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A novel hybrid approach for predicting wind farm power production based on wavelet transform, hybrid neural networks and imperialist competitive algorithm

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ABSTRACT

This paper proposes a novel hybrid approach to forecast electric power production in wind farms. Wavelet transform (WT) is employed to filter input data of wind power, while radial basis function (RBF) neural network is utilized for primary prediction. For better predictions the main forecasting engine is comprised of three multilayer perceptron (MLP) neural networks by different learning algorithms of Levenberg–Marquardt (LM), Broyden–Fletcher–Goldfarb–Shanno (BFGS), and Bayesian regularization (BR). Meta-heuristic technique Imperialist Competitive Algorithm (ICA) is used to optimize neural networks' weightings in order to escape from local minima. In the forecast process, the real data of wind farms located in the southern part of Alberta, Canada, are used to train and test the proposed model. The data are a complete set of six meteorological and technical characteristics, including wind speed, wind power, wind direction, temperature, pressure, and air humidity. In order to demonstrate the efficiency of the proposed method, it is compared with several other wind power forecast techniques. Results of optimizations indicate the superiority of the proposed method over the other mentioned techniques; and, forecasting error is remarkably reduced. For instance, the average normalized root mean square error (NRMSE) and average mean absolute percentage error (MAPE) are respectively 11% and 14% lower for the proposed method in 1-h-ahead forecasts over a 24-h period with six types of input than those for the best of the compared models.

1. Introduction

Ever-increasing growth in energy demand throughout the world, fossil fuel resources' reduction [1], and high rate of pollution and the resulting imposed costs have led the electric energy producers to move toward harvesting renewable energy [2]. Among renewable energy types, wind energy is of great importance due to its abundance and relatively low costs [3,4], leading to its enormous utilization in recent years [5]. However, intermittency of wind is the biggest challenge to implementing wind-energy a reliable autonomous source of electric power [2,6–8]. This problem becomes worse when wind power penetration in electric systems increases [9–11]. Undefined supply and its unexpected variations are main obstacles to integrate wind farms into interconnected power systems [12]. In addition, by the introduction of competitive electricity market in various countries, power producers should inform on their produced power several hours ahead to the system operator [1]. Thus, being equipped by accurate predicting tools of power supply [13], this uncertainty will be reduced and wind power's competition place will be elevated in deregulated electricity markets [11,14]. Since the output power from wind plants is highly dependent on environmental condition, the prediction of their output power comes with errors. Obviously, the errors affect system performance [15,16]. More accurate forecasts help system operators plan system operation in a way that absorbing maximum wind energy is possible with minimal complications. This effectively results in lower risks for both producers and the network [17]. Searching through the related literature revealed that huge research, in recent years, has been conducted on predicting power and speed of wind [14,18–21]. The major aim of the reported research is to highly reduce prediction error introduced in significant problems such as wind powers in competitive electricity market [22]. Although the existing methods have made considerable improvements over the years, more accurate and robust wind power forecast methods are still demanded [22]. Predictions are primarily conducted in four time intervals: very short-term,

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short-term, mid-term, and long-term [2,23]. Physical approaches and statistical techniques are the two types of fundamental methods used in literature [18,20,24,25]. The former makes use of physical characteristics of the region where the power plants are installed in order to develop prediction model [26–28]. On the other hand, the latter employs historical data for this purpose. Depending on the model parameters, predictions' accuracy will vary [20,26]. Statistical techniques are divided into two main parts: time-series and artificial neural networks (ANNs) [2]. Time series are effective in short-term predictions [21]. ANNs are among the widely used branches of statistical techniques for predicting wind's power and speed [18,22]. Compared to time-series, ANNs do not need complex mathematical relations for model description, yet they have higher learning capabilities [18]. Due to a nonlinear relation between historical data and wind's speed and power, methods which are able to model nonlinear relations between inputs and outputs should be utilized for precise predictions [29,30]. Neural networks are among the methods which are able to develop nonlinear models through a learning process [29]. In addition to the aforementioned methods, recently, hybrid methods and meta-heuristics as well as novel techniques have been reported in literature [18,29]. The aim of combining forecasting methods is to improve the accuracy of predictions by taking advantage of each method [2]. Since each method itself is sensitive to some conditions, another advantage of combining the methods is to reduce the risk when an unexpected phenomenon occurs [18,31]. For more investigations, one can read wind power forecast in literature [14,18–21]. The main contributions of this research can be summarized as follows:

(1) Proposing a novel hybrid method for short-term prediction of wind farms with high accuracy.
(2) Investigating the effect of six types of different parameters as input data of the algorithm on predictions and comparing it with four types of weather parameters – addition of pressure and air humidity parameters.
(3) Investigating the prediction accuracy of the proposed method in comparison to the other four methods presented in soft computing field.

The rest of the paper is organized as follows. Section 2 describes forecasting methodology, imperialist competitive algorithm, wavelet transform, error measurement criteria, and technical data. In Section 3, forecasting engine is proposed along with its components as well as the proposed algorithm's steps. Section 4 deals with investigation and analysis of results obtained by predictions. Finally, the paper conclusions are given in Section 5.

2. Methodology

This research proposes a novel approach to reduce further predictions error. As statistical techniques utilize historical data, a data mining problem is faced [22]. Data mining is comprised of three parts: data preparation, modeling, and model evaluation. The first step in preparation of data is to extract target data from data sources. In contrast to the other techniques, in this research, a complete set of weather conditions are used as initial data [32]. The next step is data pre-process. Data should be prepared for learning the purpose using various techniques. Therefore, data normalization methods and wavelet transform are used in this research. Modeling refers to a group of processes in which multiple sets of data are combined and analyzed to uncover relationships or patterns. The goal of data modeling is to use past data to inform future efforts. For modeling, a proper technique should be used in a right place. Thus, an appropriate primary predictor should be used to improve the results and help main predictor. Radial networks such as RBF neural networks can be used as the primary predictor. This is because these networks have a special ability to model nonlinear relations and explore local characteristics of the input data. For main predictor, one can use the series combination of several neural networks, including MLP which uses different methods for learning. MLP Neural networks are good at capturing global data trends and modeling nonlinear behaviors. Combination of neural networks of RBF and MLP leads to a consideration of total set of local and global behaviors of the target variables. Meta-heuristic approaches have high exploration capabilities. For further optimization of predictor's engine, the meta-heuristic technique of ICA is used. Considering the above descriptions, the combination of wavelet, RBF, and series neural networks consisting of three types of MLP with different learning strategies along with meta-heuristic algorithm of ICA for prediction are used. In the model evaluation step, using weather parameters of the next day and/or a specific day, the predicted value is evaluated with respect to the real value based on error criteria. These components are described next.

2.1. Wavelet transform

Wavelet transform is a mathematical approach widely used in signal processing applications. This allows to distinguish specific patterns hidden in massive data. Modeling is required when dealing with predictions using time-series and neural networks. Neural networks as general approximators have limited capabilities in approximation of highly nonlinear systems [22]. Wavelet transform has the ability of displaying functions and detecting their local features in time–frequency domain in a simultaneous manner. Low-resolution wavelets and high-resolution wavelets can approximate general behaviors (low frequency) and local behaviors (high frequency) of function, respectively. The use of these features leads to the convenient training along with neural network, precise for modeling highly nonlinear signals [33]. Wavelet transforms are mainly divided into two groups: continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT) [34,35]. The CWT is defined as [36,37]:

$$\mathrm{CWT}_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} \psi^*(t)x(t)dx, \quad a > 0 \tag{1}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \quad a > 0 \text{ and } -\infty < b < +\infty \tag{2}$$

where $x(t)$ is the signal to be analyzed, $\psi_{a,b}(t)$ is the mother wavelet scaled by a factor a and shifted by a translated parameter b, and $*$ denotes complex conjugate. In a continuous wavelet transform, if scaling and displacement parameters are continuous, CWT will be very slow due to overlapping feature and duplicity of neighbor data. In addition, it will have additional and useless data [12]. Therefore, the mother wavelet can be scaled and translated using certain scales and positions known as DWT. The DWT uses scale and position values based on powers of two, called dyadic dilation and translations, which are obtained by discretized the scaling and translation parameters, denoted as [36,37]

$$\mathrm{DWT}_x(m,n) = 2^{-\left(\frac{m}{2}\right)} \sum_{t=0}^{T-1} x(t)\psi\left(\frac{t-n\cdot 2^m}{2^m}\right) \tag{3}$$

where T is the length of the signal $x(t)$. The scaling and translation parameters are functions of the integer variables m and n, where $a = 2^m$ and $b = n{\cdot}2^m$, and t is the discrete time index. Stephane Mallat's multiresolution theory is typically used to employ DWT in related literature [38]. This technique is composed of two major steps: decomposition and reconstruction. Figs. 1 and 2 illustrate related steps in decomposition and reconstruction in this technique