PREDICTION OF POWER GENERATION IN WIND TURBINES

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Abstract - Wind energy is a promising alternative source of clean and renewable energy that can help mitigate climate change. Accurate prediction of power generation in wind turbines is critical for the effective integration of wind energy into the power grid. In this study, we compare the performance of two popular machine learning algorithms, linear regression and random forest, for power generation prediction in wind turbines. We use wind speed and direction as input variables and power generation as the output variable. Our results show that random forest outperforms linear regression in terms of prediction accuracy and robustness.

Key Words: Power Generation, wind turbines, Random forest, power prediction, wind power, machine learning

1.INTRODUCTION

Wind energy is a renewable energy source that uses the kinetic energy of wind to produce electricity. It is a clean and sustainable source of energy that does not emit greenhouse gases or other pollutants, making it an attractive alternative to fossil fuels. Wind turbines are the primary technology used to generate electricity from wind energy, and they work by converting the kinetic energy of wind into electrical energy through the use of a generator.

Wind energy has been growing rapidly in recent years due to the increasing demand for renewable energy sources, and it has become one of the fastest-growing energy sources globally. The growth of wind energy has been driven by a combination of factors, including technological advancements, government incentives and policies, and the increasing awareness of the need for sustainable energy sources to combat climate change.

Wind turbines generate electricity based on the amount of wind that is available to turn the blades of the turbine. However, wind energy is highly variable, and the amount of wind that is available can fluctuate rapidly, making it difficult to predict the amount of power that a wind turbine will generate at any given time. This variability in wind energy can lead to fluctuations in power generation, which can cause problems for the electrical grid and make it challenging to integrate wind energy into the grid.

Power generation prediction in wind turbines is essential for ensuring the stability and reliability of the electrical grid. Accurately predicting the amount of power that a wind turbine will generate allows grid operators to manage the supply and demand of electricity more effectively and to integrate wind energy into the grid more efficiently. It also allows wind farm operators to optimize the performance of their turbines, reducing maintenance costs and increasing energy production.

The objective of this study is to develop a model for predicting power generation in wind turbines using two different machine learning algorithms: random forest and linear regression. The study aims to compare the performance of the two algorithms and to determines the which algorithm is more affective at prediction of power generation in the wind turbines using machine learning algorithms. To achieve this objective, the study will use historical data on wind speed and power generation from a wind farm and will train the machine learning models using this data. The study will then evaluate the performance of the models by comparing the predicted power generation to the actual power generation. The results of the study will provide valuable insights into the effectiveness of different machine learning algorithms for predicting power generation in wind turbines, which can be used to improve the performance and efficiency of wind farms.

2. LITERATURE REVIEW

"Machine Learning-Based Digital Twin for Predictive Modeling in Wind Turbines," by M. Fahim, V. Sharma, T. - V. Cao, B. Canberk, and T. Q. Duong. One of the main forms of renewable energy that results in a sustainable and effective energy solution are wind turbines. It doesn't emit any carbon pollutants that would harm the environment. Due to the unpredictability of wind speed, monitoring wind farms and predicting their ability to produce electricity is a challenging issue. As a result, the management team's ability to effectively organise the consumption of energy is constrained [1].

Lain, S., Contreras Montoya, and Ilinca. A Review of the Calculation of Wind Turbine Power Losses Due to Icing. Energies This article's goal is to examine the methods that have been applied over the last 15 years to calculate the amount of power lost by wind turbines as a result of adverse weather exposure. The use of computational fluid dynamics (CFD) for the three-dimensional numerical simulation of wind turbines is emphasized, as is the combination of the blade element momentum theory and two-dimensional CFD simulation. (BEM). There is also a short overview of other methodologies, including deep learning, image analysis, and forecasting models [2].

An aggregative machine learning method for predicting wind turbine output power was developed by S. Netsanet, J. Zhang, D. Zheng, R. K. Agrawal, and F. Muchahary. The operation of today's grid requires accurate forecasting of the power production of renewable sources in order to achieve maximum energy efficiency and a carbon-free ecosystem. Through the use of an aggregative approach, this research develops a reliable, efficient, and accurate model for day-ahead wind turbine power output prediction. The approach uses two different kinds of artificial neural networks (radial basis and conventional feedforward networks), as well as support vector machine (SVM) and adaptive neuro-fuzzy inference system (ANFIS) techniques. It aims to compare the prediction models' individual performances before identifying an aggregate strategy that, by carefully combining the models, outperforms the individual ones. Simple averaging, regression, and outperformance were the three combining methods that were evaluated. Although the performance of the individual models was adequate on their own, the combination methods were able to outperform the individual models. The most successful of all was found to be the regression method of combining. With an NMSE of 1.03% for the test year, it was observed that the predicted output power obtained using this method matched the measured data very well. When tested with the worst instances of windy and calm weeks, the combination methods also showed more stable performance than the individual models [3].

"A Phase Current Peak Prediction Technique to Increase the Output Power of Switched Reluctance Generators for Wind Turbines," by P. C. Buck, B. Fahimi, and P. T. Balsara. A switched reluctance machine (SRM) is a highly desirable option for renewable technologies because it does not contain permanent magnets. Using the method described in this work, the phase current peak can be predicted while keeping the machine's size constant. This approach also identifies the best turn-off angle, which results in a more controllable SRG with fewer drive constraints and higher output power. In this paper, experimental and simulation findings related to the case of a wind turbine encountering varying wind speeds are described [4].

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N. Kadaganchi, P. B. Karandikar, P. Singh, D. S. Chavan, P. Kulhari, R. Giri, "Prediction of wind turbine power yield for sites with hills," This paper conducts a site assessment for four locations in Pune, India. The expected electrical output for each location is based on the wind turbine's various tower heights. For power projection, various turbine blade lengths are also taken into account. An anemometer-based location survey is part of this technique. This approach requires little money and labour [6].

3. RELATED WORK

A. DATA COLLECTION

In this project we are going to predict a wind turbine power production by using the wind speed, wind direction, month and hour data.The dataset consists of 50530 observations.

The dataset contains:

- Date/Time (for 10 minutes intervals)
- LV ActivePower (kW): The power generated by the turbine for that moment
- Wind Speed (m/s): The wind speed at the hub height of the turbine (the wind speed that turbine use for electricity generation)
- TheoreticalPowerCurve (KWh): The theoretical power values that the turbine generates with that wind speed which is given by the turbine manufacturer
- Wind Direction (°): The wind direction at the hub height of the turbine (wind turbines turn to this direction automatically)

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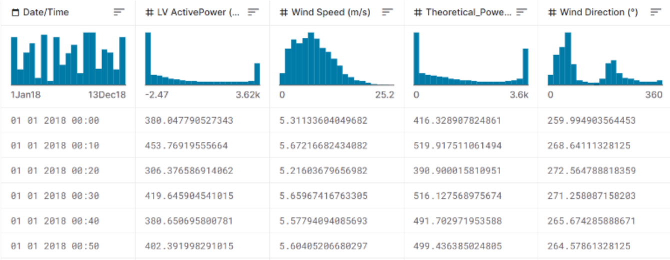

Date/Time	LV ActivePower (...	Wind Speed (m/s)	Theoretical_Powe...	Wind Direction (°)
1Jan18 13Dec18	-2.47 3.62k	0 25.2	0 3.6k	0 360
01 01 2018 00:00	380.047790527343	5.31133604049682	416.328907824861	259.994903564453
01 01 2018 00:10	453.76919555664	5.67216682434082	519.917511061494	268.64111328125
01 01 2018 00:20	306.376586914062	5.21603679656982	390.900015810951	272.564788818359
01 01 2018 00:30	419.645904541015	5.65967416763305	516.127568975674	271.258087158203
01 01 2018 00:40	380.650695800781	5.57794094085693	491.702971953588	265.674285888671
01 01 2018 00:50	402.391998291015	5.60405206680297	499.436385024805	264.57861328125

Fig -1: Dataset

B. DATA PREPROCESSING

In this study, we examined the data of 50530 observations, Extracted a substring from columns to create month, hour, day, year variables.

date/time	lv activepower (kw)	wind speed (m/s)	theoretical_power_curve (kwh)	wind direction (°)	month	hour	day	year
01 01 2018 00:00	380.047790527343	5.31133604049682	416.328907824861	259.994903564453	1	0	1	2018
01 01 2018 00:10	453.76919555664	5.67216682434082	519.917511061494	268.64111328125	1	0	1	2018
01 01 2018 00:20	306.376586914062	5.21603679656982	390.900015810951	272.564788818359	1	0	1	2018
01 01 2018 00:30	419.645904541015	5.65967416763305	516.127568975674	271.258087158203	1	0	1	2018
01 01 2018 00:40	380.650695800781	5.57794094085693	491.702971953588	265.674285888671	1	0	1	2018

Fig -2: Extracting a substring from columns to create month, hour, day, year variables.

For Creating visualization we need to either use aggregated data or use a sample from the big data. So we will get a random sample form the data set.

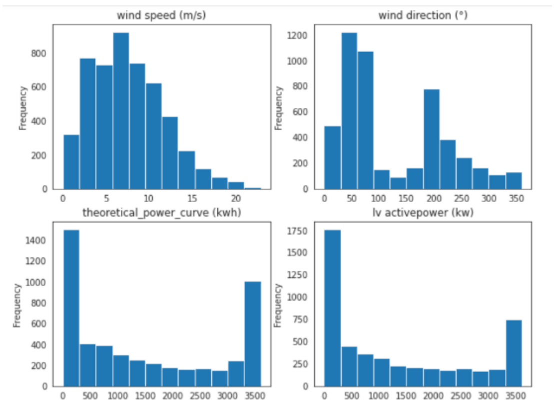

Fig -3: Random sample from the dataset.

C. REPRESENTATION OF CLASSICAL ALGORITHMS

Random forest: Random forests are an ensemble learning approach for classification, regression, and other assignments that produces the class that is the mean forecast (regression) or method of the classes (classification) of the individual decision trees. Each decision tree in a random forest independently predicts a new set of samples when it is introduced, then the predictions from all the trees are combined to produce the final outcome. After the random forest has created a significant number of decision trees in accordance with a particular random formula, this is done. This method operates by creating a lot of decision trees while training. Random decision forests are the best solution for decision trees' propensity to overfit their training set. The combined trees and the outcome that the grove of trees is capable of producing are directly related. Using random forest, the stowing is given an additional layer of irregularity in order to produce predictions that are more precise and effective. Random Forest is a fantastic supervised learning technique that can train a model to predict which classification results in a specific sample type pertain to based on the distinctive characteristics and classification outcomes of a given dataset. utilising a decision tree The "bagging" (bootstrap aggregating technique) is used by Random Forest to create different training sample sets. The random subspace division method divides internal nodes according to the best attribute from a group of attributes chosen at random. The input samples are categorised using the voting technique, and the numerous decision trees that result serve as weak classifiers. A robust classifier is created by combining several poor classifiers. After a large number of decision trees have been constructed in accordance with a specific random rule, each decision tree in the forest separately predicts on this new set of samples.

Linear Regression: Linear regression is a machine learning method based on supervised learning. A regression procedure is carried out. Regression models a target prediction value using independent variables. It is mainly used to establish the relationship between variables and forecasting. The number of independent variables used and the type of relationship between the dependent and independent variables that is taken into consideration in different regression models. A regression's dependent variable can be called many various things. Regressand, endogenous variable, criterion variable, or outcome variable are all terms that can be used to describe it. The exogenous variables, predictor variables, and regressors are other names for the independent elements. A few of the disciplines that use linear regression to examine and predict the behaviour of a particular variable include finance, economics, and psychology. Two examples of how linear regression can be used in finance are to understand the relationship between a company's stock price and its earnings or to forecast the value of a currency based on its past performance. One of the most important supervised learning methods is regression. we are regressing. Given that XY is continuous and regression needs us to determine the value of Y,we need a function that predicts Y.

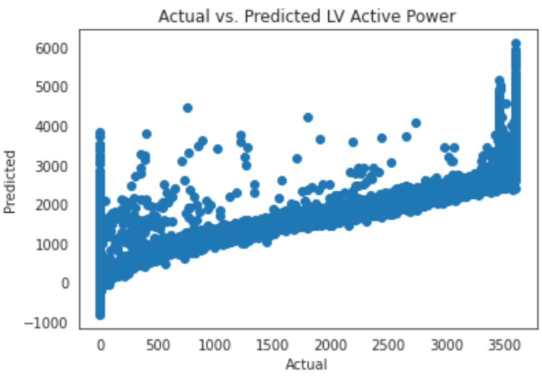

Fig -4: Actual vs. Predicted LV Active Power

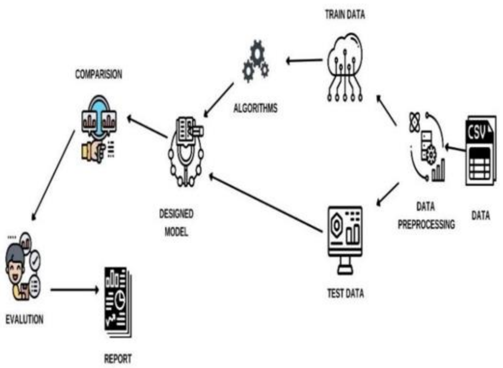

Fig -5: Machine Learning Model Architecture

4. RESULT

In this experiment, we examined two machine learning classifiers random forest and linear regression, for predicting power in the wind turbines and we took the best model based on the errors present in the models, we got random forest as the best model.

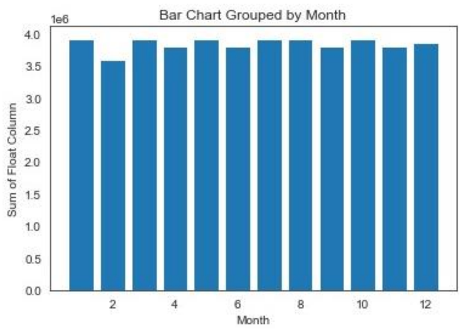

Fig -6: Power Prediction by month

	Time	year	month	day	hour	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	wind direction (°)
0	2023-04-01 00:00:00	2023	4	1	0	498.186777	5.655500	538.966726	71.170158
1	2023-04-01 01:00:00	2023	4	1	1	215.749550	4.660089	262.342535	26.043684
2	2023-04-01 02:00:00	2023	4	1	2	21.640994	2.500083	32.799622	38.317766
3	2023-04-01 03:00:00	2023	4	1	3	0.000000	1.368876	0.000000	249.307880
4	2023-04-01 04:00:00	2023	4	1	4	0.000000	0.716423	0.000000	66.348602
...	...	...	...	...	...	...	...	...	...
692	2023-04-29 20:00:00	2023	4	29	20	1617.174571	8.054619	1576.899855	79.831759
693	2023-04-29 21:00:00	2023	4	29	21	2135.344191	9.123518	2225.684852	79.807407
694	2023-04-29 22:00:00	2023	4	29	22	3290.624828	11.835491	3437.397121	81.784677
695	2023-04-29 23:00:00	2023	4	29	23	2650.774471	9.987305	2576.731338	82.583523
696	2023-04-30 00:00:00	2023	4	30	0	0.000000	0.736490	0.000000	76.593682

Fig -7: Power Prediction in the month of April 2023.

5. CONCLUSION

Our results suggest that random forest is a more effective algorithm for power generation prediction in wind turbines compared to linear regression. Random forest can handle nonlinear relationships between input variables and output variables, which is important for modeling the complex dynamics of wind turbines. Random forest can also handle interactions between input variables, which can lead to more accurate predictions. Linear regression, on the other hand, assumes a linear relationship between input variables and output variables, which may not capture the nonlinearities in wind turbine performance.

Accurate prediction of power generation in wind turbines is critical for optimizing the performance of wind farms and facilitating the integration of wind energy into the power grid. Our study shows that random forest outperforms linear regression in terms of prediction accuracy and robustness for power generation prediction in wind turbines.

Future research in wind power prediction should focus on developing more accurate and robust prediction models that can handle the variability of wind speed and direction, and the impact of environmental factors on wind turbine performance. This can be achieved through the use of advanced machine learning algorithms, deep learning techniques, and the integration of real-time sensor data. Additionally, efforts should be made to improve the availability and quality of wind power data, particularly in remote locations. Finally, more research is needed to investigate the optimal integration of wind energy into the power grid and the impact of wind power prediction on the reliability and stability of the power system.

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