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Early & Accurate Forecasting of Mid Term Wind Energy Based on PCA Empowered Supervised Regression Model

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Abstract

Wind energy is a renewable energy resource used for generating electricity without affecting the environmental balance. Hence forecasting of the wind speed is an important parameter to generate the electricity as well as utilization of electric power at the peak in deficiency, moreover controlling the overload of the grids. Machine learning algorithms (MLAs) are a part of the AI model which can be used as an intelligent management system to predict the generated power from wind speed. In this examination in general exploration performed into two prediction phases: Development stage and assessment Stages. In the Development stage, information about the environment should be accessed. This data is pre-processed with the help of Principal Component Analysis (PCA) to reduce the irrelevant attributes. After that MLA's such as Decision Tree (DT), Random Forest (RF), KNN, Linear regression (LR) & multilayer Neural Network model (MLP-ANN) models are utilized in testing datasets to predict the wind energy. The Power which is determined necessities to check and separate from the first ability to refresh the framework until and except if the necessary dependability is assembled from learning. In the assessment stage, the prepared expectation framework is then utilized to anticipate the Power for the test samples. In this research four statistical performance indicators & training time used to identify the best-fitted model. In the analysis section, it is seen that PCA Based DT outperformed the others algorithm by means of MAE, MSE, RMSE, Regression & Training time.

Keywords

Machine Learning techniques, Performance metrics, Regression Analysis, Wind speed prediction.

INTRODUCTION

Reduction of fuel energy, rapidly increase of pollution level, global warming and energy crisis have together influenced the researcher for clean and pollution-free sources of energy([2], 2018; [9], 2020). In recent days the most challenging thing are the problems related to energy and mankind facing it in huge manner. For deficiency in the energy and electric power, there are various countries are under economic stress ([10], 2021). Amount of natural resources has decreasing continuously & rapidly due to their usage has increased in very recent times ([40], 2020). The decrease in these assets has expanded their costs as well as caused a destabilization in the economies of different agricultural nations ([23], 2018).

The crisis/reduction in natural energy resources is forcing researchers to find new way of sources and mankind to fund in alternate energy sources. Wind energy-based force age is acquiring ubiquity since it can possibly create power on a business scale ([7], 2008). Wind Energy is now the new alternate source of energy. It is also effective and free from pollution, which encouraging mankind and countries to gain the power consumption from it only. The problems are well known, however, that there are several common problems, We must address these issues. Energy from wind fluctuates, which can be used to create the reliability of the power distribution system ([1], 2009). Thus, the main aim in wind power is using wind power means addressing its unpredictability. Researchers are dealing with creating models for anticipating future breeze speed/power on a short-term as well as long-term basis. The principal focal point of this examination is the advancement of Mid-term wind power Model for foreseeing power. Wind power forecast fluctuates on schedule consistently tallies. Wind power forecasting is necessary to maintain a balance between electricity output and consumption ([27], 2013).

In recent years, many statistical methods have also been integrated with artificial intelligence (AI) techniques, notably artificial neural networks (ANN). Non-ANN strategies are viewed as gray-box factual techniques meaning they are not as precise as ANN strategies ([36], 2019). While different creators order the AI strategy as a non-measurable term and arrange wind gauging as a solitary classification. Models which follow statistical method are more handy and better for using. AI is recognized as a phenomenon using multiple models. AI on the other side uses machine learning models includes Random Forest, Decision Tree .and linear Regression([17], et al., 2021; [22], 2017). The Statistical methods and ANN is usually suit for the short term forecasting. The methodology obtains 5 days in front of wind speed estimating, utilizing both deterministic and probabilistic methodologies on a dataset containing wind meteorology information from Wind farm Kolkata, India.

This paper proposes five non-identical AI-based algorithms for medium Term Wind Power forecast. This methodology uses a blend of AI procedures for highlight determination and relapse which depends on AI strategies.

Rather than recently revealed ML-based methods for momentary wind power forecast, the suggested PCA-ML uses a combination of PCA algorithms to remove extraneous features from datasets in the pre-processing to improve the accuracy of the dataset during the application of ML The proposed PCA-ML forecast framework has shown exact expectations consistently while considering a little wind power unit. The subsequent paper is organized as follows: In Section II, highlights different existing system designed by ML techniques with different sets of datasets for the generation of different span of wind speed forecasting described in literature review. In section III, the strategy of the proposed expectation model is introduced including information gap, PCA & flowchart of overall process. Section IV describes the steps of all the proposed MLAs used in this research. Section V & VI presents result analysis followed by conclusion.

LITERATURE REVIEW

The basic aspects of existing wind speed forecasting techniques are shown in Table 1.

Table 1. Existing wind Speed Forecasting scheme

Si No	Year of Publishing	Nature of the dataset	Algorithm used	Outcomes of the research
1	(K. Chen & Yu, 2014)	Datasets gathered from three sites in Massachusetts, USA.	unscented Kalman filter is integrated with support vector regression based state-space model	Proposed model outperformed than ANNs, SVR.
2	(J. Chen et al., 2018)	Data collected from a wind farm in Inner Mongolia, China,	LSTM, SVM and External optimization algorithm.	proposed model outperformed than ML Models.
3	(Liu et al., 2014)	Data set collected from a wind farm, North China after 0.5 hrs interval.	Wavelet Transform, GA) and SVM	Proposed model provides more accurate prediction than Hybrid GA-SVM without WT.
4	(Y. Wang, 2014)	7 days historical data from China	A Hybrid genetic algorithm & wavelet neural network.	Proposed model predicts the wind speed about 92%.
5	(Nurunnahar et al., 2017)	7years historical dataset of wind speed Bangladesh meteorological division	Two very potential ML approaches: SVR and BPNN	Both the models predicts the wind speed about 99% accuracy.
6	(Huang et al., 2016)	Dataset collected from USA National renewable Energy Laboratory (*NREL*)	A hybrid techniques used empowered by variational mode decomposition, Partial autocorrelation function (PACF), and weighted regularized extreme learning machine (WRELM)	In this research VMD reduced the randomness of the dataset, PACF perform the feature extraction & ELM performs the prediction of the wind flow.
7	(Shao & Deng, 2018)	Dataset collected from USA National renewable Energy Laboratory (*NREL*)	wavelet decomposition with AdaBoosting neural network	Wavelet decomposition used to reduce the data randomness so that hybrid AdaBoost neural network model predicts the wind flow with higher degree accuracy.
8	(X. Wang, 2017)	Wind farm data collected from China, 2012.	Hybrid model SVM integrated PSO.	Proposed hybrid model predict the wind flow better accuracy than SVM & PSO.
9	(Ningsih et al., 2019)	The data used was obtained from the	Two Deep learning algorithm Recurrent	Proposed model predict the highest accuracy using

		Nganjuk Meteorology and Geophysics Agency (BMKG), East Java.	Neural Network & Long Short Term Memory Proposes wind speed predictions using.	Adam optimizer (both model) for the train & test data sets are 92.7% & and 91.6% respectively.
10	(Datta, 2018)	National Oceanic and Atmospheric Administration	ANN	Proposed model is very effective for prediction of small datasets.
11	(Jia et al., 2016)	Wind farm in Tianjin, China	Hybrid Improved Artificial bee colony algorithm incorporated with back propagation (BP) neural network.	Proposed model has a high convergence rate & prediction capability than hybrid GA-ANN.
12	(Zhu et al., 2017)	Three wind speed data are collected from West Texas Mesone.	Four neural network model proposed: *ANN*, *CNN*, *LSTM*, and a hybrid model convolutional LSTM.	Among all the neural model ConvLSTM was outperformed by means of less computational time & high prediction accuracy.
13	(Z. Wang & Mazharul Mujib, 2017)	Meteorological data from Dalian Meteorological Bureau	Hybrid ANN incorporated with DT	Proposed model accurately store the data as well as predict with higher degree of accuracy.

CLASSIFICATION OF FORECASTING MODEL

Order of wind power anticipating can be as per time span, techniques and standards, foresee object, input information, and gauging information. There are four classes that the determining framework is partitioned by time skylines. These are extremely short moment, short moment, medium-term, or long term ([18], 2011; [19], 2007; [38], 2011). Table 2 below shows the order of various time span with their comparing reach and applications.

Table 2. Classification of Wind energy Generation on the basis of Different time range

Si No	Time Horizon	Time Expand	Application Purpose
1	Very short time duration	Few Seconds to few minutes	Wind turbine control
2	Short Time Duration	Few minutes to 3 days	Economic dispatch control
3	Medium Time duration	3 days to one week	Online & offline decision control of a generator
4	Long time duration	Few weeks to few months	Feasible study of Wind turbine

The determining framework as per techniques and standards is partitioned into two classes. First are the actual methodology and the other one is the factual methodology where distinctive AI model used ([31], 2018). Under physical approach researcher identify following forecasting domain like: point forecasting, regional forecasting, and wind farm forecasting while statistical approach researcher forecast the data with into two different methods: wind speed forecasting by using indirect method & wind power forecasting using direct method.

Exact forecasts of environmentally friendly power creation help to oversee wind or sunlight-based plants, plan support, and get the ideal cost of energy. It decreases the requirement for extra adjusting energy and saves the ability to coordinate wind power.

Knowledge gap & Novelity

One cannot predict the exact and accurate wind speed and due to this reason also the wind speed the figure assumes a significant part in wind power framework arranging, unit responsibility choice, load adjusting choice, upkeep game plan, and energy stockpiling limit improvement. Speed of wind is non-linear and it is not stationery as well and for this reason it is difficult to calculate or acquire exact wind speed information. Due to all this reason many investing took place by large amount of input data and variables for getting the estimation of wind speed. Overall two steps have performed in this study research. In the primary stage PCA is utilized to eliminate the insignificant highlights from the real datasets and at last five diverse AI calculations are applied to anticipate the five days before information through relapse models.

Materials & Methods

In this investigation, AI techniques are created dependent on the past upsides of estimated wind speed information. Because of the nonlinear, non-fixed traits and the stochastic variants in the wind speed time series, The correct prediction of wind speed is acknowledged to be a tough endeavour

([26], 2021). In this work, to work on the precision of the wind speed gauging model, an examination of five models is directed to figure wind speed thinking about accessible chronicled information (https://www.renewables.ninja/). Qualities of the gathered information in 1 hour of the interval of time.Dataset contain 8760 rows with four attributes. For testing purpose we consider 876 numbers of data.

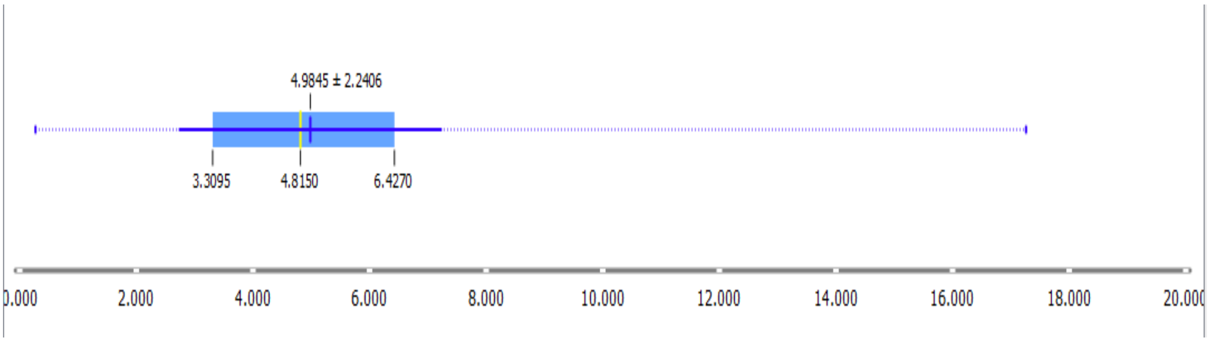

Figure 1. Box Plot for wind speed

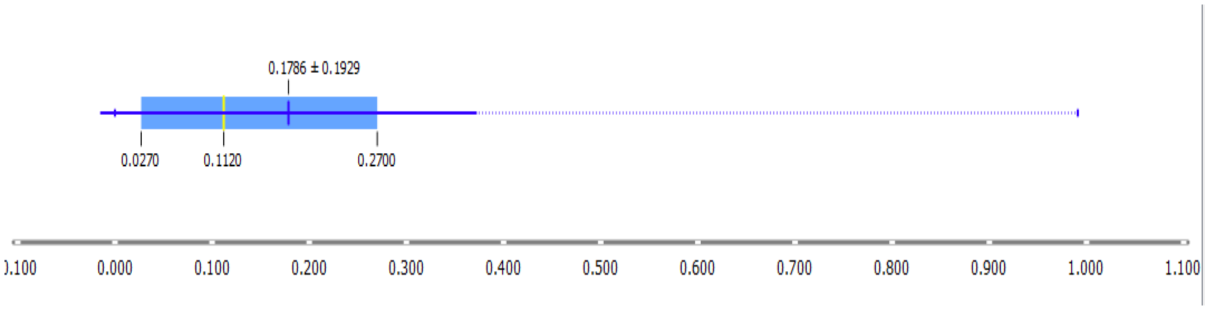

Figure 2. Box plot for Electricity Generation

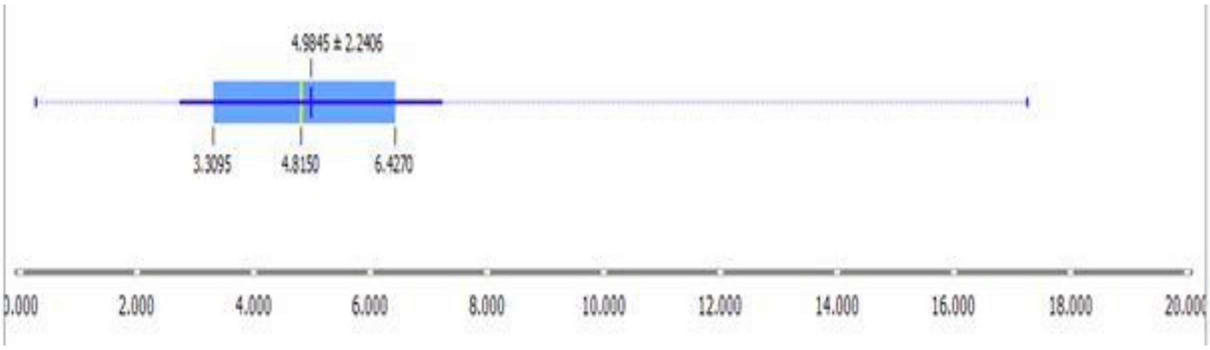

Figure 1 & Figure 2 representing the Box plot for the wind speed & Electricity generation of the present research primary input attributes & output parameter respectively. In Table 3 name of the attributes, nature & their role in the present model are described.

Table 3. Datasets Information for the present model

Si No	Name of the attributes	Types	Role
1	Time	Date Time	Meta
2	Local time	Date Time	Features
3	Electricity Generation	numeric	Features
4	Wind Speed	numeric	Target

Flowchart

In present research the overall process is segmented into three parts, in first segment Principle Component Analysis (PCA) is used in data pre-processing stage to remove the irrelevant attributes from the dataset & improve the accuracy of the model. In second stage five different ML regression model utilized which is followed by the evaluation stage where five performance metrics are used to identify the best fitted model for the present research.

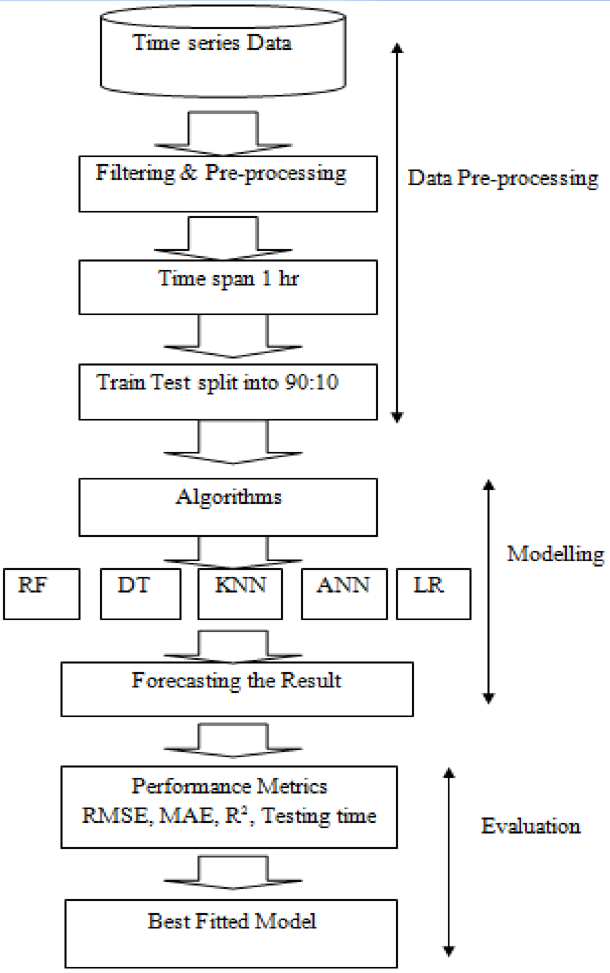

Figure 3. Flowchart for the present research

Principle Component Analysis (PCA)

PCA is an unsupervised Feature Reduction method utilized to convert the irrelevant datasets into low dimensional data with minimum reconstruction error ([25], 2021; [30], 2021). PCA is a statistically rigorous method for simplifying data and generating a new collection of variables known as principal components. Every re produced component is proportionally related with original variables. The fundamental benefit of PCA is that the principal components of every dataset are orthogonal to each other, so there is no redundant data after pre-processing.

Algorithm of PCA:

Input: Data Matrix

Output: Reduced set of arrangements

Step 1: Create N x d information framework (X) with one row has a data point x_n

Step 2: Subtract mean x from each line vector x_n.

*Step 3: **Σ** of the yield in step 2 is the Covariance matrix of X.*

Step-4: Find eigenvectors and Eigenvalues of Σ.

Step 5: Identify the largest value of Eigenvector in Principle Component

Step-6: Output PCs

MACHINE LEARNING ALGORITHMS

Decision Tree

To construct the Decision tree model ([3], 2021) we have to follow the following steps:

1. Sorting out the best component in the given dataset that can be designated as the root hub.
2. Subsets are made by parting the dataset accessible for preparation.
3. Singular subset ought to have comparative qualities for a component.
4. Apply for the above advances over and again until you track down the terminal hub for every one of the parts of the tree. The terminal hubs will contain the anticipated qualities.

Random Forest:

The demonstration of Random forest ([37], 2021) are as follows:

1. Select the preparation dataset for directed learning.
2. Pick a specific arrangement of highlights and information tests from the preparation set on an irregular premise.
3. Make a choice tree utilizing the randomized inspected information by choosing the element with the best split as the root hub.
4. Rehash stages 2 and 3 to make various choice trees.
5. The total of the multitude of trees gives the consequence of the random forest.

Linear Regression:

The demonstration of Linear regression ([8], 2021) are as follows:

1. Importing libraries & loading the datasets
2. Split the datasets into dependent & independent variables
3. Splitting the datasets into train (2/3) & test (1/3).
4. Setting the model parameters & indentify the best fit model
5. Predict the output

Table 4. Parameters settings of the applied Algorithm

Algorithm	
KNN	(n_neighbors=5, *, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None,
DT	ccp_alpha=0.0,criterion='mse', max_depth=None, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0,

	min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort = 'depreciated', random_state=None, splitter='best',
Random Forest	bootstrap=True, ccp_alpha=0.0, criterion='mse', max_depth=None, max_features='auto', max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1, oob_score=False, random_state=None, verbose=0, warm_start=False
ANN	hidden_layer_sizes=100, activation='relu', max_iter=200,solver='adam', alpha=0.0001, learning_rate='constant', max_fun=15000, , learning_rate_init=0.001, , random_state=None, power_t=0.5, validation_fraction=0.1,shuffle=Truetol=0.0001, verbose=False, n_iter_no_change=10, momentum=0.9, nesterovs_momentum=True, early_stopping=False, beta_1=0.9, beta_2=0.999, epsilon=1e-08, batch_size='auto',
LR	fit_intercept=True, normalize=False, copy_X=True, n_jobs=None, positive=False

RESULTS & DISCUSSION

In any predictive model there are a number of performance metrics are used for testing the model ([9] [10] [11] [13] [16] [17] , 2017a, 2017b, 2018a, 2018b, 2020a, 2020b). In this research we used four performance metrics for evaluation of the wind forecast using five machine learning regression models are Mean absolute error (MAE), Mean square error (MSE) & Root mean square error (RMSE) & Regression (R^2). All these performance metrics are described in Equation (2)-(5). Let n is the number of observations in the test dataset, x_t & y_t are estimated & predicted values of wind speed and E_t is the residual represented in Equation (1) given by

$$E_t = x_t - y_t \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_i^n |E_t| \tag{2}$$

$$\text{MSE} = \frac{1}{n}\sum_1^n |E_t^2| \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_1^n |E_t^2|} \tag{4}$$

$$R^2 = 1 - \frac{\sum_1^n |E_t^2|}{\sum_1^n (x_{t} - \bar{x})^2}\ , \tag{5}$$

Where, $\bar{x}$ = mean value of the actual wind speed

The tested environment has following features processor and platform: Intel i3, sixth era processor, OS: Ubuntu 20.04 and RAM 8 GB, python 3.7.6, and Jupyter journal 6.03.The improved internal parameters (hyperparameters) for the forecasting algorithms employed in this study are shown in Table 6.The effective amount of veiled neurons has been choosing to acquire the highest R2 and lowest RMSE and MAE value.

Table 5. Description of name of the Model, description & purpose

Name of the Model	Description	Purpose
DT, RF, LR , ANN & KNN	Machine learning algorithms with Deterministic Approach	Forecasting
MAE, RMSE, Regression & MSE	Mathematical formulation	Forecasting performance indicator

Five applied machine learning models, their description & the purpose in this research described in Table 5. In this work we applied five ML model: DT, RF, LR, and ANN & KNN for the forecasting of the wind speed for coming five days where data predicts for 1 hour span. For verifying the best ML model four statistical features: MAE, MSE, RMSE & regression model as a wind forecasting performance indicator.

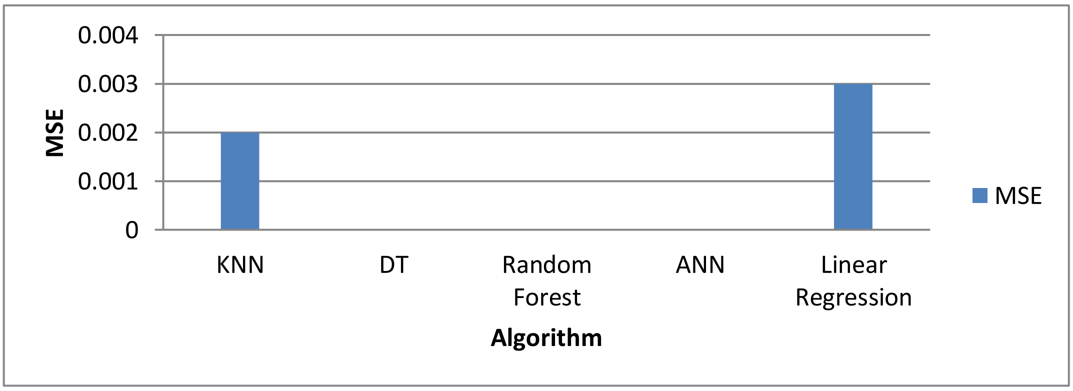

Figure 4. Comparative study based on MSE

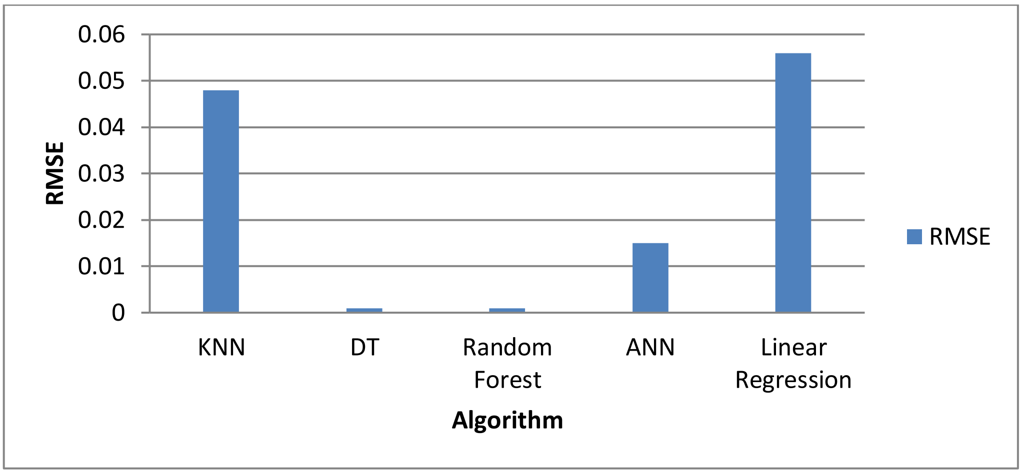

Figure 5. Comparative study based on RMSE

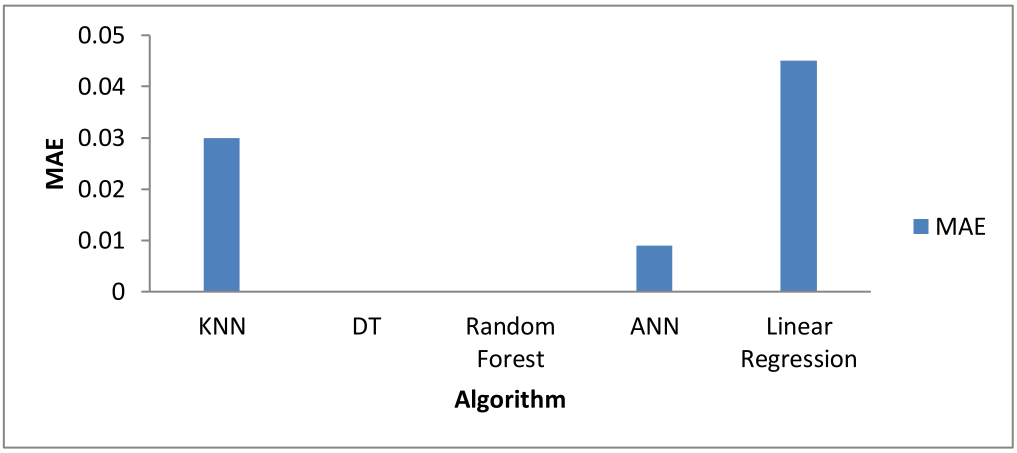

Figure 6. Comparative study based on MAE

Table 6. Parametric Comparison of the Algorithms

Name of the algorithm	MSE	RMSE	MAE	R^2	Training Time(Sec)
KNN	0.002	0.048	0.030	0.937	72
DT	0.000	0.001	0.000	1.000	28
Random Forest	0.000	0.001	0.000	1.000	33
ANN-MLP	0.000	0.015	0.009	0.994	47
Linear Regression	0.003	0.056	0.045	0.915	68

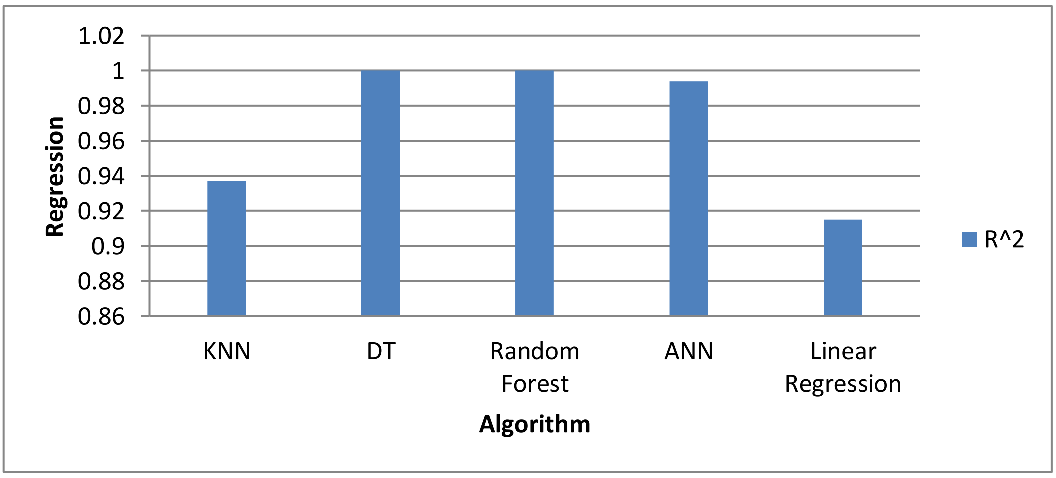

Figure 7. Comparative study based on R^2

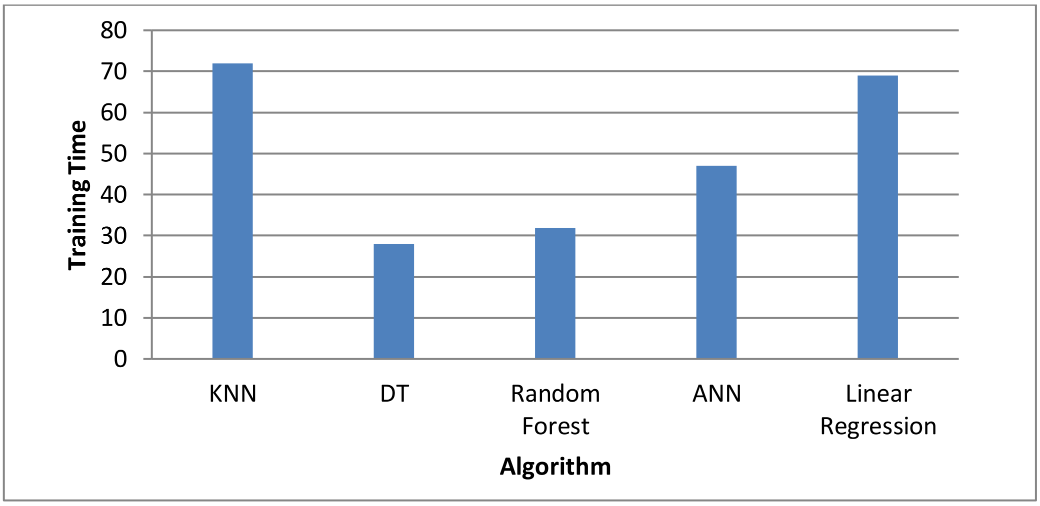

Figure 8. Comparative study based on Training time

Figure 4 to Figure 8 are represent the comparative study of different algorithm on the basis of MSE , RMSE , MAE , regression & Training Time, while Table 6 showing this statistical results in tabular form. Figure 9 represent scatter plot between wind speed v/s wind energy generations for the train datasets.

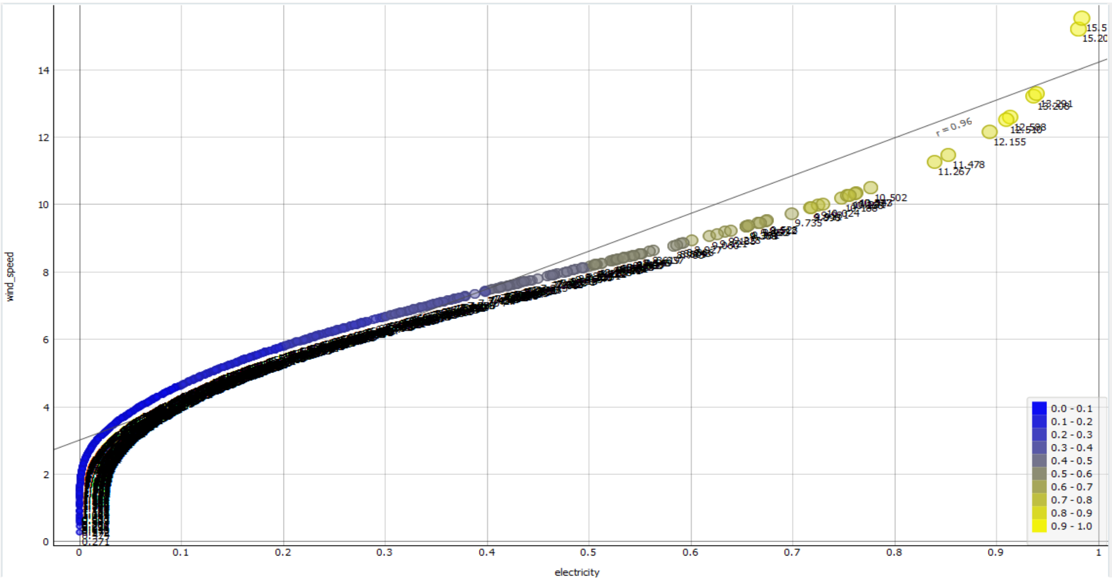

Figure 9. Scatter plot for wind speed v/s generation of electricity

CONCLUSION

Wind energy is a one of renewable energy whose production is totally depends upon the condition of the weather. Sometimes unpredictable nature of the weather may cause higher degree of uncertainty in wind energy generation. When the prediction of wind velocity is greatly varied then the additional devices are used in for storing the energy to overcome this condition & left the grid not overloaded. Hence a feasible solution has to be applied in this situation so that it can predict the small, mid-term, and elongated-term wind speed & helps to take both operational and strategic decisions. The exact range of electricity which is created from wind energy is a one step above for enhancing the whole ecosystem and also the decrement of pollution of environment. So in modern research there are a several AI models are proposed to improvements in generation of electricity and predictability of operating modes renewable energy resources.

A wind power forecast model based on hybrid Principal Component Analysis (PCA) and machine learning techniques is proposed in this research. Datasets comprises 8760 datasets with 4 attributes, for testing purpose we used 876 numbers of datasets. Overall operation has been performed into three phases. In first phase, PCA is applied to eliminate the irrelevant attributes from the datasets to improve the model accuracy. In second phase five machine learning algorithms: KNN, DT, RF, MLP-ANN & LR are used to predict the test datasets. On the last phase four statistical performance indicators: MAE, MSE, RMSE & Regression and training time used to identify the best fitted model. From the result analysis it has been seen that PCA based Decision tree model outperformed than the other machine learning algorithm while Linear Regression & KNN performance was not upto the mark. As a result, it is expected that the PCA-DT model can also be used as a wind power prediction model.

Prediction of wind power stills an open challenge for the present research. In this research only dependable variable is wind energy which is solely depends upon the independent variable wind velocity. For large number of independent variables how the model fitted with the examined model is one of the future scopes.

Data Availability

Wind speed data which is used in this study have been taken from the Kolkata, India (https://www.renewables.ninja/).

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