ANN-based evaluation of wind power generation: A case study in Kutahya, Turkey

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Abstract
Wind energy is one of the most significant and rapidly developing renewable energy sources in the world and it provides a clean energy resource, which is a promising alternative in the short term in Turkey. The wind energy potential in various parts of Turkey is becoming economical due to reductions in wind turbine costs, and in fossil fuel atmospheric pollution. This paper is to present, in brief, wind potential in Turkey and to perform an investigation on the wind energy potential of the Kutahya region. A wind measurement station was established at Dumlupinar University Main Campus in order to figure out the wind energy potential in the province. This study analyses the electricity generation capacity of the Kutahya region, Turkey, which uses the wind power system. In the study, the wind data collected from wind measurement stations between July 2001 and June 2004 (36 months) were evaluated to determine the energy potential of the region. Using this energy potential value, the power generation capacity of Kutahya was investigated for 17 different wind turbines. In this analysis, an ANN-based model and Weibull and Rayleigh distribution models were used to determine the power generation. In the ANN model, different feed-forward back propagation learning algorithms, namely Pola-Ribiere Conjugate Gradient, Levenberg–Marquardt and Scaled Conjugate Gradient were applied. The best appropriate model was determined as Levenberg–Marquardt with 15 neurons in a single hidden layer. Using the best ANN topology, it was determined that all the turbines were profitable except turbine type 1. The system with the turbine type 3 was decisively the most profitable case as determined at the end of the study according to Net Present Value concept.

Keywords: Levenberg–Marquardt; Net Present Value; Pola-Ribiere Conjugate Gradient; Rayleigh distribution; Scaled Conjugate Gradient; Weibull distribution

1. Introduction

The most important issue of today is to use natural energy sources in an efficient way which will not pollute the environment. The energy producers have an obligation to solve the environmental problems caused while producing energy for humanity's need today as well as tomorrow. There is a relation between energy and the environment. Environmental pollution increases with energy production and consumption; therefore, both the subjects must be handled together. In this regard, energy resources are necessary to be evaluated in terms of reserves, geographic distribution, production rates, pricing stability, business conditions, source credibility, and environmental interaction. Under these conditions, a sustainable and environmentally clean use of energy sources is urgently needed.

The wind potential assessment of a site requires the knowledge of the distribution law of the wind speed measured on the site. The statistical treatment of these measurements makes it possible to have a discrete distribution law. However, to obtain a more accurate analysis of the wind potential, a continuous distribution law is essential. For this purpose, the Weibull and Rayleigh models are often used (Thiaw, 2010). Previous studies have proven that the Weibull distribution function has its merits in wind resource assessment due to its great flexibility and simplicity, but particularly, it has been found to fit a wide collection of recorded wind data (Ulgen and Hepbasli, 2002; Dorvlo, 2002; Karsli and Gecit, 2003; Sulaiman *et al.,* 2002; Celik, 2004; Keyhani *et al.,* 2010; Arslan, 2010; Ouammi *et al.*, 2010; Ozgur and Kose, 2006; Jaramillo and Borja, 2004; Chang *et al.,* 2003).

Wind energy potential is not easily estimated because, contrary to solar energy, it depends on the site characteristics and topography to a large degree, as wind speeds are influenced strongly by local topographical features. The classification and characterization of an area as having high- or low-wind potential requires significant effort, as wind speed and direction present extreme transitions at most sites and demand a detailed study of spatial and temporal variations of wind speed values. Before determining the wind farm site, the hourly and monthly mean wind speed, wind speed distributions as well as the wind power densities should be analysed carefully (Keyhani *et al.,* 2010).

In the literature, several studies dealing with artificial neural networks (ANNs) are available. One such example is the work of Dombaycı and Gölcü (2009). They developed an ANN model to predict the ambient temperature for Denizli, another city in Turkey. The results show that the ANN approach is a reliable model for ambient temperature prediction. Kalogirou *et al.* (1999) programmed an ANN to learn to predict the performance of a thermosiphon solar domestic water heating system. An ANN was conditioned to use performance data for four types of systems, all employing the same collector panel under varying weather conditions. Li and Shi (2010) investigated three different ANNs namely adaptive linear element, back propagation, and radial basis function to predict wind speeds. The results show that even for the same wind data set, no single neural network model outperforms other universally in terms of all evaluation metrics. Moreover, the selection of the type of neural networks for best performance is also dependent upon the data sources. Mohandes *et al*. (1998) in their study used neural networks technique for wind speed prediction and compared its performance with that of an autoregressive model. Results on testing data indicate that the neural network approach outperforms the autoregressive model as indicated by the prediction graph and by the root mean square errors. Öztopal (2006) in his study presented the necessary weighting factors of surrounding stations to predict about a pivot using an ANN technique. The developed ANN model was found to predict the wind speeds for the winter season very accurately. Çam *et al.* (2005) in their study developed an ANN model to predict the average wind speed and wind energy values for the seven regions of Turkey. The network has successfully predicted the required output values for the test data; the mean error levels for the regions differed between 3% and 6%. Determining a distribution law for the speeds can be considered as a nonlinear regression problem, in which the distribution law (Weibull and Rayleigh) is identified so as to get nearer the discrete law. As regards function approximation, the techniques based on the ANN approach have, however, shown that they can deliver very good performances (Thiaw, 2010; Carolin and Fernandez, 2008; Jafarian and Ranjbar, 2010).

In this study, the wind data collected between July 2001 and June 2004 (36 months) was evaluated to determine the energy potential of the region. Using this potential, the power generation capacity of Kutahya was investigated for 17 different wind turbines. For this purpose, an ANN-based model was used besides Weibull and Rayleigh distribution models. In the ANN model, different feed-forward back propagation learning algorithms, namely Pola-Ribiere Conjugate Gradient (CGP), Levenberg–Marquardt (LM) and Scaled Conjugate (SCG) Gradient, were applied. Finally, the models were evaluated using the net present value (NPV) analysis.

2. Materials and methods

2.1. Study area

2.1.1. Site description

The study area is the city of Kutahya, which is surrounded by mountains from the east and south, is located at an altitude of 969 m and has a population of 200 000. Situated at 39°42′ latitude and 29°93′ longitude, it lies on the Western Central part of the Aegean Region and therefore displays geographical properties similar to those of the Aegean, Marmara and Central Anatolia regions. The main campus of Dumlupinar University is the site of the study; it is situated at 39°29′6,34′′ latitude and 29°54′4,04′′ longitude and located at an altitude of 1094 m as shown in Figure 1 (Kose *et al.,* 2004; Ozgur *et al.,* 2009).

2.1.2. Wind characteristics of the region

According to data obtained between the years 1975 and 2010, average annual temperature, average sunshine duration time and average rainfall in the Kutahya province are measured as 10.8 °C, 5.8 hours and 45.4 kg/m^2, respectively (DMI, 2011). Kutahya has a transition climate (otherwise known as a semi-continental climate). In general, Kutahya has low wind speeds and therefore, limited wind energy potential. However, there may be specific sites and applications where wind is a cost-effective option.

As seen in Figure.2a, average wind speed, blowing from the direction of North (N) and South-South-West (SSW) is 6.24 m/s and 6.00 m/s, respectively. In this study, the prevailing wind direction was determined as East (E) with a frequency distribution rate of 18.15% (see Figure.2b) (Ozgur, 2006).

The wind data used in the study was collected between July 2001 and June 2004 in 10 minute intervals and from various parts of the region (for detailed information see reference (Kose *et al..,* 2004; Ozgur *et al..,* 2009; Ozgur, 2006; Ozgur and Kose, 2006). The maximum monthly average wind speed was recorded as 5.3 m/s in February, when the minimum wind speed was recorded as 3.9 m/s in September. The wind data used in the study is as given in Figure 3.

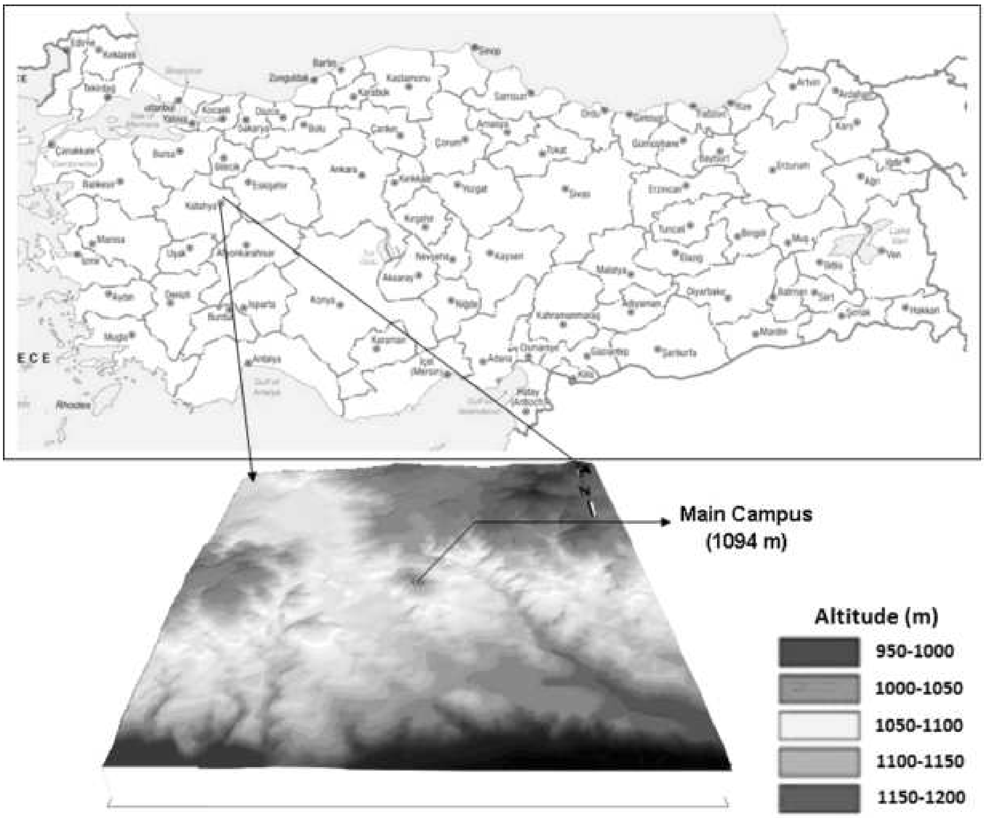


Figure.1: The main campus of Dumlupinar University, Kutahya

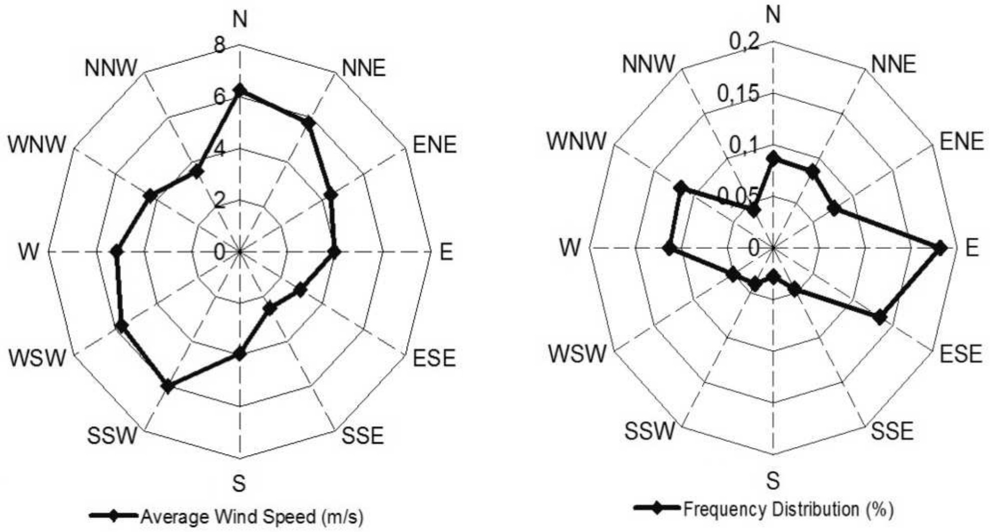


Figure 2: The wind characteristics on the main campus of Dumlupinar University; a) Average wind speed; b) Frequency distribution

2.2. Selected wind turbines

In the study, 17 different turbine models fabricated by four different manufacturers were selected to determine the power generation capacity of the study area. The installed capacities (*IC*) of these turbines range between 200 and 1650 kW, where the hub heights range between 36 and 85 m. The technical characteristics of related turbines are given in Table 1 (Ammonit, 2011).

2.3. Classical method for wind potential and energy generation

2.3.1. Weibull distribution function

Weibull probability density function (PDF) is a special case of the generalized two-parameter gamma distribution. The Weibull distribution can be characterized by $f(V)$ of PDF and $F(V)$ of cumulative distribution function (Bury, 1975; Fawzan, 2000). The PDF of the two-parameter Weibull distribution

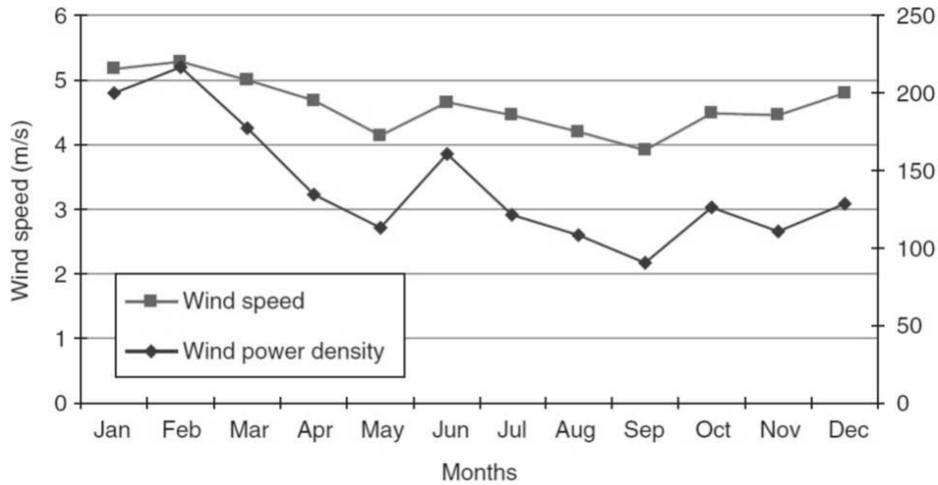


Figure 3: Monthly mean values of wind speed

Table 1: Technical specifications of wind turbines

Turbine type	*Turbine model*	*Hub height (m)*	*IC (kW)*	*Cut-in speed (m/s)*	*Cut-out speed (m/s)*	*Rated speed (m/s)*	*N (years)*
1	NEG Micon NM750/44	55	750	4	24	17	20
2	NEG Micon NM750/48	60	750	4	24	16	20
3	Enercon E-30/200kWNH50m	50	200	3	25	12	20
4	Enercon E-30/200kWNH36m	36	200	3	25	12	20
5	Enercon E-40/200kW55m	55	500	3	30	19.5	20
6	NEG Micon NM600/48	60	600	3	20	17	20
7	NEG Micon NM1500/64	80	1500	4	24	17	20
8	NEG Micon NM900/52	70	900	4	24	16	20
9	Nordex N54/1000	68.5	1000	4	24	16	20
10	Nordex N60/1300	70	1300	4	24	16	20
11	Vestas V44/600	55	600	4.50	20	17	20
12	Vestas V47/660	55	660	4	24	17	20
13	Vestas V66-1.65MW	67	1650	4	24	18	20
14	Nordex N43/600	55	600	3	24	18	20
15	Enercon E-40/600kW78m	78	600	3	25	14	20
16	Enercon E-58/1000kW70.5m	70.5	1000	3	25	14	20
17	Enercon E-66/1500kW85m	85	1500	3	25	14	20

is given by the following equation:

$$f(V)=\left(\frac{k}{c}\right)\left(\frac{V}{c}\right)^{k-1}\exp\left[-\left(\frac{V}{c}\right)^{k}\right],\quad 0<V<\infty \tag{1}$$

where *c*, *k* and *V* are the scale parameter, shape parameter, and wind speed, respectively. The cumulative distribution function is given by the equation (Hennesey, 1977; Stevens and Smulders, 1979; Garcia *et al.*, 1997):

$$F(V)=1-e^{-(V/c)^{k}} \tag{2}$$

Here, the relation between c and k is as follows:

$$\frac{\overline{V}}{c}=\Gamma(1+\frac{1}{k}) \tag{3}$$

where $\overline{V}$ is the average wind speed. $\Gamma(...)$ is the Gamma function, and is given as

$$\Gamma(t)=\int_{0}^{\infty}e^{-x}x^{t-1}dx \tag{4}$$

The standard deviation of the wind speed (σ) is determined by the following equation:

$$\frac{\sigma}{\overline{V}}=\frac{\sqrt{\Gamma(1+2/k)-\Gamma^{2}(1+1/k)}}{\Gamma(1+1/k)} \tag{5}$$

After calculating the parameters c and k, the most frequent wind speed and the maximum energetic wind speed are given by Eq. (6) and (7), where $\bar{V}$ is the average wind speed. $\Gamma(...)$ is the Gamma function, and is given as

$$\Gamma(t) = \int_0^\infty e^{-x} x^{t-1} dx \tag{4}$$

The standard deviation of the wind speed (σ) is determined by the following equation:

$$\frac{\sigma}{V} = \frac{\sqrt{\Gamma(1+2/k) - \Gamma^2(1+1/k)}}{\Gamma(1+1/k)} \tag{5}$$

After calculating the parameters c and k, the most frequent wind speed and the maximum energetic wind speed are given by Eq. (6) and (7), respectively, which are as follows:

$$V_{MP} = c\left(\frac{k-1}{k}\right)^{1/k} \tag{6}$$

$$V_{\max E} = c\left(\frac{k+2}{k}\right)^{1/k} \tag{7}$$

The shape parameter, k, commonly ranges between 1.5 and 3.0. When it assumes the value 2.0, it is called the Rayleigh distribution, and the PDF for the Rayleigh distribution can then be simplified as shown in Eq. (8).

$$f(V) = \frac{2V}{c^2} \exp\left[\left(-\frac{V}{c}\right)^k\right] \tag{8}$$

2.3.2. Power extracted from wind

The kinetic energy in air of mass 'm' moving with speed V is given by the following in SI units:

$$Kinetic\ \ energy = \frac{1}{2} m V^2 \text{ joules.} \tag{9}$$

The volumetric flow rate is A·V, the mass flow rate of the air in kilograms per second is ρAV, and the power is given by the following (Patel, 1942):

$$P = \frac{1}{2}(\rho AV)V^2 = \frac{1}{2}\rho AV^3 \text{ watts.} \tag{10}$$

Here, ρ and A, respectively, define the density in kg/m^3 and the area swept by the rotor in m^2. Therefore, the wind-power density is given by the Eq. (11) in terms of the Weibull PDF, and the wind energy density is given by Eq. (12) for a period T.

$$\frac{P}{A} = \int_0^\infty P(V) f(V) dV = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) \tag{11}$$

$$\frac{E}{A} = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) T \tag{12}$$

From the technological point of view, a wind turbine that converts the kinetic energy of the wind to electrical energy, starts to generate power at a cut-in wind speed (V_1), and this process continues until a wind speed of V_R, at which the nominal power generation P_R is obtained. After this nominal point, the turbine starts to decelerate itself in a controlled manner until a speed of V_0, called the cut-out wind speed, is reached. With reference to these benchmarks, the energy achieved from an ideal turbine is given as follows:

$$E_{TW} = T\int_0^\infty P(V) f(V) dV = T\left(\int_{V_1}^{V_R} P(V) f(V) dV + \int_{V_R}^{V_0} P_R f(V) dV\right) \tag{13}$$

Substituting the Eq. (10) in Eq. (13), it can be rewritten as

$$E_{TW} = \frac{\rho}{2} TA\left(\int_{V_I}^{V_R} V^3 \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV + {V_R}^3 \int_{V_R}^{V_0} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV\right) \tag{14}$$ *

Because of the several losses occurring during the transmission mechanisms of the wind turbine, all the power carried by the wind can never be converted to electricity. In this regard, the actual power achieved from the turbine (P_T) is calculated from the turbine-performance curve described by Eq. (15).

$$P_T(V) = \begin{cases} 0 & , V < V_I \\ \left(a_1 V^3 + a_2 V^2 + a_3 V + a_4\right) P_R, & V_1 \le V < V_R \\ P_R & , V_R \le V < V_0 \\ 0 & , V \ge V_0 \end{cases} \tag{15}$$

where a_1, a_2, a_3, and a_4 are the regression constants of the turbine-performance curves (Arslan, 2010; Wu, 2002). Combining the Eqs. (1), (10), and (15), Eq. (16) gives the actual energy released from a wind turbine.

$$E_{TA} = T\int_{V_1}^{V_0} P_T(V) f(V) dV = TP_R \int_{V_1}^{V_R} (a_1 V^3 + a_2 V^2 + a_3 V + a_4) \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV + TP_R \int_{V_R}^{V_0} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV \tag{16}$$

* *Equations 14, 16 and 19 have been shrunk in order to fit the column. They are given in their full size at the end of the paper.*

Therefore, the efficiency of the turbine (η) is the ratio of the real to the ideal energy-generation processes and is given by the following equation:

$$\eta = \frac{E_{TA}}{E_{TW}} \tag{17}$$

As observed from Eqs. (15)–(17), the turbine efficiency is a function of not only the wind characteristics but also wind distribution. In 1926, Betz first discovered that the wind power theoretically decreased with the wind speed. According to Betz, neglecting the transmission losses, the obtainable power from wind is approximately 59% of the total carried by it. In other words, the turbine efficiency cannot exceed the value of 59% (Golding, 1955; Considine, 1977).

For the period T, the generated nominal wind energy from a turbine operating with full capacity is given by Eq. (18).

$$E_{TR} = TP_R \tag{18}$$

After this classification, two important parameters – capacity and availability factor – should be defined for the estimation of power generated from a wind turbine. The capacity factor is defined as the ratio of the real-energy generation to nominal-energy generation and is given as follows (Ozgur, 2006; Decher, 1994):

$$C_F = \frac{E_{TA}}{E_{TR}} = \int_{V_1}^{V_R} \left(a_1V^3 + a_2V^2 + a_3V + a_4\right)\frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k}\,dV + \int_{V_R}^{V_0} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k}\,dV \tag{19}$$

The availability factor is the operating percentage of a turbine and is given by the following equation:

$$A_F = P(V_I \le V < V_0) = \int_{V_I}^{V_o} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k}\,dV \tag{20}$$

If the wind speed measurement has been made from a height of H_1 above the ground, it is possible to assess the wind speeds at a height H_2 by the relation:

$$V_e = V_m\left(\frac{H_2}{H_1}\right)^{\alpha} \tag{21}$$

where α is a parameter that depends on the soil roughness (Thiaw, 2010; Ozgur et al., 2009; Ozgur, 2006; Patel, 1942).

2.4. ANN modelling of wind power generation

Artificial neural networks are examples of the way that the biological neural system works. Nerve cells contain neurons. Neurons are interconnected in various ways and create a network. Likewise, ANN is a network applied successfully in a number of application areas such as medicine, economics, engineering, neurology, meteorology, etc. The ANN modelling is carried out in two steps: the first step is to train the network whereas the second is to test the network with data, which are not used for training. The unit element of an ANN is the neuron. As in nature, the network function is determined largely by the connections between the elements (Fu, 1994; Tsoukalas and Uhrig, 1997; Oztemel, 2003).

In an ANN, each unit is a basic unit of information process. Units are interconnected via links that contain weight values. Weight values help the neural network to express knowledge. There are several neural architectures. One of these architectures, widely used in engineering applications, is multilayer neural network (MLNN).

The MLNN consists of three layers at least: an input layer, an output layer and one hidden layer. The input and output layers represent the input and output variables of the model and the hidden layers hold the network's ability to learn the non-linear relationships between the input and output (Oztemel, 2003; Kalogirou, 2000). To obtain these relationships, several learning algorithms are available, one of which can be used. The most widely used algorithm is the feed-forward back propagation learning algorithm. It is a gradient descent algorithm. The most widely used algorithms are Levenberg-Marguardt (LM), Pola-Ribiere Conjugate Gradient (CGP) and Scaled Conjugate Gradient (SCG) in the field of energy. LM algorithm appears to be the fastest method for feed forward neural networks. CGP and SCG algorithms are a version of the Conjugate Gradient algorithm. Each of the conjugate gradient algorithms that have been discussed so far requires a line search. This line search is computationally expensive, since it requires that the network response to all training inputs be computed several times for each search (Hagan and Menjah, 1994; Fletcher and Reeves, 1964; Moller, 1993). ANN with a feed-forward back propagation algorithm learns by changing the connection weights, and these changes are stored as knowledge. The performance of the configured model is determined using some statistical methods such as the percent root mean square error (*PRMSE*), covariance (*Cov*) and the coefficient of multiple determinations (R^2). These statistical parameters are formulated in terms of output value (y_{output}), target value (y_{actual}), average of target ($\bar{y}_{actual}$) and pattern (n) as follows (Arslan, 2011):

$$PRMSE = \sqrt{\frac{\sum_{m=1}^{n}\left(\frac{y_{output} - y_{actual}}{y_{output}}\right)^2}{n}} \times 100 \quad (22)$$

$$Cov = \frac{\sqrt{\frac{\sum_{m=1}^{n}\left(y_{output} - y_{actual}\right)^2}{n}}}{\left|\bar{y}_{actual}\right|} \times 100 \quad (23)$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(y_{output} - y_{actual}\right)^2}{\sum_{m=1}^{n} y_{actual}^{\;2}} \quad (24)$$

In this study, different feed-forward back propagation learning algorithms, namely Pola-Ribiere Conjugate Gradient (CGP), Levenberg–Marquardt (LM) and Scaled Conjugate Gradient (SCG) were applied. Inputs and outputs were normalized in the (0–1) range depending on the non-linear transfer function; logarithmic sigmoid (logsig), was used as given:

$$f(z) = \frac{1}{1 + e^{-z}} \quad (25)$$

where z is the weighted sum, and given in terms of bias (b), weight (w) and output (y),

$$z_j = \sum_{i=1}^{n} w_{ij} y_i + b_j \quad (26)$$

2.5 Economic analysis

The wind power plants handled herein have been evaluated economically using net present value (*NPV*) analysis. NPV is a powerful tool for the feasibility studies and can be determined with the following equation (Ozerdem *et al*., 2006; Zheng, 2009):

$$NPV = \sum_{t=0}^{N} \frac{B_t - C_t}{(1+r)^t} \quad (27)$$

Where B_t and C_t are the benefit and cost in the t^{th} year respectively during the program, r represents the discount rate and N is the timescale of the plant.

To this end, the cost parameters selected for the on-grid configuration were the wind turbine (C_{WT}) including installation and commissioning, and salvage (C_{sal}) where the benefits were greenhouse gases (C_{CO2}), repair and maintenance ($C_{O\&M}$), and the electricity sale (C_e). Accordingly, the general cost (C) and the benefit (B) of the system are as given in Equations (28) and (29).

$$C = C_{WT} - C_{sal} \quad (28)$$

$$B = C_{CO2} + C_e - C_{O\&M} \quad (29)$$

In this study, the unit costs used in the study were taken as 88 US$/MWh for electricity sale (C_e), 1250 US$/kW for wind turbine including installation and commissioning (C_{WT}), %5 of c_{WT} (C_{sal}), 17.5 US$/MWh for operating and maintenance ($c_{O\&M}$) and 93.2 US$/MWh for greenhouse gases (C_{CO2}) (Arslan, 2010; Green Economy, 2010; Blanco, 2009).

3. Results and discussion

In the ANN modelling of a wind power plant, the values of three inputs, turbine type, hub height and wind speed, were used. Generated power of the system was obtained as output. Different models were performed by using the software MATLAB. These models were built up using a dataset including 314 patterns. In the training step, 220 of these patterns (70% of total) were used. The remaining patterns, randomly selected from a number of 94, were used for testing. An increased number of neurons (from 6 to 16) were used to define the output accurately in a single hidden layer for 2000 epochs in the training algorithms. According to statistical performance evaluation, the summarized results are given in Table 2.

According to Table 2, all the studied ANN models are very satisfactory and can be used for the pre-feasibility of a wind power plant with an acceptable accuracy. The LM training algorithm with 15 neurons in a single hidden layer was determined as the best model. Different models with more hidden layers were also tested but none was as much accurate as LM 15. The architecture of LM 15 is shown in Figure 4.

In the training step of this topology, *PRMSE* was determined as 0.4908% when the values of *Cov* and R^2 obtained were 0.5074 and 0.9995. These values were respectively 0.6475, 0.9606 and 0.9991 in the testing step. The statistical evaluation shows that the trained ANN model can be used for the designing of a wind power plant considered suitable for Kutahya, since it has high accuracy. The comparisons of the actual and ANN outputs are shown in Figure 5.

In this study, the wind data, appropriate to World Meteorology Organization (WMO) standards, collected between July 2001 and June 2004 in 10-minute intervals were evaluated to determine the energy potential of the region. This data was used to determine the power generation capacity taking 17 different turbine models into consideration in Weibull and Rayleigh distribution models. Besides these, technical characteristics of these turbines were also modelled using ANN to give the power generation capacity. The results are given in

Table 2: A comparison of error values for studied ANN topologies

Algorithm	*Train*			*Test*		
	CoV	*PRMSE*	R^2	*CoV*	*PRMSE*	R^2
CGP 14	4.1213	3.8952	0.9694	5.2604	3.7239	0.9737
CGP 15	2.7089	2.6564	0.9867	3.6979	2.7567	0.9868
CGP 16	2.7272	2.7586	0.9865	3.9002	2.8213	0.9855
LM 14	0.6085	0.6000	0.9993	0.9963	0.6831	0.9990
LM 15	*0.5074*	*0.4908*	*0.9995*	*0.9606*	*0.6475*	*0.9991*
LM 16	0.5909	0.5630	0.9993	0.9472	0.6475	0.9991
SCG 14	3.1010	3.3463	0.9826	4.4538	3.4445	0.9816
SCG 15	2.9901	3.0489	0.9838	3.8324	2.7796	0.9868
SCG 16	2.2494	2.2151	0.9908	3.1519	2.2317	0.9905

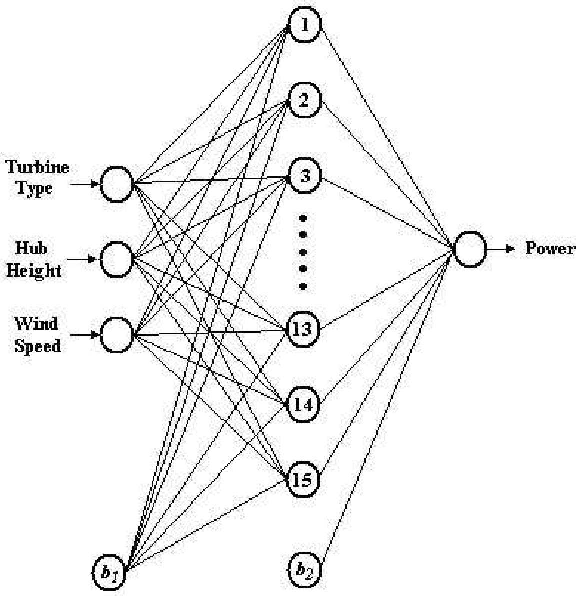


Figure 4: The architecture of the best ANN topology

Table 3: *NPV* results for a discount rate of 0.14

Turbine type	Capacity (kW)	NPV ($)	Payback period (year)
1	750	-68,979	>20
2	750	128,959	12.69
3	200	225,893	4.93
4	200	23,737	14.14
5	500	121,815	11.21
6	600	255,349	8.77
7	1,500	257,747	12.69
8	900	245,386	10.72
9	1,000	90,493	15.10
10	1,300	170,083	13.77
11	600	52,811	15.19
12	660	191,450	10.45
13	1,650	17,548	19.19
14	600	111,447	12.37
15	600	212,654	9.57
16	1,000	422,187	8.80
17	1,500	398,898	10.82

Figures 6–8. According to these figures, the results of the ANN model are more accurate than those of Weibull and Rayleigh (Arslan, 2010; Ozgur *et al.*, 2009; Ozgur, 2006; Ozgur and Kose, 2006).

For the economic evaluation of cost and benefit, the *NPV* concept was used, which included the greenhouse gas emission criteria. The calculations were based on the average energy generation of three years. The NPV results ratified for a discount rate of 0.14 (TCMB, 2010) are given in Table 3.

According to Table 3, the wind power generation is profitable for the existing turbine type 1. *NPV* values oscillate between US$ –68,979 and 422,187. Since the greater *NPV* means the more profitable, the most appropriate case seems to be the system with the turbine type 16. However, the least payback period is obtained for type 3 with an *NPV* value of US$ 225,893. So, this means that the most appropriate case is actually the system with the turbine type 3, when the capacities of the turbines are taken into consideration.

4. Conclusion

A highly unique flexible ANN algorithm was proposed to evaluate the wind power generation systems because of nonlinearity of the neural networks. The results analytically obtained were used to train the several ANN algorithms such as CGP, LM and SCG. The trained algorithms were then tested and evaluated by the statistical methods such as *Cov*, *RMS* and R^2. These statistical values showed that the best algorithm was LM. The degree of accuracy, between the real data and training data, is 99.95% for ANN algorithms, whereas the degree of accuracy, between the real data and testing data, is 99.91% for LM 15.

In this paper, the trained algorithms also show that the predicted values can be used to install a wind system with less data and high accuracy. Besides these, the best ANN topology gives more sensitive results in comparison to Weibull and

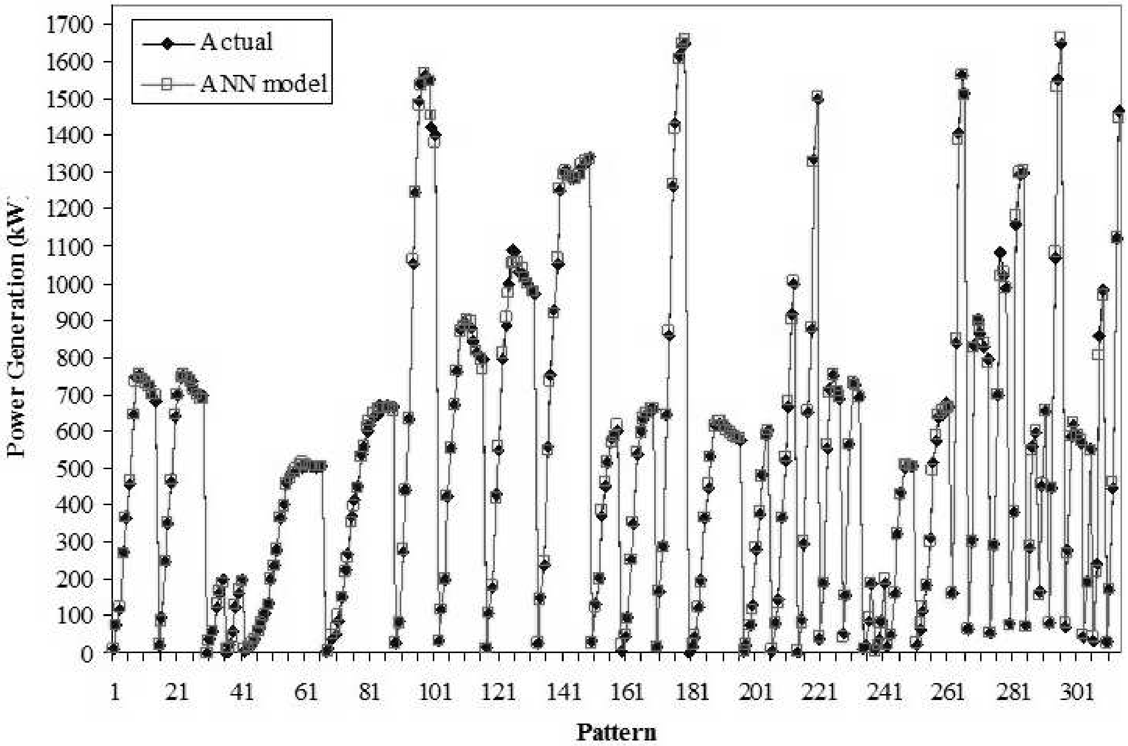
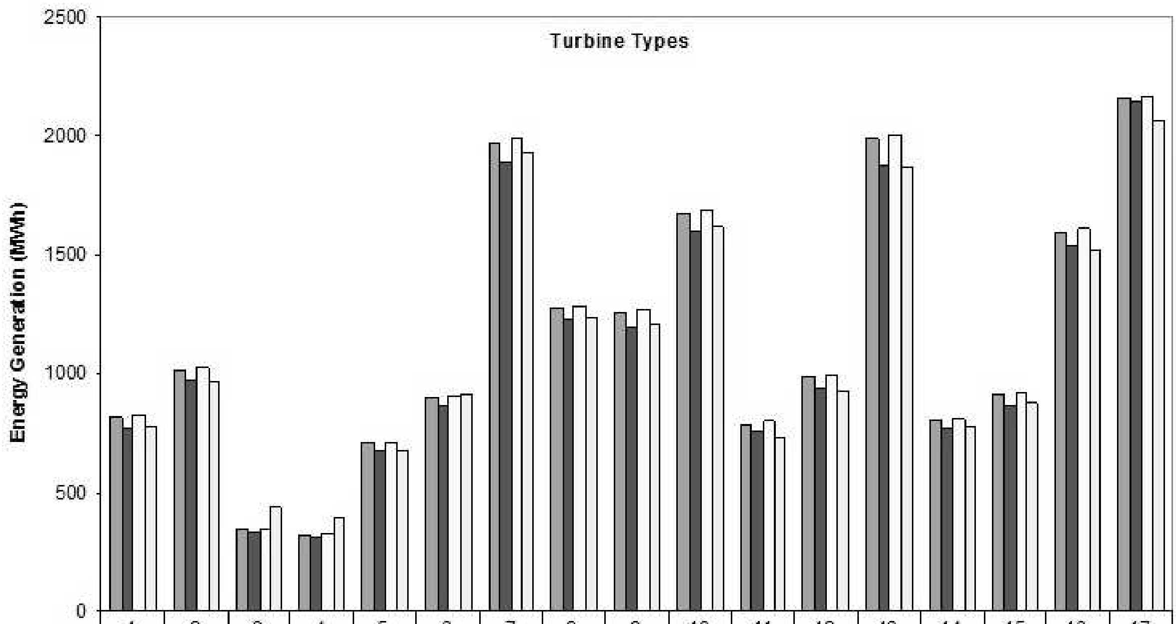


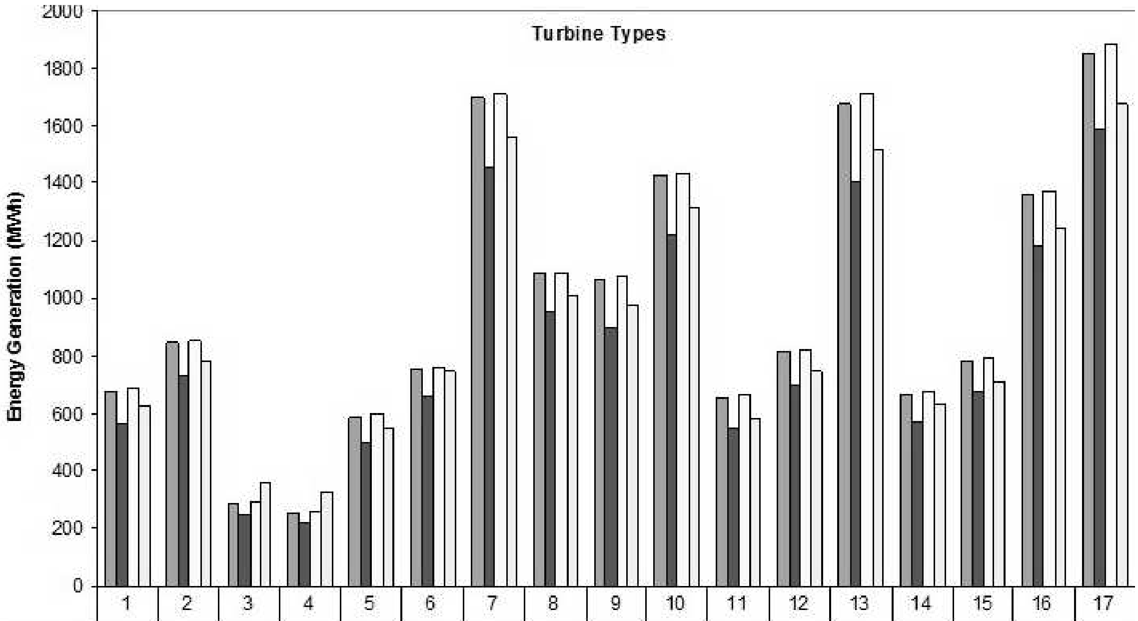
Figure 5: A comparison of ANN prediction and analytic design results for LM 15



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Actual	817.2	1014.1	345.7	321.9	710.8	900.3	1972.4	1275.4	1256.0	1673.3	789.6	984.1	1988.2	802.8	909.4	1597.6	2161.2
Rayleigh	772.1	975.0	333.8	310.1	674.6	870.8	1891.8	1234.7	1197.7	1603.1	756.5	944.6	1880.4	767.9	871.2	1537.8	2143.5
Weibull	821.9	1020.3	347.4	324.7	713.9	908.5	1991.4	1285.2	1266.2	1685.2	799.9	991.3	2003.4	807.5	916.3	1607.9	2164.4
ANN model	776.3	964.4	435.8	396.4	675.8	913.5	1929.1	1241.3	1208.7	1620.7	724.9	923.8	1869.6	778.7	875.6	1521.5	2063.3

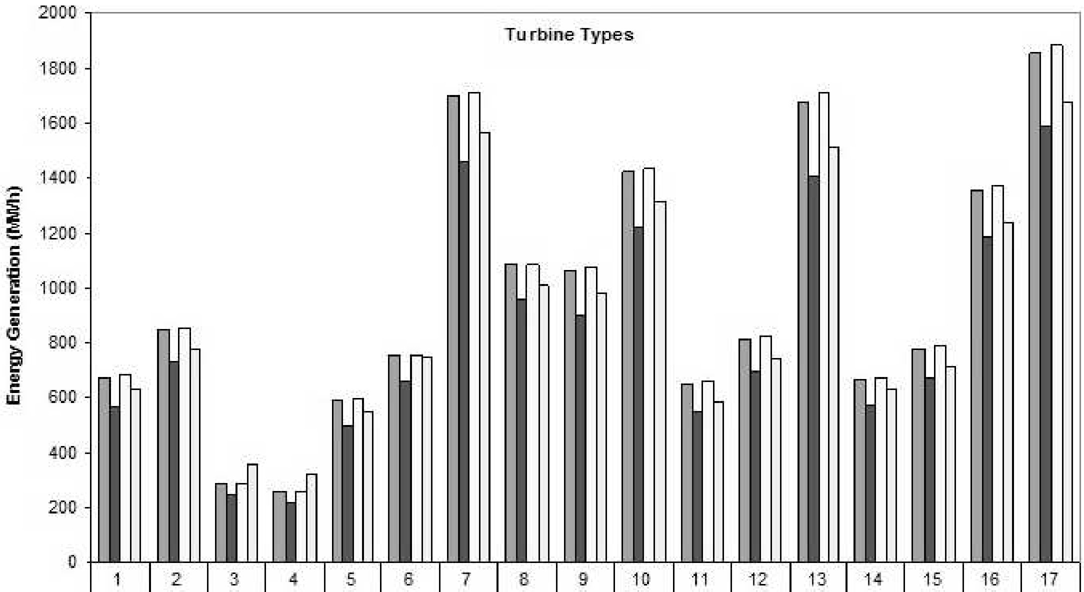
Figure 6: A comparison of the values of electricity production (July 2001 – June 2002)

Rayleigh distribution models. So, the neural network topology can be used for the feasibility studies of wind power projects. In this study, the *NPV* analysis-based ANN topology shows that the wind power systems for different 16 turbine types are profitable in Kutahya.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Actual	673.1	847.3	286.6	257.1	588.7	753.8	1697.0	1086.3	1063.5	1423.7	650.9	815.5	1674.4	665.0	781.4	1358.5	1852.5
Rayleigh	564.7	734.1	249.2	220.8	498.0	658.4	1457.0	953.8	901.3	1218.9	548.5	697.9	1402.4	570.4	673.9	1184.7	1584.2
Weibull	687.2	853.4	287.4	260.4	598.7	757.9	1711.2	1088.4	1075.5	1431.1	662.4	824.5	1712.2	672.3	790.9	1372.1	1882.1
ANN model	630.1	781.1	359.3	325.1	551.4	747.2	1562.6	1010.5	978.4	1314.2	582.8	745.9	1513.2	634.0	711.8	1240.1	1673.1

Figure 7: A comparison of the values of electricity production (July 2002 – June 2003)



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Actual	673.1	847.3	286.6	257.1	588.7	753.8	1697.0	1086.3	1063.5	1423.7	650.9	815.5	1674.4	665.0	781.4	1358.5	1852.5
Rayleigh	564.7	734.1	249.2	220.8	498.0	658.4	1457.0	953.8	901.3	1218.9	548.5	697.9	1402.4	570.4	673.9	1184.7	1584.2
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ANN model	630.1	781.1	359.3	325.1	551.4	747.2	1562.6	1010.5	978.4	1314.2	582.8	745.9	1513.2	634.0	711.8	1240.1	1673.1

Figure 8: A comparison of the values of electricity production (July 2003 – June 2004)

Equations 14, 16 and 19 repeated

$$E_{TW} = \frac{\rho}{2} TA \left(\int_{V_I}^{V_R} V^3 \frac{k}{c} \left(\frac{V}{c} \right)^{k-1} e^{-(V/c)^k} \, dV + {V_R}^3 \int_{V_R}^{V_0} \frac{k}{c} \left(\frac{V}{c} \right)^{k-1} e^{-(V/c)^k} \, dV \right) \qquad (14)$$

$$E_{TA} = T\int_{V_1}^{V_0} P_T(V) f(V) dV = TP_R \int_{V_1}^{V_R} (a_1 V^3 + a_2 V^2 + a_3 V + a_4) \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV + TP_R \int_{V_R}^{V_0} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV \quad (16)$$

$$C_F = \frac{E_{TA}}{E_{TR}} = \int_{V_1}^{V_R} \left(a_1 V^3 + a_2 V^2 + a_3 V + a_4\right) \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV + \int_{V_R}^{V_0} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV \quad (19)$$

Nomenclature

A	area swept by the rotor (m^2)
ANN	artificial neural network
A_F	availability factor
B	benefit (US$)
b	bias number
C	general cost (US$)
c	scale parameter (m/s)
CF	capacity factor
CGP	Pola-Ribiere conjugate gradient
Cov	covariance
C_{CO2}	cost of greenhouse gases (US$)
C_e	cost of electricity sale (US$)
C_{sal}	cost of salvage (US$)
$C_{O\&M}$	cost of operation and maintenance (US$)
C_{WT}	cost of wind turbine (US$)
c_{CO2}	unit cost of greenhouse gases (US$/MWh)
c_e	unit cost of electricity sale (US$/MWh)
c_{sal}	unit cost of salvage (US$/MW)
$c_{O\&M}$	unit cost of operation and maintenance (US$/MWh)
c_{WT}	unit cost of wind turbine (US$/MW)
E_{TA}	actual energy released from turbine (kWh)
E_{TW}	energy achieved from an ideal turbine (kWh)
F(V)	cumulative distribution function
f(V)	Weibull distribution function
IC	installed capacity (kW)
k	shape parameter
LM	Levenberg–Marquardt
m	air of mass (kg)
MLNN	multi-layer neural network
N	lifetime of the plant (year)
NPV	net present value (US$)
n	pattern
PDF	probability density function
PRMSE	percent root mean square error
P_R	nominal power generation (kW)
P_T	actual power achieved from the turbine (kW)
r	discount rate (%)
SCG	scaled conjugate gradient
V	wind speed (m/s)
V_e	wind speed estimated at height H_2 (m/s)
V_{MP}	most frequent wind speed (m/s)
$V_{max\,E}$	the maximum energetic wind speed (m/s)
V_m	wind speed measured at the reference height H_1 (m/s)
V_R	rated wind speed (m/s)
V_1	cut-in wind speed (m/s)
V_0	cut-out wind speed (m/s)
y	output
y_{output}	output value
y_{actual}	target value
$\bar{y}_{actual}$	average of target
z	weighted sum
$\Gamma(\ldots)$	gamma function
σ	standard deviation of wind speed
η	efficiency of turbine (%)
α	ground surface friction coefficient
ρ	air density (kg/m^3)

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