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A new strategy for predicting short-term wind speed using soft computing models

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ABSTRACT

Wind power prediction is a widely used tool for the large-scale integration of intermittent wind-powered generators into power systems. Given the cubic relationship between wind speed and wind power, accurate forecasting of wind speed is imperative for the estimation of future wind power generation output. This paper presents a performance analysis of short-term wind speed prediction techniques based on soft computing models (SCMs) formulated on a backpropagation neural network (BPNN), a radial basis function neural network (RBFNN), and an adaptive neuro-fuzzy inference system (ANFIS). The forecasting performance of the SCMs is augmented by a similar days (SD) method, which considers similar historical weather information corresponding to the forecasting day in order to determine similar wind speed days for processing. The test results demonstrate that all evaluated SCMs incur some level of performance improvement with the addition of SD pre-processing. As an example, the SD+ANFIS model can provide up to 48% improvement in forecasting accuracy when compared to the individual ANFIS model alone.

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1. Introduction

Wind energy is considered as one of the fastest growing energy resources in the world. Globally, wind energy saw an average annual growth rate of 31% over the past five years. By 2020, 12% of the world's electricity could feasibly come from wind power. Wind represents a clean and sustainable source of energy and is in abundant supply. However, the increase in wind power

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penetration requires a number of issues to be addressed including the management of wind power generation variability, market integration, interconnection standards, power quality, power system stability and reliability, etc., and as such, the power grid operators and energy traders face a number of challenges due to the substantial growth of increased wind power penetration in electricity energy systems [1,2]. Since the wind power produced by a wind farm depends critically on the stochastic nature of wind speed, unexpected variations of a wind power output may increase operating costs for the electricity system.

The relationship between wind speed and wind power is highly nonlinear (i.e., basically cubic), hence, any error in the wind speed forecast will actually generate a larger error in wind power production. When an entire wind farm is considered, the relationship becomes more complex as speed and directional components of the wind are used by individual turbines to achieve an optimal power output of the wind farm [3]. Correspondingly, the application of short-term wind speed forecasting (30-min to 6-h-ahead) is instrumental in the planning of economic load dispatch and load increment/decrement decisions making with respect to the management of a significant amount of wind power.

Several methods are reported in the literature for short-term wind speed forecasting such as the persistence method, physical modeling approaches, time-series techniques, soft computing methods, etc. The persistence method, also known as a 'Naive Predictor', is generally used as a benchmark for comparing other tools for short-term wind speed forecasting. This method simply uses the past hour wind speed value as the forecast for the next hour. Wind forecasting methods are usually first tested against the persistence method in order to baseline its performance [3]. Numerical weather prediction (NWP) is a physical modeling approach used in forecasting wind that utilizes various weather data and operates by solving complex mathematical models [4,5]. Also, a number of time-series forecasting models have been successfully applied to short-term wind speed forecasting. The time-series based model uses historical data to tune the model parameters and error minimization occurs when the patterns match historical ones. Some examples of time-series models are autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), fractional ARIMA (fARIMA), seasonal ARIMA (sARIMA), single exponential technique, double exponential, grey predictors [3,6–10]. These time-series models perform well in the areas where the data is low frequency in nature such as weekly patterns, but can have difficulties when there are rapid variations and high-frequency changes of the target signal, e.g., wind speed. Furthermore, wind speed is a result of the complex interactions between large-scale forcing mechanism, e.g., pressure and temperature gradients, rotation of the earth and local characteristics of the surface. These attributes make accurate wind speed forecasting more difficult and highly model dependent.

Soft computing methods are well known for their capabilities when dealing with non-linear systems and have garnered significant attention in the area of wind forecasting. Soft computing is a generalized term that encompasses the fields of neural networks (NNs), fuzzy logic, evolutionary computation, machine learning and probability reasoning. An advantage of the soft computing model (SCM) is its lower data dependency compared to statistical models and can also handle data non-linearity more effectively [11,12]. Another advantage of SCMs is that they do not require a priori knowledge of the wind data model [13]. However, drawbacks of SCMs include the inherent implicit or hidden input/output data relationship and the possibility of overly excessive computational requirements [10]. Among SCMs, NNs have been widely used in various forecasting applications and numerous types of NNs including backpropagation NN (BPNN), probabilistic NN, radial basis function NN (RBFNN), self-organizing feature maps (SOFM), cascade correlation NN, extended Kalman filter (EKF)-based NN, support vector machine (SVM), and adaptive resonance theory NN have been previously suggested [14–17]. Some evolutionary optimization techniques, e.g., particle swarm optimization (PSO), genetic algorithms (GA) have been used for updating the weight of a neuron while training the NN [18]. Also, fuzzy theory has been used for various forecasting applications [19,20] and another approach for short-term wind speed forecasting based on the fuzzy ARTMAP technique was explored in [21].

Approaches using a hybrid intelligent system for wind speed forecasting are becoming more popular, namely neuro-fuzzy methods. Fuzzy logic and NNs are natural complementary tools. A wide comparison among ARMA, NNs, and adaptive neuro-fuzzy inference system (ANFIS) models are presented in [22] for forecasting wind power in five forecasting horizons (1 h, 3 h, 6 h, 12 h, and 24 h). Li et al. [23] proposed the use of a Bayesian combination method using NN models and showed improved wind speed forecasting accuracy. Cadenas and Rivera [24] used a hybrid ARIMA-NN model for wind speed forecasting and their results demonstrated that the forecasting performance of this hybrid model for a fixed prediction horizon was significantly better compared to that of the ARIMA and the NN models working separately. Blonbou [25] presented an adaptive very short-term wind power prediction scheme using NNs as predictor along with adaptive Bayesian learning and Gaussian process approximation. The results showed that the NN predictor performs better than the persistence model and the Bayesian framework permits the prediction of the interval within which the generated power should be observed. Recently, Bhaskar and Singh [26] applied an adaptive wavelet neural network (AWNN) based wind speed forecast model and utilizes multiresolution decomposition of wind speed signal. It was found that the AWNN model has better forecasting accuracy and a faster training ability when compared to a conventional feed forward neural network (FFNN). Given the wide variations of wind forecasting algorithms, a standardized protocol for evaluating short-term wind power prediction systems was introduced in [27,28] where the authors also provided guidelines for using a minimum set of error measures. It was emphasized that a rigorous use of data is required as well as the fact that both training and testing data sets should be clearly defined and separated. Giebel et al. [29] presented a literature overview on the state-of-the-art in short-term wind power prediction. The authors stated that wind power prediction tool is not "plug-and-play" as it highly depends on wind farm site, and when installed to a new site, a considerable effort is needed for tuning the models based on the characteristics of the local wind profile. As explained here, several forecasting methods are available for wind speed forecasting, however, there is still a need of an efficient and robust forecast tool.

This paper describes short-term wind speed forecasting approaches by considering various SCMs, and the combined approach of an SCM and the similar days (SD) method for data pre-processing. The forecasting is applied to data obtained from the North Cape wind farm located in the Prince Edward Island (PEI), Canada. This paper reports the results obtained for 1-h-ahead (case-I) and 3-h-ahead (case-II) wind speed forecasts for the randomly chosen days of multiple seasons of the year 2010. The forecasting horizon in both the cases are 24 h and 72 h. In this paper, the following forecasting procedures are analyzed:

(i) forecasting based on averaging a selected number of similar wind speed days corresponding to forecast day, i.e., SD method.
(ii) forecasting based on considering BPNN only.
(iii) forecasting based on considering RBFNN only.
(iv) forecasting based on considering ANFIS only.