

ANALYSIS OF HEIGHT AFFECT ON AVERAGE WIND SPEED BY ANN

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Abstract- The power generated by wind turbines depends on several factors. Two of them are the wind speed and the tower height of wind turbine. In this study, the annual average wind speed based on the tower height is predicted using Artificial Neural Networks (ANN) and comparisons made with conventional model approach. The back-propagation multi layer ANNs were used to estimate annual average wind speed for three locations in Turkey. The Model has been developed with the help of neural network methodology. It involves four input variables-wind speed of measured location, desired height on measured location, height above ground level of measured location and Hellmann coefficient and one output variables-annual average wind speed. The model accuracy is evaluated by comparing the conventional model results with the actual measured and calculated values.

Keywords- Artificial neural networks, Average wind speed forecasting, Hellmann coefficient

1. INTRODUCTION

Sustainability of power supplies is one of the most challenging issues that the world faces today since the conventional sources of energy, mainly the fossil fuels, are coming to an end [1]. On the other hand, demand for energy increases not only in developing countries but all over the world. To this end, renewable energy sources such as sun, wind, wave and hydrogen are being discovered as life-saving jackets. Actually some renewable sources such as water energy have already been in use. Even in this field, researchers are heading towards un-exploited areas such as developing mini power plants in the upper parts of rivers.

Wind energy is the fastest developing renewable energy resource because of its several advantages, such as ease of development, environmental friendliness, cost effectiveness and the existence of several feasible sites to establish wind farms. Therefore, design of wind power plants receives much more attention than ever before. The most important part of a wind power plant is the wind turbine which transforms the wind's kinetic energy into mechanical or electric energy. The system basically comprises a blade, a mechanical part and an electric engine connected to each other. The energy of wind is the function of wind speed, the specific mass of air, the area of air space where the wind is captured and the height at which the rotor is placed. Since wind energy is proportional to the third power of wind speed, wind speed is the most important factor that affects wind energy. Hence the location of the wind farm is crucial in order to exploit winds of enough speed.

In the last decade, a lot of studies have been performed to estimate the wind speed and wind potential in different parts of the world using Artificial Neural Networks (ANN) [2-11].

Alexaidis et al.[2] reported the possibility of including the output of global physical meteorological models with neural networks and autoregressive models, though they show that the neural computation approach provides better results than the autoregressive models.

A research was developed on ANN and the results were compared with AR model by Mohandes et al.[3]. The ANN model had been widely used because of its excellent ability in its learning from experience. The mean of monthly and daily wind speed prediction were tested based on the root mean square errors. In [4], Sfetsos presented a novel approach based on ANN model and time-series of target station. Ten minutes data was used to do multi-speed forecasting and the average results were used to generate the mean hourly predictions. Çam et al.[5] presented prediction of average wind speed and wind power values using ANNs in seven regions of Turkey. Oztopal[6] developed a suitable ANN approach for spatial modeling and prediction of wind velocity at any desired point, provided that there is a set of surrounding wind measurement sites. Cadenas and Rivera [7] presented comparison of two techniques for wind speed forecasting in the South Coast of the state of Oaxaca, Mexico. These methods were the Autoregressive Integrated Moving Average (ARIMA) and ANN applied to a time series conformed by 7 years of wind speed measurements. In [8], Barbounis and Theocharis developed a neural network model, the recurrent neural networks for long-term prediction. Their training method was a class of optimal on-line learning algorithms. Bilgili et al.[9] developed a model based on the ANN method and spatial correlation. The mean montly wind speeds of reference stations were used to predict the target stations' wind speed. In [10], wind speed, relative humidity and generation hours were used as input variables to train an ANN-based network by Carolin and Fernandez. The similar work was done by Xiao et al. using a back-propagation network [11]. Cadenas and Rivera [12] investigated the short term wind speed forecasting in the region of La Venta, Oaxaca, Mexico, applying the technique of ANN to the hourly time series representative of the site.

The power generated by each wind turbine depends on parameters such as wind speed and the height of wind turbine tower. In this study, annual average wind speed that isn't measured on the desired tower height of wind turbine is predicted by Artificial Neural Networks (ANN) and the findings of the ANN are compared to those of the conventional approach. The analyses are carried out using most commonly measured average wind speed at 10 m and 30 m [13-14]. The ANN used in this study consists of four input parameters; therefore the annual average wind speed is predicted depending on four variables. The performance of ANN model is evaluated by comparing the conventional model results with the actual measured and calculated values.

The rest of the paper has the following structure: The next section presents the structure of the artificial neural network used to predict average wind speed. Section 3 describes formulation of the problem. The proposed models are compared and evaluated. Finally, Section 4 presents the main conclusion of the paper.

2. ARTIFICIAL NEURAL NETWORKS

Suppose that a three-layer neural network as shown in Fig.1 as n_i input neurons, n_h hidden neurons and n_o output neurons. If o_j^m represents the output of the j -th neuron in the m -th layer and w_{ij}^m the weight on connection joining the i -th neuron in the $(m-1)$ -th layer to the j -th neuron in the m -th layer, then

$$O_j^m = f \left[\sum_i (w_{ij}^m x O_i^{m-1}) \right], \quad m \geq 2 \quad (1)$$

where the function $f(\cdot)$ can be any differentiable function. Usually the sigmoid function is used as follows:

$$f(x) = 1 / (1 + e^{-x}) \quad (2)$$

This function limits the outputs o_j^m among 0 and 1. It is possible to shift the function $f(\cdot)$ along x-axis by adding a threshold value to the summation term of (1) before the function $f(\cdot)$ is applied [15].

To achieve the required mapping capability, the neural network is trained by repeatedly presenting a representative set of input/output patterns with back propagation error and weight adjustment calculation in order to minimize the global error E_p of the network, i.e.,

$$E_p = \frac{1}{2} \sum_{j=1}^{n_o} (t_{pj} - o_{pj}^m)^2 \quad (3)$$

where t_{pj} is the target output of neuron j and o_{pj}^m is the computed output from the neural network corresponding to that neuron. Subscript p indicates that the error is considered for all input patterns.

Minimization of this average sum-squared error is carried out over the entire training patterns. As the outputs o_{pj}^m are functions of the connection weights w^m and the outputs o_{pj}^{m-1} of the neurons in layer $m-1$ which are functions of the connection weights w^{m-1} , the global error E_p is a function of w^m and w^{m-1} . Here w with superscript refers to the connection matrix. A backpropagation algorithm is used in the optimization [16-17].

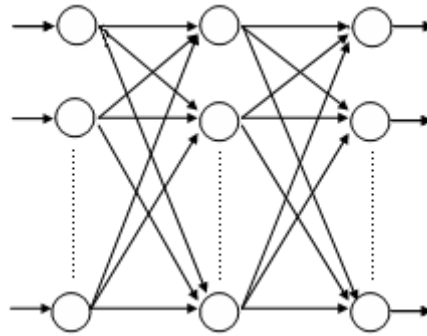


Figure 1. Configuration of the ANN with three layers

3. FORMULATION OF THE PROBLEM

The wind speed on the desired tower height of wind turbine can be defined as the following equation [13];

$$V_w = V_{ref} \left(\frac{H}{H_{ref.}} \right)^\mu \quad (4)$$

Here,

V_w : annual average wind speed of desired height on measured location (m/s)

$V_{ref.}$: annual average wind speed of measured location (m/s)

H : desired height on measured location (m)

$H_{ref.}$: height above ground level of measured location (m)

μ : Hellmann coefficient (dimensionless)

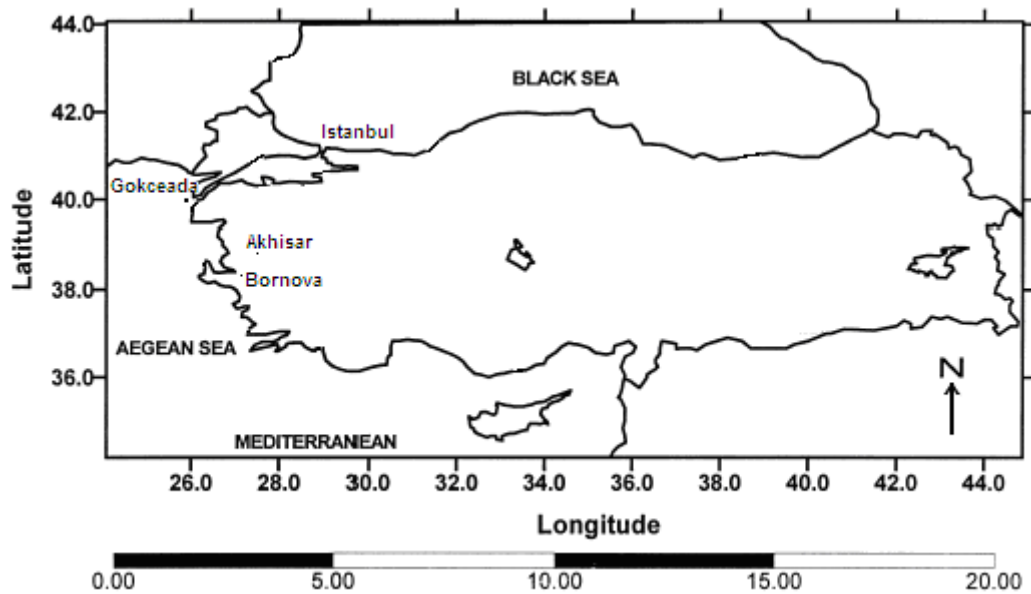


Figure 2. Location Map

Effect of height on average wind speed is found via Equation (4) as conventional method (CM). Data found by CM and measured data (at 10 m for Akhisar, Gokceada and Bornova in Turkey) are presented in Table 1. Figure 2 shows the location map of the study area.

Considering the desired height on measured location, the average wind speed can be re-expressed for ANN as;

$$V_w = f(V_{ref.}, H, H_{ref.}, \mu) \quad (5)$$

where $V_{ref.}$ wind speed of measured location, H desired height on measured location, $H_{ref.}$ height above ground level of measured location, μ Hellmann coefficient. As seen from Equation (5), assessment of the wind speed is quite cumbersome, for which an effective procedure is needed. The procedure is designed to estimate annual average wind speed for different heights. The different heights considered are 5m, 10m, 15m, 20m, 25m, 30m, 35m and 40m. These data and its parameters are shown in Table 1. The input parameters are taken as those included in Equation 5. Therefore, the vector of input parameters becomes;

$$x(t) = [V_{ref.}, H, H_{ref.}, \mu] \quad (6)$$

Table 1. Training samples (calculated data by CM and measured data)

Measured Location	$V_{ref.}$ (m/s) (measured data)	$H_{ref.}$ (m) (reference height)	H (m) (desired height)	μ (Hellmann Coef.)	V_w (m/s) (calculated data)
Gokceada	6.91	10	35	0.14	8.23
Gokceada	6.91	10	30	0.14	8.06
Gokceada	6.91	10	25	0.14	7.85
Gokceada	6.91	10	20	0.14	7.61
Gokceada	6.91	10	10	0.14	6.91
Gokceada	6.91	10	5	0.14	6.27
Akhisar	6.49	10	40	0.18	8.33
Akhisar	6.49	10	35	0.18	8.14
Akhisar	6.49	10	30	0.18	7.91
Akhisar	6.49	10	25	0.18	7.66
Akhisar	6.49	10	20	0.18	7.36
Akhisar	6.49	10	15	0.18	6.98
Akhisar	6.49	10	10	0.18	6.49
Bornova	2.70	10	35	0.28	3.83
Bornova	2.70	10	30	0.28	3.67
Bornova	2.70	10	20	0.28	3.28
Bornova	2.70	10	15	0.28	3.03
Bornova	2.70	10	12	0.28	2.85
Bornova	2.70	10	10	0.28	2.70
Bornova	2.70	10	5	0.28	2.23

The output vector then takes the form of;

$$y(t) = [V_w] \quad (7)$$

where V_w annual average wind speed of desired height on measured location.

As a result, the ANN structure used takes the form of a three-layer network, number of neurons being 4 in input, 5 in hidden and 1 in output layer.

Once the ANN structure is formed, the next step is to train the network to check whether the structure is capable of producing the output variables from the inputs satisfactorily. To carry out this process, a set of data is normally needed. To this end, 20 training samples are formed for all input and output variables (Table 1). The performance of training process is measured according to whether the training error is the lowest. The structure of the network (number of layers and neurons), training and momentum coefficients can be altered to minimize the error. The three-layered network trained above is ready to be tested since the actual performance of an ANN network is observed during the testing phase. The trend of training error with respect to the number of hidden layer is shown in Figure 3 and with respect to iteration number in Figure 4.

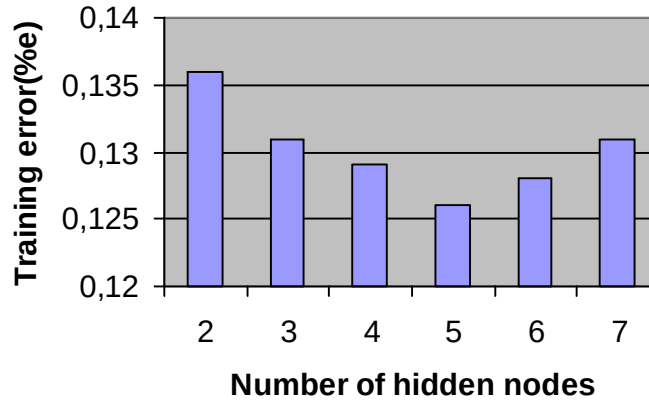


Figure 3. The effect of number of nodes in hidden layer

The testing process was carried out using 12 different training samples and the outputs are presented in Table 2. As seen from Table 2, the performance of the network is satisfactory with small deviation from the results of the conventional method (CM).

For the evaluations of model performance mean percent error (MAPE) defined by Eq. (8) was computed from the results produced by the proposed ANN models:

$$MAPE = \frac{1}{p} \sum_j \left(\frac{t_j - o_j}{t_j} \times 100 \right), \quad (8)$$

where t is the target value, o is the output value, and p is the number of data items. Referring to Table 2, the mean percent errors for testing wind velocity of desired height data are very small, ranging from -1.87% to 1.80%.

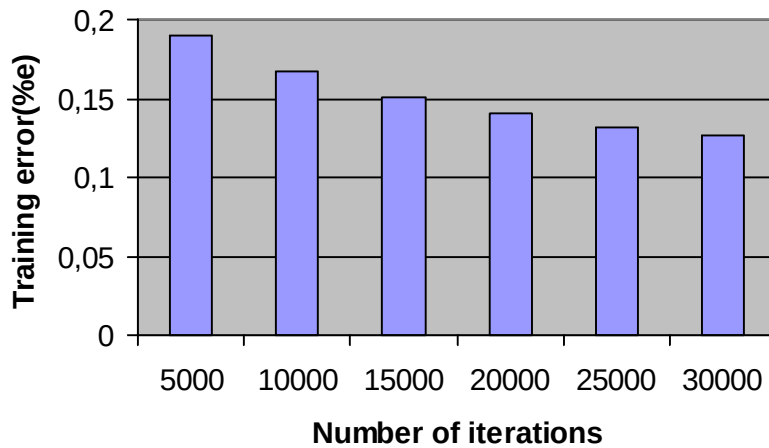


Figure 4. Comparing between training errors which is taken from different iteration

Table 2. Comparison of wind speed as obtained by ANN and Conventional method (CM)

Test No	By ANN V_w (m/s)	By CM V_w (m/s)	Error (%)
1	8.52	8.39	-1.54
2	7.21	7.31	1.36
3	3.08	3.12	1.28
4	3.26	3.32	1.80
5	6.74	6.80	0.88
6	7.70	7.76	0.77
7	8.69	8.53	-1.87
8	4.53	4.47	-1.34
9	8.54	8.50	-0.47
10	6.62	6.57	-0.76
11	2.52	2.48	-1.61
12	6.27	6.19	-1.29

4. CONCLUSIONS

There is a complex relationship between the parameters used in wind turbine installation. Some parameters that need to be assessed in wind turbine installation are wind speed of measured location, desired height on measured location, height above ground level of measured location and Hellmann coefficient. The design process requires an understandable and reliable algorithm connecting these parameters, since separate assessment of all parameters is impossible. This study proposes an ANN algorithm to grasp this complex relationship. The annual average wind speed based on the height is one of the most important factors in use of wind energy and the ANN algorithm proposes an estimation process.

The results obtained from CM data were taken as target values and compared the results obtained with ANN (Table 2). At the 30.000th iteration, which is quite a small number for ANN exercises, the test outputs for 12 samples have reached the target values with almost 100 % success. In other words, the output parameter V_w is obtained with 0.126% error at this iteration. Trials showed that a 3 layer network with 4, 5 and 1 neurons respectively yielded the best results. The exercise introduced here has shown that the ANN algorithm can well be applied to wind turbine installation processes and selected location variables can be estimated from others. In the near future, wind will be one of the major sources of energy and design tools of this kind will be in higher demand.

The proposed approach is illustrated in this paper by using a test example system. Test results have demonstrated that the trained ANN can accurately predict annual average wind speed for different heights through its generalization and adaptability capabilities. As the speed of computation using the trained ANN is quite fast, it is possible to implement such trained ANN for annual average wind speed evaluations.

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List of symbols

V_w	wind velocity of desired height on measured location (m/s)
$V_{ref.}$	wind velocity of measured location (m/s)
H	desired height on measured location (m)
$H_{ref.}$	height above ground level of measured location (m)
E_P	global error of the network
n_h	hidden neurons
n_i	input neurons
n_o	output neurons

Greek Letters

μ	Hellmann coefficient
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