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Machine Learning Method for Forecasting Wind Power Using Continuous Wind Speed Data

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Abstract: - Among various nonconventional energy sources, wind energy is a noteworthy and suitable source with the ability to generate electricity continuously and sustainably. However, there are a number of drawbacks to wind energy, including high basic utilization costs, the static nature of wind farms, and the challenge of locating energy that is wind-efficient. regions. Using five machine learning methods, long-term wind power prediction was done in this study using daily wind speed data. We suggested an effective way to forecast wind power values using machine learning techniques. To demonstrate how machine learning algorithms, perform, we carried out a number of case studies. The outcomes demonstrated that long-term wind power values might be predicted using machine learning algorithms in relation to past wind speed data. Additionally, the consequences show that machine learning-based Models could be used in places other than those where they were taught. This study showed that, by employing a model of a base site, machine learning algorithms could be applied frequently prior to the development of wind plants in an undisclosed environmental region, provided that it makes sense.

Keywords: Machine learning, wind speed, wind energy, Algorithm, LASSO.

I. INTRODUCTION

Governments, nations, and energy corporations are paying more attention to Nonconventional energy sources due to their inherent qualities of being cost-free, environmentally benign, and natural. Wind power is one of the most useful nonconventional energy source. and possible source of usable energy [1-3]. Wind energy is a acceptable energy source that can be used to power systems that need constant power generation. It can also be used to build wind turbines on existing farms without taking away from their agricultural land, and its seasonal fluctuations can be predicted. There are a few difficulties with using wind energy, though. Initially, the expenses of the initial investment are higher than those of traditional power plants. Furthermore, given that wind turbines are not readily transportable, the Prospective areas' wind energy potential needs to be thoroughly examined. Thirdly, the transmission lines needed to link wind-efficient regions to the national grid are situated in isolated areas. Ultimately, wind turbines have the potential to harm nearby fauna, produce noise, and contribute to aesthetic contamination.

In the other side, machine learning is a branch of computer that aims to give computers or other objects the capability to understand without having to be actively used. Its objective is to create techniques Using algorithms to make predictions based on data and learn from data [4,5]. It is feasible to effectively use machine learning method to forecast output features based on past records, model input features in relation to anticipate output, and explain the dataset's behaviour.

Numerous researches on wind power forecasting utilizing different inspection techniques and over a range of time periods can be found in the literature. While persistence and statistical approaches are used in preliminary studies about wind power consequence, current work prefer to employ machine learning algorithms, in particular random

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Forest classification algorithms. The primary justification for utilizing machine learning algorithms is their ability to bring models based on initial data moderately than a generic model and adjust to shifting patterns within datasets. Because of its great accuracy and simplicity, short-term wind power forecasting is the subject of several literature research. Nevertheless, research on long-term wind power consequence is scarce, particularly for the year ahead. Consequence wind power is more difficult due to the year-ahead prediction. This study's primary contribution is a wind power forecast for the coming year based on historical wind power values. utilizing machine learning methods, wind power prognosticate was carried out in this study utilizing daily wind speed data. Because wind speed has an unpredictable fluctuation, we choose to employ daily wind power forecasts. To determine whether the algorithms could yield results that were appropriate for each place, the suggested method was applied to a number of potential locales. Lastly, we evaluated our models against the wind speed data of four distinct sites in order to more clearly illustrate the effectiveness of our suggested machine learning dependent wind power consequence models. This study demonstrated that, by employing a model of a base site, "machine learning algorithms" could be productively applied prior to the development of wind plants in an undisclosed geographic region, provided that it makes sense.

Here is a summary of the study's primary contributions

• Various machine learning methods utilized for long-term wind energy predictions.

• To model wind power over the long run, five machine learning methods were employed.
• The building of a new wind farm at an unidentified site will benefit from the results.

2. Literature survey

One may categorize the research on wind energy prognosticate into two groups, for example, long-term and short-term prognosticate. Short-term techniques for wind power prognosticate endeavour to predict wind power concerning brief time frames, such as one hour to multiple days in advance, whilst long-term wind energy prognosticate techniques attempt to predict wind power concerning more extended time frames, such as multiple days to a year in advance. For example, statistical and machine learning techniques are two distinct subcategories within each category. Rajagopalan and Santoso [6] used statistical techniques for short-term wind power prognosticate. Forecasts as well as for the information from several wind farms. An study connected with the ARIMA prototype and contrasted the outcomes with tenacity techniques [7]. Using two statistical prototypes—a "univariate ARIMA" model and a "multivariate NARX model"—Cadenas et al. [8] conducted wind power prognosticate and build that the NARX model outperformed the ARIMA model in one-step ahead predictions. Dowell and Pinson [9] presented a strategy for very short-time wind power prognosticate of many energy firms in various places. A meteorological-statistic model was presented by Lima et al. [10] to guarantee precise wind power prognosticate up to 72 hours in advance. Wang et al. [11] predicted short-term wind power using the ARMA model, and their results were satisfactory. An ARMAX-based statistical technique using time series decomposition and non-linear regression was proposed by Robles-Rodriguez and Dochain [12]. linearity handling for precise 48-hour wind power predictions. In order to catalog and rectify forecast errors, Pearre and Swan [13] presented statistical techniques that produced good results for forecasts made 1-6 hours in advance [14]. Utilizing data input based on the predicted wind speed and the next hour, the plant can produce power over a 48-hour period. Rahmani and colleagues. for wind energy prognosticate, l. [15] suggested a hybrid optimization technique combining features from particle swarm and ant colony models. A Machine Learning-based Short Term Loan was proposed by Najeebullah et al. [16]. A wind power prediction system that combines regression and feature selection methods from machine learning. For wind speed prognosticate, Chi et al. [17] employed support vector machine, multi-layer perceptron, and linear regression techniques. A hybrid model for wind power prognosticate based on decomposition and the AdaBoost-extreme learning machine was proposed by Peng et al. [18]. Lahouar and Slama [19] forecasted wind power using the Random Forest algorithm by taking into account a number of weather conditions in addition to wind speed. Li et al. Data mining-based techniques for wind power prognosticate were presented by l. [20] and Sun et al. [21]. Deep belief network deep learning was proposed by Wang et al. [22]. An ARIMA and clustering-based approach was presented by [23-30] to more accurately anticipate wind speed over a one-year period for the purpose of calculating wind power. Barbounis et al. [31] employed local recurrent neural networks in long-term machine learning wind power prognosticate to predict a wind plant's wind power three days in advance with respect to four neighboring areas' meteorological data. In order to anticipate wind output one hour to one year in advance, Khan et al. [32] devised a method based on artificial neural networks and Cartesian Genetic Programming. In order to anticipate medium-term wind generation for three distinct sites,[33] presented a hybrid of seasonal content adaptation, Elman "recurrent neural network", and support vector regression. The application of "feedforward artificial neural networks" for each day mean wind energy prognosticate was examined by Dumitru and Gligor [34]. Ouyang and Yan ng [35] presented a two-step hybrid wind power prognosticate model that forecasts wind speeds three months ahead of time using both physical and data mining-based methodologies energy to run a wind farm. Six distinct machine heuristic artificial intelligence methods were examined by Maroufpoor et al. [36] in order to forecast wind speed using meteorological factors. Even though there have been a number of recent researches, statistical approaches are not the first methods that are recommended for wind power prognosticate when the literature is examined since statistical strategy cannot adapt. theirself to nonlinear wind detail, have trouble managing big data sets, and have trouble predicting the long term [18,22,25].

3. Overview and description of the issue

This section introduces the machine learning techniques that are employed for this work, defines the wind energy prognosticate issues, and presents wind power analysis depend on wind speed per hour.

3.1 Problem Definition

primary goal of this work is to forecast generated wind power in association to everyday wind speed data. The investigation of the produced wind energy's eligibility for financing is another issue with this study. A casting model intended for use in several places. Algorithms for machine learning were used to tackle these issues. Values for hourly wind power were computed following the procedure presented in below Section. We retrained the algorithms using the identified wind power details, produces a wind power value, and try-out their ability to provide sufficient wind power values depend solely on each day mean wind power readings. Additionally, the actual deviation's impact was examined.

3.2 Estimates of wind energy production based on hourly wind speed

Diagram created by wind turbine organization and wind speed details can compute the energy outcomes of wind turbines [37, 38]. The power plot of the turbine under consideration and the wind speed details prepared as a time series constitute the basis of the calculating process. The power graph and "technical characteristics" of the wind turbine under investigation are presented in Figure 1 and Table 1, respectively. A 1 MW wind turbine was chosen for this investigation since wind power plants commonly use them. To predict the wind consequence of the wind turbine, an algebraic formula of degree n can be derived based on the power graph of the wind turbine among the "cut-in" and "rated speed" as shown in Eq. (1).

$$Pi(V) = \begin{cases} 0, & V < Vcis \\ (a_n V^n + a_{n-1} V^{n-1} + \cdots + a_1 V + a_0), & Vci \leq V < VR \\ P_R, & VR \leq V < Vcos \\ 0, & V \geq Vcos \end{cases}$$

Eq-1

where P_R is the rated power, $P_i(V)$ is the power generated in the relevant wind speed, a_n a_{n-1} a_1, a_0 are regression constants, and v_{cis}, v_R, and v_{cos} are the cut-in and cut-out speeds.

The turbine's energy output for the duration under consideration can be computed using Equation (2).

$$E_c = \sum_{I=1}^{N} P(V_I)\Delta t$$

Table 1 Technical Specification of wind Turbine

S. No	Turbine Characteristics	Value
1	Rated Power (kW)	1000
2	Height of Hub (m)	60

3	Rotor Diameter (m)	55.0
4	Number of blades	3
5	Swept Area	2300.0
6	Cut in Speed (Vcis) m/s	4.0
7	Rated Speed (VR) m/s	15.0
8	Cut off wind speed	28.0

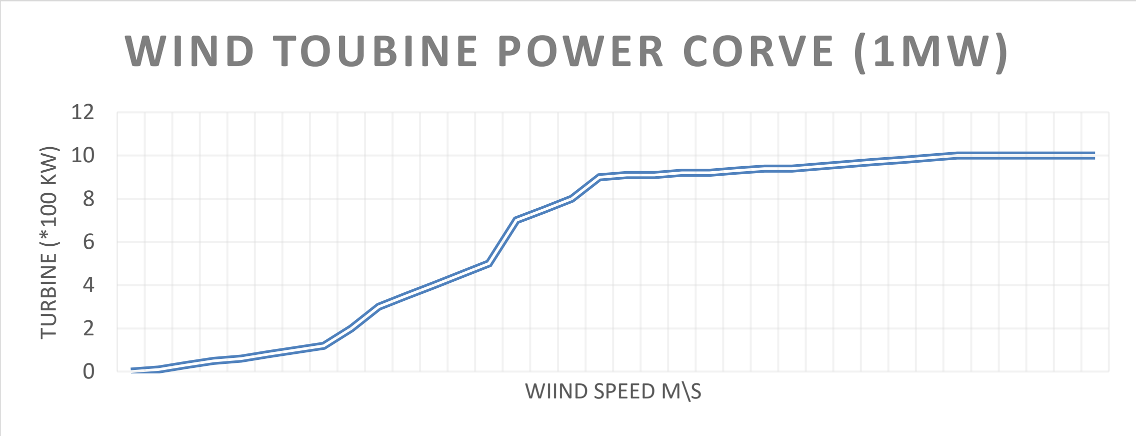

Figure-1 "Power Graph for MW wind Turbine"

3.3 Machine Learning

Within the subject of computer science, machine learning target to provide computers or different devices the quality to learn with no their needing to be manually operated. Its goal is to provide strategy and algorithms for "data-driven learning" and data-driven prognosticate [4,5]. The behaviour of the dataset, the model's input features in relation to the proposed output, and the forecasted output in relation to the dataset's history records are all correctly described by machine learning methods. There are various reasons why machine learning is significant. First of all, in situations where there is no mathematical model for the input-output tuple or where the relationship between inputs and outputs is unclear, machine learning algorithms function well. Machine learning algorithms have the ability to recognize environmental changes and adjust to them. Algorithms for machine learning can manage intricate systems with multiple components and data flow between them. There are numerous machine learning techniques, each with a focus on a certain set of issues. Classification and regression methods are commonly utilized in prognosticate. Many of these methods were first developed as classification algorithms and then updated to extract actual values from the dataset that was provided. Regression analysis is the name given to this subset of categorization. The methods for regression analysis employed in this investigation were presented in this section: These methods were chosen for regression problems because to their high performance and wide application in the literature. These algorithms' theoretical underpinnings differ from one another, and this would reveal which theoretical foundation and algorithm performs better when applied to the wind power prognosticate problem. The performance and runtime of each algorithm are influenced by a number of algorithm parameters. Based on our challenge, we employed a trial-and-error approach to determine the optimal settings for each method. The last portion of each algorithm contains the parameter value that we reported after running the algorithms with various parameter values and using the best observed results.

3.3.1 Least Absolute Shrinkage Selector Operator regression

A variant of linear regression known as LASSO "Least Absolute Shrinkage Selector Operator" regression has been developed [40]. Due to its ability to balance estimations. Consequences of the subset of indicator that reduces the prediction error for a calculable reciprocation variable is the goal of "LASSO regression". With the exception of setting some feature coefficients to zero by parameter, LASSO regression differs from linear and ridge regression. LASSO can thus modify a feature's influence to a greater or lesser extent. In order to improve prediction accuracy and model interpretability, LASSO regression selects and regularizes variables, making it an efficient method. Regression is carried out by LASSO using Eq. (3), where N is the sample number, j denotes the parameter coefficients, and is the prediction.

$$(\propto, \beta) = \arg\min \left\{ \frac{1}{N} \sum_{I=1}^{N} \left(y_i - \alpha - \sum_{j=1}^{p} x_{ij} \,.\, \beta_j \right)^2 \right\}$$

Eq-3

3.3.2 k Nearest Neighbor regression

A popular instance-based lazy learning classification technique called k Nearest Neighbor attempts to categorize test instances according to how similar they are to the number of k class centers in terms of their attributes [41, 42]. The Euclidean, Manhattan, or Minkowski distances are used to calculate the closeness. It begins with k random points and groups the training examples according to how near these k centers they are. To best model the positions of class centers for k, an iterative technique is used. Test instances are then categorized according to how closely their features match these k, where v denotes a class label, yi denotes the class label of the ith nearest neighbor, and I (.) is the function that yields a value of 1 in the case that the argument is true and 0 in the absence of it. In this investigation, Minkowski distance was chosen as the distance metric, and k was set at 4.

$$y^l = argmax \sum_{neighbors} I(v = y_i)$$

Eq-4

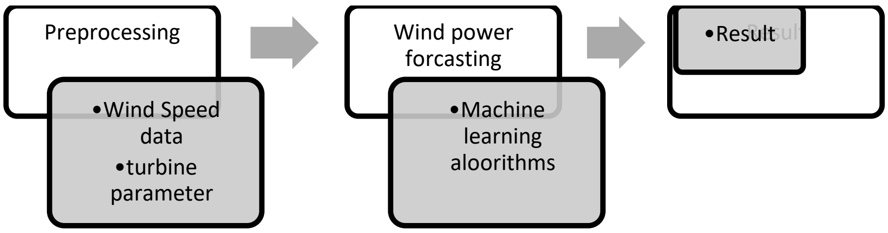

Figure-2 Experimental set up flow-

3.3.3. Extreme Gradient Boost regression

The “gradient boosting decision tree” algorithm has been enhanced with the “eXtreme Gradient Boost” algorithm, which builds boosted trees quickly and in parallel [43]. The xGBoost method is quick and scalable in this sense. By building stronger decision trees, the method aims to reduce the objective function. Regression analysis is another application for the xGBoost method. It can find optimal solutions more quickly because it is faster and more efficient than other boosting alternatives.

3.3.4 Support Vector regression

Regression version of the “Support Vector” Machines technique is called “Support Vector Regression” [45]. The goal of nonlinear SVR is to use the input hyperplanes to determine a regression function. The SVM algorithm is most frequently used in SVR applications. Using training data instances, the SVR algorithm attempts to fit a plane within a certain distance using the input variables.

4. A machine learning algorithm-based approach for estimating wind power

In the current study, the daily mean wind speed and standard deviation were used to forecast the daily total wind power using machine learning algorithms. The hourly wind speed values were present in the original dataset. The values of hourly wind speed were transformed into values of daily mean wind speed and standard deviations. The work's approach is outlined in 1st Algorithm.

Step 1The first phase of Algorithm 1 involves calculating the hourly wind power.

Step 2 Involves converting the 5-year wind speed monitoring dataset D to the daily mean and actual deviation system using the pre-process-dataset function. Additionally, the calculate-daily-total-power function is used.

Step 3 To convert hourly power numbers to “daily total power values”.

Step 4 The fit-algorithm function is used to train the candidate “machine learning algorithms” using the training data.

Step 5 The algorithms return the per day mean and actual deviation details of the test data along with the anticipated power levels with respect to the generated model.

Step 6 The calculate-algorithm-performance function is used to assess the algorithms performances depends on their projected details using many metrics.

Step 7 The strategy finally returns the predicted values.

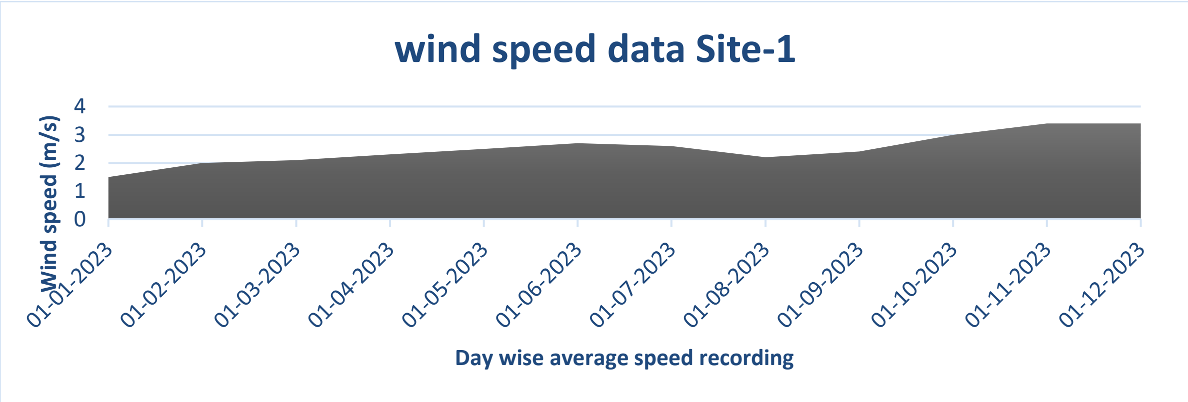

Fig. 3(a)

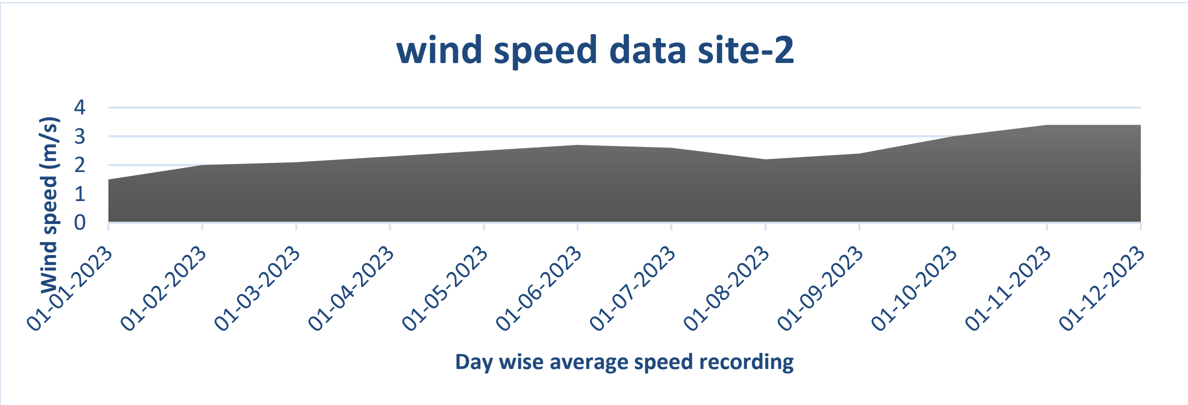

Fig. 3(b)

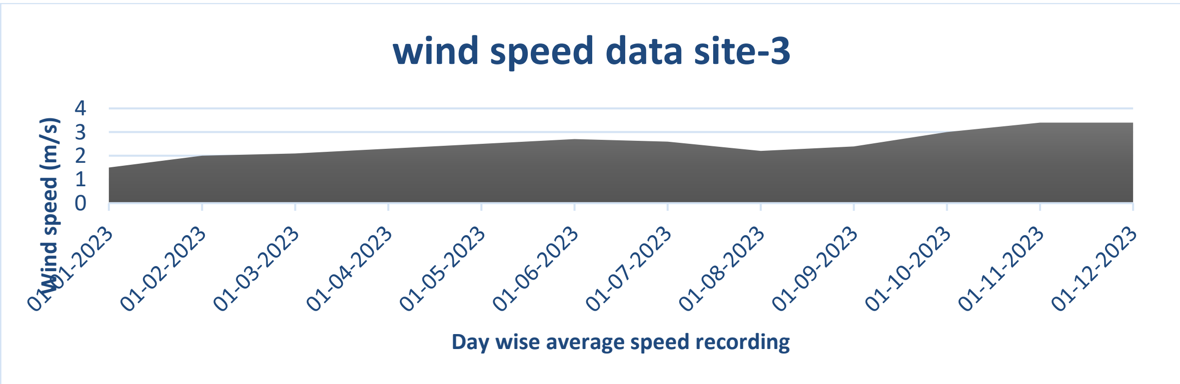

Fig. 3(c)

Figure-3(a)(b)(c) (wind speed Vs Day wise wind speed at different site)

5. Result and Discussion

This portion presents the dataset first, followed by an analysis of the “machine learning strategy” consequences in wind power prognosticate. The “Mean Absolute Error” (MAE), “Root Mean Squared Error” (RMSE), and R2 values of the algorithms are used to assess them. Fig. 2 presents the experimental setup.

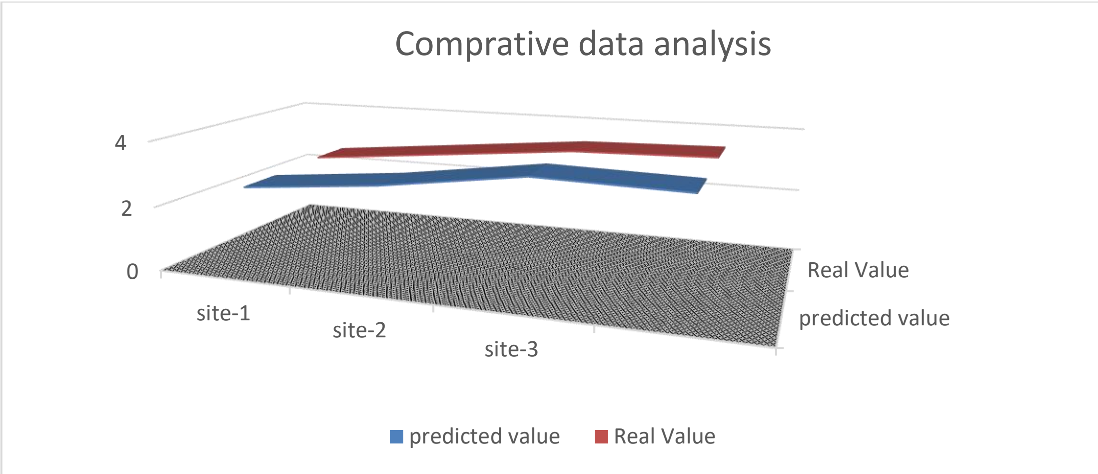

Figure 4. (Comparative data analysis between real and predicted value,)

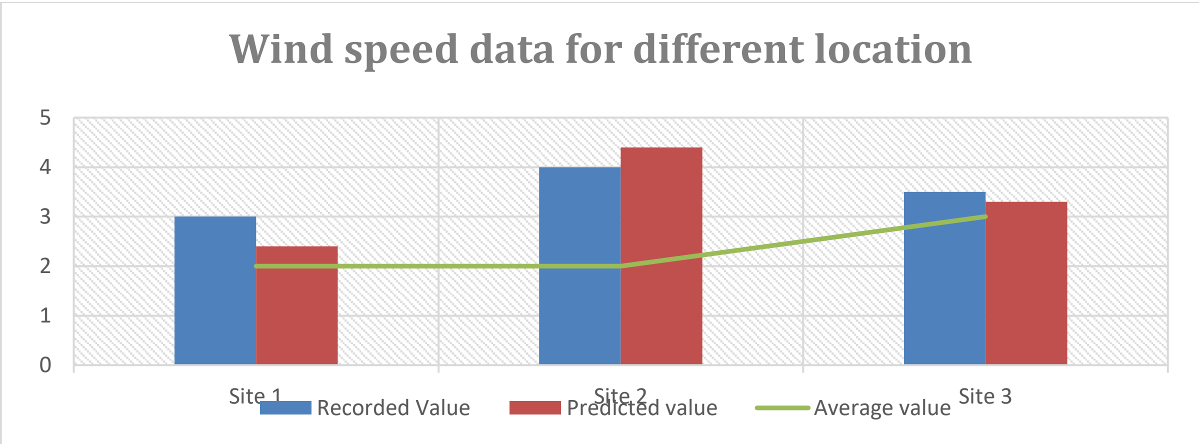

Figure 5 (Wind speed details at different locations)

Conclusions

Table:2

Metric / Algorithm	Site-1			Site-2			Site-3		
	R^2	“RSME”	“MAE”	R^2	“RSME”	“MAE”	R^2	“RSME”	“MAE”
LASSO	0.75	216.02	166.25	0.85	251.36	126.99	0.84	515.01	176.99
KNN	0.92	129.51	32.56	0.94	165.00	64.52	0.92	374.90	147.92
XGBoot	0.90	137.01	26.70	0.98	76.14	56.05	0.95	281.38	139.00
SVR	0.99	11.49	6.49	0.91	168.00	7.75	0.88	336.61	12.83
RF	0.88	37.50	8.00	0.93	175.90	72.51	0.92	286.49	143.20

Given its natural, affordable, and clean characteristics, wind energy is one of the primary nonconventional energy sources. Wind turbines may be used to generate electricity at any time of day, which makes them ideal for systems that need it constantly. The initial investment expenses of wind energy, the need for thorough analysis prior to creating a “wind plant”, the distance between wind-efficient locations and national grids, and the energy's disruptive impacts on the environment make employing wind energy difficult. Related to every wind speed detail, "machine learning strategy" were used in this work to predict wind power. The provided wind speed estimates were specifically forecasted using categorization techniques. Daily wind velocity and actual deviation were used to model each day complete wind power, whereas the per hour wind speed information utilized to construct the per day mean wind speed values. Several sites were used to test the suggested method's ability to generate results that were acceptable for the trained location. The long-term daily total wind power forecasting capabilities of the xGBoost, SVR, and RF algorithms were demonstrated by the findings. With an MAE of 7.048 and an R2 value of 0.995, RF is the best algorithm among them. Because of its linear base, the LASSO algorithm is the worst. The LASSO's R2 score of 0.862, however, is largely respectable. SVR becomes the optimal algorithm with standard deviation removed from the dataset. 32.63 MAE and an R2 value of 0.955. Furthermore, the daily total wind power values of places other than the model-trained location may be accurately predicted by these three algorithms: XGBoost, SVR, and RF. The methods used to anticipate wind power at various locations have R2 values greater than 0.95. Because Bozcaada has different and higher wind speed property than other sites, it has the lowest R2 value. A noteworthy result of this research is that "machine learning strategy" can be effectively placed prior to the prepare of wind farms in unidentified geographic regions, provided that it makes sense to do so by utilizing a base location's wind power model.

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