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An improved neural network-based approach for short-term wind speed and power forecast

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ABSTRACT

Accurate forecasts of wind speed and wind power generation are essential for the effective operation of a wind farm. This paper presents an improved radial basis function neural network-based model with an error feedback scheme (IRBFNN-EF) for forecasting short-term wind speed and power of a wind farm, where an additional shape factor is included in the classic Gaussian basis function associated with each neuron in the hidden layer and a simple parameter initialization method is proposed to effectively find initial values of two key parameters of the basis function when performing neural network training. A wind farm near central Taiwan area connected to Taipower system is served as the measurement target. Provided with 24 h of input data at 10-min resolution (i.e. 6 × 24 input time steps) for training the proposed neural network, a look-ahead time up to 72 h (i.e. 6 × 72 forecasted output time steps) have been performed. Test cases for different months over 2014 are reported. Results obtained by the proposed model are compared with those obtained by four other artificial neural network-based forecasting methods. It shows that the proposed model leads to better accuracy for forecasting wind speed and wind power while the computational efficiency is maintained.

1. Introduction

Wind power is one of the most rapidly growing renewable energy sources and is regarded as an attractive alternative to conventional electric power generated from fossil fuels [1]. Though the integration of wind power into the power system provides many advantages, the high penetration of wind power also brings a number of challenges in system operations and planning, mainly due to its uncertain and intermittent natures. It is known that short-term forecasts (ranging from 1 h up to 72 h) are useful in power system operations planning and for electricity trading in power markets where wind power and energy storage can be traded or hedged. The short-term forecast of wind speed is also critical to the operation of wind turbines so that dynamic controls can be accomplished to increase the energy conversion efficiency and reduce the risk of overloading [2]. With the increasing penetration of wind power, the forecast of wind speed or wind power thus plays a vital role in improving energy market efficiency, reducing the amount of reserves while maintaining the system security, and maximizing revenue of wind power sell in the electricity market.

Artificial intelligence (AI) and machining learning (ML) based approaches are frequently adopted for wind forecasting, some commonly seen techniques include multi-layer perceptrons (MLP) [3], radial basis function neural network (RBFNN) [4], recurrent neural networks (RNN) [5], and support vector regression (SVR) [6]. In general, the AI and ML models can better handle non-linear relationship between input and output and are more flexible in forecasting applications; however, they describe the relationship in implicit ways and sometimes are computationally intensive.

In recent years, substantial works have been made for wind speed and wind power predictions. It is known that the numerical weather prediction (NWP)-based method is with better forecasting precision over a longer time frame but requires more physical information. Cassola and Burland [7] proposed a method using NWP and Kalman filtering to predict wind speed. Kalman filtering was used to filter the outputs of the NWP to retrieve accurate results. Shi et al. [8] compared the performances of autoregressive integrated moving average (ARIMA), artificial neural network (ANN), and SVM models in short-term wind speed predictions. Results showed that both performances of the hybrid ARIMA-ANN and

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ARIMA-SVM were better than those of the individual ARIMA, ANN and SVM models. Haque et al. [9] presented performance analyses of short-term wind speed predictions using soft computing models formulated by back propagation neural network (BPNN), RBFNN, and adaptive neural fuzzy inference system (ANFIS). Carpinone et al. [10] developed discrete-time Markov chain models for wind power forecasting and allowed to directly obtain an estimate of the wind power distributions on a very short-term horizon without requiring restrictive assumptions on wind power probability distribution. Troncoso et al. [11] assessed the performance of different types of regression trees for a very short-term measured wind speed forecasting of wind farms. Similar conclusions were also reported in literature of wind power forecast [12–16]. The above studies showed that the hybrid methods were successful in wind speed and power forecasts with satisfactory accuracy.

Among the aforementioned artificial neural network-based (ANN-based) and hybrid methods, the RBFNN has a wide range of applications for modeling identification, time series prediction, and other research areas [17]. The RBFNN has several advantages over other ANN-based methods because of its capability of approximating highly nonlinear functions, the sequential manner of training process, and the use of local approximation [18], [19]. However, when applying RBFNN for forecasting, the challenge is that it is difficult to decide the parameters of the center and standard deviation for each Gaussian basis function of a hidden neuron, where both parameters are essential for supervised and unsupervised learning decisions. It is known that many approaches have been proposed to determine such parameters. For instance, Kanungo and Mount [20] presented using K-means clustering to given a set of data points in d-dimensional space, so as to minimize the mean squared distance from each data point to its nearest center for a number of empirical studies. Egrioglu et al. [21] proposed a forecasting model as the neural network with fuzzy c-means clustering method to forecast a university enrolment data. Valverde et al. [22] reported forecasting wind power output or aggregated load demands in the probabilistic load flow problem by Gaussian mixture models to represent non-Gaussian correlated input variables, where an expectation–maximization clustering algorithm was used for finding maximum posteriorly estimates of parameters in statistical models. The aforementioned methods can be applied to search for cluster centers of the Gaussian basis functions of all neurons in the hidden layer; the nearest neighbour rule then can be adopted to determine the appropriate size of each standard deviation [23]. Also, the initial center value for each basis function can be randomly selected. These RBFNN parameter-setting methods often affect both the training convergence and solution accuracy.

To improve the forecasting accuracy and tackle the aforementioned drawbacks of applying RBFNN for forecasting applications, this paper proposes an improvement of the classic RBFNN by including a new weight (i.e. a shape parameter) in the Gaussian basis function with error feedback scheme in the neural network structure to enhance the convergence and solution accuracy of the training algorithm for wind speed or wind power forecast, where a parameter initialization method is proposed for searching better initial center and standard deviation values of the Gaussian basis function associated with a hidden neuron. Three representative cases for forecasting wind speed and wind power up to 72 h ahead with a 10-min resolution are performed based on the proposed IRBFNN-EF model. Results are also compared with those obtained by BPNN, classic RBFNN, ANFIS, and RBFNN with error feedback (RBFNN-EF) forecasting models, where the RBFNN-EF is also a model proposed by the authors through incorporating the error feedback scheme to the classic RBFNN. Quantitative evidences reported in Section 5 show that the proposed IRBFNN-EF model leads to more accurate forecast than other models while the computationally efficiency is maintained.

The remaining part of the paper is organized as follows. Section 2 gives an overview of existing wind speed and power forecasting approaches. In Section 3 and 4, the proposed method and the solution procedures are described. Section 5 presents the test results obtained by using the proposed and other methods under comparisons. It is then followed by the conclusions in Section 6.

2. Wind speed and wind power forecasting methodology

The purpose of wind speed and wind power forecasting is to provide such information that can be expected in certain look-ahead time intervals, depending on the time horizons to be studied. Based on power system operation requirements, the forecast can be divided into four different horizons: very short-term, short-term, medium-term, and long-term. Typically, very short-term forecasts are used for electricity market clearing and regulation actions [24]; short-term forecasts are for economic dispatch; medium-term forecasts are used for power system management and energy trading; long-term forecast are often used for maintenance scheduling of the wind turbines.

Researches in the areas of forecasting wind speed and wind power have been devoted to the development of effective and reliable application tools and many approaches have been proposed. These tools can be classified whether the terrain information at the location of the wind farm is used as an input or not. Two mainstreams are the physical and the statistical approaches. In some models a combination approach is used in an attempt to integrate the advantages of both approaches.

The physical approach of forecasting, in contrast to statistical approach, uses the detailed physical description to model the on-site conditions at the location of the wind farm [25]. The detailed physical descriptions of the wind farms and their surroundings are provided, which includes wind farm layout, wind turbine power curve, and terrain information. Then, the refined wind speed data is plugged into the corresponding wind power curve to calculate the wind power output. If the data is available, model output statistics are performed to reduce the forecast error. The alternative approach for wind speed or wind power forecasting is based on statistical modeling. The statistical approach describes the relation between wind power or wind speed forecasting and may use NWP and on-line measured data. The statistical approach generally requires historical data to build the statistical model [26].

Commonly seen statistical approaches are conventional and ANN-based methods [4], [27]. In the conventional statistical approach a time series model is applied to forecast future wind power or speed. According to the forecasting process, which was proposed by Box-Jenkins, this model is divided into four main steps to make a mathematical model of the problem including model identification, estimation, diagnostics checking, and forecasting. Several types of time-series models may be considered, including autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), and ARIMA. In regard of ANN-based methods, the NWP forecasts and further meteorological variables are transformed into the wind speed or power forecast by the ANN which has been trained by the large sets of historical data in order to learn the dependence of the output on input variables. Also, hybrid models by combining different approaches to improve the forecast accuracy have drawn much attention [27], [28].

3. Proposed wind speed and wind power forecasting method

As shown in Fig. 1, this paper proposes an improved RBFNN