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Predicting the wind power density based upon extreme learning machine

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A B S T R A C T

Precise predictions of wind power density play a substantial role in determining the viability of wind energy harnessing. In fact, reliable prediction is particularly useful for operators and investors to offer a secure situation with minimal economic risks. In this paper, a new model based upon ELM (extreme learning machine) is presented to estimate the wind power density. Generally, the two-parameter Weibull function has been normally used and recognized as a reliable method in wind energy estimations for most windy regions. Thus, the required data for training and testing were extracted from two accurate Weibull methods of standard deviation and power density. The validity of the ELM model is verified by comparing its predictions with SVM (Support Vector Machine), ANN (Artificial Neural Network) and GP (Genetic Programming) techniques. The wind powers predicted by all approaches are compared with those calculated using measured data. Based upon simulation results, it is demonstrated that ELM can be utilized effectively in applications of wind power predictions. In a nutshell, the survey results show that the proposed ELM model is suitable and precise to predict wind power density and has much higher performance than the other approaches examined in this study.

1. Introduction

Nowadays, the current trend of fossil fuels consumption as well as environmental problems have further motivated incentives towards developing renewable and clean energy sources. As an appropriate renewable energy source, wind energy is being largely harnessed in various regions around the world to enhance the sustainability and reduce some negative environmental issues raised by excessive exploitation of fossil fuels. Owing to the outstanding nature of wind energy which is free, environmental friendly and inexhaustible, countries are performing tremendous efforts to assign a high priority to wind energy harnessing [1]. In fact, adaptation and utilization of the wind energy has received considerable attention all over the world as an alternative source to meet the energy demand. Wind energy is now viewed as the fastest growing source because its development has been characterized by a remarkable rate and this trend is expected to continue. Although investment on wind energy to generate electricity is the cheapest one among all renewables, inappropriate locations for wind turbines installation eventuates in losing huge amounts of money. Therefore, for providing secure wind energy utilization as well as enhancing the efficiency of wind energy markets, wind resources evaluation particularly in terms of realizing wind speed and power predictions is an imperative task [2]. Nevertheless, since the frequency distribution of wind speed may provide different wind power densities for the same wind speed, the knowledge of wind power density would be further reliable. Wind power density resembles the level of accessible energy at the site for converting to electricity by using wind turbines.

Despite the fact that a vast number of mathematical models have been suggested to simulate the wind energy related parameters, there are still disadvantages of the models such as being very

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demanding in terms of computation time. As a consequence, during the last decade, a large number of scientists worldwide have applied artificial intelligence and computational intelligence techniques to estimate, simulate and optimize various important elements in the realm of wind energy.

Shamshirband et al. [3] performed an investigation on the probability density functions of wind speed and directions based upon the ANFIS (adaptive neuro-fuzzy inference system). They compared the results of ANFIS technique with four wind distribution approaches of Weibull, Frechet, Gumbel and Joint probability density functions. They concluded that ANFIS can represent the wind speed and direction distribution favorably. Karki et al. [4] developed a probabilistic methodology to determine the wind variability and measure the wind power commitment risk throughout the operation of wind energy conversion systems. Chang [5] employed the PSO (particle swarm optimization) technique to assess the wind energy in Taiwan based upon the Weibull distribution function. He calculated the Weibull parameters, the wind speed distribution as well as many important parameters for wind energy evaluation. The obtained results indicated that the PSO method is viable in applications of wind energy. Ma et al. [6] utilized wind power data for all locations distributed across Ireland to suggest some scenarios for attaining the knowledge of error and fluctuation distribution of predicted short-term wind power. Bigdeli et al. [7] predicted the wind power time series for a wind farm located in Alberta, Canada. They developed some hybrid models by combining the NN (neural network) with ICA (imperialist competitive algorithm), GA (genetic algorithm) and PSO techniques. The achieved results showed that the hybrid NN-ICA outperforms other hybrid models. Mohandes and Rehman [8] applied three approaches: the PSO, the AIM (Abductory Induction Mechanism) and the PER (Persistence) for forecasting the 12-h ahead wind speed in Saudi Arabia. They found close agreement between the predicted wind speed data and the measured ones. Petković et al. [9] applied the ANFIS to control and design the wind generator system with CVT (continuously variable transmission). The ANFIS scheme regulated the CVT ratio to achieve the highest power generation efficiency of the wind turbine with extracting maximum wind energy. Bhaskar and Singh [10] proposed an approach, consisted of two steps, to predict wind power based upon the AWNN (adaptive wavelet neural network) as well as the FFNN (feed-forward neural network).

NN, as a major AI (Artificial Intelligence) approach, has been recently introduced and applied in different engineering fields. This method is capable of solving complex nonlinear problems which are difficult to solve by classic parametric methods. NNs can be trained by several algorithms including the GD (Gradient Descent), GDA (Adaptive Learning Rate Gradient Descent Momentum), GDX (Gradient Descent with Adaptive Learning Rate Back Propagation), OSS (One-Step Secant), SCG (Scaled Conjugate Gradient), CGB (Fletcher–Reeves Conjugate Gradient), CGP (Powell–Beale Conjugate Gradient) and CGF (Polak–Ribiere Conjugate Gradient Methods Gradient Descent) [11].

Nevertheless, the major disadvantage of NNs is its learning time requirement. Huang et al. [12,13] introduced an algorithm for single layer feed forward NN which is known as ELM (Extreme Learning Machine). The ELM algorithm is able to decrease the required time for training a NN. In fact, it has been proved that by utilizing the ELM, learning becomes very fast and it produces good generalization performance [14]. Accordingly, several researchers have been attracted towards applying ELM to solve the problems in considerable scientific areas [15–20].

A few studies have also been conducted by applying ELM to the wind energy field. Wu et al. [21] performed an investigation to develop an ELM-based model for estimating wind speed and sensorless control of wind turbine systems. Salcedo-Sanz et al. [22] combined the CRO (coral reefs optimization) with ELM to predict short-term wind speed in a wind farm situated in USA. Wan et al. [23] using ELM proposed a model for short-term probabilistic wind power forecasting in a wind farm of Australia.

Reviewing the literature indicates that there is no specific utilization of ELM in estimating wind power density. Therefore, the aim of this research work is to develop an ELM-based model in order to predict the monthly wind power density. The merit of ELM is verified by comparing its predictions accuracy with SVM (Support Vector Machine), ANN (Artificial Neural Network) and GP (Genetic Programming) successfully employed in wind energy area estimations. The wind power density values are calculated based upon the standard deviation and power density methods of the Weibull function to extract the required data for training and testing the models. Afterwards the performance evaluation is accomplished statistically by providing comparisons between the predicted results and the calculated wind powers using real data.

The ELM is a powerful algorithm with faster learning speed compared with traditional algorithms such as the BP (back-propagation). It also has a better performance too. ELM tries to get the smallest training error and norm of weights.

The organization of the remaining part of this paper is as follows: Section 2 explains the wind data and wind power estimation. Section 3 presents the description of ELM. The comparative results and discussion are brought forward in Section 4. Finally, the conclusions are presented in Section 5.

2. Wind data and power

2.1. Wind data

Basically, wind speed is measured at a desired site by utilizing anemometers established in a wind mast. In this study, we utilize 3-h wind speed data for the period of five years. In fact, the used wind speed data for this study have been measured at the elevation of 10 m above the ground level in 3-h interval periods. In the first step of analysis, the 3-h wind speed data were averaged to obtain daily data. As mentioned, the main objective of this study was evaluating the suitability of ELM algorithm to predict monthly wind power density based on existing methods of standard deviation and power density. Therefore, using the achieved daily data of each month, the monthly calculations were conducted over each specific month to evaluate the adequacy of ELM approach to predict wind power density. The extracted wind power densities from both Weibull methods were used to train and test the developed models. To achieve reliable evaluation and comparison, the developed models were tested with a data set that has not been used during the training process. For this purpose, the monthly data were divided into two subsets for training and testing.

2.2. Wind power density

To determine the potential of wind energy in a location, the knowledge of the wind speed and the mean wind power is essential. Nevertheless, because of high variation in wind speed in some sites, the amount of standard deviation is very high; thus, with lower average wind speeds and higher standard deviation, higher wind power is probable. Consequently, the wind power density should be estimated to assess the wind resource potential with further reliability. The wind power can be computed from measured wind speed values and the probability distribution function. The following equation can be used to calculate wind power density from measured wind speeds [24,25]: