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Wind resource estimation using wind speed and power curve models

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A B S T R A C T

Estimation of wind resource in a given area helps in identifying potential sites for establishing wind farm and aids in the calculation of annual energy produced. Estimation of annual energy improves the wind power penetration in the electricity grid and in electricity trading. In this paper, wind resource estimation has been carried out using wind speed forecasting models and wind turbine power curve model. The time series model of wind speed for day ahead forecasting is developed based on linear and non-linear autoregressive models with and without exogenous variables. The daily wind speed data of five different locations in New Zealand have been used for this analysis and the annual energy produced has been obtained. The standard deviation between the mean wind speed of the previous day and the mean wind speed during corresponding day five years and ten years ago has been used as exogenous variables. The neuralnet based non-linear model built using exogenous variables (NLARX) performs better in three locations and wavenet based non-linear model performs better in the remaining two locations. Wind resource is estimated using a wind turbine power curve modeled using a five parametric logistic expression, whose parameters were solved using Differential Evolution (DE).

1. Introduction

Wind resource estimation is the essential prerequisite for identifying potential wind farm sites both onshore and offshore. Estimates of wind energy will also help the wind farm owners to choose the ratings of wind turbines to be installed. Wind resource is defined as the actual long-term kinetic energy content of the wind at specific height and location [1]. An overview of the various methods used to estimate wind resource at a particular site has been presented in Ref. [1]. Eight different methods of wind resource assessment have been outlined namely, folklore, measurements only, measure-correlate-predict (MCP), global databases, wind atlas methodology, site data-based modeling, mesoscale modeling and combined meso/microscale modeling. Complex terrain, offshore sites, high elevation, forest sites etc are the few challenges faced by wind resource estimation techniques.

A brief survey of the various research works that are going on in the field of wind resource assessment has been presented here. An analytical predictive model that could be used for carrying out a pre-assessment study of a potential site for wind farm establishment has been developed in Ref. [2]. This model could be used by wind farm investors to identify potential sites for wind farm and also to assess the wind energy that could be generated. The model was found to outperform the conventional Weibull statistics model. The Annual Energy Production (AEP) of a potential wind farm site has been estimated using Bayesian approach in Ref. [3]. The approach effectively addresses the uncertainties that exist due to limited availability of data and the inherent uncertainty in wind speed, air density, surface roughness exponent and power performance of the turbine. The wind energy potential of a site has been predicted using weighted error functions in artificial neural networks in Ref. [4]. The frequency of wind speed and the power performance curve has been used to develop the weighted form of the error function.

Forecasting of wind energy using automatic tuning of Kalman filters by maximum likelihood methods has been developed in Ref. [5]. New multivariate Kalman filters have been used to forecast wind power and the model parameters are automatically optimized through site-dependent fine-tuning. Generalized feed-

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forward neural networks have been used to predict an annual wind speed probability density distribution in Ref. [6]. This approach uses the same input parameters as the Weibull function and is observed to give better results for energy output calculations. The wind energy estimation of the Wol-Ryong coastal region has been presented in Ref. [7]. The power spectrum analysis was conducted on the horizontal and vertical wind speed over a wide range of frequencies to ascertain a potential site for wind farm. The wind and wave energy resources along the Caspian Sea have been evaluated in Ref. [8]. Seasonal and diurnal changes in wind speed have been analyzed and the long term wind potential has been estimated using the MCP method. Evaluation of wind speeds and vertical wind shears simulated by the Weather Research and Forecasting Model using seven sets of simulations with different Planetary Boundary Layer (PBL) parameterizations has been studied in Ref. [9]. Determination of the PBL parameterization that would perform best for wind energy forecasting and development of validation methodology that take into account different wind speeds has been the main focus of this evaluation. The ability of four different numerical models to forecast the mean wind speed variation across sites with wide range of terrain complexities, wind climates and surface characteristics has been evaluated in Ref. [10]. The coupled Numeric Weather Prediction (NWP) models performed best since they had the ability to simulate the unsteadiness of the flow as well as the phenomena due to atmospheric stability and other thermal effects. The impact of climate change on the wind energy resource of Ireland has been considered using an ensemble of Regional Climate Model in Ref. [11]. Wind energy assessment has been done based on three probability density functions namely two-parameter Weibull, Logistic and Lognormal functions in Ref. [12]. Among the three, the Logistic function provided a better result for wind speed distribution modeling.

In this paper, wind resource estimation has been performed based on wind speed and power curve models (Fig. 1). Linear and non-linear autoregressive models with and without exogenous variables have been built for wind speed prediction. The predicted wind speed is extrapolated to 100 m using the power law (Eq. (1)).

$$\frac{y(z)}{y(z_r)} = \left(\frac{z}{z_r}\right)^{\alpha} \tag{1}$$

where $y(z)$ is the wind speed at height z, $y(z_r)$ is the reference wind speed at height z_r, and α is the power law exponent. The parameter α varies with elevation, time of day, season, nature of terrain, wind speed and temperature. Lange and Focken state that heights greater than 1 km approximately are the domain of large scale synoptic pressure systems which include the well-known highs and lows [13]. The influence of ground is rather weak and hence the wind field is largely dominated by the Coriolis force which results due to the rotation of the earth and by the horizontal gradients of temperature and pressure. The wind turbine power data is statistically generated and the power curve is modeled using five parameter logistic function. The wind turbine power curve modeled using five parameter logistic function whose parameters are solved using Differential Evolution (DE) has been reported to produce the best power curve model in Ref. [14]. Hence the proposed model for wind resource assessment will definitely give a very accurate value. The AEP has been calculated using Eq. (2).

$$\mathrm{AEP} = \sum_{i=1}^{N} \overline{P}(y_i) \tag{2}$$

where N is the total number of hours in a year, y is the wind speed and $\overline{P}$ is the average hourly power output which is calculated from wind turbine power curve model.

2. Models for forecasting wind speed

A forecasting model is characterized by the forecast data, forecast horizon and forecast accuracy. The forecast data comprises of the time series data of mean daily wind speed. The forecast horizon is defined as the time span in future for which the parameter will be predicted. The forecast accuracy is the performance measure of the forecasting technique, which can be ascertained using suitable performance metrics.

Three different models have been built for wind speed namely autoregressive (AR) model, AR model with exogenous variable (ARX) and non-linear ARX model (NLARX) for day ahead forecasting. The schematic representation of the wind speed models and the modeling techniques used has been described in Fig. 2.

2.1. AR model

The AR model structure is given by Eq. (3)

$$A(q)y(t) = e(t) \tag{3}$$

where $y(t)$ is the output signal at time t, $e(t)$ is the white noise at time t and q is the backshift operator. $A(q)y(t)$ is the autoregressive (AR) part and $A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \cdots + a_{n_a}q^{-n_a}$, where $a_1,\ldots,a_{na}$ are the parameters of AR part and n_a is the AR order. The AR model is a special case of ARX model with no input [15]. In this

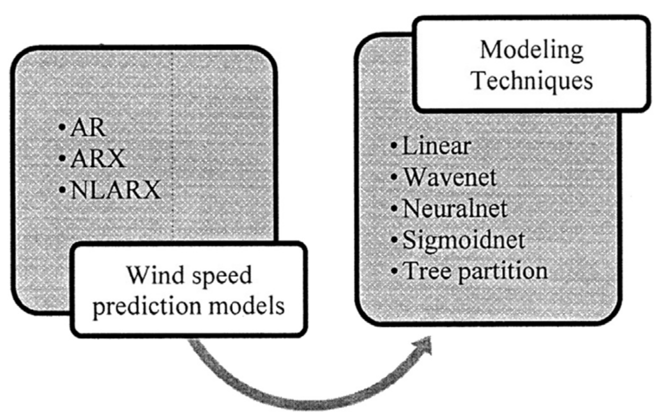

Fig. 2. Wind speed forecasting models.

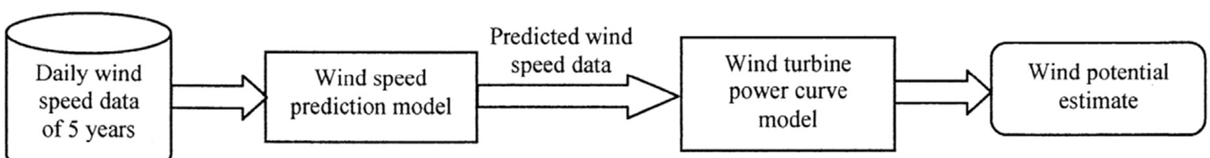

Fig. 1. Proposed method for wind potential estimation.