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A simple hourly wind power simulation for the South-West region of Western Australia using MERRA data

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ABSTRACT

A simple simulator capable of generating synthetic hourly values of wind power was developed for the South West region of Western Australia. The global Modern Era Retrospective Analysis for Research and Applications (MERRA) atmospheric database was used to calibrate the simulation with wind speeds 50 m above ground level. Analysis of the MERRA data indicated that the normalised residual of hourly wind speed had a double exponential distribution. A translated square-root transformation function $y_n = (\sqrt{(1.96 + y_e)} - 1.4)/0.302$ was used to convert this to a normal-like distribution so that autoregressive (AR) time series analysis could be used. There was a significant dependency in this time series on the last 3 h m so a third order AR model was used to generate hourly 50 m wind speed residuals. The MERRA daily average 50 m wind speed was found to have a Weibull-like distribution, so a square root conversion was used on the data to obtain a normal distribution. The time series for this distribution was found to have a significant dependency on the values for the last two days, so a second order AR model was also used in the simulation to generate synthetic time series values for the square root of the daily average wind speed. Seasonal, daily, diurnal, and hourly components were added to generate synthetic time series values of total 50 m wind speed. To scale this wind speed to turbine hub height, a time varying wind shear factor model was created and calibrated using measured data at a coastal and an inland site. Standard wind turbine power curves were modified to produce an estimate of wind farm power output from the hub-height wind speed. Comparison with measured grid supervisory control and data acquisition (SCADA) data indicated that the simulation generated conservative power output values. The simulation was compared to two other models: a Weibull distribution model, and an AR model with normally distributed residuals. The statistical fit with the SCADA data was found to be closer than these two models. Spatial correlation using only the MERRA data was found to be higher than the SCADA data, indicating that there is still a further source of variability to be accounted for. Hence the simulation spatial correlation was calibrated to previously reported findings, which were similar to the SCADA data.

1. Introduction

With the increasing focus on low emission power generation systems to mitigate global warming and the successful operation of several wind farms in the South West region of Western Australia (SWWA), it becomes worthwhile to consider the potential for expansion of wind power generation in this region. The SWWA is characterised by a Mediterranean climate [1], which is dominated by the eastward passage of high pressure sub tropical anti cyclonic cells. Mainly in winter, low pressure systems from the south cross the state every seven to ten days. Hence there are distinct differences in the seasonal wind speed variation at different places within SWWA. Frequently, there is a strong diurnal sea/land breeze along the coastline [2], more often in the summer months. This sea breeze can also penetrate as far inland as Kalgoorlie [3], which is about 350 km from the nearest coast.

The wind speed at any site can be represented as the sum of several components operating at different temporal scales: seasonal, daily, diurnal, dependent and random. The seasonal component arises from the cyclical variation in the prevailing atmospheric systems as the earth orbits the sun. The daily component arises from the passage of weather systems across a region with typical durations from 2 to 8 days [4]. The diurnal component arises from the sea/land breeze system caused by temperature

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differences between the land and ocean. The dependent component arises because atmospheric phenomena can be persistent, resulting in a relationship between the wind speed at a particular time to the wind speed at previous times. Finally, most physical processes contain a random fluctuation component and wind speed is no different.

For a model to adequately represent the wind power generation potential at any one place in the SWWA, it is necessary to capture the variability at each temporal scale [5]. It will also be necessary to capture the spatial differences in these variabilities across the whole region of the SWWA. There have been several simple models that generate synthetic time series values of wind speed at one or more sites (eg. Refs. [6,7]). These models attempt to mimic the observed statistical nature of the wind speed. There are also detailed models of wind speed at multiple sites or across a region that use meteorological physics, and tend to require much more computing power [8]. This study will focus on the development of a statistical model designed to operate across the SWWA region.

The two parameter Weibull distribution has been the most widely used simple statistical representation of overall wind speed behaviour [8]. The probability density function for this distribution is given by:

$$f(v) = \left(\frac{k}{\lambda}\right)\left(\frac{v}{\lambda}\right)^{k-1} e^{-\left(\frac{v}{\lambda}\right)^{k}} \quad v \geq 0$$
$$f(v) = 0 \quad v < 0 \tag{1}$$

where v is the wind speed (m/s), f(v) is the probability density function, k is the shape parameter, and λ is the scale parameter. However, Carta et al. [9] also reviewed other probability density functions used to represent wind speed frequencies, and concluded that although the Weibull distribution has some advantages over other distributions, it cannot adequately represent many of the wind speed probability density functions that might be encountered in the real world. Gunturu and Schlosser [10] found that use of the Weibull distribution could lead to both over and under estimations of the wind power resource available.

Auto Regressive Moving Average (ARMA) models [11] have also been widely applied to the statistical representation and prediction of many kinds of time series data (for example [12–14]) as well as wind speeds. ARMA models are a combination of Auto Regressive (AR) models, and moving average (MA) models, where the windspeed value at time t is represented as the sum of a linear combination of wind speed values at previous times and the linear combination of a series of random values. Purely Auto Regressive models use only the random value at the present time:

$$y(t) = \sum_{k=1}^{p} \varphi_k y(t-k) + \rho r(t) \tag{2}$$

where y(t) is the wind speed residual at time mark t, y(t−k) is the wind speed residual at timemark t−k, and r(t) is a series of uncorrelated white noise error values which is identically distributed with a normal frequency distribution, zero mean, and standard deviation of one. y(t) is multiplied by the wind speed standard deviation and then added to the mean wind speed to get a wind speed value. φ_k are the AR parameters, and σ is the random noise parameter. The value of ρ is adjusted depending on the value of the AR parameters so that the standard deviation of y(t) remains at one. The AR order p is the maximum value of k with a non-zero value of φ_k. This is commonly written as an AR(p) model. ARMA models can capture the temporal dependency inherent in wind speed time series, while using a simple Weibull distribution cannot. However, Papaefthymiou and Klockl [15] asserted that the frequency distribution (equivalent to the probability density function or PDF) of ARMA models rarely match the measured data, which can lead to under or over estimation of wind power.

Wind speed behaviour can also vary over several temporal scales, such as seasonal, daily, diurnal, and hourly. Seasonal variation is commonly modelled using one or more sinusoidal cycles (eg, [8] and [16]). Daily average wind speeds vary from the seasonal average and can have a skewed distribution [17]. Weibull, lognormal, modified normal and modified exponential distributions have been used to represent these distributions (eg Refs. [17–19]). Carlin and Haslett [20] proposed the use of a "squared normal" distribution to simply model Weibull-like distributions, based on Western Australian wind data. Daily wind speeds have also been found to have an autoregressive dependency (eg Refs. [21–23]).

A common way of modelling diurnal trends has been to calculate the average measured wind speed at every hour of the day for each month or season (eg Ref. [8]). Fixed cyclic functions have also been used (eg Ref. [19]). However these approaches don't explicitly catch the variation in peak daily wind speed magnitude and time that occurs throughout each month or season. ARMA models and high order AR models have also been developed that model diurnal variation (eg Refs. [6,24]). Suomalainen et al. [23] concluded that these approaches were not sufficiently realistic and developed a model that identified day types defined by the time of day that the peak wind speed occurs, and defining a diurnal pattern for each day type.

After the seasonal, daily, and diurnal components of wind speed have been removed, what is left is the de-trended hourly wind speed. Similarly to the daily wind speed, the value at a particular time has a dependency on the values at previous times, and ARMA models have been commonly used to model this effect.

However, the above form of ARMA equation has been found to be generally suitable for use only if the time series data and the error values are normally distributed. If the data is not normally distributed, then the choice of distribution for the random error values needed to produce the same distribution as the data is not clear [25]. For example, Ward and Boland [16] found that detrended wind speeds at sites in South Australia had a double exponential distribution (also called a Laplace distribution). But Damsleth and El-Shaarawi [26] found that even the simplest AR model (of order 1) would not necessarily generate a time series with a double exponential distribution, even if the random variable was given a double-exponential distribution. Lawrance and Lewis [25] suggested an alternate form of auto-regressive equation, but with impractical restrictions on the allowable values of the autoregressive coefficients.

A possible solution is to convert the de-trended wind speed time series values into a normal distribution using a data transformation function. Mach et al. [27] tested a number of transformations on different types of data. If the data is found to have an exponential distribution, then the authors recommended a power transformation to convert the data to a normal distribution. Although a double exponential distribution is symmetric about the mean, unlike a standard exponential distribution, this might point the way to a suitable transformation function. If the data is found to have a Weibull-like distribution (such as daily wind speeds), then Mach et al. [27] recommended the use of a Box-Cox or power law transformation to convert to a normal distribution. Widger [28] used the square-root normal distribution to model wind speeds, suggesting that taking the square-root of the data (power law 1/2) may effectively convert a Weibull-like distributed wind speed time series into a normal-like distributed series. Carlin and Haslett [20] used a square-root transformation function on Western Australian wind data, and Brown et al. [29] used a square-root transformation