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WIND POWER FORECASTING: A SURVEY

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Abstract: A number of wind power prediction techniques are available in order to forecast the uncertainty of the wind, which is used to estimate the wind power generation probability for the grid. It is receiving more attention with the recent advancement of smart grid, which provides a challenge of integrating wind power into the grid. Several methods are proposed to provide wind power prediction. In the recent years there is a lot of research happening to predict wind power with several mathematical methods and biologically inspired computing models to reduce the prediction error. In this paper a detailed review of the wind power forecasting techniques have been provided.

Keywords:foraging,intermittent,autoregressive,stochastic, liberalized,ram

INTRODUCTION

The use of wind energy has been developed significantly throughout the world, in order to get the ideal for a future with electricity without pollution. But the integration of wind farms in the power networks has become an important problem for the unity of commitment and control of power plants in electric power systems. Wind is considered one of the weather variables which more difficult to be predicted. Intermittent in nature, the electricity produced in a wind farm is difficult to be short-term forecasted. It is even difficult in the next few hours and, in general, any benefits obtained from the wind farms is not optimal, and may be necessary to increase the power plant spinning reserve. Hence, the need to administer energy resources and the advent of alternative energy, particularly wind power, necessitate the use of advanced tools for short-term prediction of wind speed or what is the same thing, the wind production. End-users (independent power producers, electrical companies, system operator distribution, etc.) which recognize the contribution of wind forecast for a safe and economic operation of the network. Especially, in a liberalized electricity market, forecasting tools improve the position of wind energy compared with other available forms of generation.

Wind power forecasts do not provide the solution by themselves. However, being used as a key input to various decision making processes related to power system operations and participation in electricity markets, they comprise a necessary and cost-effective element required for the optimal integration of wind power into energy systems. Quality of the forecasts is very important and thus improving prediction systems' performance has been set as one of the priorities in wind energy research needs for the period 2000-2020.

In this paper we have presented a review of many wind power forecasting methods which have been successfully proved efficient by researchers. Wind power forecasting is divided into categories depending upon the time duration and methods are analysed as per that

LITERATURE REVIEW

The stochastic nature of wind makes it difficult to develop models which accurately predicts future wind speed and direction, thus also the future power output from a wind turbine. As a result, many different approaches have been tried to find the ideal power prediction model. This is especially seen in the work by [1] which gives an extensive literature overview of the state of the art short-term wind power prediction models, based on review of more than 380 journal and conference papers. [3] divides the prediction horizon into the following categories:

1. Immediate-short-term: From seconds up to 8 hours ahead forecasts,

2. Short-term: A day ahead forecasts,

3. Long-term: Multiple days ahead forecasts,

with the applications for each time horizon given in Table 2.1.

Table 2.1: Time scale of forecast models and their applications [3].

Time scale	**Range**	**Application**
Immediate Short Term	8 hours ahead	- Real-time grid operations -Regulation actions
Short Term	Day Ahead	- Economic load dispatch Planning -Load reasonable decisions -Operational security in electricity marked
Long Term	Multiple Days Ahead	-Maintenance planning -Operation management - Optimal operating cost

There are mainly two approaches used to when developing wind power prediction models: (i) a physical approach and (ii) a statistical approach [1]. The former is a deterministic method which use physical considerations and input data to make predictions of the future power output [2]. These physical models are based on predictions of the lower atmosphere or numerical weather predictions (NWP) using input data such as temperature, pressure, surface roughness and obstacles obtained from weather forecasts [3]. The statistical approach predicts the future power output using historical obtained data, which could also include NWP results, and is a pure mathematical approach which does not consider any of the physical processes of wind [2]. The main idea is use these vast amounts of historical data to find a relationship to the power output. This typically involves time series analysis [3] and artificial neural networks, which often include the use of recursive techniques. For look-ahead times above 3-6 hours, models using a time series approach are usually outperformed by models involving a NWP [1]. In order to get the best from each approach, a hybrid approach is typically used in most operational and commercial models today [1]. Table 2.2 shows an overview of some of the wind forecasting models described by [3], with their corresponding time horizon and approach.

Table 2.2: Some forecasting models for wind speed and power with their respective time horizon and approach used [3].

Model	Time horizon	Approach
WPMS	Immediate short term	Statistical
ANEMOS	Immediate-short-term, short-term	Statistical & Physical
ARMINES	Immediate-short-term, short-term	Statistical & Physical
WPPT	Short-term	Statistical
Prediktor	Short-term	Physical
Previento	Long-term	Statistical & Physical
WEPROG	Long-term	Statistical & Physical

Forecast models used to predict more specific events or scenarios of power production are also being developed. In a recent study [4] notes the lack of ability of current forecasting models to properly handle extreme situations related to wind generation, being a result of either extreme weather phenomena or critical periods for power system operation. A ramp is one such event, defined in the study as a steep and high increase or drop in power production from a wind farm within a time period of a few hours. The study proposes a methodology, which used together with numerical weather prediction ensembles, provides reliable forecasts with greater accuracy regarding climatology Due to its simplicity and because many natural processes are considered as Markov processes [5], Markov chains have become a popular tool for developing wind power prediction models based on time series analysis. A Markov chain represents a system which, based on the input data, calculates the probability of going from one state to another. The order of the Markov chain decides how many previous time steps influencing the probability distribution of the current state. Such states could for instance represent a given power output, wind direction or wind speed. Another advantage using Markov chain is the possibility of not only making point predictions, but also probabilistic forecasts, , i. e. give information about how likely it is for a given prediction to occur. A study by [5] discuss how first and second order Markov chain models can be used for generating synthetic wind speed time series, which may further be used as input to a wind energy system. [2] recommends instead to use wind power measurements directly as input to a Markov chain model in making a immediate term forecast of the power . Argument being that for wind speed forecasts, the forecast would have to model the wind farm power curve of interest, take into account individual turbine curves, site orographic characteristics and wake effects, before finally converting the wind speed forecast into a power forecast. A process which could amplify the prediction error and which would be avoided using power data directly. Instead of giving a specific wind speed forecast or power forecast [6] suggest using Markov chain models for predicting the 1 hour ahead categorical change in the wind power. In this case the power change in the last hour, the current wind power and the 20-minute power trend are used to provide a probabilistic forecast of three states, -1: a negative trend, 0: no change is expected and 1: a positive trend is predicted.

According to [7] wind speed prediction can be clustered into two main categories, that is, physical methods and statistical methods.

Physical methods, which take into account physical factors, that is, temperature, pressure, wind farm layout, and local terrain, are based on numerical weather prediction (NWP) tools that provide weather forecasts by utilizing mathematical models of the; these models require long operation times and large amounts of computational resources. Landberg initially proposed the concept of applying NWP tools as an input; tools such as the wind atlas analysis and application program (WAsP) and PARK are now used for wind prediction correction [8]. Statistical methods that are used to determine the relation between historical wind speeds by generally recursive techniques can be utilized for short-term wind speed forecasting. Many models have been developed to improve wind speed forecasting accuracy, including autoregression (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), artifiial neural networks (ANN), fuzzy logic (FL), support vector machine (SVM), and spatial temporal models [9]. Torres et al. [10] used ARMA and persistence models to forecast the hourly wind speed up to 10 h ahead. Th ARIMA and ANN approaches have been used for wind speed time series forecasting on the south coast of the state of Oaxaca, Mexico [11]. Three types of ANN models, namely, adaptive linear element, back propagation, and radial basis function, were investigated for hourly mean wind speed forecasting at two observational sites in North Dakota [12]. A fuzzy model was proposed for wind speed prediction and provided wind speed forecasts from 30 min to 2 h ahead [13]. Zhou et al. [14] suggested a systematic study on fie-tuning least-squares support vector machines (LS-SVM) model parameters for one-step-ahead wind speed forecasting for the fist time. A methodology to characterize the stochastic processes applied for wind speed at different geographical locations via scenarios was provided [15]. Moreover, hybrid models that hybridize multiple features of diffrent predictive models are usually adopted for wind speed forecasting because this type of model can comprehensively capture the intricate characteristics of wind speed series. Combining several forecasting methodologies is another strategy that can signifiantly improve predictive performance by taking advantage of each method's performance with respect to data sets, capability of describing nonlinearity and linearity, as well as prediction horizons; these combined models can be superior to individual models [12]. Li et al. proposed a hybrid model consisting of the ANN and Bayesian approaches, and the results indicated that the hybrid approaches produced forecasting errors that were always smaller than those produced by ANN [16]. Monfared et al. [17] developed an ANN and FL hybrid model to predict actual wind speed time series sampled in Rostamabad from 2002 to 2005, which demonstrated that this approach requires less computational time and provides better prediction performance. Salcedo-Sanz et al. [18] combined a hybridized ANN with a mesoscale model, and this combined strategy produced superior forecasting results. Additionally, Cadenas and Rivera investigated hybrid models that consisted of ANN and ARIMA and concluded that the hybrid models outperformed the individual ANN and ARIMA approaches [19].

Conclusion: Different approach for wind power forecasting method are discussed in briefly. And development of some forecasting technic improvement in wind power generation.ARIMA,ARMA,ANN are different methods to forecast wind power.

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