Wind Speed Forecasting Using Back Propagation Artificial Neural Networks in North of Iran

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In recent years, wind power generation is rapidly gaining popularity due to the major concerns about the excessive emissions and global energy crisis. In addition, this kind of power systems have shown more security options than others. Due to the highly variable and intermittent nature of the wind energy, it is crucial to achieve higher accuracy of long-term wind speed forecasts for improving the reliability and economic feasibility of power systems. The forecasting is the best standard for comparing the of algorithm with current analytical methods. By importing the intelligent algorithms, we can overcome the obstacles of prediction and eliminate the volume of which are the main problems of determining the uncertainty nature of such renewable energy systems. Hence, this paper proposes a novel methodology for long-term wind speed forecasting using back propagation artificial neural network. The neural networks are powerful tools for solving the complex problems and providing tolerable standpoint from distributed energies. Simulation result illuminates that the proposed algorithm can offer highly features of compatibility and accuracy for wind predictions in comparison with actual wind speed reports of Iran Meteorological Organization.

keywords: *Back-propagation artificial neural network (BP-ANN); wind speed forecasting.*

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1. INTRODUCTION

Nowadays, uncertain nature of electricity demand and intermittent nature of renewable energies such as solar and wind may lead to some unexpected load-generation mismatch, cascaded failures, and catastrophic wide area blackouts of large power systems [1–4]. Meanwhile, accurate forecasting of renewable energy sources increases their penetration in economic-environmental operation of future interconnected poly-generation grids [5–9]. In this context, wind speed is subject to several different meteorological parameters, such as Coriolis force, friction, Rossby waves, pressure gradient, intensity of sunshine, relative humidity, and earth's temperature which make its forecasting difficult and complicated. Recently, many scholars have focused on short and long term wind speed and power forecasting. For example, authors [10] integrated a wavelet transform and convolutional neural network to improve the accuracy of wind speed forecasts. Reference [11] proposed a hybrid secondary decomposition algorithm (SDA) and Elman neural networks for precise wind speed forecasting. SDA method is the combination of wavelet packet and fast ensemble empirical mode decomposition method. Decomposing an original wind speed data into the appropriate and the detailed components is the subject of SDA algorithm, which consists of wavelet packet and fast ensemble empirical mode for improving the performance of ELMAN model prediction method [12]. Reference [13] efforts to select a valid structure of input sets for wind power forecasting using fuzzy neural networks. Firstly, discrete wavelet transform and singular spectrum analysis are applied to eliminate the data noises and determine a pattern from the original wind power series. By implementing a fuzzy neural network with supervised rule that searches the consequent parameters for best fitting values, the prediction of wind power for a targeted number of forward time series can be possible. A solution structured by a support vector regression (SVR) method is developed in [14] for short-term wind speed prediction, composed of a nonlinear and machine learning algorithm. In addition, this concept and the genetic algorithm use all invariant wind speed time series to estimate an objective function for site of wind speed. This algorithm has an ability to be compared with persistence autoregressive models consisting of Akaike's information criterion and ordinary least squares method. Sparse Bayesian classification (SBC) and and Dempster-Shafer theory (DST) is discussed in [15] for short-term probabilistic wind energy forecasting. By applying SVM and SBC methods, the range of prediction error discretizes into some multifold periods which leads to the estimation of conditional probability of each interval. Therefore, the probability distributed function (PDF) of SVM prediction error can be made up by cooperation of probabilities of intervals using DST method. It can be concluded that PDF of wind generation is achievable via SVM spot forecast method. Shi et al. [16] proposed a hybrid model for a very short time wind power prediction (15-minute-ahead) which includes Grey relational analysis and wind speed distribution features. Three unique local recurrent neural network methods are applied for hourly and direction wind speed forecasting up to 72-h as follows [17]: infinite impulse response multilayer perceptron, local activation feedback multilayer network, and diagonal recurrent neural network. Ma et al. [18] described an optimization technique to preprocess the original wind speed data and obtain a smoother sequence which Singular spectrum analysis optimized by brain storm optimization interferences in its model. Therefore, predictions have been conducted in a generalized dynamic fuzzy neural network state. A smaller and simpler structure of neural network can accelerate the learning rate while leading to a compatible prediction. Many methods participated in day-ahead wind speed forecasting such as combination of weather research and forecasting (WRF) simulation, a Cuckoo search (CS) optimized fuzzy clustering, and Apriori association process consisting of 96 steps [19]. As mentioned, time scales for wind speed forecasting has various intervals from minutes to weeks so that the desired wind power penetration in power systems is gained. Therefore, this paper proposes an exquisite methodology which consists of back propagation artificial neural network (BP-ANN) for long-term wind speed forecasting. The proposed methodology is exerted on an actual data study of a windy region located in Manjil, Iran, as a case study. The available meteorological data is used to prove the higher accuracy of the wind speed forecasts. The remainder of this paper set out as follows: Section 2 formulates the proposed wind speed forecasting approach. Afterwards, case study and discussions is drawn in Section 3. Finally, Section 4 concludes the paper.

2. WIND SPEED FORECASTING USING BACK-PROPAGATION ARTIFICIAL NEURAL NETWORK

A single hidden layer (BP-ANN) consists of an input layer, a hidden layer, and an output layer as illustrated in Fig. 1. The first step of training is about entering a set of selected inputs to the node. In the next step, hidden layer prepared to accumulate the sets of activation values of node in which each input of node multiplied by weight vectors. Hence, the activation value of each node can be calculated through a function which transforms all inputs of node into its optimal value. The search for determining the optimal output value of layer will be conducted before the output is applied to another layer as input, so that the mean squared error (MSE) becomes reasonable. In other words, BP-ANN is trained in three steps [20]:

- Forward the input data
- Compute and propagate error backward
- Update the weights

The main characteristics of BP-ANN are self-learning and self-organizing capabilities. Generally, the linear and the sigmoid functions are the most publicized functions which are suitable for the hidden and output layers, respectively. Therefore, equations (1) and (2) demonstrate the input and output values of the

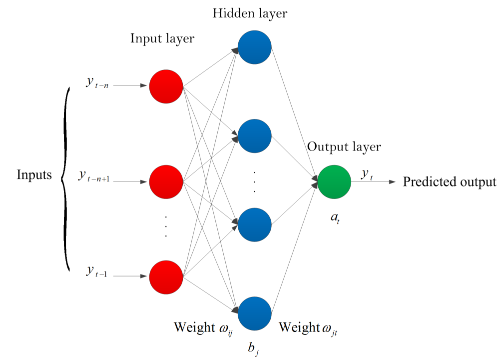

Fig. 1. Different layers of BP-ANN structure

hidden layer, respectively. Moreover, equations (3) and (4) contain all input and output values of the output layer, respectively.

$$x_j = \sum_{i=t-1}^{t-n} \sum_{j=1}^{h} w_{ij} \times y_i + b_j \tag{1}$$

$$y_j = \frac{1}{1+\exp(-x_j)} \quad j = 1, ..., h \tag{2}$$

$$x_t = \sum_{t=1}^{T} w_{jt} \times y_j + a_t \tag{3}$$

$$y_t = x_t, \quad t = 1, ..., T \tag{4}$$

where,
x_j,y_j : Input and output of the j^{th} node of the hidden layer.
$w_i j$: Weight between i^{th} input layer neuron and j^{th} hidden layer neuron.
b^j, a^j : Bias of the input and the hidden layers which are within the range of [-1, 1].
n, h, t : Number of input, hidden, and output layer nodes.
x_t, y_t : Indication of parameters of output layer which are input and output values at time horizon t , respectively.
w_{ij} : Connection weights of the j^{th} hidden and output layers.
According to aforementioned concept, using gradient descent method which uses sum of squared error can simplify the back propagation algorithm for adjusting the weight vectors of network (In this paper the magnitude is the main priority). As presented in equation (5), MSE between network prediction results y_t, and expected output $\hat{y}_t$ is minimized through modification of weights by passing back the output error from hidden layer to the input one. Where, T is the number of iterations which created and based on the group of weight vectors and bias vectors.

$$MSE = \frac{1}{2} \sum_{t=1}^{T} (\hat{y}_t - y_t)^2 \tag{5}$$

The propagation process is described by changing the weights of hidden and input neurons as (6), (7), (8) and (9). The process will be operated as equation (7), because of the dependency of error on another elements of network:

$$\triangle w_{jt} \propto -\frac{\partial MSE}{\partial w_{jt}} \tag{6}$$

$$\triangle w_{jt} = -\eta\left(\frac{\partial MSE}{\partial y_t}\right)\left(\frac{\partial y_t}{\partial x_t}\right)\left(\frac{\partial x_t}{\partial w_{jt}}\right)$$
$$= \eta(\hat{y}_t - y_t)\left(\frac{\partial((1+\exp(-x_t)))^{-1}}{\partial x_t}\right)y_j$$
$$= \eta(\hat{y}_t - y_t)y_t(1-y_t)y_j$$
$$\text{for} \quad j = 1, ..., h \quad \text{for} \quad t = 1, ..., T \tag{7}$$

in which,
∂w_{jt} : Weights of hidden neurons.
η : Learning rate.
$\frac{\partial MSE}{\partial y_t}$: Derivative of the error in accordance with the activation.
$\frac{\partial y_t}{\partial x_t}$: Derivative of the activation values in accordance with the total input vectors.
$\frac{\partial x_t}{\partial w_{jt}}$: Derivative of the total input vectors in accordance with the weights.
iImplementation of above equations leads to the selection of optimal weight vectors for the hidden layers as follows:

$$\triangle w_{ij} \propto -\frac{\partial MSE}{\partial w_{ij}} \tag{8}$$

Therefor,

$$\triangle w_{ij} = -\sum_{t=1}^{T}\left[\left(\frac{\partial MSE}{\partial y_t}\right)\left(\frac{\partial y_t}{\partial x_t}\right)\left(\frac{\partial x_t}{\partial y_j}\right)\right] \times \left(\frac{\partial y_j}{\partial x_j}\right)\left(\frac{\partial x_j}{\partial w_{ij}}\right)$$
$$= \eta\sum_{t=1}^{T}[(\hat{y}_t - y_t)y_t(1-y_t)w_{it}]y_j(1-y_j)y_i$$
$$\text{for} \quad i = t-n, ..., t-1 \quad \text{for} \quad j = 1, ..., h \tag{9}$$

The flowchart of the proposed BP-ANN based wind speed forecasting algorithm is depicted in Fig. 2.

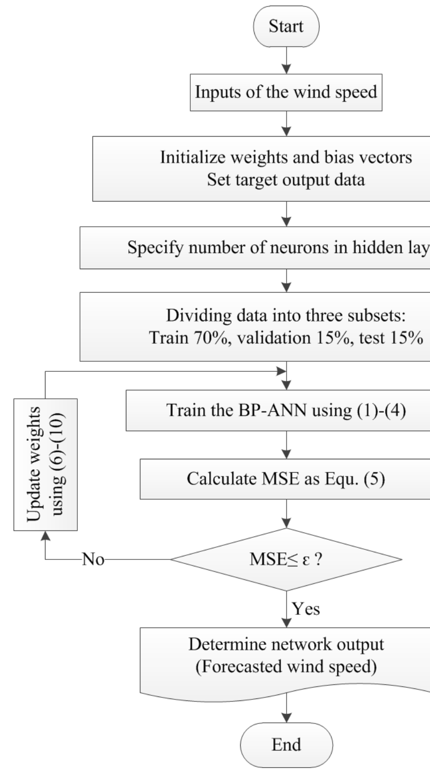

Fig. 2. Flowchart of the proposed wind speed forecasting method

3. SIMULATION RESULT AND DISCUSSIONS

A. Training Parameters of BP-ANN

In this study, total wind speed data are categorized into three sets: the training set 70%, the validation set 15%, the testing set 15%. The training data set is used to train the time series neural network. In this stage, the search for finding the optimal values of weight and bias vectors will be started in the hypothesis space until the correlation constraint becomes acceptable. In other words, training is the process of finding values for the weights so that MSE is minimized. While, the validation set is used to stop the training of the neural network when it begins to overfit the data. The test dataset is not used during the training and validation processes of neural network construction but is used subsequently to test the trained neural network. The applicable elements for the BP-ANN structure have been gained as: 3 input neurons, 15 hidden and one for the output layer at each time horizon t. Hence, the proper parameters for BP-ANN are procured after consecutive iteration.

B. Robustness and Effectiveness of the Proposed Approach

The choice of 38880 total input neurons (taking into account 3 measuring station with 20 m height in Manjil, Iran, for wind speed reporting during 9/23/2009 to 12/21/2009 with 10-minute time intervals), one hidden layer with 15-hidden neurons for each input neuron, 12881 total output neurons, and 79 delay neurons are considered for the network structure. Actual and forecasted wind speed from 9/23/2010 to 12/21/2010 with 10-minitue time-steps and MSE have been shown in Figs. 3, 4, 5 and 6 and 7, respectively. To enhance image quality and improve the appearance of diagrams, the observed and predicted wind speed during a sample day within time series have been displayed in Figs. 3, 4, 5 and 6. The blue line represents the real measured wind speeds collected from Iran Meteorological Organization and the red line indicates the predicted values. The ability to provide good estimations of future wind speed level is evident from these figures. As it is possible to see in Fig. 7 and thereby as it is obvious, the performance of networks for the set of samples reaches 10^{-6} after 100 epochs, which is equal to the expected error (ε). Finally, the iteration process of BP-ANN terminates and the ultimate forecasting model is extracted.

4. CONCLUSION

In this paper, BP-ANN based wind speed forecasting method was discussed to indicate the compatibility and the reliability of aforementioned algorithm. The wind speed data reported by Iran Meteorological Organization for Manjil, Iran during 9/23/2009 to 12/21/2009 using the sampled 10-minute measurements at three wind measuring stations have been used for long-term wind speed prediction over 9/23/2010 to 12/21/2010. After generating the framework of BP-ANN, the input and target variables are needed for training and testing parts phases, respectively. Simulation result demonstrates that the proposed algorithm forecasts the wind speed effectively with minimum MSE and high accuracy level.

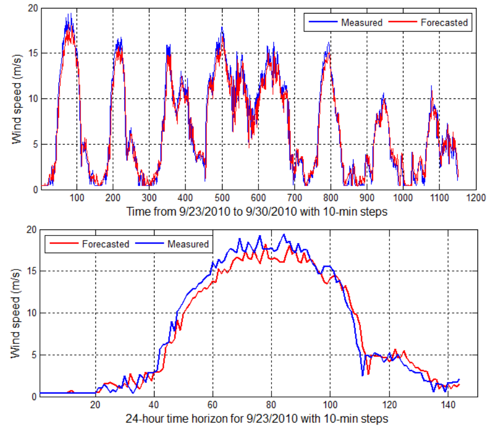

Fig. 3. Actual and forecasted wind speed from 9/23/2010 to 9/30/2010

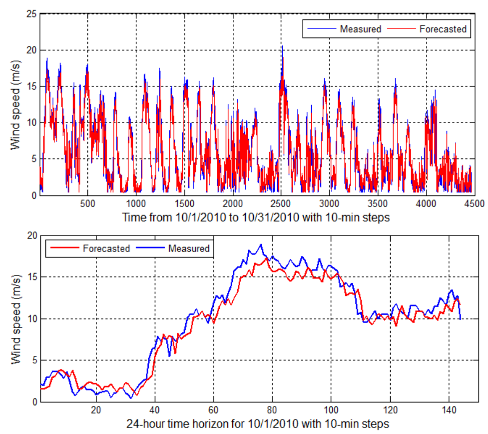

Fig. 4. Actual and forecasted wind speed from 10/1/2010 to 10/31/2010

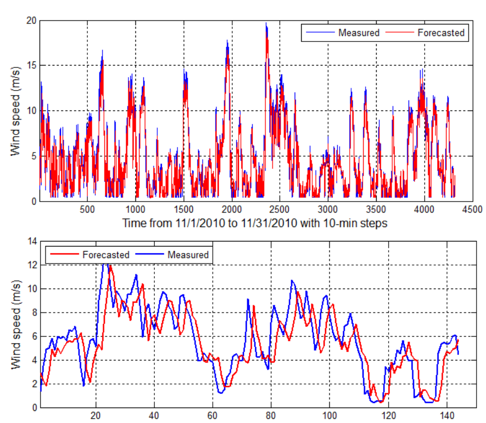

Fig. 5. Actual and forecasted wind speed from 11/1/2010 to 11/31/2010

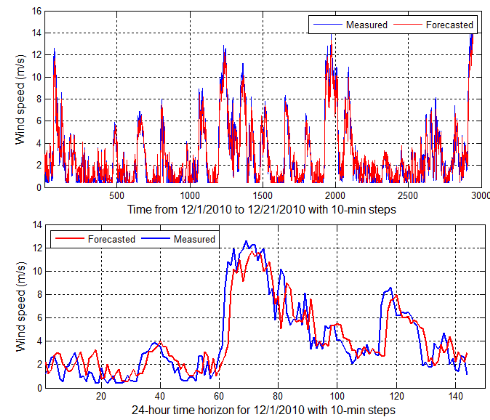

Fig. 6. Actual and forecasted wind speed from 12/1/2010 to 12/21/2010

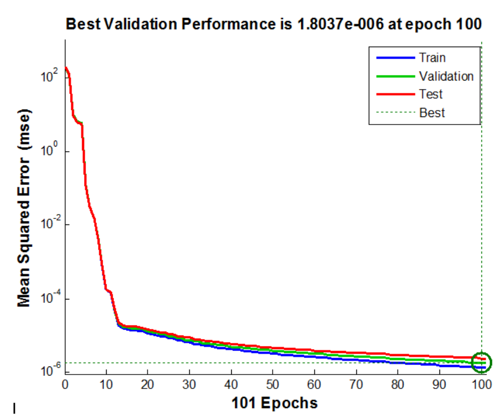

Fig. 7. MSE for training, validation, and testing phases

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