide experience in the

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field tests. A number of wind power forecasting methods have been developed and launched on wind sites. The wind power forecasting methods can be generally categorized into six groups, persistence method, physical method, statistical method, spatial correlation method, artificial intelligence method, and hybrid approach.

This paper presents a detailed review on existing tools used in wind speed and wind power prediction over time-scales, and further identifies possible developments in the future.

## 2. Classification of Wind Power Forecasting According to Time-Scales

Various methods classified according to time-scales or methodology, are available for wind power forecasting. Time-scale classification of wind power forecasting methods is different in various literature descriptions. However, combined with some literatures [7-9], according to the time-scales wind power forecasting methods can be divided into 4 categories:

- Ultra-short-term forecasting: From few minutes to 1 hour ahead.
- Short-term forecasting: From 1 hour to several hours ahead.
- Medium-term forecasting: From several hours to 1 week ahead.
- Long-term forecasting: From 1 week to 1 year or more ahead.

**Table 1** also presents the specific time-scale in view of the operation of electricity systems. The applications of specific time-scale in electricity systems are consequential different.

## 3. Overall of the Wind Power Forecasting Method

### 3.1. Persistence Method

Persistence method uses a simple assumption that the wind speed or wind power at a certain future time will be the same as it is when the forecast is made [9]. If the measured wind speed and wind power at $t$ are $v(t)$ and $P(t)$, then the forecasting wind speed and wind power at $t+\Delta t$ can be formulated as the following term:

$$v(t+\Delta t)=v(t) \quad (1)$$

$$P(t+\Delta t)=P(t) \quad (2)$$

The persistence method is somehow more accurate than other wind forecasting methods in ultra-short-term forecasting. But the accuracy of persistence method will degrade rapidly when with the time-scale of forecasting is increasing [10].

The persistence method is not only the simplest but is also the most economical wind speed or power forecasting method. Electrical utility uses the persistence method for ultra-short-term forecasts. Hence, any forecast method that is developed should, first, be tested against classical benchmark of persistence method to check how

**Table 1.** Time-scale classification for wind forecasting.

| Time-scale | Range | Applications |
|---|---|---|
| Ultra-short-term | few minutes to 1 hour ahead | • Electricity market clearing<br>• Real-time grid operations<br>• Regulation actions |
| Short-term | 1 hour to several hours ahead | • Economic load dispatch planning<br>• Load reasonable decisions<br>• Operational security in electricity market |
| Medium-term | several hours to 1 week ahead | • Unit commitment decisions<br>• Reserve requirement decisions<br>• Generator online/offline decisions |
| Long-term | 1 week to 1 year or more ahead | • Maintenance planning<br>• Operation management<br>• Optimal operating cost<br>• Feasibility study for design of the wind farm |

much it can improve over the persistence derived forecasts [11].

### 3.2. Physical Methods

Physical method is based on lower atmosphere or numerical weather prediction (NWP) using weather forecast data like temperature, pressure, surface roughness and obstacles. NWP model is developed by meteorologists for large scale area weather prediction [5]. In general, wind speed obtained from the local meteorological service and transformed to the wind turbines at the wind farm is converted to wind power [7]. Physical methods are to increase the real resolution of NWP model in order to achieving accurate prediction of the weather [9]. The physical methods are rendered on supercomputers as they need lots of computations.

Physical systems use parameterizations based on a detailed physical description of the atmosphere, to reach the best prediction precision. Usually, wind speed given by the weather service on a coarse grid is transformed to the onsite conditions at the location of the wind farm [6].

Existing commercial wind power forecasting methods use NWP wind forecasts as the input data. Physical systems, using the input data from NWP, carry out the necessary refinement of these output data (wind speed forecast) to the on-site conditions by methods that are based on the physics of the lower atmospheric boundary layer [12].

### 3.3. Statistical Methods

Statistical methods aim at finding the relationship of the on-line measured power data. For a statistical model, the historical data of the WECS may be used. Statistical models are easy to model and cheaper to develop compared to other models. Basically, statistical method is good for short time periods. The disadvantage with this method is that the prediction error increases as the prediction time increases.

Statistical methods include the auto regressive (AR), auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA), Bayesian approach, and gray predictions. Statistical methods can be used to solve the problems in engineering, economics and natural sciences that have a great deal of data where the observations are interdependent.

Firat *et al.* [13] presented a new statistical method based on AR model and independent component analysis. Based on the obtained results, the proposed method obviously gives higher accuracy compared with direct forecasting.

Since the wind speed has very good succession and randomness, it is quite appropriate to use ARMA model of times series to forecast the wind speed. Erdem and Shi [14] proposed four approaches based on ARMA method for the forecasting of the tuple of wind speed and direction. The results showed that the component model is better at predicting the wind direction than the traditional-linked ARMA model, whereas the opposite is observed for wind speed forecasting.

Li *et al.* [15] presented an ARMA model combines with wavelet transform for wind speed prediction. The wavelet transform is used to pick up the low frequency parts of the whole wind speed. ARMA model is used to forecast the wind speed on the gentled data. The combination model can effectively improve the prediction accuracy.

Palomares-Salas *et al.* [16] used an ARIMA model for time-series forecast involving wind speed measurements. The paper presents the process of model validation, along with a regression analysis, based in real-life data. Results show that ARIMA model is better than back propagation neural network for short time-intervals to forecast.

Miranda and Dunn [17] focused on one-hour-ahead wind speed prediction using the Bayesian approach to characterize the wind resource. This paper presented the development and simulation results of an AR model using the Bayesian approach. The simulation results indicated that the Bayesian approach can be a useful tool in both wind speed and wind power predictions.

### 3.4. Spatial Correlation Models

The spatial correlation models take the spatial relationship of different sites' wind speed into account. In spatial correlation models, the wind speed time-series of the predicted point and its neighboring points are employed to predict the wind speed [5]. A spatial correlation model is used for predicting wind speed at one site based on measurements at another site. Its behavior has been tested with satisfactory verification using data collected over seven years [18].

Alexiadis *et al.* [19] illustrated a technique for forecasting wind speed and power output up to several hours ahead, based on cross correlation at neighboring sites. Based on spatial correlation models, this paper developed an ANN approach that significantly improves forecasting accuracy comparing to the persistence forecasting model.

Barbounis and Theocharis [20] suggested a locally feedback dynamic fuzzy neural network (LF-DFNN) with application to the wind speed prediction using spatial correlation. According to the position of the base site, remote meteorological stations are installed at two reference sites, such that the positions of the three sites are lined along the direction of the prevailing winds. In this paper, the LF-DFNN is employed for predicting multi-step ahead wind speed in base site, using spatial information from remote meteorological stations. Simulation results revealed that the LF-DFNN exhibits superior performance compared to other network models evaluated on this application.

### 3.5. Artificial Intelligence Methods

Recently, with the development of artificial intelligence (AI), various new AI methods for wind speed and power prediction have been developed. The new developed methods include artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic methods, support vector machine (SVM), neuro-fuzzy network, and evolutionary optimization algorithms.

ANN could deal with non-linear and complex problems in terms of classification or forecasting. The ANN models can represent a complex nonlinear relationship and extract the dependence between variables through the training process [21]. ANN based methods include back propagation neural networks, recurrent neural networks, radial basis function (RBF) neural networks, ridgelet neural network, and adaptive linear element neural network. ANN based method is an appropriate method to apply into the problem to forecast the wind power.

Sfetsos [22] presented an ANN method for the forecasting of mean hourly wind speed data using time series analysis. The proposed methodology has an additional benefit for utility that have significant wind penetration level and use hourly interval for power system operational procedures such as economic dispatch and unit commitment.

Chang [23] described a wind power forecasting methodologies based on back propagation neural network. The developed model for short-term wind forecasting showed a very good accuracy to be used by a 2400kW WECS in Taichung coast for the energy supply.

More and Deo [24] presented two wind forecasting methodologies based on back propagation neural network and recurrent neural network. The neural networks forecasting are found to be more accurate than traditional statistical time series analysis.

Chang [25] gave a method to do time series prediction forecast of wind power generation using RBF neural network. The good agreements between the realistic values and forecasting values are obtained; the numerical results show that the proposed forecasting method is accurate and reliable.

Guo *et al.* [26] investigated a modified empirical mode decomposition (EMD) based feed-forward neural network (FNN) wind forecasting method. The proposed method shows the best accuracy comparing with basic FNN and unmodified EMD-based FNN through multi-step forecasting the mean monthly and daily wind speed in Zhangye of China.

Li and Shi [27] investigated three types of typical ANN, namely, adaptive linear element, back propagation, and radial basis function, to forecast the wind speed. The comparing results of three types of ANN show that even for the same wind dataset, no single ANN model outperforms others universally in terms of all evaluation metrics. Moreover, the selection of the type of ANN for best performance is also dependent upon the data sources.

Yang *et al.* [28] introduced an ANFIS method to interpolate the missing and invalid wind data. The performance tests are given, 12 measured wind data sets from a wind farm in North China are interpolated and analyzed, respectively. The test results proved the effectiveness of ANFIS method.

Zeng and Qiao [29] described a SVM-based method for wind power forecasting. Simulation studies are carried out by using real wind speed and wind power data obtained from the National Renewable Energy Laboratory. Results show that the proposed SVM method outperforms the persistence model and the RBF neural network-based model.

Zhou *et al.* [30] described a systematic study on fine tuning of least-squares support vector machines (LSSVM) model parameters for one-step ahead wind speed forecasting. Three SVM kernels, namely linear, Gaussian, and polynomial kernels, are implemented. It is found that LSSVM methods can outperform the persistence model in the majority of cases.

Xia *et al.* [31] presented a neuro-fuzzy network method for short-term wind power forecasting. The forecasting approach is applied for the wind power forecasting of a real wind farm located in China. The test results showed that the trained neuro-fuzzy networks are powerful for modeling the wind farm and forecasting the wind power.

Jursa and Rohrig [32] presented a new short-term prediction method based on the application of evolutionary optimization algorithms for the automated specification of neural networks and the nearest neighbour search. The test results showed that the wind power prediction error can be reduced by using the proposed automated specification method.

### 3.6. Hybrid Methods

The object of hybrid models is to benefit from the advantages of each model and obtain a globally optimal forecasting performance [10]. Since the information contained in the individual forecasting method is limited, hybrid method can maximize the available information, integrate individual model information and make the best use of the advantages of multiple forecasting methods thus improving the prediction accuracy [8]. The hybrid methods combine different approaches such as mixing physical and statistical approaches or combine short-term and medium-term models [11].

Many types of hybrid models were utilized to predict wind power. The types of combinations can be:

- Combination of physical and artificial intelligence approaches
- Combination of statistical and artificial intelligence approaches
- Combination of alternative artificial intelligence models

Zhao *et al.* [33] investigated a hybrid wind forecasting method consists of a NWP model and ANN models. The NWP model is established by coupling the Global Forecasting system (GFS) with the Weather Research and Forecasting (WRF) system together to predict meteorological parameters. This hybrid forecasting system is profitable for increasing the wind energy penetration level in China.

Shi *et al.* [34] presented two hybrid models, namely, ARIMA-ANN and ARIMA-SVM, for wind speed and power forecasting. This paper systematically and comprehensively investigates the applicability of the proposed hybrid models based on two case studies on wind speed and wind power generation, respectively. The results show that the hybrid approaches are viable options for forecasting both wind speed and wind power generation time series, but they do not always produce superior forecasting performance for all the forecasting time horizons investigated.

Guo *et al.* [35] described a new hybrid wind speed forecasting method based on a back propagation neural network and the idea of eliminating seasonal effects from actual wind speed datasets using seasonal exponential adjustment. The test results showed that the proposed method performed better than the single back propagation neural network.

Catalão *et al.* [36] proposed a hybrid approach, based on the combination of ANN with wavelet transform, for short-term wind power forecasting in Portugal. The wavelet transform is used to decompose the wind power series into a set of better-behaved constitutive series. The test results presented confirm the considerable value of the proposed hybrid approach in forecasting wind power.

## 4. The Future of Wind Forecasting

Due to the high penetration of wind power in the electricity system, the forecast accuracy of wind power prediction systems becomes increasingly important. In recent years, many scholars have done a lot of research on wind power prediction. The forecast accuracy has improved constantly, and it can be expected that intense research and development efforts are already on track. In order to further improve wind power forecasts, combined with some literatures [5,9,37,38], anticipated improvements for the further research include the following areas:

- Study on more novel artificial intelligence methods and improve their training algorithms to achieve the forecast accuracy. In addition, new methods on complex terrain are the focus of future research.

- Do further research on the hybrid methods combine different approaches such as mixing physical and statistical approaches to achieve good results both in long-term and short-term prediction.
- The existing prediction method should put into use in actual WECS. Do further research on the practical application of the methods, not only in theoretical.
- Establish the more accurate evaluation system and the standard for measurement of performance of methods.
- Further improvements in the NWP models and more frequent updates of the weather predictions will improve the input data for wind power forecasting.
- Deepen further research on the use of online wind measurement data, especially for short-term wind forecasting.
- Do further research on the adaptive parameter estimation. The models have ability to automatically adapt to the changes of the farms and the surroundings.
- Deepen further research on the NWP models designed for offshore environment. Improve the availability of meteorological data to validate NWP outputs for the offshore locations.

## 5. Conclusion

This paper presented a review on forecasting of wind speed and power under different time-scales. Six categories of forecasting methods, which have their own characteristics, were discussed. Papers were selected to emphasize the diversity of forecasting methods and the time-scales of forecasting methods. Some of these methods have good performances at short-term prediction while others perform better in different time-scale prediction. It is difficult to evaluate the performance of various methods, as the existing applications were in different time-scale and different way. But various wind forecast methods are available in the power system, which will help the wind farm owners to identify their wind forecasting method as per their needs. Based on the development history of wind speed and power prediction, the future development directions of wind speed and power forecasting are proposed in the end.

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