A literature review of wind forecasting technology in the world

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***Abstract*—Large intermittent generations have grown the influence on the grid security, system operation, and market economics. Although wind energy may not be dispatched, the cost impacts of wind can be substantially reduced if the wind energy can be scheduled using accurate wind forecasting. In other words, the improvement of the performance of wind power forecasting tool has significant technology and economic impact on the system operation with increased wind power penetration.**

Forecasting has been a vital part of business planning in today's competitive environment, especially in areas characterized by a high concentration of wind generation and a limited capacity of network. The target of this paper is to present a critical literature review and an up-to-date bibliography on wind forecasting technologies over the world. Various forecasting aspects concerning the wind speed and power have been highlighted. These technologies based on numeric weather prediction (NWP) methods, statistical methods, methods based upon artificial neural networks (ANNs), and hybrid forecasting approaches will be discussed. Furthermore, the difference between wind speed and power forecasting, the lead time of forecasting, and the further research will also be discussed in this paper.

***Index Terms*—wind power forecasting, numeric weather prediction, statistical methods**

I. Introduction

The increase on wind generation requires solutions to a number of research fields, which include market integration and design, real-time grid operations, interconnection standards, ancillary service requirements and costs, power quality, transmission capacity upgrades, power system dynamic, stability, and reliability. Wind's intermittency was the best-known challenge and was considered as a major barrier against further wind power penetration, which would result in increasing the levels of regulation and reserves required to maintain reliability. An IEEE/PES summary pointed out at wind penetrations of up to 20% of system peak load, system operating cost, such as unit commitment cost, would increase arising from wind variability and uncertainty. Consequently some utilities limited the allowable amount of wind power on their systems. The limit of wind power penetration in Penghu of Taiwan is an example. However, several factors could improve the attractiveness of wind power to a utility:

- Improvements in the model accuracy of wind power forecasting
- Shorter start-up and ramping times for thermal plants
- Changes in conventional plant mix such as a larger amount of fast response plants or energy storage
- Load management to better accommodate fluctuations in available wind power

Several studies have indicated that wind energy will not cause the significant impacts on reserves if the technique of wind power forecasting can be improved [1]. Moreover, a number of studies [2~8] have assessed the financial benefits of good forecasting and have proven that an advanced forecasting technique is required. Accurate forecasts of power generation are also of importance to electricity transmission. As wind farms grow in capacity, the strain they place on the transmission grids also becomes more pronounced because the transmission grid may not be able to transmit all the wind power. Experience from the world has highlighted that accurate and reliable forecasting systems for wind power are widely recognized as a major contribution for increasing wind penetration.

Under deregulated electricity markets, energy imbalance charges based on market prices would provide appropriate incentives for accurate wind forecasting. A good technology for wind power forecasting can help develop well-functional hour-ahead or day-ahead markets and adopt market designs that are more appropriate to weather-driven resources. In addition, most wind farms are built in remote areas, which could lead to transmission congestion. This is another reason for needing accurate wind power forecasts.

In Europe, a 4-year project ANEMOS [9] has launched by 22 partners from 7 countries including research institutes, universities, industrial companies, utilities, TSOs, and agencies. The aim of this 4-year project is to develop advanced wind power forecasting models including statistical, physical, and combined approaches. In the frame of the ANEMOS project, emphasis is given to the development of appropriate prediction models for the offshore. Furthermore, in order to estimate the benefit of forecasting in a model of the Nord Pool electricity market, the WILMAR project supported by the European Commission has developed the market model for the simulation of wind power predictions. California ISO currently has a centralized wind forecasting program. One of the project targets

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it to develop high quality forecasts for the day-ahead and hour-ahead scheduling and real time forecasting for ISO operations.

II. Characteristic for the Time Series of Wind Speed

Wind prediction is complex due to the wind's high degree of volatility and deviation. Therefore, in real electricity markets, system operators have barely begun to factor wind forecast information into their daily operations and reserve determination. However, in terms of academic researches, many publications have introduced short-term or long-term wind forecasting technologies and experience. Some of the experience could be directly adopt, but some must be modified in order to make it suitable for a specific region. Most importantly, the wind forecast models should be periodically modified in order to cope with environment changes.

Real-world time series are diverse. Some time-series data change seasonally, slowly and relatively smoothly. Monthly electricity demand may represent such a time series. Other time series can exhibit relatively chaotic behavior, making them difficult to predict. A wind speed time series, such as in Fig. 1, possesses these characteristics, which was recorded in Dongchi island of Penghu during a month. The signals of Fig. 1 are highly nonlinear random process, which changes its mean and standard deviation at any time. No typical patterns can be directly found from the signal and the prediction for such kinds of data requires special care. In Fig.1, the difference between the maximum and minimum value of wind speed is up to 15.9 m/s. Therefore, load forecasting has much higher accuracy compared to wind forecasting. In general, electricity load can be predicted with about 1.5% accuracy for a 24 h forecast, but the average reported error for the wind forecasting is in the order of 10%~20% of the installed power for a 24 hour horizon.

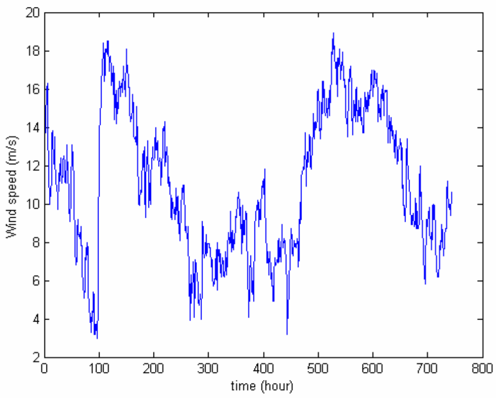
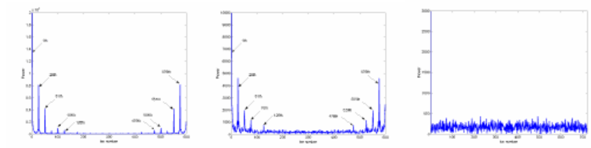


Fig. 1 The variation of wind speed in Dongchi island of Penghu over a month

Time series for power load, electricity price, and wind speed represent diversified characteristics. For example, load curves represent strong seasonal character (daily, weekly, and seasonally); price curve shows less strong seasonal character along with sudden spikes, and wind curve illustrates much more random signals compared to price and load curves. Fig.2 (a) ~ (c) shows their typical frequency spectrum respectively. It can be seen that the frequency domain for load is dominated by several specific frequencies, which results from daily and weekly variations. Similar frequencies appear in the price spectrum because they also contribute to the fluctuation of the electricity price curve. However, the spectrum for wind speed cannot give us any significant frequency value. The sample data for this wind speed in time domain have been modeled by ARIMA models and shown in Table 1. It is clear that only the AR (1) model could trace slightly the wind speed fluctuation because the MA parameter plays a key role on these ARIMA models. As a result, for the wind power forecasting, the statistical method with historical data cannot be utilized alone to predict wind variables. Instead, methods based on numeric weather prediction, AI technologies, and hybrid models should be considered. Moreover, the input valuables for the forecasting module have to take wind speed predictions and real wind power measurement into account.



(a) load (b) price (c) wind speed

Fig. 2 Frequency spectrum for different time series

Wind power prediction technology is not "plug-and-play" since it is always site-dependent. The wind values are affected by large-scale atmospheric conditions and the morphology of the surface landscape. Therefore, it should take the characteristics of the local wind profile, climatic condition, and terrain type into account. For example, if the scale of changes in the atmosphere is low, the wind speed would be more stable. Consequently the wind power forecasting would be more accurate in that region. In addition, wind speed forecasting in an onshore complex terrain situation is different to that in an offshore situation. Due to the differences in each local characteristic, it is difficult to compare prediction systems based on available results.

TABLE I
Several ARIMA Models for Wind Speed Time Series

Model Type	AR parameter	MA parameter
ARIMA (1,1,1)	(-0.0147)	(-0.9946)
ARIMA(2,1,1)	(-0.0044 , 0.0058)	(-0.9842)
ARIMA(3,1,1)	(0.0011 , 0.0199 , -0.0342)	(-0.9816)
ARIMA(4,1,1)	(-0.0024 , 0.023 , -0.0225 , -0.0455)	(-0.9816)

The sea surface roughness is very low, and the thermal stratification of the atmosphere, the thermal stability of the wind, is very different from the near neutral case observed onshore. Additionally, the low roughness increases the influence of stability on the wind speed profile. That is, the wind speed in an offshore environment is more persistent than those onshore. As a result, future major developments of wind power capacities are more likely to take place offshore and long term offshore wind monitoring should be examined so as to gain more insight on the offshore wind characteristics.

III. Overview of Wind Forecasting Methods

Several state-of-the-art techniques have been identified for wind forecasting. These techniques can be cataloged into numeric weather prediction (NWP) methods, statistical methods, methods based upon artificial neural networks (ANNs), and hybrid approaches. NWP methods could be the most accurate technique for short-term forecasting. However, in general, statistical, ANN methods, or several advanced hybrid methods based on observations perform more accurately over the very short-term forecast range.

A. Persistence models

The simplest way to forecast the wind is to use persistence. This method uses the simple assumption that the wind speed at the time t + x is the same as it was at time t. In other words, the persistence technique is based on the assumption of a high correlation between the present and future wind values. This method was developed by meteorologists as a comparison tool to supplement the NWP models. In fact, the simplified method is even more effective than a NWP model in some very short-term predictions (several minutes to hours) [10]. As expected, the accuracy of this model degrades rapidly with increasing prediction lead time.

B. Numeric Weather Prediction (NWP)

Several physical models have been developed based on using weather data with sophisticated meteorological for wind speed forecasting and wind power predictions [11][12]. These models take into considerations several factors including shelter from obstacles, local surface roughness and its changes, and effects of orography, speed up or down, scaling of the local wind speed within wind farms, wind farm layouts and wind turbines power curves. The NWP system usually provides wind speed forecasts for a grid of surrounding points around the wind generators. According to the type of NWP system, these forecasts are given with a spatial resolution. The physical approach uses a meso- or micro-scale model for the downscaling, which interpolate these wind speed forecasts to the level of the wind generators [13]. For running the downscaling models, it is necessary to have a detailed description of the terrain surrounding the wind generators. However, collecting the information of terrain conditions is one of the main difficulties in the implementation of physical models. Several more sophisticated flow modeling tools, such as mesoscale meteorological model (MM5), CFD, have been used for the wind speed prediction. These advanced models have the potential to improve the modeling of the wind flow, particularly in complex terrain. However, further validation work and more computer power are required before these models are used.

Since NWP models are complex mathematical models, they are usually run on super computers, which limits the usefulness of NWP methods for on-line or very-short-term operation of power system. In other words, meteorological models with high resolution are often more accurate but require high computation time to produce forecasts, and as a consequence, they do not update frequently their outputs. In addition, based on some operation experience, accurate predictions with high resolution would improve accuracy slightly but pay expensive cost. Therefore, the performance of physical models is often satisfactory for long (larger than 6 hours ahead) time horizons and they are on the other hand inappropriate for short-term prediction (several minutes to one hour) alone due to difficulty of information acquisition and complicated computation.

An unstable atmospheric situation can lead to very poor numerical weather predictions and thus to inaccurate wind power ones. In contrast, as the atmospheric situation is stable, one can expect more accurate predictions for power because wind speed is the most sensible input to wind power prediction models. In general, a common approach to short-term wind power prediction is refining the output of numerical weather prediction (NWP) models operated by weather services to obtain the local wind conditions. In Taiwan, the present NWP model is run twice daily with a horizontal resolution of 5 km, forecasting up to 72 hours ahead.

C. Statistical and ANN methods

The statistical time series and neural network methods are mostly aimed at short-term predictions. Typical time series models are developed based on historical values. They are easy to model and capable to provide timely prediction. In several predictions, they use the difference between the predicted and actual wind speeds in the immediate past to tune the model parameters. The advantage of the ANN is to learn the relationship between inputs and outputs by a non-statistical approach. These ANN-based methodologies do not require any predefined mathematical models. If same or similar patterns are met, ANNs come up with a result with minimum errors.

The advantage for other statistical methods is to provide relatively inexpensive statistical forecasting models that do not require any data beyond historical wind power generation data. However, the accuracy of the prediction for these models drops significantly when the time horizon is extended.

D. Hybrid methods

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

- Combination of physical and statistical approaches
- Combination of models for the short term and for the medium term
- Combination of alternative statistical models

The object of hybrid models is to benefit from the advantages of each model and obtain a globally optimal forecasting performance. For example, several statistical methods are used to determine the optimum weight between the on-line measurements and the meteorological forecasts in ARX type models. In general, system participants can compare historical predictions with actual output data where available to enable tracking of the performance of wind forecasting tools. It should be highlighted that the importance of evaluating the performance of a model against a variety of criteria, and particularly of using both RMSE and MAE of forecasts.

IV. Difference between wind speed and wind power forecasts

The wind power of a wind turbine depends on the wind speed varies on a wide range of time, which depends on regional weather patterns, seasonal variations, and terrain types. The theoretical relationship between the energy (per unit time) of wind that flows at speed v (m/s) through an intercepting area A (m^2) is

$$p = \frac{1}{2}\rho A v^3 \tag{1}$$

where ρ is the air density (kg/m^3), which depends on the air temperature and pressure. The easiest approach converting wind speed to wind power forecasting is to use the manufacturer power curves. However, the real relationship between the power generated by the whole wind farm and the velocity of the wind can, however, be more complex than Eq. (1), which would results from the aging of the wind turbines and control factors. Furthermore, power curves can be classified into global, cluster, and turbine curves. The relationship between the wind velocity and the output power should be treated as a nonlinear and stochastic time-varying function of wind speed, which could not be described by a deterministic machine power curve. For example, we can use ANN structures or fuzzy logic as a specific area power curve. Moreover, the transformation of wind speed to power in a wind park is more difficult, which would use multiple wind direction and speed in order to achieve a wind farm matrix.

In Ireland, the study [14] shows that using a power curve derived from measured wind and power can improve the forecast RMSE by nearly 20% in comparison to use the manufacturer's power curve only. In addition, due to the non-linearity of the power curve, wind speed forecasting errors are amplified in the high-slope region between the cut-in wind speed of the turbine and the plateau at rated wind speed, where errors are dampened. That is, the nonlinearity of the wind turbines' power curves leads to a further amplification of the error, and small deviations in the wind speed may result in large deviations in the power. As a result, a proper aggregate model of wind plants is needed to perform more accurate forecasting studies because a large amount of wind power can smooth power output curves [15].

V. Literature review for wind speed and power forecasts

Reference [16] describes several statistical forecasting models known as autoregressive moving average (ARMA) models to predict both wind speed and wind power output in hour-ahead markets. The contribution for this paper is not to develop models to compete with commercial accurate forecasting models. Instead, it is to investigate the feasibility of relatively inexpensive statistical forecasting models that do not require any data beyond historical wind power generation data. The experience form [16] indicates that the model parameters could be a function of time and the ability of ARMA forecast models would differ when applied to different time periods. In reference [17], the authors predicted the hourly average wind speed up to 1~10 hours in advance by using ARMA models. In order to consider seasonal wind characteristic, the authors have adjusted a different model to each calendar month. The California ISO prototype forecasting algorithm [18] for short-term wind generation adopted a modified ARIMA model to compute the 2.5 hour ahead forecasted growth/decline factor. The model's coefficients were adaptively adjusted to achieve the best accuracy, and the bias self-compensation scheme was combined into the model by introducing an additional term into the modified ARIMA model. In this research [18], the authors indicated the necessity to involve forecasted weather parameters and unit status information into the model. In addition, they highlighted that the use of energy (MWh) instead of power (MW) as a forecasted parameter makes wind generation more predictable.

In reference [19], a recurrent higher-order neural network (RHONN) model was developed for wind power forecasting in a wind park. This model can be used to predict wind speed or power in time scales from some seconds to 3 hours. The optimal architecture of the model was selected based on the cross validation approach and was solved using the nonlinear Simplex method of Box. Reference [20] introduces an adaptive neuron-fuzzy inference system (ANFIS) to forecast wind vector 2.5 min ahead, which takes both speed and direction into account. An ANFIS uses a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method. Its design is flexible and capable of handling rapidly fluctuating data patterns. This means that it covered the criterion necessary for very short-term wind prediction. The work in [21] employs the technique of neural networks (feed forward and recurrent networks) and statistical time series respectively to forecast daily and monthly wind speed in India. The results from [21] show that the neural networks perform better than the ARIMA models. However, the average of daily and monthly wind speed could be more sooth than that of hourly wind speed, which implies that it is not difficult to obtain a more accurate forecasting result for daily and monthly wind speed. In reference [22], a method based on artificial neural network (ANN) was utilized to predict the average hourly wind speed. A multilayer perceptron neural network with three-layer feed-forward architecture was adopted as their forecasting system. The input selection was determined on the basis of correlation coefficients between previous wind speed observations. The proposed method can be applied to predict wind speed without the need of meteorology data, but could be attained a poor accuracy. Reference [23] also utilized ANN to predict day-ahead wind power in Germany. For the training of the ANN, historical predicted meteorological parameters and contemporaneous measured power data were used to learn physical coherence of wind speed and wind power output. The ANN application can easily use additional meteorological data, such as air pressure or temperature, to improve the accuracy of the forecasts. In addition, this method is superior to others by the use of power curves of individual plants. Reference [24] illustrates a technique for forecasting two-hour-ahead wind speed and power based on cross correlation at neighboring sites. According to the study [24], it is recognized that the downwind speed is delayed as related to upwind speed. Consequently the wind speed measured at remote sites can be used to predict the wind at the local site, and the ANN was utilized to construct the relationship between time series at the local site and the remote site. In reference [25], a methodology synthesizing both ANN technology and the linear regression are introduced, where ANN was used to handle short-term patterns and the long-term trend information is provided by a trend identification module, which performs the first order linear regression. Reference [26] utilized the 4-8-1 neural network to estimate wind power. The four inputs include measured data for wind velocities and directions from two meteorological towers. Moreover, compressing functions for the four input valuables were used to help the ANN learn and perform better. The proposed ANN in [26] was used to estimate the wind power generation directly based on the measured wind velocity and direction without manufacture's power curve. The superior ANN results lies in its ability to learn the dynamic performance of a wind turbine under changing wind conditions.

A method for establishing wind speed correlation between neighboring stations was presented in reference [27]. The aim of this method is to estimate the wind speed for a particular site by using the wind speed of nearby sites. The proposed method takes into account the evolution of the sample cross correlation function (SCCF) of wind speed between two nearby sites at various time lags. This calculation detects the time lag in which the SCCF has the highest value. This would be the time lag that the two series must obtain for the ANN training phase. Reference [28] proposed a statistical forecasting system by using a combination of statistical forecasting equations for 1~48h ahead wind power. The combination coefficients for each model are time-varying, which is similar to nonparametric models. The target for the combination is to provide a better performance than those of individual models. Its advantage is to build a site-independent prediction system not only for a specific wind farm, but also for any other wind parks.

Reference [29] deals with the 72 hour ahead forecasting for wind speed and power based on meteorological information. Three types of local recurrent neural networks are employed as forecasting models. Six major inputs of the network comprise the wind speeds and directions of the three nearby sites of the wind park. The contribution of this paper is to propose a method to combines time series approaches and atmospheric modeling simultaneously. Reference [30] focuses on 1~10 day ahead prediction for wind speed. The authors utilized the forecasting results from the numerical weather prediction (NWP) computer model run by the European Centre for Medium Range Weather Forecasting (ECMWF). This atmospheric model has a spatial resolution of about 60km and forecasts are issued every 12 hour. Moreover, these forecasts for wind speed were converted into the corresponding power output of a wind farm. However, it was assumed in this paper that the relationship between wind speed and power output was idealized. In addition, there was no any correction between the results of the NWP model and the final predictions for wind power.

Reference [31] developed a methodology that used a Bayesian framework to model the wind speed time series as an autoregressive process, where the Markov Chain Monte Carlo (MCMC) simulation is used to estimate the model parameters. The outputs from Bayesian model are given in the form of probability distributions; that is, the AR model parameters include the expected value (mean) and a confidence interval, which would provide a proper forecasting range. Reference [32] presented one-day ahead prediction of wind speed using annual and seasonal trends. The authors pointed out that wind speeds variation for a specific site may have some sort of common trend over specific periods of time. As a result, the wind speed in the present year can be predicted by the wind data from the previous years. However, some good performance on the forecasting could be attained at some time just by chance. The forecasting system in [33] adopted the numerical weather prediction (NWP), but refined the output of the NWP models to attain the local wind power by using spatial extension, model output statistics (MOS), and wind turbine power curve. The principal of this system is to decrease the NWP prediction error based on spatial smoothing (the combined power output of many wind farms distributed over a large region). The key procedure connecting the spatial distribution of sites is the cross-correlation coefficients of the difference between prediction and measurement for the single sites. Reference [34] also indicates that the spatial diversity has the beneficial effect of smoothing some variations in electrical output and hence improves the wind forecasting accuracy. Based on the study [34], system wide forecasting errors for multiple dispersed wind plants may be reduced by perhaps 30–50% when compared with the errors of individual wind plants due to the smoothing effects of geographic dispersion.

Reference [35] presents a novel technique for one hour ahead wind speed forecasting based on the Grey model GM (1,1). The results from the forecasting model were used as inputs to the power curve model to predict the output power. However, this technique may be suitable for a specific site with a specific wind characteristic, but would not be suitable for other areas. In the 2000 IEA expert meeting on wind forecasting techniques [36], four different systems for wind power forecasting was summarized, including physical, statistical, and hybrid models. Moreover, the experts indicated that wind power forecasting should be in term of a MW level rather than a wind speed, and a forecasting should be accompanied with an associated uncertainty. Reference [37] introduces a methodology for assessing the risk of short-term wind power forecasts by using meteorological risk (MRI) index and production risk (PRI) index. The MRI and RPI are defined to measure the spread of the weather forecasts and the spread of the wind power forecasts respectively at a given period, which implies that the relation between wind power and weather predictions is high. Reference [38] presents a wind forecasting system that uses on-line SCADA measurements and numerical weather predictions (NWP) as inputs to predict wind power. These forecasts are updated every hour based on the most recent wind power measurements. Several commercial and practical modules for wind power forecasting belong to this type. Furthermore, [38] has developed a weather stability index called the “meteo-risk index” and has established a roughly linear relationship between this index and the magnitude of the forecast errors for individual wind farms. Based on the frequency of occurrence of different weather situations as expressed by the meteo-risk index, and its effect on the standard deviation of the wind power forecast errors, best- and worst-case scenarios have been established which correspond to the most accurate and least accurate that the total wind power forecast error is ever likely to be.

VI. Conclusions

There is clearly a requirement for accurate wind forecasting in order that wind power can be integrated into the scheduling and dispatch decisions of the power system operators. Moreover, the restructuring and deregulation of the electricity industry taking place throughout the world will increase the importance of wind power forecasting to system operators and traders. This paper has reviewed the forecasting techniques that were applied to the wind speed and power up to 2006. Papers were selected to emphasize the diversity of forecasting methods and the problems that wind generators will suffer from.

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