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Prediction of Extreme Wind Speed Using Artificial Neural Network Approach

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Abstract: Prediction of an accurate wind speed of wind farms is necessary because of the intermittent nature of wind for any region. Number of methods such as persistence, physical, statistical, spatial correlation, artificial intelligence network and hybrid are generally available for prediction of wind speed. In this paper, ANN based methods viz., Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are used. The performance of the networks applied for prediction of wind speed is evaluated by model performance indicators viz., Correlation Coefficient (CC), Model Efficiency (MEF) and Mean Absolute Percentage Error (MAPE). Meteorological parameters such as maximum and minimum temperature, air pressure, solar radiation and altitude are considered as input units for MLP and RBF networks to predict the extreme wind speed at Delhi. The study shows the values of CC, MEF and MAPE between the observed and predicted wind speed (using MLP) are computed as 0.992, 95.4% and 4.3% respectively while training the network data. For RBF network, the values of CC, MEF and MAPE are computed as 0.992, 95.9% and 3.0% respectively. The model performance analysis indicates the RBF is better suited network among two different networks studied for prediction of extreme wind speed at Delhi.

Keywords: Artificial neural network; Multi layer perception; Correlation coefficient; Mean absolute percentage error; Model efficiency; Radial basis function; Wind speed.

1. Introduction

Wind is renewable source of energy and is almost the fastest growing energy resource in the world, which offers many benefits to human beings. Wind energy has been getting immense attention because renewable energies have got tremendous focus. Due to increase in cost of fossil fuel and the various environmental problems, it is important to appreciate the potential of electricity generation from nonconventional sources. The effective use of wind energy is the conversion of wind power into valuable forms of electricity. The distribution of wind speed is important for power generators [1]. For the purpose, the predicted variations of meteorological parameters such as wind speed, relative humidity, solar radiation, air temperature, etc. are needed in the renewable industry for design, performance analysis, and running cost estimation of the systems. Moreover, for proper and efficient utilization of wind power, it is important to know the statistical characteristics, persistence, availability, diurnal variation and prediction of wind speed. The wind characteristics are needed for site selection, performance prediction and planning of wind turbines. Of these characteristics, the prediction of mean monthly and daily wind speed is very important. For the purpose, number of methods has been employed for the wind power forecasting. The wind power forecasting methods can be generally categorized into six groups such as persistence, physical, statistical, spatial correlation, artificial intelligence network and hybrid [2]. In this paper, application of ANN method in prediction of wind speed is discussed with illustrative example.

2. Theoretical Description of ANN

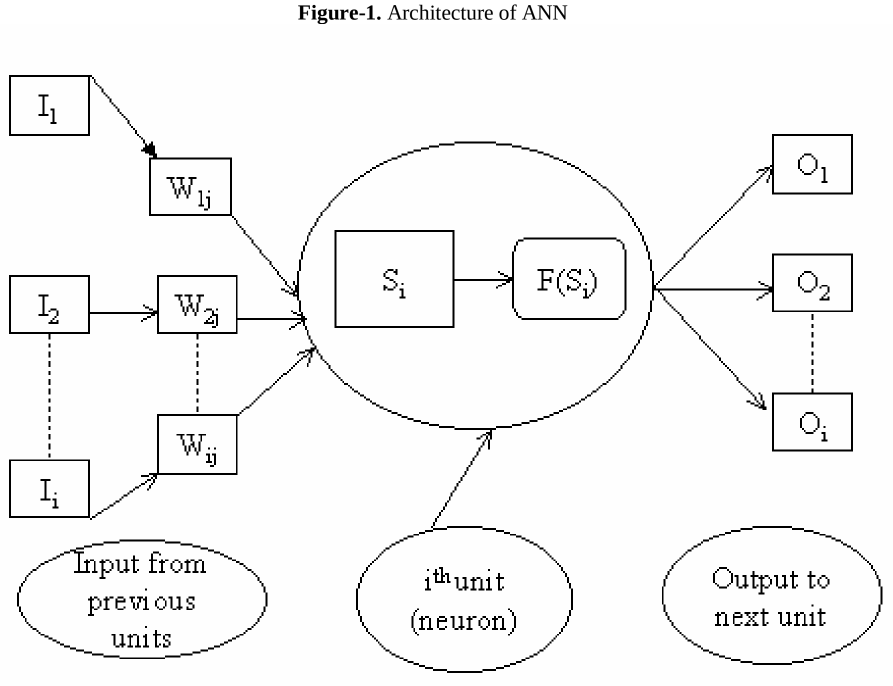
ANN modelling procedures adapt to complexity of input-output patterns and accuracy goes on increasing as more and more data become available. Figure 1 presents the architecture of ANN that consists of input layer, hidden layer, and output layer [3]. In turn, these layers have a certain number of neurons or units, so the units are called as input units, hidden units and output units. From ANN structure, it can be easily understood that input units receive data from external sources to the network and send them to the hidden units, in turn, the hidden units send and receive data only from other units in the network, and output units receive and produce data generated by the network, which goes out of the system. In this process, a typical problem is to estimate the output as a function of the input. This unknown function may be approximated by a superposition of certain activation functions such as tangent, sigmoid and polynomial. A common threshold function used in ANN is the sigmoid function (f(S)) expressed by Eq. (1), which provides an output in the range of $0 \leq f(S) < 1$.

$$f(S_i) = [1+\exp(-S_i)]^{-1} \text{ and } F(S_i) = f'(S_i) \quad \dots (1)$$

$$S_i = \sum_{i=1}^{N} I_i W_{ij} + O_i, \; j=1,2,3,\dots..M \quad \dots (2)$$

where S_i is the characteristic function of i^{th} layer, I_i is the input unit of i^{th} layer, O_i is the output unit of i^{th} layer, W_{ij} is the synaptic weights between i^{th} input and j^{th} hidden layers, N is the number of observations and M is the number of neurons in the hidden layer [4]. The sigmoid function is chosen for mathematical convenience because it resembles a hard-limiting step function for extremely large positive and negative values of the incoming signal and also gives sufficient information about the response of the processing unit to inputs that are close to the threshold value.

Figure-1. Architecture of ANN



3. Literature Review of ANN

With the development of Artificial Intelligence (AI), a number of various AI methods have been developed for prediction of wind speed. The new developed methods include Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System, Fuzzy Logic, Support Vector Machine, Neuro-Fuzzy Network (NFN) and Evolutionary Optimization Algorithm. Out of these methods, ANN could deal with non-linear and complex problems in terms of classification or forecasting. The ANN models can represent a complex nonlinear relationship and extract the dependence between variables through the training process [5]. In ANN, number of training algorithms such as Multi Layer Perceptron (MLP), Recurrent (REC), Radial Basis Function (RBF), Ridgelet and Adaptive Linear Element (ALE) are used for training the network. Sfetsos [6] applied ANN method for forecasting of mean hourly wind speed data using time series analysis. The proposed methodology has an additional benefit for utility that have significant wind penetration level and use hourly interval for power system operational procedures such as economic dispatch and unit commitment. Chang [7] described wind power forecasting methodologies using MLP network. The developed model for short-term wind forecasting showed a very good accuracy to be used by a 2400kw wind energy conversion system in Taichung coast for the energy supply. More and Deo [8] presented two wind forecasting methodologies based on MLP and REC networks. They also found that the results obtained from ANN methods are more accurate than traditional statistical time series analysis.

Chang [9] adopted a method to do time series prediction of wind power generation using RBF network. They expressed that the good agreement between the realistic values and forecasting values are obtained; and the numerical results showed that the proposed forecasting method is accurate and reliable. Li and Shi [10] compared three types of networks namely, ALE, MLP and RBF to forecast the wind speed. They found that no single ANN model outperforms others universally in terms of all evaluation metrics even for the same wind data set. Moreover, the selection of the type of ANN for best performance is also dependent upon the data sources. However, the research reports indicated that there is a general agreement in applying ANN based method for prediction of wind speed. Therefore, in the present study, ANN based methods viz., MLP and RBF networks are used to predict the wind speed with illustrative example.

3.1. Multi-Layer Perceptron Network

MLP network is the most widely used for prediction of wind speed and its architecture with single hidden layer is shown in Figure 1. Gradient descent is the most commonly used supervised training algorithm in MLP in which each input unit of the training data set is passed through the network from the input layer to output layer [11]. The network output is compared with the desired target output and output error (E) is computed using Eq. (3).

$$E = \frac{1}{2}\sum_{i=1}^{N}\left(X_i - X_i^*\right)^2 \qquad \text{... (3)}$$

where, X_i is the observed wind speed for ith sample and X_i^* is the predicted wind speed for ith sample.

$$\Delta W_{ij}(M) = -\varepsilon\frac{\partial E}{\partial W_{ij}} + \alpha\Delta W_{ij}\left(M-1\right) \qquad \text{... (4)}$$

where, W_{ij} is the synaptic weights between input and hidden layers, $\Delta W_{ij}(M)$ is the weight increments between ith and jth units during M neurons (units) and $\Delta W_{ij}(M-1)$ is the weight increments between ith and jth units during $M-1$ neurons. In MLP network, momentum factor (α) is used to speed up training in very flat regions of the error surface to prevent oscillations in the weights and learning rate (ε) is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima [12].

3.2. Radial Basis Function Network

RBF network is supervised and three-layered feed forward neural network. The hidden layer of RBF network consists of a number of nodes and a parameter vector, which can be considered the weight vector. In RBF, the standard Euclidean distance is used to measure the distance of an input vector from the center. The design of neural networks is a curve-fitting problem in a high dimensional space in RBF. Training the RBF implies finding the set of basis nodes and weights. Therefore, the learning process is to find the best fit to the training data [13]. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center. The transfer function of a RBF is mostly built up of Gaussian rather than sigmoid. The Gaussian functions decrease with distance from the center. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center.

The Euclidean length is represented by r_j that measures the radial distance between the datum vector $\underline{X}(X_1, X_2, ...X_M)$ and the radial center $\underline{X}^{(j)} = (W_{1j}, W_{2j}, ...W_{Mj})$ can be written as:

$$r_j = \left\|\underline{X} - \underline{X}^{(j)}\right\| = \left[\sum_{i=1}^{M}\left(X_i - W_{ij}\right)^2\right]^{1/2} \qquad \text{... (5)}$$

where $r_j = \|\ \|$ is the Euclidean norm, $\Phi()$ is the activation function and W_{ij} is the connecting weight between the ith hidden unit and jth output unit. A suitable transfer function is then applied to r_j to give $\Phi(r_j) = \Phi\left\|\underline{X} - \underline{X}^{(k)}\right\|$. Finally, the output layer (k-1) receives a weighted linear combination of $\Phi(r_j)$.

$$X^{(k)} = W_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi(r_j) = W_0 + \sum_{j=1}^{N} c_j^{(k)}\Phi\left(\left\|\underline{X} - \underline{X}^{(j)}\right\|\right) \qquad \text{... (6)}$$

where, $\Phi(r_j)$ is the response of the jth hidden unit and W_0 is the bias term. For both MLP and RBF networks, the units (or) neurons in the hidden layer are decided by the following equation:

$$H_M = \frac{I_P + O_P}{2} + \sqrt{S_N} \qquad \text{... (7)}$$

where, H_M is the number of neurons in hidden layer, S_N is the number of data samples used in MLP and RBF networks, I_P is the number of input parameter and O_P is the number of output parameter [14].

3.3. Normalization of Data

By considering the nature of sigmoid function adopted in ANN, the training data set values are normalized between 0 and 1 using Eq. (8) and passed into the network [15]. After the completion of training, the output values are denormalized to provide the results in original domain.

$$NOR(X_i) = \frac{X_i - Min(X_i)}{Max(X_i) - Min(X_i)} \qquad \text{... (8)}$$

where, $NOR(X_i)$ is the normalized value of X_i, $Min(X_i)$ is the series minimum value of X_i and $Max(X_i)$ is the series maximum value of X_i.

3.4. Model Performance Analysis

The performance of predicted wind speed using MLP and RBF networks are evaluated by Model Performance Indicators (MPIs) viz., Correlation Coefficient (CC), Model Efficiency (MEF) and Mean Absolute Percentage Error (MAPE), and are:

$$CC = \frac{\sum_{i=1}^{N}\left(X_i-\overline{X}\right)\left(X_i^*-\overline{X^*}\right)}{\sqrt{\left(\sum_{i=1}^{N}\left(X_i-\overline{X}\right)^2\right)\left(\sum_{i=1}^{N}\left(X_i^*-\overline{X^*}\right)^2\right)}} \quad \ldots (9)$$

$$MEF\ (\%) = \left(1-\frac{\sum_{i=1}^{N}\left(X_i-X_i^*\right)^2}{\sum_{i=1}^{N}\left(X_i-\overline{X}\right)^2}\right)*100 \quad \ldots (10)$$

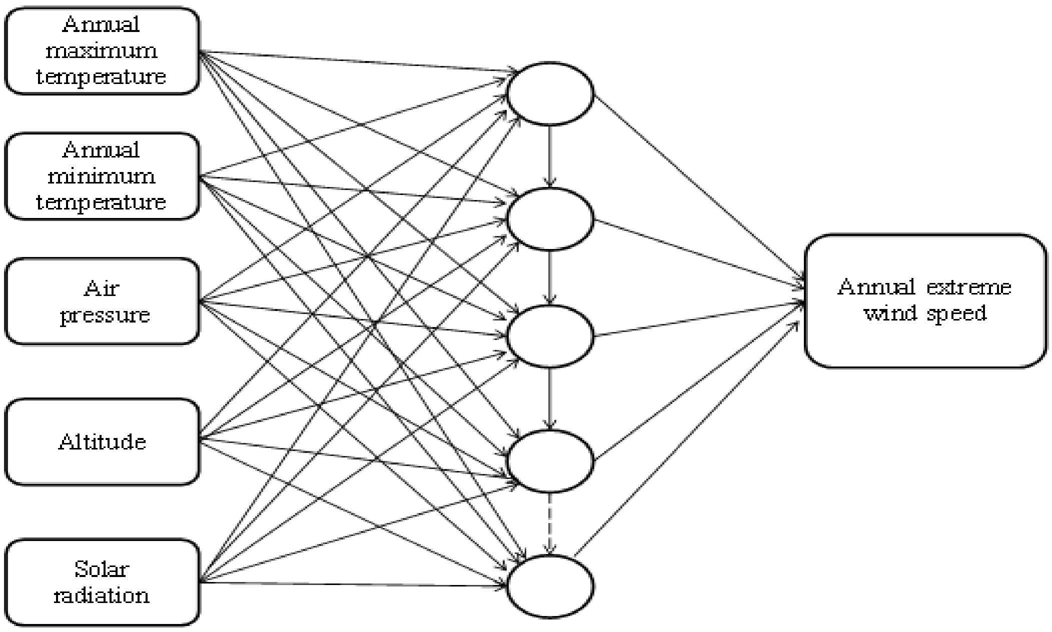
$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{X_i-X_i^*}{X_i}\right)\right|*100 \quad \ldots (11)$$

where $\overline{X}$ is the average observed wind speed and $\overline{X^*}$ is the average predicted wind speed [16].

4. Application

In this paper, a study on prediction of annual extreme wind speed (km/hr) for Delhi region was carried out. ANN based methods viz., MLP and RBF networks were used for training the network. For MLP and RBF networks, the meteorological parameters viz., minimum and maximum temperature, solar radiation, air pressure and altitude were considered as the input units and predicted annual extreme wind speed was the desired output unit. Figure 2 gives the ANN architecture for prediction of annual extreme wind speed. The annual series of meteorological parameters was derived from the daily data recorded at Delhi for the period 1969 to 2013 and used. The data for the period 1969 to 1998 was used for training the network and data for the period 1999 to 2013 was used for testing the network.

Figure-2. ANN architecture for prediction of wind speed



5. Results and Discussions

Statistical software, namely, SPSS Neural Connection was used to train the network data with different combinations of parameters to determine optimum network architectures of MLP and RBF networks for prediction of annual extreme wind speed at Delhi.

5.1. Prediction of Wind Speed using MLP and RBF Networks

In the present study, the input units were normalized and applied to the network as the units of the parameters are different. The momentum factor (α) and learning rate (ε) were fixed as 0.8 and 0.07 while optimizing the network architecture of MLP. The network data was trained with the optimum network architectures of MLP and RBF, as given in Table 1. The networks were tested with model parameters for prediction of wind speed. The output unit was denormalized to obtain the value of annual maximum extreme wind speed in km/hr. The model performance of MLP and RBF networks were evaluated by MPIs and also given in Table 1 for the region under study.

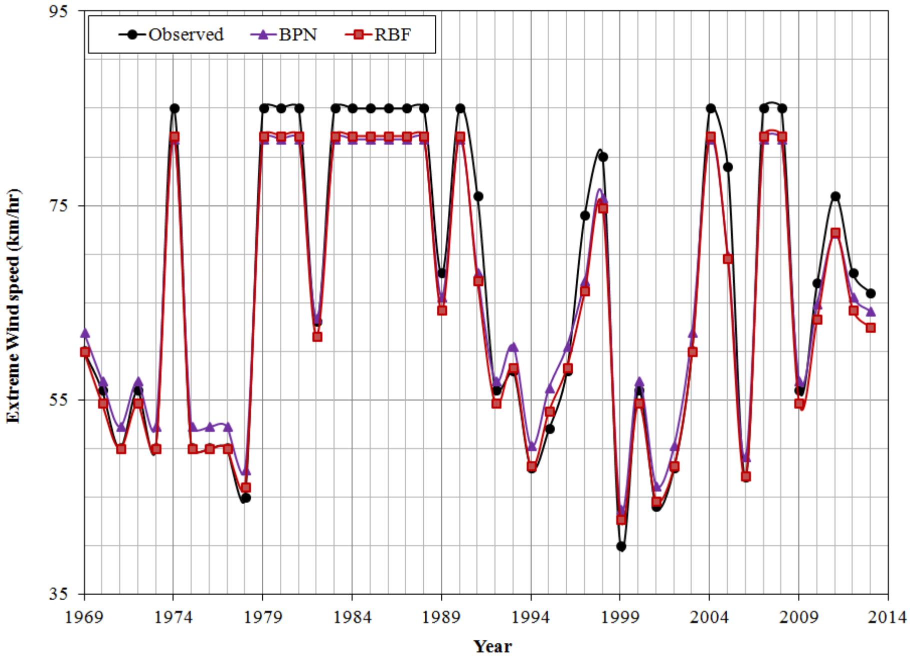
Table-1. Network architectures with MPIs of MLP and RBF networks

Network Architecture and MPIs	MLP		RBF	
	Training	Testing	Training	Testing
Network Architecture	5-10-1		5-15-1	
CC	0.992	0.990	0.992	0.990
MEF (%)	95.4	94.9	95.9	94.7
MAPE (%)	4.3	4.5	3.0	3.8

From Table 1, it may be noted that: (i) The results of MPIs obtained from RBF network is comparatively better than the corresponding values of MLP network while training the network data and therefore the network architecture of RBF is better suited network for prediction of wind speed for Delhi; (ii) The percentage of MEF is computed as about 95% while testing the data set with RBF network; (iii) The percentages of MAPE obtained from MLP and RBF networks are 4.5% and 3.8% respectively while testing the network data; and (iv) There is generally a good correlation between the observed and predicted wind speed using MLP and RBF networks, with CC values vary between 0.990 and 0.992.

Based on the results obtained from performance analysis with the aid of MPIs, it was observed that the RBF network gave high prediction accuracy than MLP network for Delhi. Figure 3 give the plots of observed and predicted wind speed (using MLP and RBF networks) for Delhi.

Figure-3. Plots of observed and predicted wind speed (using MLP and RBF networks)



5.2. Analysis Based on Descriptive Statistics

The descriptive statistics such as average, Standard Deviation (SD), Coefficient of Variation (CV), Coefficient of Skewness (C_S) and Coefficient of Kurtosis (C_K) for the observed and predicted wind speed (using MLP and RBF networks) were computed and given in Table 2.

Table-2. Descriptive statistics of observed and predicted wind speed for Delhi

Statistical parameters	Observed wind speed		Predicted wind speed			
			MLP		RBF	
	Training	Testing	Training	Testing	Training	Testing
Average (km/hr)	67.8	64.1	67.0	62.0	65.8	63.1
SD (km/hr)	15.5	15.6	12.8	12.6	14.0	13.6
CV (%)	22.9	24.3	19.1	20.3	21.3	21.6
C_S	-0.013	-0.006	0.068	0.120	0.103	0.226
C_K	-1.815	-1.319	-1.716	-1.022	-1.747	-1.095

From Table 2, it may be noted that the percentage of variation on the average predicted wind speed using MLP network, with reference to average observed wind speed, is 1.2% during training period and 3.3% during testing period. For RBF network, percentage of variation on the average predicted wind speed with reference to average observed wind speed during training and testing periods were computed as 2.9% and 1.6% respectively.

6. Conclusions

The paper described the procedures involved in prediction of wind speed using MLP and RBF networks for Delhi. From the results of data analysis, the following conclusions were drawn from the study:

i) Optimum network architectures such as 5-10-1 of MLP and 5-15-1 of RBF were used for training the network data.
ii) The values of CC, MEF and MAPE between the observed and predicted wind speed (using MLP network) were computed as 0.992, 95.4% and 4.3% respectively while training the network data. For RBF network, the values of CC, MEF and MAPE were found to be 0.992, 95.9% and 3.0% respectively.
iii) The values of CC, MEF and MAPE between the observed and predicted wind speed (using MLP network) were found to be 0.990, 94.9% and 4.5% respectively while testing the network data. For RBF network, the values of CC, MEF and MAPE were computed as 0.990, 94.7% and 3.8% respectively.
iv) Analysis based on MPIs and descriptive statistics showed that the RBF network is comparatively better than MLP network for the data under study. MLP and RBF networks were tested by predicting wind speed for Delhi for which measured data are available; and the results indicated the developed RBF network gives high prediction accuracy.
v) The percentage of variation on the average predicted wind speed with reference to average observed wind speed was found to be 1.6% while testing the network data with RBF network, which is comparatively less than the corresponding value of MLP network.
vi) The results presented in the paper would be helpful to the stakeholders for planning, design and management of hydraulic and civil structures in Delhi region.

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References

[1] Sahin, A. D., 2004. "Progress and recent trends in wind energy." *Progress in Energy and Combustion Science,* vol. 30, pp. 501-543.
[2] Chang, W. Y., 2014. "A literature review of wind forecasting methods." *Journal of Power and Energy Engineering,* vol. 2, pp. 161-168.
[3] Pallavi, M., Swaptik, C., Sangeeta, R., Nikhil, B., and Roshan, S., 2012. "Dual artificial neural network for rainfall-runoff forecasting." *Journal of Water Resource and Protection,* vol. 4, pp. 1024-1028.
[4] Amr, H. E., El-Shafie, A., Hasan, G. E., Shehata, A., and Taha, M. R., 2011. "Artificial neural network technique for rainfall forecasting applied to Alexandria." *International Journal of the Physical Sciences,* vol. 6, pp. 1306-1316.
[5] Wu, Y. K., Lee, C. Y., Tsai, S. H., and Yu, S. N., 2010. "Actual experience on the short-term wind power forecasting at Penghu-From an Island perspective." In *Proceedings of the 2010 International Conference on Power System Technology.*Hangzhou. pp. 1-8.
[6] Sfetsos, A., 2002. "A novel approach for the forecasting of hourly wind speed time series." *Renewable Energy,* vol. 27, pp. 163-174.
[7] Chang, W. Y., 2013. "Wind energy conversion system power forecasting using radial basis function neural network." *Applied Mechanics and Materials,* vol. 284-287, pp. 1067-1071.
[8] More, A. and Deo, M. C., 2003. "Forecasting wind with neural networks." *Marine Structures,* vol. 16, pp. 35-49.
[9] Chang, W. Y., 2013. "Application of back propagation neural network for wind power generation forecasting." *International Journal of Digital Content Technology and its Application,* vol. 7, pp. 502-509.
[10] Li, G. and Shi, J., 2010. "On comparing three artificial neural networks for wind speed forecasting." *Applied Energy,* vol. 87, pp. 2313-2320.
[11] Wang, Y. M., Traore, S., Kerh, T., and Leu, J. M., 2011. "Modelling reference evapotranspiration using feed forward back propagation algorithm in arid regions of Africa." *Irrigation Drainage,* vol. 60, pp. 404-417.
[12] Jalal, S., Özgur, K., Oleg, M., Abbas-Ali, S., and Bagher, N., 2012. "Forecasting daily stream flows using artificial intelligence approaches." *ISH Journal of Hydraulic Engineering,* vol. 18, pp. 204-214.
[13] Ma, L., Luan, S. Y., Jiang, C. W., Liu, H. L., and Zhang, Y., 2009. "A Review on the forecasting of wind speed and generated power." *Renewable and Sustainable Energy Reviews,* vol. 13, pp. 915-920.
[14] Chow, S. K. H., Lee, E. W. M., and Li, D. H. W., 2012. "Short-term prediction of photovoltaic energy generation by intelligent approach." *Energy Build,* vol. 55, pp. 660-667.
[15] Sudheer, K. P., Srinivasan, K., Neelakantan, T. R., and Srinivas, V., 2008. "A nonlinear data-driven model for synthetic generation of annual streamflows." *Hydrological Processes,* vol. 22, pp. 1831-1845.
[16] Chen, J. and Adams, B. J., 2006. "Integration of artificial neural networks with conceptual models in rainfall-runoff modelling." *Journal of Hydrology,* vol. 318, pp. 232-249.