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Spatial Wind Speed Forecasting Using Artificial Neural Networks

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Abstract: Spatial interpolation is a commonly used technique to simulate wind speeds in areas which are devoid of such measuring devices. In this paper authors examine the applicability and efficiency of Artificial-Neural- Network (ANN) formalism aimed at interpolating wind speeds in space domain. Additionally, the effect of the correlation between the wind speed at target site and its correlated neighboring site is also examined in the present paper. Hourly wind speed data set comprising of wind speeds recorded from April 2016 to August 2018 provided by Energy Sector Management Assistance Program of World Bank is used for the study. The study is supported by including four different wind speed measuring stations in Pakistan, namely, Tando Ghulam Ali, Umer Kot, Sujawal and Sanghar. Best estimates from ANN model are obtained for Tando Ghulam Ali (MAPE= 7.37%) and worst estimates are observed for Sanghar site (MAPE= 10.61%).

Keywords: Spatial interpolation, artificial neural network, prediction, target station, wind speed.

Introduction

Among the renewable energy resources, wind energy is one of the fastest growing and economically viable sources of renewable energy being currently explored. An understanding of wind characteristics is crucial for a proper selection of wind site and for the construction of an efficient wind power generation system. In areas where it is not feasible / practical to install wind speed measuring devices and no past records of wind speeds are available, the assessment of wind potential for such areas cannot be conducted. Consequently, such areas are rendered inoperable. The future growth and development of wind energy conversion systems in un-sampled areas require simulation techniques to forecast wind speeds. Spatial correlation is a widely used technique for forecasting wind speeds at a location using wind speeds in neighboring sites which have wind speed measuring devices. Spatial correlation technique is based on a law, known as Toblers law (Tobler, 1970) which is stated as, “everything is related to everything else, but near things are more related than distant things”. Several approaches can be found to estimate wind speed at un-sampled areas using data from two or more nearby stations (Alexiadis, et al. 1999). Based on this concept, few of these techniques are referred to inverse distance weighting, local polynomial, thin plate spline and kriging (Luo, et al. 2008) techniques. One of the approaches is the Measure-Correlate-Predict (MCP) (Joenson et al. 1999) method. Şen and Şahin (1997) used point cumulative semi veriogram method (PCSV) to find the spatial dependence function (SDF) value between pair stations and estimated wind speeds of the Marmara Region in Turkey.

ANN methodology is widely used technique for estimation, prediction and approximation of function in linear and non-linear problems. In such problems where analytical solution to problems turns out to be complex, ANN which is based on learning mechanism proves to be an effective approach for problem solving. Studies around the globe are conducted for spatial interpolation of wind speed using the ANN approach. Recently artificial neural network (ANN) is used for spatial interpolation of environmental data (Gardner and Dorling 1998). Bechrakis and Sparis (2004) used ANN for forecasting wind speeds at the target station using wind speeds from a strongly correlated site among the nearby stations. The simulation results show that higher Sample Cross Correlation Function calculated among the studied sites gave a good estimate of wind speeds.

In a study Philippopoulos and Deligiorgi (2012) evaluate the ability of ANNs for spatial prediction of mean hourly wind speed, using only wind speed data from nearby sites located in coastal complex topographical region in Chania, Grace. Bilgili et al. (2007) gave predictions of monthly wind speeds of an un-sample target station using artificial neural networks in the eastern Mediterranean region of Turkey. Öztopal (2006) used ANN method for spatial interpolation of wind velocity at a site with no prior records of wind speeds using wind speed data of its surrounding sites in turkey.

Bilgili and Sahin (2013) predicted daily, weekly, and monthly wind speed in some regions of Aegean and Marmara of Turkey. Authors predicted wind speeds for target stations using wind speed data from reference sites as input to ANN. In a study Poitras and Cormier (2011) compared the performance of Neural Networks and Particle Swarm Optimization methods to forecast daily wind speeds for a target station using meteorological data from five reference stations. It is observed that higher the correlation factors between the two sites, better predictions are achieved (Bechrakis and Sparis, 2004). Akinci and Nogay (2012) used a cross correlation function for wind speed for predicting target station wind speeds. Some other significant studies can be seen in refs. (Cellura et al. 2008; Maran et al. 2014; Öztopal et al. 2000; Mohandes et al. 1998).

Aim of the present study is to assess the applicability and performance of ANN technique for the spatial prediction of mean daily wind speeds at a site by using wind speed data from reference sites. The study also examines the importance of the correlation amongst all the stations wind speed data. ANN model is proposed, the inputs to the proposed model are wind speeds recorded in neighboring sites and model outputs are wind speeds for the target study site. The credibility of the proposed model is tested using statistical error analysis.

Materials and Methods

Study Area and experimental data

Study is conducted in a network of four cities located in the Southern province of Pakistan, that is, Sindh. Weather is subtropical with hot dry summers and rainy season during the months from May to September. During hot summer, temperatures go as high as 50 degrees C in some areas whereas in winter, lowest temperature recorded is 2 degrees C. These areas receive ca. 180 mm of rainfall annually mostly during the months of July-August. Hourly wind speed data obtained from Energy Sector Management Assistance Program (ESMAP) (RE Resource Mapping 2012) is used. The study area is a network of four meteorological stations, namely Tando Ghulam Ali, Umer Kot, Sujawal, and Sanghar. Geographical locations of the four stations are shown in Fig. 1. The mean wind speed varies from as low as 5.76 m/s in Umer Kot to as high as 6.48 m/s in Sujawal.

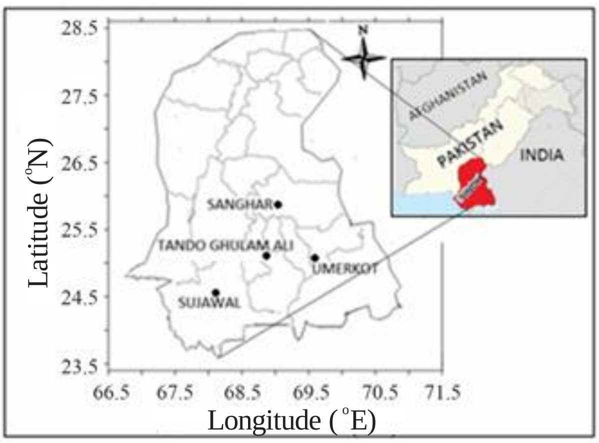

Fig. 1 Map of the study region and their geographical locations.

Wind speed data used in the study is for the period from April 2016 to August 2018 and missing data points in the data set are interpolated using available wind speed data. Four datasets each consisting of 16930 hourly averaged data points are used for four study sites. The number of data points in each set is then reduced by computing daily averages resulting in 882 wind speed data points for the given duration. Anemometers at all stations are installed at a height of 40 m above ground level.

Artificial neural networks

In a neural network the fundamental processing unit is a neuron. Neuron in an artificial neuron network mimics a biological neuron as a simplified mathematical entity. ANN is a layered network of interconnected neurons. Each neuron computes a weighted sum of its input to generate either 1 or 0 at its output, depending upon as the weighted sum is either above or below a certain threshold value. The weighted sum of ‘n’ input signals are computed by artificial neural network. The output of a neuron is computed using the following mathematical relation,

$$y_i = \varphi_i\left(\sum_{j=1}^{n} w_{ij}x_{ij} - \theta_i\right) \tag{1}$$

where ‘y_i’ is the output from the i^{th} neuron, φ is the unit step function or activation function, ‘x_{ij}’ are the input signals, ‘θ_i’ is the threshold associated with i^{th} neuron and ‘w_{ij}’ is the weight related with the j^{th} input. Activation function modifies each input y_i, such that it produces a binary output of either 1 or 0 depending upon if input surpasses or does not surpass threshold limit. Activation function is an important element of a neural network and is used for deep learning. It provides a nonlinear complex mapping of inputs to output variable and introduces nonlinear properties to ANN. In the absence of an activation function, ANN produces a linear regression output. Activation function is also responsible for providing a back-propagation strategy to optimize the outputs. This optimization strategy performs computation of error gradients in the presence of weights. Weights are optimized using gradient descend or any other optimization technique to reduce error. Activation functions are of numerous forms depending upon the complexity of learning mechanism. One such activation function is a standard sigmoid function depicted in the shape of an alphabet ‘S’. Mathematically sigmoid function is expressed as

$$f(x) = \frac{1+e^{-x}}{2+e^{-x}} \tag{2}$$

where ‘x’ values range between -2 to 2. Another activation function is a hyperbolic tangent function also knows as Tangent Hyperbolic function and is given as

$$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} \tag{3}$$

here 'x' values lie between -1 and +1. A linear activation function is expressed by the following mathematical expression,

$$f(x) = x \tag{4}$$

where 'x' lies in the range from $-\infty$ to $+\infty$. Specifically, activation function modifies the input signal at a node in the network and produces an output signal. The output signal then becomes an input signal for the next layer in the network. The final output of the model is the output of the activation function or step function at the output layer.

ANN architecture consists of a layered structure of neurons; layers in the network are organized as an input layer, number of hidden layers and an output layer. Such a multi-layered organization is known as the multilayer perceptron (MLP). MLP is most widely used in meteorological studies for temporal and spatial forecasting of wind speeds. Weights ('w_{ij}') associated with connections are adjusted via a learning scheme. Typically used learning schemes are supervised and unsupervised learning schemes. In a supervised learning scheme, inputs and desired outputs are applied to the ANN and weights are adjusted in order to minimize a predefined error function. In case of unsupervised learning scheme, training is performed by identifying different classes of data and only the inputs fed into the network. There is no quantifiable, best answer for the layout of the network in any particular application. This implies that the number of the hidden layers and the total amount of neurons in each layer are not predetermined but are optimized for best results.

ANN architecture for spatial analysis of wind speed

In the present study, the input parameters ('x_{ij}') to ANN model are the daily wind speeds (in m/s) for the three reference stations, day of the year whereas the output variable ('y_i') is the wind speed for the target station. Trial and error procedure is the best approach of a network architecture model for each station and the performance of the architecture is assessed using the validation data set. The training data adjust network weight ('w_{ij}') according to the predetermined mean square error (MSE). In multi-layered architecture for the input layer or the training algorithm of the model feedforward-Levenberg-Marquardt algorithm (TRAINLM) is used, for hidden layer a Logistic sigmoid transfer function (logsig) is used and for the output layer of the network a linear transfer function (purelin) is used as activation functions. The schematic of ANN architecture used in the present study is shown in Fig 2. The Neural Network Toolbox from Matlab® is used to implement this network. The full data set is randomly divided as 70% training part, 15% testing and 15% validation parts.

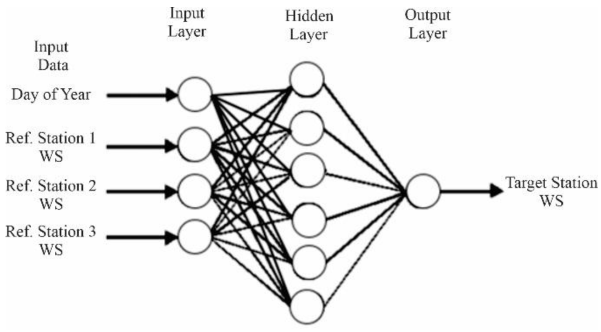

Fig. 2 Artificial neural network architecture (WS = Wind Speed).

Model-performance evaluation

In order to evaluate the performance of the adopted model, various performance evaluation procedures are used. Differences between measured and predicted values can be accurately quantified by using the statistical error analysis. Formulation and application of such procedures are extensively discussed in ref. Willmott et al. (1985). To evaluate the efficiency of developed ANN models following error analysis are criteria for all schemes and stations are used in the present paper.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(ws_{e,i} - ws_i\right) \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(ws_{e,i} - ws_i\right)^2} \tag{6}$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{ws_{e,i} - ws_i}{ws_i}\right|\right)\right)\times 100 \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(ws_i - ws_{e,i}\right)^2}{\left(ws_i - \overline{ws_i}\right)^2} \tag{8}$$

Where '$ws_{e,i}$' and 'ws_i' denote the estimated and measured average daily wind speeds respectively, and 'n' are the number of observations.

Results and Discussion

ANN model evaluation

The number of data points (882 daily wind speed data points) for each station is first divided into two segments, first segment is the data set from April 2016 to February 2018 used for training the network and the second segment is the data set consisting of wind speed points from March 2018 to August 2018. The second set is used for testing the network. The testing data set is not used during training session of the network. The performance evaluation of different ANN architectures is obtained by computing error in estimated and observed data. ANN architecture that is the number of

Table 1 Performance evaluation for prediction of daily mean wind speed using different ANN architectures.

Target station	Reference stations	Architecture of ANN neurons in hidden layers	The Performance Values for model			
			R^2	MAPE (%)	RMSE(m/s)	MBE(m/s)
Sanghar	Sujawal Tando Ghulam Ali Umerkot	4-40-1	0.887	10.73	0.716	-0.018
Sujawal	Sanghar Tando Ghulam Ali Umerkot	4-20-1	0.885	9.21	0.682	-0.029
TandoGhulamAli	Sanghar Sujawal Umerkot	4-10-1	0.921	7.75	0.614	0.01
Umerkot	Sanghar Sujawal Tando Ghulam Ali	4-60-1	0.891	9.89	0.69	0.041

hidden layers of neurons in the ANN model and model statistics for each station are presented in Table 2. The coefficient of determination (R^2 value) obtained for the data set, for all stations range from 0.885 to 0.921. Predicted values are consistent with the measured values as indicated by higher R^2 and the lower MBE, MAPE and RMSE estimates. The performance of ANNs is satisfactory, particularly for Tando Ghulam Ali station (R^2 = 0.921, MAPE = 7.75%, RMSE = 0.614 m/s, MBE = 0.01 m/s).

The correlation coefficients have lowest value of 0.728 for the correlation between Sanghar and Sujawal stations and highest value of 0.909 for correlation between Tando Ghulam Ali station and Sujawal stations. Best performing station is Tando Ghulam Ali, where the correlation between three reference station is highest (0.845, 0.909, 0.838) and worst performing station is Sujawal where the correlation between two reference station is lowest (0.909, 0.774, 0.728) as shown in Table 2.

Predictions of daily wind speeds from the constructed ANN model

Predictions from the constructed ANN model are obtained using 180 days of daily measured wind speeds, that is, from March 2018 to August 2018. The ANN model prediction values are plotted against the actual values for all stations, as shown in Figs. 3-6. Variation in Predicted values from ANN models follows the observed data within the acceptable range. Statistical error analysis for each station is given in Table 3. Plot of Fig. 4 shows that measurements for Tando Ghulam Ali (R^2 = 0.917, MAPE = 7.37%) stations have fairly close agreement with the corresponding measurements. This fact further supports the point that developed ANN models give good results for this station. Sanghar (R^2 = 0.885, MAPE = 10.61%) performed worst. The prediction of ANN for most of the days is in good approximation for the actual values, though the daily average wind speed varies rapidly from day to day.

Table 2 Correlation coefficients of wind speeds amongst study stations

	Tando Ghulam Ali	Umer kot	sujawal	sangur
Tando Ghulam Ali	1	0.845	0.909	0.838
Umerkot	0.728	1	0.774	0.881
Sujawal	0.909	0.774	1	0.728
Sangur	0.838	0.881	0.728	1

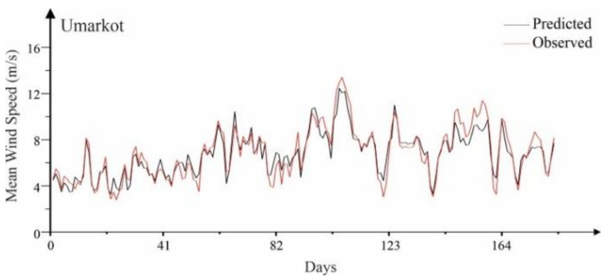

Fig. 3 Predicted and daily measured wind speeds, March - August 2018 (Umarkot)

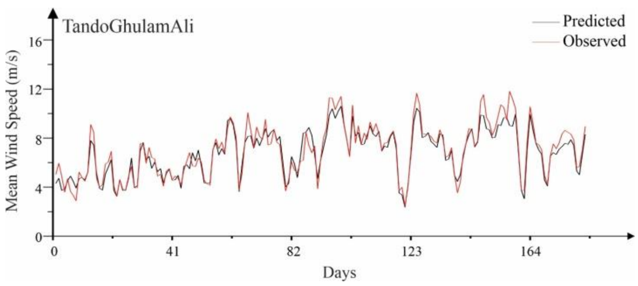

Fig. 4 Predicted and daily measured wind speeds, March - August 2018 (Tando Ghulam Muhammad)

Table 3. Observed and predicted model-performance statistics for all stations.

Target station	The Performance Values for model			
	R^2	MAPE (%)	RMSE (m/s)	MBE (m/s)
Tando Ghulam Ali	0.917	7.37	0.685	0.357
Umerkot	0.891	9.79	0.88	0.098
Sanghar	0.885	10.61	0.915	-0.19
Sujawal	0.856	8.15	0.674	0.158

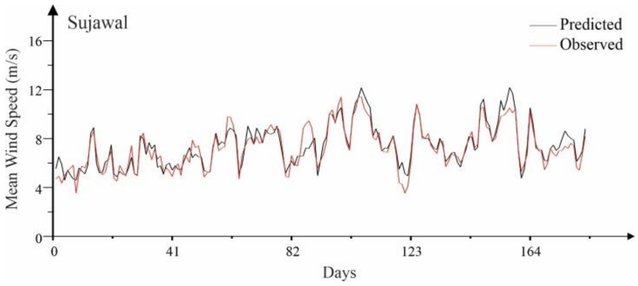

Fig. 5 Predicted and observed outputs (Sujawal)

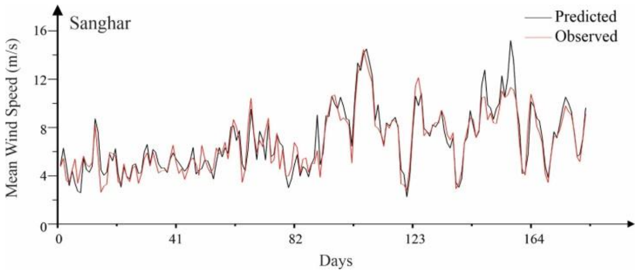

Fig. 6 Predicted and observed outputs (Sanghur).

According to the result of the testing process, the MAPE values range from 8.1 to 10.6%. The maximum correlation coefficient between the measured and predicted value is found to be 0.949 for wind speeds of Sanghar station. On the other hand, the minimum correlation coefficient is found to be 0.908 for wind speeds of Tando Ghulam Ali station.

Conclusion

In the present study, the ANN model has been developed for predicting daily wind speeds of a target station using wind speed data from neighboring station. This prediction model is developed for four locations in the Sindh province, Pakistan. A fairly good cross-correlation coefficient of the wind speed between the stations is obtained. Error Comparisons between predicted and recorded wind speed of target station shows that results obtained from these models are within acceptable limits. Best predicted result is achieved from ANN model for Sujawal station (MAPE = 7.37%) and worst result is obtained for Sanghar (MAPE = 10.61%) as shown in Table 3. In addition, it is found that the performance of the model also depends on the wind speed correlation among stations. In our study, it is concluded that the higher the correlation amongst the target station and neighboring station, better is the simulation achieved using the model. The advantage of the proposed ANN model is the use of wind speed data obtained from neighboring station. The wind speeds of the target station are predicted with acceptable accuracy, without the use of any other climatic parameters. Furthermore, using wind speeds data from the neighboring stations, the un-sampled future wind speeds at the target station are predicted promptly and with reasonable accuracy without the use of any other climate parameter.

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