Computing Models for Wind Speed Prediction in Renewable Energy Systems

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ABSTRACT
The energy is an important factor for the development of social and economic of any country. In recent years, utilizing renewable energy and reducing pollution have become important in the whole world. Wind power is one of the strongest growing forms of renewable energy. Now a days, wind power generation increases rapidly. .A detailed study of the models helps energy planning, research and policy making. The available wind energy mainly depends on the wind speed. For the wind-farm operator, this poses difficulty in the system scheduling and energy dispatching, as the schedule of the wind-power availability is not known in advance. In this paper, we describe different technique for forecasting wind speed. The model based on the neural network, demonstrated a good agreement and produced the wind forecast with high accuracy.

Keywords-
ARMA, ANN, NWP

1. INTRODUCTION
The wind energy is the important potential renewable energy resources currently available. Many countries have developed wind power to meet the customers electricity demands. With accurate wind speed data, the power producer can predict the power output .This is useful for power system planning and scheduling, and storage capacity optimization. Due to the random fluctuation characteristics of wind speed, the prediction results of wind power may change rapidly. This increases the importance of the accurate wind speed prediction. To increase the accuracy of wind speed prediction, there are many approaches proposed, including the physical method, the conventional statistical method like ARMA model, the spatial correlation model and the artificial intelligence method, and so on .Artificial neural networks (ANN) simulate the human brain in processing information through a series of interconnected neurons, and have excellent ability of mapping complex and highly nonlinear input output patterns without the knowledge of the actual model structure .

As the mass focuses more and more on the use of clean power energy, wind power raises the proportions in electric power network, precise prediction of wind speed can help efficiently low down or avoid the bad effect to electric system caused by wind power, help the schedule department adjust schedule plan in time, improve the competition of wind power in the electric power market. It is commonly acknowledged that wind energy is the leading renewable energy generation method. In order to successfully integrate wind energy with traditional generation supplies it is necessary to have the ability to accurately forecast the available yield of a wind.

2. NEED FOR FORECASTING WIND SPEED
Wind speed prediction from past observations has applications in many fields such as Target tracking, Rocket launch, Ship Navigation Missile guidance, Satellite launch, Electrical power demand forecasting, etc. The most important factor influencing wind power generation is the local wind speed. The immediate requirement is for the development of improved short range forecasting methods which improve power transmission scheduling and resource allocation and hence the reliability of the power grid.

3. MODELS
There are different types of models available for wind speed prediction. Mainly Wind speed forecasting models are divided in two categories. They are physical and statistical models. The Physical models are based on physical reasoning and employ meteorological (Numerical Weather Prediction – NWP) and topological information. The statistical models, on the other hand, use explanatory variables and on-line measurements. There also exist hybrid models, which combine elements of both types of Physical and Statistical models.

They are again classified as Statistical, Intelligent systems, Time series, Fuzzy logic, neural networks models. Models constructed based on meteorological, topological data and wind turbine technical information using numerical methods. They are based on non-statistical approaches. They depend on the experience of a meteorologist. These models are explained below.

3.1. Auto Regressive Moving Average (ARMA) Model
ARMA models are widely used in hydrology, dendrochronology, and many other fields. Auto-regressive Moving-average (ARMA)

models are mathematical models of the persistence, or autocorrelation, in a time series. ARMA models can effectively be used to predict behavior of a time series from past values alone. ARMA models are a generalization of Auto-Regressive (AR) and Moving Average (MA) models and a special case of Auto-regressive Integrated Moving Average (ARIMA) models.

Auto-Regressive (AR) models and Moving-Average (MA) models are combined to form one model called Auto-Regressive Moving Average (ARMA) model. The order of AR model is the time steps which the model will go back to predict the future value and the order of MA model is the past difference steps which the model will go to predict the future value. The autoregressive model includes lagged terms on the time series itself, and that the moving-average model includes lagged terms on the noise or residuals. Combing the lagged terms; it gives what are called auto-regressive moving-average, or ARMA, models. The order of the ARMA model is included in parentheses as ARMA (p, q), where p is the auto-regressive order and q the moving average order. The simplest and most frequently used ARMA model is ARMA (1, 1) model.

$$\theta t + a1\theta t\text{-}1 = \text{Є}t + b1\text{Є}t\text{-}1$$

Where θt is the mean-adjusted series in year t, θt-1 is the series in the previous year i.e. lag of one, a1 is the lag-1 autoregressive coefficient, Where Єt and Єt-1 are the residuals or the noise or the random-shock at times t and t-1, and b1 is the first-order moving average coefficient. The residuals Єt are assumed to be random in time (not auto-correlated), and normally distributed.. Mathematically:

$$Ls\ (\theta t) = \theta t\text{-}s \quad (3)$$

In short form the ARMA (p, q) model is written as:

$$\psi(L)\ \theta t = \psi\ (L)\ \text{Є}t \quad (4)$$

This is most general form of ARMA (p, q)

Auto-Regressive Integrated Moving-Average (ARIMA) models the generalized forms of ARMA models. They are applied in some cases where data shows the evidence of non-stationary, where an initial differencing step can be applied to remove the non-stationary; the differencing step corresponds to 'integrated' part of ARIMA. Stationary in simple terms implies that the probability density of the data does not change when data is shifted in time or space. The condition which is necessary is that the mean and variance (if they exist) should remain same when data is shifted.

3.2. Time-series prediction model

The statistical time series 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 data from a wind farm were collected once every ten minutes and they were grouped into three groups by ten days, the data of the first ten days were used to be the learning sample for network training, and the data of the last ten days were used to be the prediction sample for correcting. Input vector should be unitized, so it would avoid the difference between physic and unit upon BP neural network model.

Time series is a set of sequential data points of a parameter that are usually spaced at equal time intervals. A time-series prediction model employs the past events of the parameter to determine its future values. The time-series model is expressed as follows:

$$\hat{y}(t + T) = f(y(t), y(t - T), \ldots, y(t - nT)) \quad (1)$$

where T is the sampling time, $\hat{y}(t + T)$ is the predicted parameter, $y(t), y(t - T), \ldots, y(t - nT)$ are observed values of the parameter, and n indicates the number of past values (inputs) of the time-series model $f(.)$. Parameter selection is beneficial for obtaining the most accurate prediction results and reduction of data redundancy. The most important predictors among $y(t)$, $y(t - T), \ldots, y(t - nT)$ of (1) can be selected by the boosting-tree algorithm and are based on the domain knowledge.

3.3. Statistical (ARX) model

This model utilizing solely measured data for predicting the power production of a wind park. This model is also referred to as the WPPT model.
The model is based on equation

$$\sqrt{p_{t+k}} = a_1\sqrt{p_t} + b_1\sqrt{w_t} + b_2 w_t + m_t + e_{t+k}$$

$$m_t = m + c_1 \sin\left(\frac{2\pi t}{24}\right) + c_2 \cos\left(\frac{2\pi t}{24}\right)$$

where pt denotes the measured power production at time t, wt is the measured wind speed at time t, et+k is an i.i.d. (independent and identically distributed) noise sequence and mt is a function describing the diurnal variation of the wind. This model is also referred to as the WPPT model. The coefficients in the forecasting relation are estimated using the least square method.

The model is applied for predicting the output power of a wind farm for look-ahead times between 1 and 12 hours. It is observed that the distribution is concentrated between -20% and +30% for all investigated look-ahead times. For a 1-hour look-ahead time, errors are concentrated in the 10% interval, with a probability of 85%, whereas the error practically does never exceed the 30% boundary (probability 99.2%) Time-scale classification of wind forecasting methods is vague. Different types are,

- Very short-term forecasting: From few seconds to 30 minutes ahead.
- Short-term forecasting: From 30 minutes to 6 hours ahead.
- Medium-term forecasting: From 6 hours to 1 day ahead.
- Long-term forecasting: From 1 day to 1 week ahead.

3.4. Persistence models

Persistence model is the simplest way to forecast the wind. 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). The accuracy of this model degrades rapidly with increasing prediction lead time.

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3.5. 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. 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. 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 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.

3.6. Hybrid model

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

1. Combination of physical and statistical approaches
2. Combination of models for the short term and for the medium term
3. 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.

3.7. ANN model

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. The Elman recursion neural network model is proposed firstly by Elman J. L. in 1990, which can be called Elman network for short. Elman recursion neural network is a kind of recurrent neural network (RNN) with great adaptive ability to time-varying patterns The researches on Elman network have been developed with nonlinear modeling, transfer function and field of application, such as nonlinear stable adaptive control, solar activity forecasting and so on. The Elman networks are a form of recurrent neural network by adding recurrent links into hidden layer as a feedback connection which allows the network to learn to recognize and generate temporal patterns.

3.8. Support vector machines

Support vector machines (SVM) are a set of related supervised learning methods used for classification and regression. Their common factor is the use of a technique known as the "kernel trick" to apply linear classification techniques to non-linear classification problems. SVMs are based on the concept of decision planes that define decision boundaries. A decision plane is a boundary between a set of objects having different class memberships.

Linear SVM method helps in classifying some data points into two classes by a hyper-plane. The hyper plane is so chosen as to separate the data points "neatly", with maximum distance to the closest data point from both classes; this distance is called the margin. If such a hyper-plane exists, it is known as the maximum-margin hyper-plane or the optimal hyper-plane, as are the vectors that are closest to this hyper-plane, which are called the support vectors.

In Non-linear SVM**,** original feature space can always be mapped to some higher-dimensional feature space where the training set is separable using Regression. The basic idea behind support vector machines (SVM) for regression is to map the data into a high dimensional feature space through a nonlinear mapping. Once mapping is done then SVMs perform a linear regression in this feature space

4. DISCUSSION ON THE PERFORMANCE OF MODELS

Comparing the error distribution of the forecasting models discussed in this paper, the neural network model presents the best performance. This is evident, where the different characteristics of the error distributions are apparent. With the neural network model, the percentage of errors concentrated in the ±10% interval is highest for all forecasting horizons, while the maximum forecasting error is also lower for the statistical model .Again the neural network model delivers best results for all forecasting horizons.

5. 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. Papers were selected to emphasize the diversity of forecasting methods and the problems that wind generators will suffer from. The neural network model presents best performance as compared to other models.

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