Wind Speed Prediction in Non-Monitored Areas Based on Topographic Radial Basis Neural Network (T-RBNN)

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Abstract. This paper shows an improved method for the prediction of wind speed in the areas where wind monitoring station is not available. The model has nine meteorological inputs, and one output, which is wind speed. The model was developed using Matlab/Simulink (R2016). The model was trained, tested and validated for accuracy purposes. The overall performance of the model was judged using statistical measures. It was realized that the developed model is capable of reproducing wind speed in the areas not covered by measurements. The root mean square and covariance of the developed model was 7.18 % and 0.0098 respectively.

1. Introduction

Wind power is well-recognized renewable energy producing, clean, safeguarded and foreseeable electric power. It has absolutely negligible carbon emission, and has reduced operational cost, that can be operated during the day and night times, with virtually zero greenhouse gas emission [1-2]. Before a wind energy system is installed, detailed wind resource assessment (WRA) must be conducted properly. The most important parameter of the WRA is wind speed, followed by wind direction. Because of this, wind speed must be measured or predicted with a high degree of accuracy.

According to [3], most of the early research work conducted on wind speed prediction were performed using either physical or numerical mathematical models, for example [3-4]. However, it was realized in many studies that due to the unpredictable nature of wind speed as it propagates in the atmosphere, it will be difficult to construct a reliable mathematical function, which will model the wind speed perfectly. Furthermore, according to no mathematical model either physical or numerical that will give an approximate solution of the wind speed model.

Generally, due to those weaknesses mentioned above, researchers have devoted time in finding a suitable model that will give an acceptable solution. Soft computing prediction models are found to be acceptable in terms of reliability and accuracy.

Based on the aforementioned, a lot of studies were carried out reported in scientific studies. Generally, wind speed predictions are classified based upon prediction periods/horizons, that is very short-term, short-term, medium-term and long-term. Wind speed prediction using data mining approach has successfully implemented in [5]. Instead of predicting wind power directly, authors [6] in predicting wind speed using support vector machine (SVM). Simulating annealing and SVM was proposed to overcome the use of SVM alone [7]. The fuzzy logic approach has been tested in [8] to predict wind speed values. Wind speed prediction using Radial Basic Function Neural Network (RBFNN) was suggested by [9], the model was validated using real wind speed data, and it was found to be feasible, to reduce wind speed uncertainties. One study [10] proposed the application of Artificial Neural Network (ANN) and Artificial Intelligent (AI). ANN and Markov chain model was

implemented for short-term wind speed [11], it was reported that prediction errors and wind speed uncertainties have reduced drastically. Feed forward Neural Network designed was trained with conjugate gradient algorithm and other training algorithms. The outcomes of this show an ANN approach has lees errors. Reference wind speed data was utilized to predict wind speed of four cities in turkey by means of ANN [12]. RBFNN and Empirical Mode Decomposition was applied for short-term wind speed prediction, results comparison with conventional methods indicate the suitability of the proposed method in terms of accuracy. Cluster analysis and ANNs were successfully developed to predict wind speed in Spain [13]. An improved ANN was built to predict wind speed and direction; simulation results demonstrate the accuracy of the suggested method.

Based on the short review reported here, it is acknowledged that ANNs have simple structure, fast convergence, and self-adapting, high accuracy, unlike fuzzy logic, which require a lot of fuzzy membership's rules and problems of parameter input selection. Because of this reason ANNs are widely accepted as a predictive tool in many reported studies. Furthermore, it can be noted from the review, none of the listed research works, consider the effect of terrain in developing the ANN model. Wind speed is affected by terrain variation, because of this; this study tries to bridge the gaps by introducing a terrain-based model named topographic-RBFNN (T-RBFNN) to predict the wind speed in the location with no wind station based on the nearby wind monitoring station.

2. Methodology

2.1. Study area description and data collection
The study area is the Kano University of Science and Technology, Wudil. Kano State, Nigeria (Latitude: 11 °48' 18" N and Longitude 8 °50' 43" E). The DevisPro weather Monitoring was mounted at 5m height shown in Figure 1. The Anemometer is used to measure the wind speed and wind direction at an update rate of 5 second and averages every one hour. The average hourly data were then stored in a computer system permanent memory attached to the Davis-Pro monitoring system. The data were exported into Microsoft Excel files or further analysis.

Figure 1. Position of the wind monitoring system.

2.2. Terrain data generation
Topographical maps are expensive and mostly they are restricted for security reasons. A simple, cost effective technique has been applied here to generate a terrain data. Two software was hybridized, GEPlot and Google Earth. The areas were mapped and viewed using Google Earth, While, GEPlot was utilized to point and demarcate the variations between marked points, and to locate the latitude

and longitude of each location pointed out. All the data points were exported to Terrain Zonum Solutions (TZS) to view the digital elevation model (DEM). The DEM was viewed in Google Earth; finally the terrain data were generated and stored in a database system. Figure 2 shows the summary of the designed methodology.
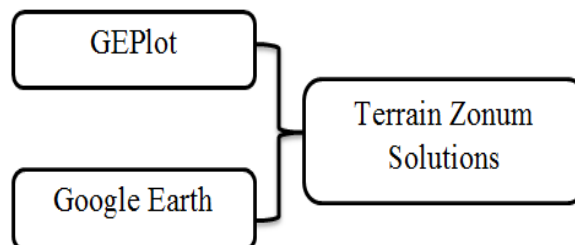

Figure 2. Terrain data generation.

2.3. T-RBFNN design
The ANN can be used without mathematical formulation. It works like the human being brain. The system learns to perform task once it is trained. ANNs have input, output and hidden layers. The neurons are connected to a large number of weights in which signal or information can pass through. Once the inputs are applied, the neurons will receive it and perform nonlinear operations. Generally, Matlab was commonly used to design and train the model. The neural network used in this work is RBFNN, among the most powerful for short-t prediction. Figure 3 shows the architecture of the ANN used in this paper.
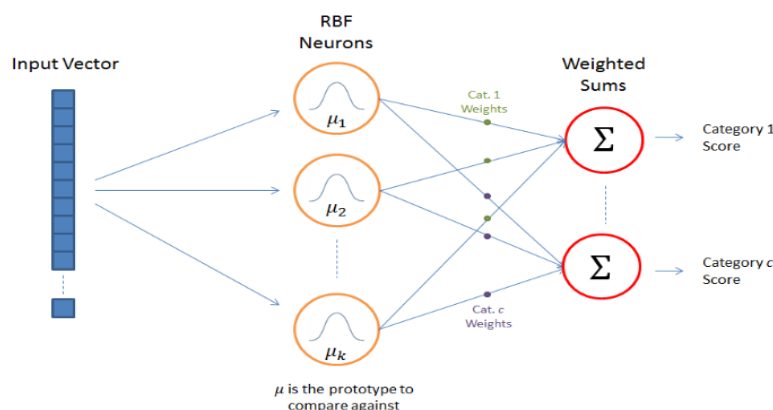

Figure 3. RBFNN model.

The input vector is the n-dimensional vector that is used to classify. The entire input vector is shown to each of the RBF neurons. Each RBF neuron stores a "prototype" vector that is only one in the vectors in the training set. Each RBF neuron measures up the input vector to its model, and produces a value in between 0 and 1 which can be a determine of likeness. If the input is the same for the model, then the output of that RBF neuron is going to be 1. As the range relating to the input and prototype increases, the response drops off tremendously to 0. The appearance of the RBF neuron's reaction is a bell curve, as shown in the network structure diagram. The transfer function used in this paper is a logistic-sigmoid function whose equation is:

$$\log istic(u) = \frac{1}{1 + e^{-u}} \tag{1}$$

The ANN is trained to solve problems rather program to do so. Learning could be possible via proper training. Training is a method to teach the network on how to behave. Learning is the outcomes of the training. Learning can be supervised or unsupervised, depending on the set goals. In this paper,

supervised learning is adopted, because training data are applied to infer the RBFNN model. Measured wind speed for a period of four years (4) (2013-2016) were segmented into three (3) parts, from 2013-2015 was used for the training, while 2015 and 2016 data were applied to test and validate the designed network. Matlab (R2013) is used to design and train the proposed model. The model has nine inputs (relative humidity (%), latitude (0N), longitude (0E), altitude (m), and month (days)) a monthly wind speed as the output (See Figure 4).
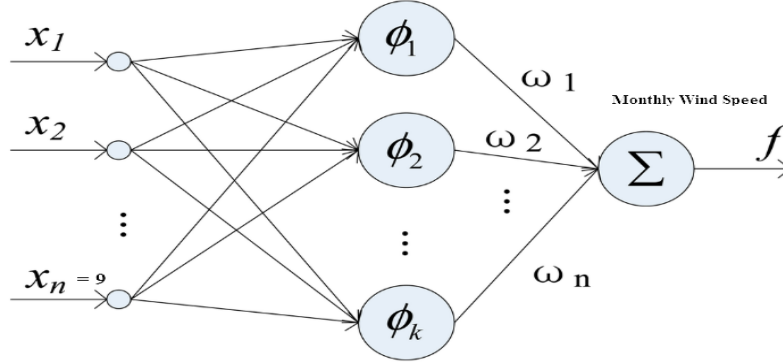

Figure 4. Developed RBFNN model.

Prior to the training, all the data were scaled to [0, 1] using minimum-maximum quotient rule, so as to avoid network confusion. To overcome the slow convergence of the network an improved algorithm, Levenberg-Marquardt algorithm (LMA) is used, in order to minimize the error between inputs and the outputs. Furthermore, to avoid under-fitting and over-fitting of the network, the number of neurons in the hidden layer carefully varied from 5-250 with a step of 5, until the optimum network is realized. Once the training, testing and validation are completed, the suitability of the model was evaluated statistically using:

$$R = \frac{\sum\limits_{i=1}^{N}(t_i - \bar{t})*(o_i - \bar{o})}{\sqrt{\sum\limits_{i=1}^{N}\left(t_i - \bar{t}\right)^2} * \sqrt{\sum\limits_{i=1}^{N}(o_i - \bar{o})^2}} \tag{2}$$

$$MAPE = \left[\frac{1}{N}\sum\limits_{i=1}^{N}\left|\frac{t_i - o_i}{t_i}\right|\right]*100 \tag{3}$$

N represents the number of data points, and t_i, o_i stands for the target (reference) value and the T-RBFNN predicted value for data point i. Bars indicate average values.

3. Results and Discussion
The third phase of the data used in this paper was predicted by means of NN models in a region with no monitoring based on the proximity of available wind stations taking into account the roughness factor and terrain variations. As discussed previously, a new t T-RBFNN approach was proposed and designed. The model consists of three layers: input, hidden, and output. The input/output vectors are the same in both structures. For better convergence, the normalized inputs, target, and sample data were chosen. It was also found that 152 neurons in a hidden layer trained L–M provides the best performances and the fewest prediction errors. Similarly, for the RBFNN design, the number of neurons in the hidden layer, type of activation, and training algorithms was carefully selected consistent with the methodology. T-RBFNN modelling starts with the training phase, and testing data sets must be designed and built. An epoch refers to a single iteration through the process of updating

the weight of each link in the network. The developed model was employed to estimate the wind speed values at two locations nearby. The time series meteorological data from 2013-2016 observed at the KUST central research lab station were used to train the forecast model and from 2011-2012 was applied to test the prediction results. Several models were designed and trained to identify the optimum network. Simulations were carried out to calculate the approximate wind speed values.
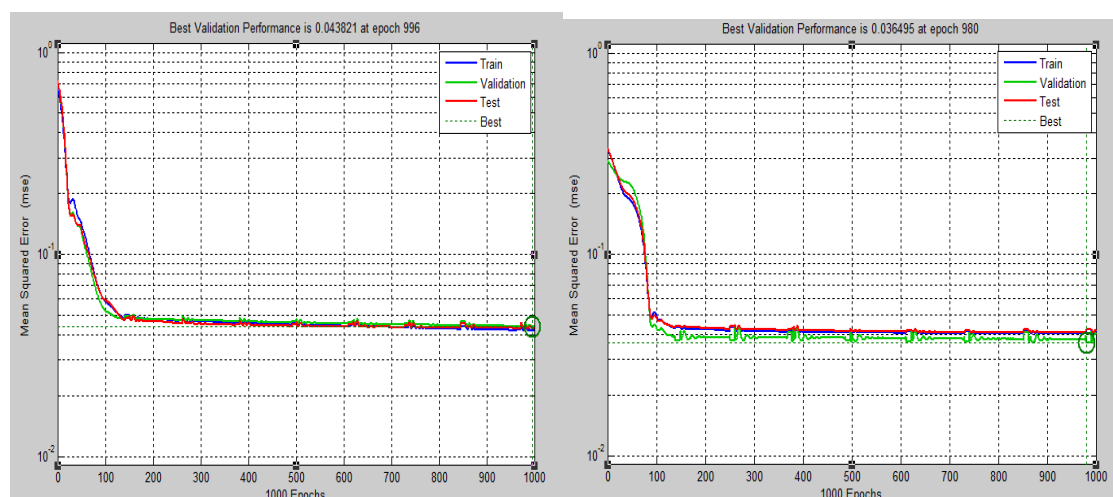

Figure 5. Developed RBFNN model ANN training (a) location 1 (b) location 2.

During the learning process, the weights were set one at a time using wind shear data between the reference area and a target position so that the desired input/output relation of the network would be achieved. The iteration is executed repeatedly until the difference between the real output of the network and the preferred output is a negligible value, which signifies that no additional advancement in the network was achieved. An example of MSE versus epoch for the learning and cross-validation is displayed in Figure 5 a and b, acquired from the reference data. It is very clear from the diagram that, right after 100-950 epochs, the MSE between the T-RBFNN predictions and test data were steadily minimized from to 0.043821 and 0.03649, at best validation points of 996 and 980 which indicates the finest validation effectiveness. Extending the training process could run to the R-BFNN to memorize the training data sets and behaves in poor generalization capability of the T-RBFNN model. The GOF of the above approach has been examined based on the correlation R; the best network has the values of 0.80276, 0.79777, and 0.81081 for lcation1, while location 2 has 0.98314, 0.9827, and 0.98292 for the training, testing, and whole data sets. The most effective training function choice was carried out by contrasting the regression results of the various training functions, such as in Figures 6 a and b), in which the match line indicates the pattern line of training. The closer the trend line is on the straight line ($Y=T$), the superior prediction outcomes can be found in the T-RBFNN prediction application. The marked series shows the situation in which the outcome results of the T-RBFNN model are exactly the same as all the target data; this signifies that this is the finest situation for the developed prediction tool. In all the error model graphs, small oscillations were noticed above 100, this would probably be as a result of changes occurred in the roughness length parameters between diverse classes. However, at the starting of the propagation, normally the wind is Geostrophic, afterward; there is an effect of a large-scale terrain slope. Although, the oscillation is minimal as a result of the perturbation due to wind flow.

Furthermore, a comparison was made between the observed wind speed and the predicted wind speed, the result is depicted in Figure 7. As shown in the figure, there is a high positive correlation between the measured wind speed and the predicted wind speed. It is important to note that the common metric for wind speed correlation has been reported [14], values from 0.75-1.00 could be

accepted as good correlation. In order to demonstrate the suitability of the proposed method, a results comparison with other models in the literature shows values between 0.55-0.76 [15-21].
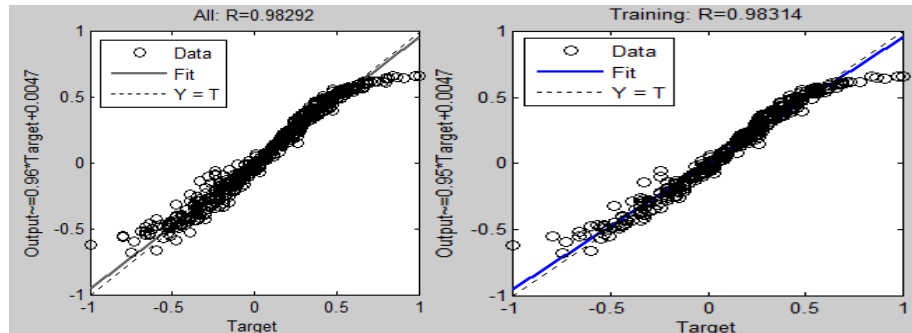

Figure 6. Regression results for (a) Location 1 (b) Location 2

The training approach for those models was thoroughly looked into. The model effectiveness was assessed according to statistical solutions correlation coefficient and mean absolute percentage error (MAPE). These values are acquired mathematically making use of Equation 2 and 3 accordingly. Table 1 shows the summary of the network based on training with most appropriate algorithms and the model with the best possible perdition precision. No results of the inappropriate neurons were provided in this paper.

Table 1: Statistical and error values of ANN

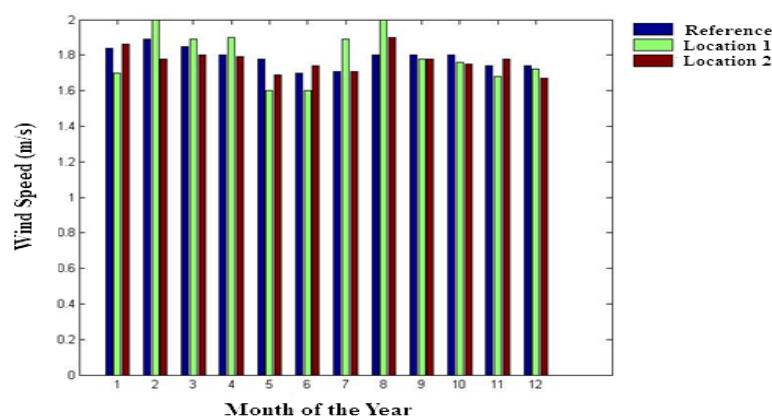| Reference Station	Target Areas	R	MAPE (%)
	Location 1	0.812	5.01
	Location 2	0.627	5.63

Fig. 7 Comparison between the predicted wind speed and measured reference wind speed (a) Location 1 (b) Location 2.

4. Conclusion
This paper demonstrates the potentiality of using an improved T-RBNN to predict wind speed in the areas not covered by measurements. The developed model was tested and validated using the nearby

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wind station. It was found that the model is suitable to reproduce wind speed with acceptable accuracy. Future works can consider using T-RBFNN with ARIMA for longer time prediction.

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