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Weighted error functions in artificial neural networks for improved wind energy potential estimation

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HIGHLIGHTS

- This paper applies the artificial neural network (ANN) to predict annual energy production of wind turbines.
- We proposed two ANNs that are based on weighted error functions to improve the accuracy.
- The proposed ANNs showed much better accuracy compared to the conventional ANNs.

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ABSTRACT

This paper presents the application of the artificial neural network (ANN) to predict long-term wind speeds of a particular site, and to estimate the annual energy production of wind turbines using the predicted wind speeds. A major finding in this study is that an ANN trained with a conventional error measure may significantly underestimate the annual energy production. An accurate prediction of the mean wind speed does not guarantee an accurate prediction of the energy production when the variance of the wind speed is underestimated. To improve the accuracy in estimating the energy production, we proposed two ANNs that are based on weighted error functions. They use the frequency of the wind speed and the power performance curve to develop the weighted form of the error function. For the site and the turbine studied in this paper, the proposed ANNs showed 8–12% improvement in predicting the annual energy production compared to the conventional ANN.

1. Introduction

A major challenge in the wind energy potential assessment is the prediction of the wind speed. The wind speed is difficult to predict because of complex interactions of geographical and physical factors such as the atmospheric pressure, the temperature, and the local topography. There have been many studies to predict short-term wind speeds as well as long-term wind speeds in the field of wind energy.

Short-term forecasting of wind speed ranges from a few seconds to days. The forecasting objective for periods in the range of a few seconds to minutes is the control of wind turbine itself. Wind forecasts in the range of hours deal with the scheduling in a power system, whereas forecasts in the range of days deal with maintenance and resource planning [1]. The short-term forecasting has extensive literature [2]. The artificial neural network (ANN) has been used extensively in this regard [3–6]. However, these approaches are outside the scope of this paper and we will focus on long-term wind energy potential assessment.

The long-term estimation problem predicts long-term wind speeds at a target site in order to estimate the wind energy potential of wind turbines. Assessment of wind energy potential prior to the construction of wind turbines is a prerequisite for the successful development of wind energy and minimization of financial risk for the wind farm developers. In general, long term wind data over several years is not available at the target site. Accordingly the key element of wind energy potential assessment is the prediction of long-term wind speed and direction at the target site using the measured long-term wind data at nearby reference sites, mostly local weather stations [7–9]. Other meteorological inputs such as the air density and turbulent characteristics are of secondary influence to the energy production, and therefore these are not considered in the present study. Note that the energy production is proportional to the cube of wind speed whereas it is proportional linearly to the air density. The variation of the air density is also much smaller than the variation of the wind speed [10]. As for the turbulence, its effect will not be significant as the potential

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estimation is conducted using averaged wind speeds such as the hourly wind speed.

The present study aims to improve the accuracy of the long-term energy estimation when the ANN is used in the prediction process. We will demonstrate that the conventional approach of minimizing the error in wind speed prediction, rather than our proposed way of minimizing the error in energy production, may cause significant error. Two new ANNs that are based on new error functions will be proposed to improve the performance in estimation of energy production. The performance of the proposed ANNs and conventional ANNs will be compared.

2. Objective of the research

2.1. Past research on wind energy potential estimation using the artificial neural network

The use of the ANN in wind energy potential estimation is gaining popularity recently. In most cases, ANNs were used in predicting the wind speed, and then the energy potential was estimated using the predicted wind speed. In some cases, ANNs directly estimated the energy potential. This section reviews past studies in this subject.

When the ANN is used to predict the wind speed of a single site, the formulation is essentially the same as the prediction of the time-series. Prediction of the time-series is a well-established topic, and the existing methods in forecasting (ex, [1]) can be applied directly to the energy potential problem. For example, More and Deo [11] followed such an approach and mentioned that their approach could be used in predicting power output. Three studies took different approaches and they are worth mentioning, although not directly relevant to our work. Mabel and Fernandez [12] used ANN to predict the energy output directly, i.e., the output of the ANN was the wind energy. The input vector to the network was composed of wind speed, relative humidity, and generation hours. Thiaw et al. [13] stated the inaccuracy of the Weibull probability density function (PDF) in some cases. The authors used an ANN to describe the distribution of the wind speed and were able to obtain more accurate estimation of the energy potential compared to the traditional approach using the Weibull PDF. Tu et al. [14] improved prediction of wind speed and power output by using both the wind speed and the previous power output in the input vector of the ANN.

Some researchers used geographic information to predict the wind energy. Their task often was to create a wind map, and naturally, the geographic information as part of the input to the ANN was useful to them. Cam et al. [15] spatially interpolated the wind speed and the power using geographic information. The input vector to the ANN was composed of latitude, longitude, altitude, and measurement height, and the output vector was composed of annual average wind speed and power. Cellura et al. [16] followed a similar approach but they also created wind speed maps using the developed approach. The input vector to the ANN was composed of information about the territory (altitude and land coverage), and the output was the mean wind speed. They combined the ANN with a Kriging interpolator. Similarly, Fadare [17] created a monthly wind speed map of Nigeria. Bouzgou and Benoudjit [18] also used geographic information such as latitude, longitude, and altitude, in addition to the date and temperature, but they proposed a new system to improve the accuracy of the wind speed prediction. The proposed system was termed as a multiple architecture system, which was composed of six different regression methods including ANN and fusion strategies to combine outputs from them.

An important subject in wind energy potential estimation is the spatial estimation of wind speed. A common scenario when wind turbines are constructed is that limited or no measurements are available at the target site, whereas long-term wind speeds are available near the target site (such as weather stations). Conventional mathematical approaches are available such as the measure–correlate–predict (MCP) algorithm [7], but many researchers began applying the ANN due to its advantages in capturing complex nonlinear relations. For this purpose, wind speeds of neighboring sites may be used as input to predict the wind speed of the target. For example, Oztopal [8] used wind speeds of nine neighboring stations, and Bilgili et al. [9] used wind speeds of four neighboring stations, in order to predict the wind speed at the target. However, newer studies found out that the inclusion of the directional information significantly improves the prediction accuracy. Lopez et al. [19] concluded that it was important to include the directional information in predicting wind speed for a complex terrain. They also combined short-term measurements from the target with long-term measurements of neighboring sites to improve the accuracy of the prediction. Velazquez et al. [20] compared ANNs with three different representations of the input vector—wind speed only, wind speed and the direction in angular magnitude, and wind velocity decomposed into Cartesian components. In most cases, the wind direction in angular magnitude performed the best, followed by the wind velocity decomposed into Cartesian components, and wind speed only. Philippopoulos and Deligiorgi [21] also confirmed the importance of including the directional information for a complex terrain. The authors provided the directional information by specifying the wind velocity as a 2-D vector.

2.2. Original contribution of the paper

Although the studies reviewed in the previous section predicted the wind speed for energy potential estimation, few papers actually predicted energy output or computed the energy output using the predicted wind speed [12,14,15]. Almost all studies predicted the wind speed only, and used conventional error measures of ANN to quantify the performance of their predictions, such as mean absolute error, mean squared error, and sum of squared error of the predicted wind speed.

However, we will show that seemingly good performance of the ANN may not always translate to an accurate prediction of the energy potential. We will illustrate that conventional error measures to quantify the performance of the ANN may be incomplete, or even inadequate, in developing an ANN that predicts the wind speed for energy potential estimation. In order to reduce the error in energy potential estimation due to the use of conventional error measures, we will propose two new weighted error measures in this paper.

An ANN is designed to provide the prediction in an average sense. ANN predictions typically show less scatter compared to the actual data, which will be illustrated later in Section 3.2 (also see [22], p. 203–204). Although this behavior is desirable for many applications, it causes significant error in energy potential estimation. To the best of our knowledge, this interesting and important observation has not been reported previously, except some scattered observations on smaller variance of the ANN prediction [18,19]. However, distortion of the probability distributions is a known issue in mathematical models. For example, Rogers et al. [7] showed that the linear regression method produced smaller variance than real measurements, which resulted in incorrect wind speed distributions and energy estimation. We shall show that a similar behavior exists in ANN, and that the proposed error measures will decrease the error associated with this behavior.