

Short and Mid-Term Wind Power Plants Forecasting With ANN

Javad Mahmoudi
MSc student of Electrical Engineering
of Sharif University
Tehran, Iran
E-mail: Jmahmoudi66@gmail.com

Majid Jamil
Material and Energy Research Center
(MERC), Department of Energy
Karaj, Iran
E-mail: m-jamil@merc.ac.ir

Hossein Balaghi
MSc student of Mechanical
Engineering of Sharif University
Tehran, Iran
E-mail: Balaghi.hossein@gmail.com

Abstract—In recent years, wind energy has a remarkable growth in the world, but one of the important problems of power generated from wind is its uncertainty and corresponding power. For solving this problem, some approaches have been presented. Recently, the Artificial Neural Networks (ANN) as a heuristic method has more applications for this propose. In this paper, short-term (1 hour) and mid-term (24 hours) power forecasting are presented for a sample wind power plant by multilayer ANN. The needed inputs data are temperature and wind speed for forecasting the power. A case study has presented.

Keywords—wind power forecasting; artificial neural network; power prediction

I. INTRODUCTION

Due to rising consumption of electricity, reduction of fossil fuel and its high pollution in world the orientation of Generation Companies (GenCo) of electricity energy have accelerated to renewable energies more than ever. Wind energy is important and available in most regions but due to uncertainty wind speed and direction, the prediction has a significant role in power generation [1].

The basic problem of connection wind power to grid utility is forecasting in competitive market. Therefore power forecasting tools will be needed [2],[3]. Precise prediction of power helps dispatch easily wind power and determines that how much reserve system should be consider for supporting of wind power units [4]. For the purpose of maintenance, the forecasting is important for electricity industry, e.g. when one turbine must be disconnected or repaired for improvement of system performance. The important of wind forecasting is clear for dispatchability and cost of producing electricity from wind. Current and future challenges to forecasting wind power are integrating and automating regional forecasts with electricity scheduling systems and incorporating climate change impacts on wind projects [5]. As the amount of wind energy requiring integration into the grid increase, short-Term forecasting became more important to both wind farm owners and the transmission as well as distribution operators [6].

II. HEURISTIC METHODES

Due to high performance of heuristic methods for algorithms identification, they can be used to predict output power of wind turbines. Artificial neural networks classify information content as significant by analysis of input and output (I/O) data. Outputs are forecasted after training system with I/O data by new inputs [7]. In this paper, a new method is presented for one hour and one day ahead forecasting of wind turbine output power.

III. ARTIFICIAL NEURAL NETWORK (ANN)

The ANN is commonly used between heuristic methods. The first neural cell was used by Mac Lorch and Pittz in 1943. This method can be trained and extract nonlinear complicated relation between input and output. Since 1990s, ANN is entered in engineering science vastly [8].

These methods have high performance in estimation and approximation of real engineering systems [9].

Figure 1 shows structure of a neural processing unit and relation units.

All inputs (X_N) are weighted with W_N at first part of cell. Combination Function (+) sums all weighted inputs at every nodes and adds a threshold value or bias (θ) for changing its status. The bias increase and decrease sum of weighted inputs

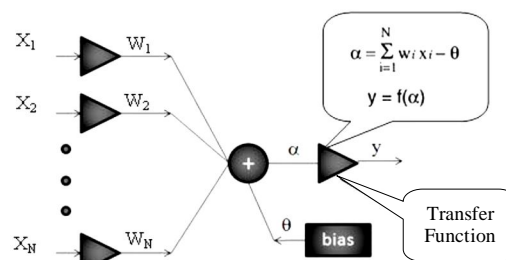


Figure 1. Structure of a neural processing unit and parameters[8]

and helps to identify network patterns better. When weighted sum of inputs reach to specified threshold, the Transfer Function (TF) is activated u to generate output (y). The outputs of this node are considered as inputs for another layer. Therefore most of the artificial neurons are multi-input and single-output. W and θ are adjustable parameters and were determined by TF and the type of training algorithm. According to the problem condition, TF can be linear or non-linear function [10].

IV. ANN IN WIND POWER PLANTS

The short-term and mid-term forecasting of wind power is needed nowadays. Recently, few projects is presented in this field by educational organizations and energy research centers in Iran. Wind uncertainty will lead to fluctuations in output power. Meanwhile, it is important to forecast the wind speed and wind direction [11]. The first step is collecting good data for making ANN then some actual data are compared with output of ANN after testing and validating network. Due to negligible error the ANN will be able to forecast outputs.

A. The Data

For a good forecasting plenty of appropriate data is needed.

In this paper, the data of some wind plants in USA is used for forecasting power. They are wind speed and weather temperature of three years from 2007 to 2009.

For training process, the Montana and Washington wind plants data are used and for testing the Stanford wind plant data is employed.

B. Activation Functions

The activation functions have to consider three features. These must be continuous, derived and uniform downward also should be easy for differentiation. The function derivatives can be expressed itself and they are saturable. This means that they attain to maximum and minimum asymptotically [12].

Bipolar Sigmoid Function (BSF) is one of the commonly used functions. The domain of BSF is between 0 and 1. It is defined as follows:

$$f_2(x) = \frac{2}{1 + e^{-x}} - 1 \quad (1)$$

And the derivative is:

$$f_2'(x) = \frac{1}{2} [1 + f_2(x)] \times [1 - f_2(x)] \quad (2)$$

Figure 2 shows this function. As shown, it is like the Hyperbolic Tangent curve. This function has a closely relation with equation 3 [13],[14].

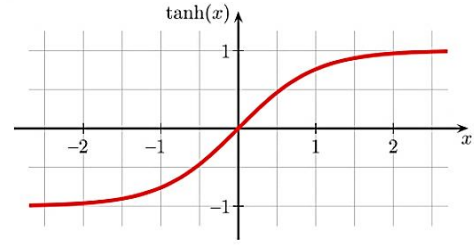


Figure 2. Bipolar Sigmoid Function with domain's (-1,1)

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (3)$$

The Hyperbolic Tangent function derivative is:

$$(\tanh(x))' = (1 + \tanh(x)) \times (1 - \tanh(x)) \quad (4)$$

In this paper, this function is used as activating function.

V. OVERALL STRUCTURE OF POWER ESTIMATOR

The wind temperature and speed are considered as ANN inputs. Since the wind turbines are equipped by wind direction tracker, so the wind direction is not considered as input. But, the wind temperature (same density) is defined as input for network because of high effect on wind. Figure 3 shows the overall structure of power estimator.

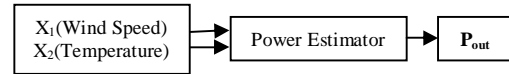


Figure 3. Overall structure of power estimator with ANN

A. Internal Structure of ANN

The two layer network of Feed-Forward is used for building network that it is included two hidden layer and an output layer. The BSF is used for hidden layer and the linear function for output layer. Figure 4 shows block diagram of internal structure of the network.

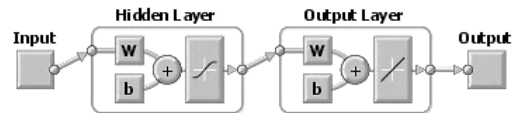


Figure 4. The block diagram of internal structure of ANN

B. Network Training

The ANN is trained by propagation algorithm of Levenberg-Marquardt (LM training). The ANN's building software uses Scaled Conjugate Gradient (SCR) automatically when the network training is faced to low memory [12]. Prediction of error is worked out by propagation algorithm.

Figure 5 shows the flowchart of training algorithm.

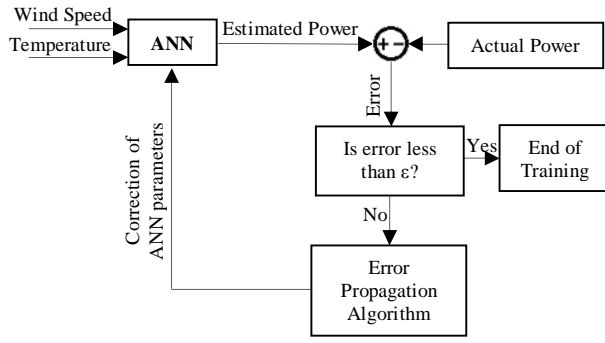


Figure 5. Flowchart of network training

ε is maximum difference between Estimated and Actual power that is defined before.

C. Assessment of Estimated Results

The Assessment of ANN's output is designed for forecasting of wind turbine output power is done by different standard criterion that are Regression (R) and Mean Square Error (MSE).

1) MSE

MSE is the mean of squares summation that are difference between Estimated and Actual power. It is so better for MSE to be very low.

$$MSE = \frac{1}{n} \sum_n [w_{real} - w_{predicted}]^2 \quad (5)$$

W_{real} is the actual output and $W_{predicted}$ is the estimated output.

2) R

R is the relation between actual and predicted output of ANN. It is desired that R to be near 1 (the equation for R is too complicated).

VI. QUALITY ASSESSMENT OF USED DATA

Table I shows some criterion about actual data for two period of time (Short-term and Mid-term).

TABLE I. FEATURE OF DATA FOR TWO PERIOD OF TIME

Period	Criterion			
	Mean Speed(m/s)	Mean Temperature(*C)	Mean Output Power(kW)	Power Standard Deviation(kW)
One hour	6.92	12.88	1.61	0.24
24 hours	7.22	10.9	1.61	0.78

a. Stanford's Wind Plant Data

The data are separated to two parts. The first part used for Network Training and another part used for Testing and Validating of network. The 70% of data is used for Training, 15% for Validating and the remaining 15% for Testing.

Figure 6 shows training's error rate of proposed ANN. According to figure 6, error rate are reduced from 10^3 to 0.3 and the building fluctuation of ANN is finished after 231 epochs and network building be finalized.

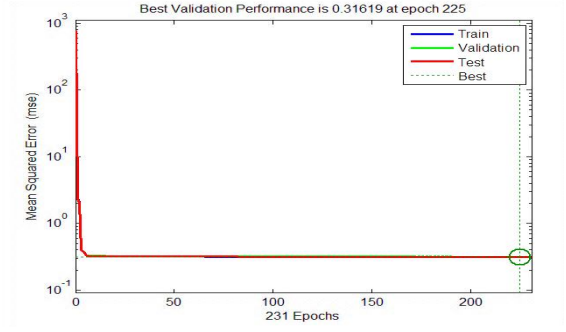


Figure 6. The error reduction curve in training phase

Figure 7 shows Regression of data that is specified for Training, Validating, Testing phase and all data.

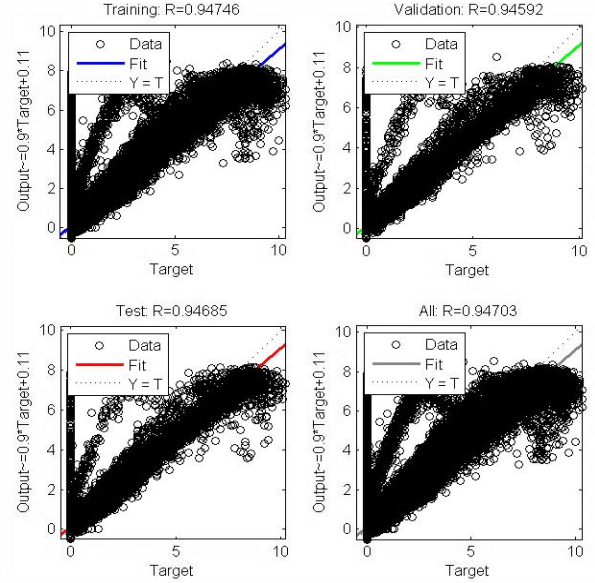


Figure 7. The Regression of ANN's data

In Table II, the value of MSE and R of Training, Validating and Testing phase are given.

TABLE II. THE VALUE OF MSE AND R IN BUILDING STAGES

Stage	Criterion		
	MSE	R	Number of Data
Training	0.312602	0.947452	90991
Validating	0.316194	0.945917	30331
Testing	0.313068	0.946845	30331

As it is seen from Table II, MSE is low in all phases also R is very close to 1. These numbers are saying that the proposed ANN has good accuracy for forecasting of wind turbine output power.

VII. FORECASTING OF WIND TURBINE'S OUTPUT POWER

The ANN is designed by MATLAB software Toolbox after the quality of data was approved. Note, when data is used for training phase it must not be used for ANN testing so in this

paper, the Stanford wind data is used for test of ANN output power forecasting .

Simulation has been done for Short and Mid-term forecasting by MATLAB software and results are given below.

A. Short-term Forecasting (one hour)

The Figures 8, 9 and 10 are shown comparison between estimated power and actual (real) power, value of error and Regression for Short-term forecasting of wind plant's output power respectively.

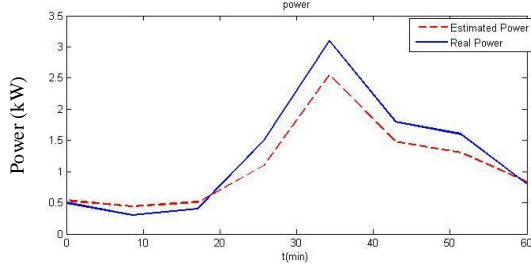


Figure 8. Comparison between real and estimated power for Short-term forecasting

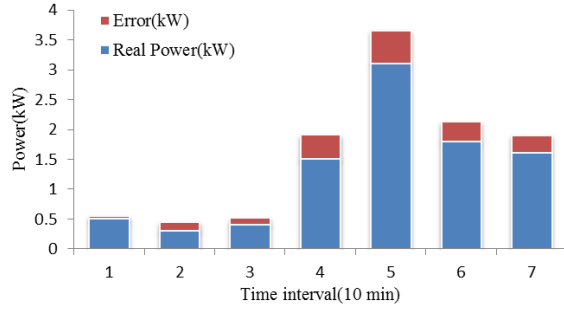


Figure 9. Error of ANN's output power for Short-term forecasting

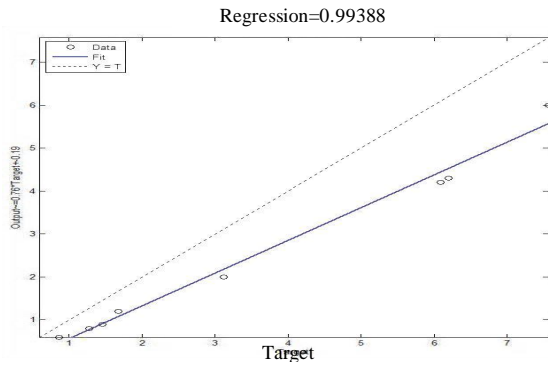


Figure 10. Regression of ANN's output power for Short-term forecasting

B. Mid-term Forecasting (24 hours ahead)

Some data are selected from Stanford's wind plant for Mid-term forecasting. These figures are shown the performance of ANN.

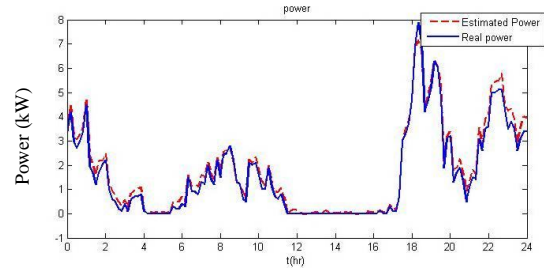


Figure 11. Comparison between real and estimated power for Mid-term forecasting

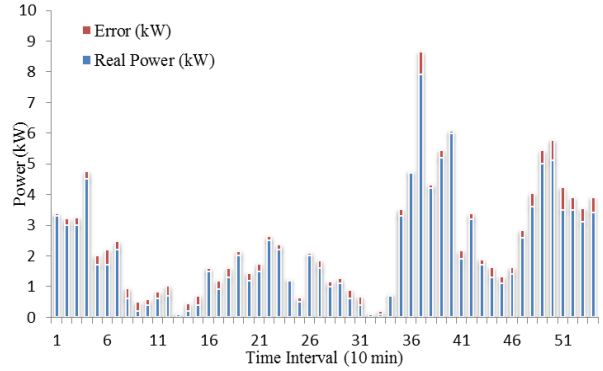


Figure 12. Error of ANN's output power for Mid-term forecasting

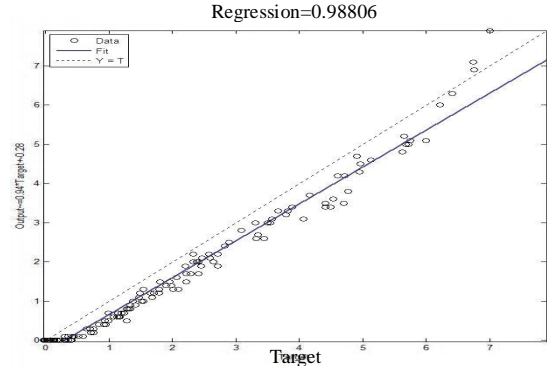


Figure 13. Regression of ANN's output power for Mid-term forecasting

VIII. ANALYSIS OF ANN'S SIMULATION

According to simulation, if the wind speed and weather temperature data are given in one hour or 24 hours, the wind plant output power will be forecasted with 0.5 kilowatt maximum error.

As in figures 10 and 13 are shown, the Regression of ANN's output power in two period (Short-term and Mid-term) is very close to one ($R_{\text{Short-term}} = R_{\text{Mid-term}} \approx 0.99$) also the maximum error of two period forecasting is low than 20% that it is an acceptable number with this uncertainty. So the designed ANN has an appropriate performance for forecasting of wind plant's output power.

The important advantages of this ANN are its adaptability with every variety in wind features and updating by last data periodically.

IX. CONCLUSION

The major application of this developed ANN is in forecasting of different periods of time. It can be an applied system for power forecasting when a wind speed prediction system and a weather parameters prediction system are cascaded with this ANN.

This work shows the capability of dispatching and for introducing wind plant in electrical market using ANN. If the available data gathered previously from the wind site is enough ample and good observations made for the site with other mentioned methods like Numerical Weather Prediction (NWP) or ANN-Fuzzy methods combined, the forecasting errors will be diminish notably.

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