LONG-TERM WIND SPEED PROJECTION BASED ON MACHINE LEARNING REGRESSION TECHNIQUES IN THE PERSPECTIVE OF BANGLADESH

Istiak Ahmed and Muhibul Haque Bhuyan

Abstract**—**Wind speed projection is a research hotspot in wind energy conversion systems because it aids to optimize the operating costs as well as boost the reliability of power generation from wind. Wind power output depends on wind speed that depends on different parameters. Non-linearity among these parameters makes machine learning methods a preferable approach. In our work, we have used eight parameters and fifteen different machine learning regression methods to predict the hourly wind speed of five different sites of Bangladesh. The results obtained from these methods are very compelling as it has a low Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). So, this sort of investigation can be effective for future wind energy-related ventures and research in Bangladesh.

Keywords**—**Wind Power, Wind Speed, Machine Learning Algorithm, Regression Methods, Renewable Energy.

I. INTRODUCTION

THERE is no denying the fact that both developed and developing countries are looking for new forms of energy for their economic sustainability. Bangladesh has targeted to generate 10% of electrical power from renewable energy sources by 2020. However, so far the achievement from renewable energy sources is only 3.5% up to 2015 [1]. New energy is attributed to novel practices of energy generation like alternative, free, or renewable energy that encompass wind energy, biofuel energy, geothermal energy, nuclear energy, distributed energy, solar energy, etc. [2, 3]. Among them, wind energy is highly regarded as one of the brighter prospects of the next generation of energy sources to mitigate the continuing energy crisis in several parts of the world. It not only serves as clean energy without pollution but also has the merit of renewability without limitation of usage [4]. However, electrical power from wind energy possesses high volatility and randomness and creates severe impacts to the power system process [5]. Hence it is imperative to predict electrical power generation from wind energy prior to building a plant in that specific region [6].

Wind speed prediction is a vital task in wind energy conversion systems because it helps to optimize the working expenditures and boost the reliability of power generation from wind energy [7, 8]. The forecast zone depends on users and should also satisfy the technical and regulatory issues and the viability of forecasting. Accuracy and efficiency are the two vital terms that should be emphasized in wind speed prediction tactics. It may be advantageous that the estimation of power production from wind source as it is a function of wind velocity that has amplitude and azimuth angle [9-11].

There are two primary forecast horizons for wind speed prediction, for example a long-term and a very short-term forecasting [2, 12]. Typically there are three types of methodologies for wind speed prediction, such as physical [13], statistical [14], and machine learning methods [15, 16]. The physical model provides point estimates, thereby limiting its effectiveness to the deterministic rather than the stochastic problems, though as a whole method may be developed to bypass this shortcoming [17]. The research works were done to find a linear or non-linear mapping with the historical wind speed data to project the forthcoming wind speed by utilizing different mathematical models, like the Auto-Regressive and Moving Average (ARMA) model [18] and the Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model [19, 20]. There are a huge number of statistical approaches to foresee the wind speed, for example Statistical Regression [21], Markov Model [22], Principal Components Analysis (PCA) [23], Bayesian methods, etc. [24]. The evaluation of the wind speed is a nonlinear regression problem. That is why, the Machine Learning models are intermittently endorsed for wind speed projecting with satisfactory prediction results [25]. Where complex systems are involved and data are abundant, Machine Learning (ML) techniques are more suitable for wind

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speed prediction [26]. Machine Learning (ML) topologies include Adaptive Neural Fuzzy Inference Systems (ANFIS) [27], Artificial Neural Network (ANN) [28], Support Vector Machine (SVM) [29], etc. to estimate wind speeds. These different models can solve the problems related to the nonlinear regression and as such these methods may be applied to different scopes to forecast anything.

II. THEORETICAL BACKGROUND ON MACHINE LEARNING REGRESSION ALGORITHMS

Machine Learning (ML) algorithms predict an unidentified reliance between the inputs that are the independent variables and the outputs that is a dependent variable in the training dataset. Here, different Machine Learning Regression (MLR) methods are employed (shown in Table I) as learning algorithms to forecast the wind speed of selected locations.

The purpose of employing the MLR methods is to choose the optimized function that optimizes the error between the actual output and the projected output using the sample dataset. The details about the methods are outlined in the following sub-sections.

TABLE I
REGRESSION METHODS USED IN THIS WORK

Categories	Method name	Abbreviation
Function	Simple Linear Regression	SLR
	Linear Regression	LR
	Least Median Square	LMS
	Multilayer Perceptron	MLP
	Radial Basis Function Neural Network	RBF
	Pace Regression	PR
	Support Vector Poly Kernel Regression	SMOReg
Lazy-Learning Algorithm	IBk Linear NN Search	IBK
	KStar	K*
	Locally Weighted Learning	LWL
Meta-Learning Algorithm	Additive Regression	AR
	Bagging REP Tree	BREP
Rule-Based Algorithm	Model Trees Rules	M5R
Tree-Based Learning Algorithm	Model Trees Regression	M5P
	REP Trees	REP

A. Functions

Under the 'Function' category there are seven methods. In the following sub-sub sections, these seven methods are described:

1) Simple Linear Regression Method

The Simple Linear Regression (SLR) method is the operation of matching linear models between each input element and output [30]. Its representation is like a linear equation as shown in equation (1) which combines a specific set of input values (x_0, x_1) and the solution for this set of input values is the projected output value (y). For example, if w_0 and w_1 are the weights of the inputs, x_0 and x_1 respectively, and x_0 is assumed as constant then the output y is given by the equation (1).

$$y = w_0 + w_1 x \tag{1}$$

2) Linear Regression Method

The Linear Regression (LR) method embodies numerical modeling of relating one dependent output variable or signal with one or more independent input variables or signals. It forecasts the output value based on the weight instances of each input. If there exists some linear dependency between the data, LR can predict the best output having the lowest squared error [31]. The prognostic model is a linearly regressed line with a set of inputs x_0, x_1, x_2, x_3,……, x_k and their corresponding weights w_0, w_1, w_2, w_3…… w_k respectively for each input variable. In this case, the first input, x_0 is assumed as constant. As a result, the final linearly regressed model is given by equation (2).

$$\mathrm{y} = \mathrm{w}_0 + \mathrm{w}_1 x_1 + \mathrm{w}_2 x_2 + \mathrm{w}_3 x_3 + \cdots + +\mathrm{w}_k x_k \tag{2}$$

After the anticipated outcome for all the inputs is collated, the weights are refurbished to minimize the summation of the squared errors, i.e., the difference between the real output and the projected output.

3) Least Median Square Method

The Least Median Square (LMS) method is another type of linearly regressed model that diminishes the median of the squared errors. In the topology of the LMS algorithm, the weights are rationalized to minimize the median of the squared errors, i.e., the difference between the real output and the projected output as in the linear regression equation (3) [32].

$$\mathrm{Median}\left(y^i - \sum_{j=0}^{k} \mathrm{w}_j x_j\right) \tag{3}$$

4) Multi-Layer Perceptron Method

The Multi-Layer Perceptron (MLP) method is based on the Feed-Forward Artificial Neural Network model. It contains neurons of massively weighted interconnects. It has three layers, such as one input layer, one output layer, and minimum one hidden layer as illustrated in Fig 1.

A supervised learning scheme well-known as backpropagation for training is used by it. The input signals are delivered to the hidden layers by the input layer. The hidden layers and the output layer raise the input signal levels by a set of weights and convert them into the output either linearly or non-linearly as shown in Fig. 1. These weights are optimized to minimize the squared errors and to attain a reasonable prediction accuracy [33].

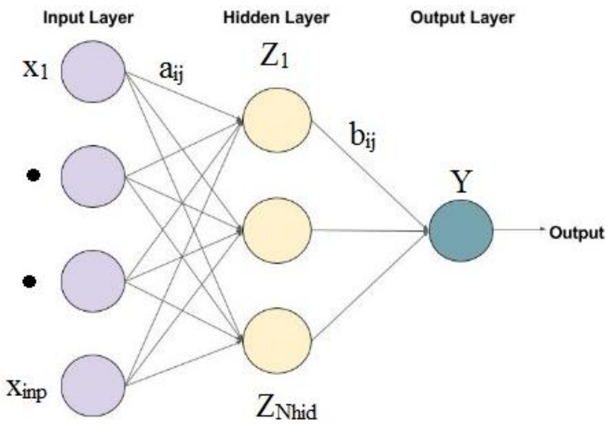

Fig. 1. Multilayer perceptron neural network

The signals that are sent from the input stratum to the hidden stratum for a distinctive MLP with one hidden stratum can be arithmetically represented as in equation (4). It is done by taking the summation of the products of the input signals, X_i and weighing factors (a_{ij}) with the addition of a bias term (a_{0j}) of the hidden layer as denoted by equation (4).

$$u_i = \sum_{i=1}^{N_{inp}} X_i a_{ij} + a_{0j} \quad (4)$$

The outputs of the hidden stratum, Z_j may be written as a function, g of the u_j by altering the equation (4) as per equation (5).

$$Z_j = g(u_j) \quad (5)$$

Sigmoid function, an activation function is the most extensively utilized transfer function that is defined in equation (6) for input variable, x.

$$g(x) = sigmoid(x) = \frac{1}{1+e^{-x}} \quad (6)$$

After that, by taking the summation of the products of hidden stratum's outputs (Z_j) and weighing factors (b_{jk}) and output stratum's bias term (b_{0j}) may be expressed as in equation (7).

$$v(k) = \sum_{j=1}^{N_{hid}} Z_j b_{jk} + b_{0j} \quad (7)$$

The outputs of the output stratum are found by using the equation expressed in (8) [34].

$$y_k = g(v_k) \quad (8)$$

5) Radial Basis Function Method

To activate a particular node, the Radial Basis Function (RBF) method is used. It is based on the normalized distance between the input and hidden nodes [35]. This different from MLP method in which sigmoid is used for the activation. To search whether the node is activated or not at a specific hidden point/node, a Gaussian function is used as expressed in equation (9) [36].

$$h(x) = exp\left\{\frac{-(x-c)^2}{r^2}\right\} \quad (9)$$

, where r is the width and c is the center of Gaussian function's plot.

6) Pace Regression Method

The Pace Regression (PR) method diminishes the deficiencies of standard regression. It generates a prognostic model by assessing the aftermaths of each input variable and using a clustering investigation to boost the statistical base for forecasting their influence upon the general regression [37].

7) Support Vector Machines Regression Method

The Support Vector Machines (SVM) regression method is a learning algorithm that uses the kernel. They are used to resolve the problems related to the classification and regression analysis. Support Vector Regression (SVR) transforms the input data, x into a space that is featured with the higher dimensions, and thus making it possible to perform linear operation [38]. Support Vector Poly Kernel Regression (SVPKR) is employed to obtain the sequential minimal optimization algorithm in this study to train the regression model based on SVM.

B. Lazy Learning Algorithm

The Lazy Learning Algorithm (LLA) has three methods, which are described in the following three sub-sub-sections.

1) IBk

It is a K-nearest neighbor classifier that chooses a suitable value of K based on cross-validation. The IBk archetype generally supports robust learning algorithms. Another favor of this algorithm is that it can withstand noise and irrelevant attributes and can represent both probabilistic and overlapping concepts [39]. For a test instance (q_i), prediction is measured according to equation (10).

$$Sim(q_i, s_j) = 1 - \frac{\sqrt{\sum_{f=1}^{N} \delta(q,s,f)^2}}{\sqrt{N}} \quad (10)$$

2) KStar (K*)

The K* is a type of classifier that utilizes an entropy-based distance function for regression based on an instance [40]. The test instance is obtained based on the analogous instances in the training set. For any function P*, the effective number of instances can be calculated by utilizing the equation (11).

$$n_0 \leq \frac{(\sum_b P*(b|a))^2}{\sum_b P*(b|a)^2} \leq N \quad (11)$$

, where N is the total number of training instances and n_0 is the number of training instances at the minimum distance from a and b is the blending parameter ranging from 0% (for n_0) to 100% (for N).

3) Locally Weighted Learning (*LWL*)

It is a kind of lazy learning method that is a locally weighted version of naive Bayes that loosens the independence assumption by learning local models at a particular prediction time [41]. The weights (w_i') are computed by the equation (12).

$$w_i' = \frac{w_i \times r}{\sum_{q=0}^{n} w_q} \tag{12}$$

And w_i is obtained using equation (13).

$$w_i = f\left(\frac{d_i}{d_k}\right) \tag{13}$$

C. *Meta Learning Algorithm*

The Meta Learning Algorithm (MLA) has two methods, which are described in the following two sub-sub-sections.

1) Additive Regression (*AR*)

The Additive Regression is a kind of Meta-Learning Algorithm that provides with estimates by incorporating different combinations from a pool of models. Residuals left by previous classifiers will be fitted with the next iteration. Predictions of each classifier are added to achieve total prediction [42].

2) Bagging REP Tree (*BREP*)

The REP tree is an algorithm that uses the principle of calculating the information gain with entropy and reducing the error arising from variance. The variance associated with REP trees can be reduced by the bagging technique [43]. Bagging can be communicated via the equation (14).

$$\hat{Y}_{BAG} = \frac{1}{B}\sum_{b=1}^{B} \phi\,(x; T_b) \tag{14}$$

, where B is the number of bootstrap samples of training set T, x is the input, $\hat{Y}_{BAG}$ is the mean value of the projected trees [44].

D. *Rule-based Algorithm*

The Rule-based Algorithm has only one method, which is described in the following sub-sub-section.

1) Model Trees Rules (*M5R*)

The M5R method creates a choice list for regression related problems by means of the Divide and Conquer method. In an individual iterative step, it constructs a tree for the desired model and generates the most fitted leaf into a rule [45].

E. *Tree-Based Learning Algorithm*

The Tree-Based Learning Algorithm (TLA) has two methods, which are described in the following two sub-sub-sections.

1) Model Tress regression (*M5P*)

The M5P is another kind of regression-related decision tree algorithm that also uses the Divide and Conquer method to construct a model tree with the help of the M5 algorithm. The tree is passed from top to bottom till a leaf node is found. In the tree, a decision is prepared at each node to track a definite branch depending upon a testing condition based on the characteristic accompanying with that node [32].

2) Reduced Error Pruning (*REP*)

The REP procedure checks for all internal nodes of a tree and determines to replace it with the most repeated class that doesn't decrease the accuracy of trees. REP traverses from top to bottom of the tree and the procedure continues until there is any more pruning left that would reduce the accuracy. Quinlan [46] used a pruning set to predict the accurateness and the process terminates with the smallest accurate subtree concerning a particular pruning set [47].

III. THE DATASET

The dataset has two components, such as the data source and the data description.

A. *The Data Source*

The data used for forecasting wind speed is obtained from the NASA database for the year 2010 to 2014. The study was carried out for 5 locations of Bangladesh that have a higher potential for wind energy [48]. The latitudes and longitudes of these places are shown in Table II.

TABLE II
GEOGRAPHICAL COORDINATES OF SELECTED LOCATIONS

Place	Latitude	Longitude
Patenga	22.2352°	91.7914°
Feni	23.0159°	91.3976°
Kuakata	21.8210°	90.1214°
Kutubdia	21.8167°	91.8583°
Cox's Bazar	21.4272°	92.0058°

B. *The Data Description*

The monthly mean wind speeds of 5 selected locations are plotted against months in Fig. 2. The months June and July have the top average wind speed. Kuakata has the highest mean wind speed over a fairly good period.

Figure 3 shows the wind frequency rose graph in different directions for the selected sites.

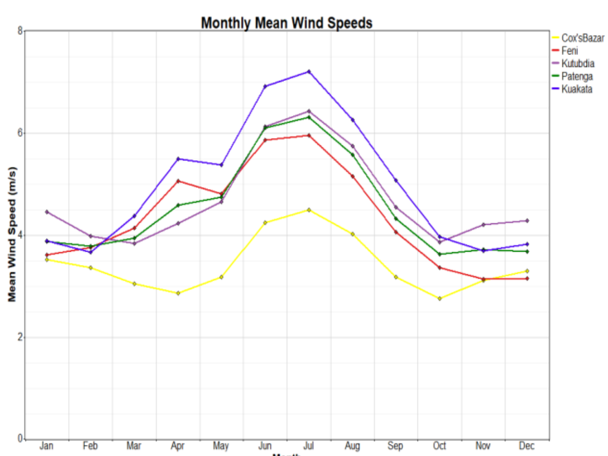

Fig. 2. Monthly wind speed of the selected locations

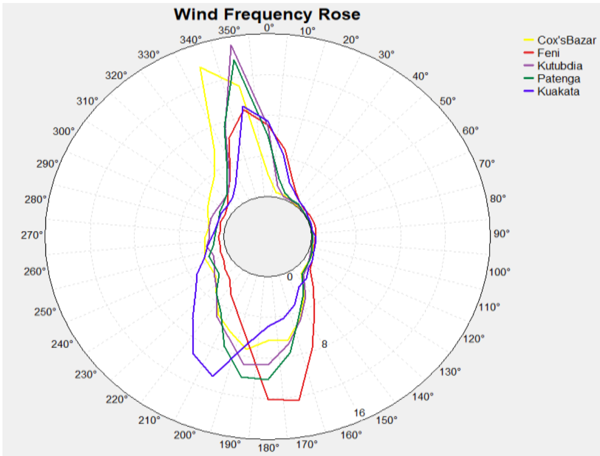

Fig. 3. Wind frequency rose at differnet direction of selected locations.

Seven input parameters are used in our study to forecast wind speed. These are Location (L), Surface pressure (SP), Temperature (TM), Relative Humidity (RHM), Wind Direction (WD), Maximum Wind speed (WS_max), Minimum Wind Speed (WS_min), and Mean Wind Speed (WS). Wind speed data was taken at 50 m height above the ground.

IV. Evaluation Metrics

To assess prediction accuracy, three unique criteria are used and from this, the implementation of different methods can be understood. Table III shows different performance indicators and related formulas where n is the total number of data points, *p* is the predicted observation and *a* is the actual observation.

Table III
Performance indicator and formula

Performance Indicators	Formula
Correlation Coefficient (R)	$\frac{\sum_i^n\left(p_i-\frac{1}{n}\sum_i^n p_i\right)\left(a_i-\frac{1}{n}\sum_i^n a_i\right)}{\sqrt{\sum_i^n\left(p_i-\frac{1}{n}\sum_i^n p_i\right)^2\sum_i^n\left(a_i-\frac{1}{n}\sum_i^n a_i\right)^2}}$
Mean Absolute Error (MAE)	$\frac{\lvert p_1-a_1\rvert+\lvert p_2-a_2\rvert+\lvert p_3-a_3\rvert+\cdots+\lvert p_n-a_n\rvert}{n}$
Root Mean Square Error (RMSE)	$\sqrt{\frac{(p_1-a_1)^2+(p_2-a_2)^2+\cdots(p_n-a_n)^2}{n}}$

V. Results and Discussions

In this study, the whole dataset was separated into training and test set where daily average input parameters are considered for predicting wind speed. The training set comprises 7305 observations representing a span of four years (2010-2013) for five distinct areas and the test set has 1825 observations for the year 2014. The experiments related to 15 machine learning algorithms were performed using WEKA [49] toolbox. We found that MLP has the best outcome with MAE: 0.1911, RMSE: 0.2634, and a correlation coefficient of 0.9898. This is explained by the fact that the multilayered structure helps to capture non-linear relationships between inputs and output. The hidden layer distills the important patterns from the inputs and passes them onto the next layer. Subsequently, the system performs proficiently by dismissing excess data.

From Table IV, it has been observed that most of the methods, except LWL, are capable of maintaining a strong correlation with the actual observations.

Table IV
Results obtained using different methods

Regression Method	Correlation Coefficient (*R*)	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
SLR	0.9404	0.4764	0.6316
LR	0.9896	0.1928	0.2656
LMS	0.9896	0.1929	0.266
MLP	**0.9898**	**0.1911**	0.2634
RBF	0.9897	0.192	0.2638
PR	0.9896	0.1928	0.2655
SMOReg	0.9895	0.1936	0.267
IBK	0.9699	0.342	0.45
K*	0.9815	0.2741	0.3928
LWL	0.8195	0.8634	1.0622
AR	0.9556	0.4417	0.5596
BREP	0.9895	0.1965	0.2666
M5R	**0.9898**	0.1919	**0.2631**
M5P	**0.9898**	0.1919	**0.2631**
REP	0.9853	0.2293	0.316

Figure 4 supports the fact that MLP is much better than Lazy Learning Algorithms (LLA).

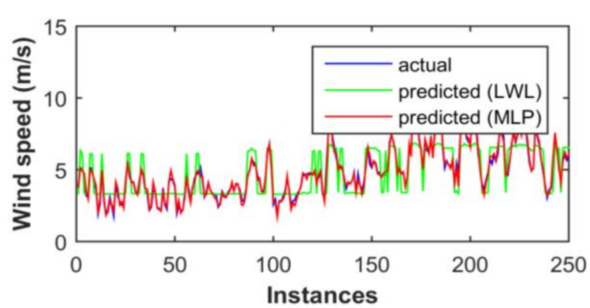

Fig. 4. Comparison of prediction between MLP and LWL

VI. Conclusion

In conclusion, this study exhibits several machine learning alternatives to the physical and statistical approach of wind speed forecasting with high prediction accuracy. This work can be extended by discovering the best subset of the dataset which will minimize the gap between actual and anticipated wind speed. Also, there is the scope of exploring the impact of handcrafted features as inputs. This, in turn, can help in the proper planning of wind power generation and uncover more areas having a high potential for wind energy.

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