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Machine Learning-Based Forecasting Models for Wind Turbine Power Output

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A B S T R A C T

Wind power is unpredictable due to chaotic nature of wind speed. This makes it important to accurately predict how much power a wind farm will generate. Predicting wind power helps balance the electricity supply and demand, which is very important for a stable power grid. These predictions also help other conventional power plants to mitigate the load demand. It also helps us trade electricity more efficiently with profitable cost. In this paper, we look at different methodologies to predict wind power. It starts by discussing how we use various algorithms to make predictions most accurately with less error. Using statistical and machine learning approaches we can able to get the solution in most precise way. Recent methodologies are the hybrid network models which have good prediction accuracy with less error. These all algorithms work on past data in large quantities which we are collecting from different wind farms. The paper gives a comparative analysis of various literatures and described which methodology is the best among all depending on various seasonal data and ultra short-term prediction.

Keywords: Wind Power Generation, Numerical Wind Prediction, Statistical Methods, AI & Machine Learning Approaches, Neural networks.

1. Introduction

Although wind energy is sustainable and good for the environment, controlling electricity networks may be difficult due to its erratic and fluctuating nature. To overcome these issues, it is critical to anticipate the amount of power generated by renewable sources prior to erecting a plant in a given location. Wind power generation increased dramatically in 2022, reaching over 2,100TWh, a notable 14% increase with a total growth of 265TWh.The second-biggest advancement in renewable energy technology, after solar photovoltaic. Nevertheless, the average annual growth rate must be raised to almost 17% in order to comply with the ambitious Net Zero Emissions by 2050 Scenario, which predicts nearly 7,400TWh of wind power output by 2030 [4][9][17].

Thus, the urgent need for further yearly capacity growth to get from the 75 GW built in 2022 to the ambitious 350 GW predicted for 2030 is highlighted by the requirement for precise projection. Reaching this ambitious objective will need intense work on the part of the public and commercial sectors. More specifically, there is an urgent need to reduce the prices of offshore wind projects and expedite the approval procedures for onshore wind projects. These initiatives highlight how crucial precise forecasting is to achieving the goals and requirements outlined for wind power in the future [14].

Complex networks are used by electrical utilities to maintain a constant balance between the supply and demand of power for consumers. In this case, grid stability and dependable electricity distribution are largely dependent on controlling and preserving this balance. In the past, dispatch able power sources like coal, gas, and nuclear have been the go-to source for grid managers to satisfy demand fluctuations and maintain stability [16].

But the addition of renewable energy sources wind power in particular has given this balance a new facet. Because wind power is unpredictable and sporadic, it can be difficult to keep the supply and demand in electrical systems in balance. The entire power supply that is available at any given moment is unpredictable due to the erratic generating patterns of wind turbines. Unpredictable wind power production means that imbalances in power generation and consumption pose a severe threat to the integrity of the grid. These imbalances can result in frequency changes and potentially system instability. In addition, these imbalances could affect market prices and require the costly installation of reserve power, among other negative economic effects [1][2][6].

It is crucial to forecast wind power output from wind farms minutes to hours in advance in order to enable load sharing and system stability and to efficiently manage local power demand and distribution. In wind power and storage markets, accurate short-term wind power prediction is essential for effective unit commitment, load dispatch, and energy trading. Furthermore, predictions with a time horizon of one to multiple days are essential for organizing upkeep of wind farms, storage facilities, and the networked electrical grid [17][18][19].

The requirements of the power system and the energy market, as well as the particular time horizon, must be taken into account when choosing a wind speed or power forecast model. There are several methodologies for predicting wind power, which may be roughly categorized as persistent, physical, statistical, and soft computing methods.

Many advanced techniques for forecasting and controlling wind energy have been developed, especially in nations where wind energy accounts for a sizable share of total energy capacity. Of these, the persistence technique forecasts the next hour based on the previous hour's wind power data it is often used as a standard to assess how well other models predict the near term. By comparison, the physical modeling technique produces a wind power forecast with low weather pattern volatility by combining complex mathematical procedures with weather prediction data [11][12].

A variety of methods, including generalized autoregressive conditional heteroscedastic (GARCH) models, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and others, are used in statistical models intended for short- and extremely short-term wind speed or power forecasts. These models organize their parameters based on previous data, but they may not be able to account for wind's stochastic character, which makes it difficult for them to produce accurate wind power or speed estimates [4][5].

More accurate forecasts are provided by wind power forecasting models, particularly those that use on machine learning. By using past wind speed and power data, these models predict future patterns and help grid operators better anticipate and control wind power intermittency.

Grid operators are able to anticipate the variable wind power generation more accurately by utilizing sophisticated forecasting algorithms. Their ability to make well-informed judgments in real time, maximizing the use of conventional power sources based on anticipated wind power output, is enhanced by this improved precision. Because of this, there is less need for extra reserve power to make up for erratic wind generation, which improves overall grid stability and lowers related costs [3][8].

The Decision Tree Regressor, Support Vector Machine (SVM) Regressor, Random Forest Regressor, GradientBoostingRegressor, XGBoost Regressor, and K-Nearest Neighbors (KNN) Regressor are indispensable tools in the intricate process of predicting wind power output using large historical datasets. These algorithms navigate through diverse environmental variables such as temperature and wind speed to decipher complex patterns and relationships affecting wind power generation. Each Regressor employs unique methodologies, such as decision tree construction, kernel-based transformations, ensemble techniques, and instance-based learning, to optimize predictions. Rigorous evaluation and adaptability to non-linear dynamics distinguish these Regressors, collectively contributing to the advancement of sustainable and efficient wind power production [13][14].

2. Literature Review

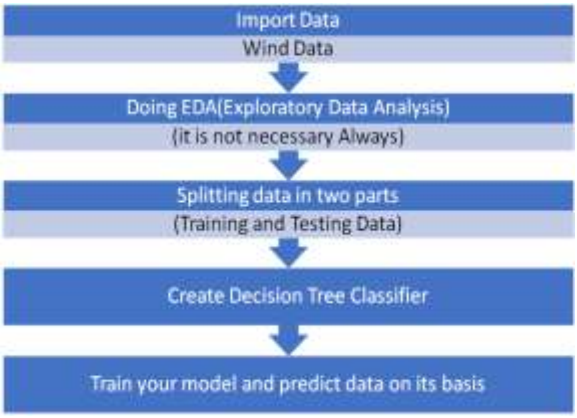
It is now possible to anticipate the energy production and performance of wind power plants with the use of machine learning.Whereas conventional analytical models depend on intricate differential equations, machine learning offers a more accurate and efficient substitute. In the context of wind turbine power output forecasting, this section examines the use of machine learning models such as Support Vector Regression (SVR), Regression Tree (RT), Random Forest (RF), and Artificial Neural Networks (ANNs).

Research in this area encompasses a variety of machine learning-based forecasting models for wind turbine power output. Studies delve into regression models, neural networks, ensemble methods, and hybrid models, aiming to predict power output based on diverse meteorological and operational parameters. Noteworthy studies, such as "Machine learning methods for wind turbine condition monitoring" by Adrian Stetco (2019), showcase the diversity of approaches within this research domain [1].The literature emphasizes the significance of meteorological data, historical power output, wind speed, direction, temperature, and other relevant variables in developing accurate forecasting models. Researchers often discuss data pre-processing and feature engineering techniques to enhance model performance. For instance, "Current perspectives on the accuracy of Deterministic Wind speed and power Forecasting" by Muhammad Uzair Yousuf (2019) provides insights into the importance of these variables [2].Studies commonly compare the performance of different machine learning models in terms of accuracy, robustness, and computational efficiency. Evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and correlation coefficients are commonly used to assess model effectiveness."Forecasting of Wind Turbine Output Power Using Machine learning"by Haroon Rashid (2019) is an example study that demonstrates the application of these metrics [3].Optimizing model performance involves feature selection techniques and hyperparameter tuning. Researchers explore methodologies to identify the most influential features and optimize model parameters for improved accuracy in power output predictions. For instance, "Feature selection and hyperparameters optimization for short-term wind power forecast" by Hui Huang (2021) provides insights into these optimization strategies [4].Literature in this field investigates short-term and long-term forecasting horizons for wind turbine power output. Time series analysis, including methods like autoregressive models and recurrent neural networks, is studied to capture temporal dependencies in the data. "A review of wind speed and wind power forecasting with deep neural networks" by Yun Wang (2021) exemplifies this exploration of time series analysis [5].Researchers also explore the integration of wind power forecasting models into broader renewable energy systems, addressing challenges related to grid stability, energy management, and the synergy between wind power predictions and other renewable sources. "Machine Learning applications in wind turbine generating systems" by M. Lydia (2021) is an example study highlighting the importance of this integration [6].Recent literature discusses emerging challenges, such as improving forecasting accuracy in complex terrains, adapting models to climate change effects, and addressing uncertainties. Studies also highlight future directions for research, potentially exploring explainable AI and hybrid models. "Hybrid Deep Learning-Based Model for Wind Speed Forecasting Based on DWPT and Bidirectional LSTM network" by Amirhossein Dolatabadi(2020) exemplifies the exploration of hybrid models and emerging challenges in wind power forecasting [7].

Methodology

Machine Learning Models:

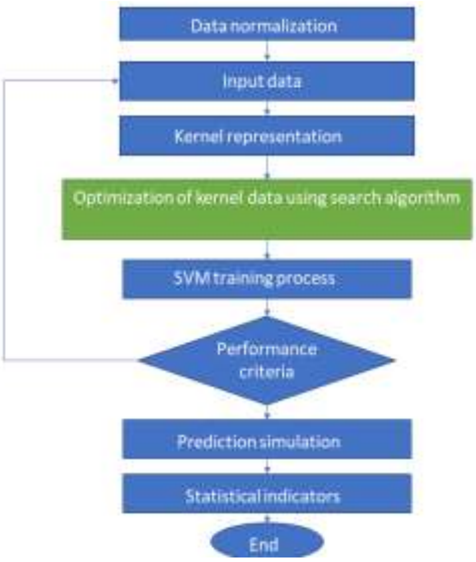
3.1 Decision Tree



One of the most important tools in the complex process of wind power production prediction using large historical datasets is the Decision Tree regressor. These datasets contain a wide range of characteristics that together affect wind power generation, such as temperature and wind speed, in addition to other environmental variables. The voyage of the regressor begins with a careful feature selection procedure that identifies the most influential elements that influence the intricate dynamics of wind power [2][3]. This methodical approach guarantees that the building of the model that follows will concentrate on the components that have the most impact on the result. Its main role is to build a tree-like structure, a complex network of nodes and branches, where each node is a critical decision point associated with a certain attribute. This tree serves as a physical representation of the model's ability to identify complex patterns hidden within the historical data, providing the foundation for its predictive power [18]. The Decision Tree navigates its branches with an acute understanding of the complex interactions between variables as it is presented with fresh data. This traversal approach yields accurate predictions of anticipated power generation, demonstrating a deep comprehension of the complex interactions among the many variables influencing wind power output. Because wind power dynamics are intrinsically complex, the Decision Tree regressor's capacity to adapt to nonlinear interactions is one of its most notable features. Furthermore, its scalability guarantees effectiveness even when working with large datasets, which is a crucial feature for capturing the complex features of wind power generation. The building of the model is not the end of its journey. In order to optimize its parameters and improve its ability to generalize to previously unknown data, it goes through a thorough assessment process utilizing validation datasets [6][7]. This dedication to continual improvement reflects the dynamic nature of the model, which enables it to adapt and change over time in response to new data. In the field of renewable energy, the Decision Tree regressor essentially acts as a cornerstone. Its data-driven methodology, in conjunction with its flexibility and scalability, greatly aids in the optimization of wind power generation, clearing the path for a more robust and ecologically aware future.

3.2 SVM

When it comes to forecasting wind power output using historical records, the Support Vector Machine (SVM) regressor is a key component. It excels in deciphering complicated patterns and negotiating the nuanced, non-linear relationships present in the dynamics of wind power generation [1][4].



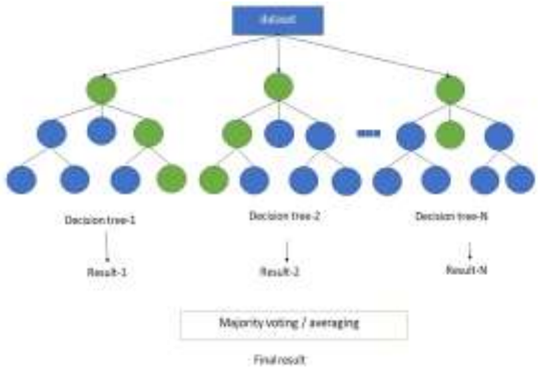
SVM begins its work by converting historical data into higher-dimensional spaces by using the kernel approach. Understanding the complex interaction of factors affecting wind power output particularly wind speed, temperature, and atmospheric conditions requires an understanding of this transition. Within the modified feature space, the creation of a hyper plane is a fundamental component of the SVM process. This hyper plane maximizes the margin between distinct classes of data points, serving as a discriminating border. Within the framework of wind power forecasting, this distinction is essential for pinpointing areas linked to different power production levels [20].

A crucial decision point arises when selecting kernel functions, such as radial basis function (RBF) kernels. With the help of these functions, SVM is able to accurately depict the complex connections and fluctuations inherent in the dataset giving rise to a sophisticated picture of the underlying patterns controlling the production of wind power. The SVM regressor optimizes its parameters through an extensive training procedure with the goal of reducing prediction errors and increasing accuracy. Its excellent potential for generalization to a variety of settings is demonstrated by its ability to estimate wind power output for fresh, unknown data, which is mostly due to its adaptability. SVM excels at managing non-linear connections, which is especially useful for dealing with the intricate interactions that make up wind power dynamics. Because of this competence, SVM may be used to estimate energy output more accurately than classic linear models [20].The voyage of the SVM regressor includes a comprehensive assessment phase in addition to training and prediction. Thorough evaluations utilizing validation datasets guarantee the model's dependability and efficiency in practical situations. Hyperparameters may then need to be fine-tuned in order to maximize the SVM regressor's performance and improve its prediction power [6].

In essence, the SVM regressor stands as a formidable force in the quest for efficient and sustainable energy production. Its capacity to navigate complexities, handle non-linear relationships, and generalize well to diverse conditions underscores its significance in the ongoing pursuit of a greener and more resilient energy landscape [8].

3.3 Random Forest

The Random Forest's noteworthy benefit is in its capacity to manage non-linear connections and variable interactions in an efficient manner. In the context of wind power, where the linkages impacting energy output can be complex and non-linear, this flexibility is very significant [24].

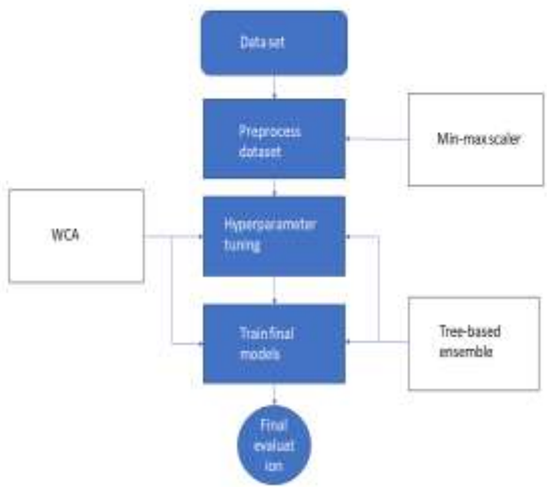


To make sure the model is accurate and has the ability to generalize, its performance is carefully evaluated using validation datasets. To maximize the prediction power of the model, parameters like the total number of trees in the forest and the maximum depth of each tree are adjusted [22][23].

In conclusion, the Random Forest regressor is an effective tool for predicting wind power output based on historical data. In the quest for effective and sustainable energy production, its ensemble methodology, capacity to manage non-linear interactions, and versatility to a wide range of datasets make it an invaluable tool [1][14].To get started, the Random Forest regressor explores a large history dataset that contains important data from prior years. Typical variables in this dataset include temperature, wind speed, and other environmental conditions that affect the generation of wind power. The regressor's strength is in the way it works as an ensemble, building many decision trees in the training stage. In order to provide variety to the model and reduce the possibility of overfitting to certain patterns in the data, each decision tree is constructed using a random subset of the dataset [3][6][7].In order to create a forest of trees that together contribute to the final forecast, the Random Forest intelligently chooses characteristics and nodes in each decision tree as it goes along. The model's capacity to represent intricate linkages and changes within the dataset is improved by this ensemble technique. For fresh, untainted data, the Random Forest regressor performs exceptionally well in the prediction stage, yielding reliable and precise estimations of wind power output. It can average out individual tree forecasts thanks to its ensemble of decision trees, producing an overall prediction that is more stable and trustworthy.

3.4 Gradient Boosting Regressor

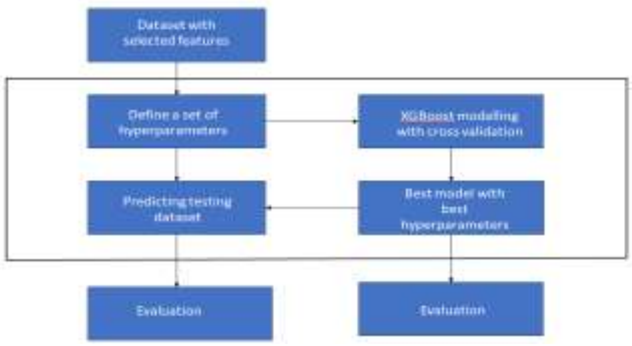
A key component in wind power production prediction is the Gradient Boosting Regressor, which performs a thorough examination of historical information from prior years [21]. This sophisticated regression approach is an essential part of ensemble learning and is very good at identifying complex patterns and maximizing prediction accuracy. The procedure starts with a thorough investigation of a number of factors that have a substantial impact on wind power output, such as temperature, wind speed, and environmental factors. This thorough comprehension serves as the basis for the Gradient Boosting Regressor's ability to identify significant patterns within the dataset. Gradient Boosting is essentially the process of building decision trees one after the other, each one intended to correct the mistakes of the one before it. By minimizing the differences between actual and forecast wind power outputs, this iterative ensemble-building approach seeks to provide a more precise and accurate prediction model. By assigning distinct characteristics differing degrees of priority during construction, the Gradient Boosting Regressor illuminates the variables that have the greatest impact on wind power generation. Understanding the relative relevance of various variables in the prediction framework requires an understanding of feature importance [1][2][3].By utilizing a gradient descent optimization technique, the model continuously modifies its parameters in order to decrease residuals, guaranteeing a more proficient capacity to predict wind power production during the course of training. Because wind power prediction involves complex dynamics, the model's capacity to explore and capture non-linear connections within the dataset is made possible by its flexibility [4][5][7].



Utilizing regularization parameters and regulating decision tree depth are two ways that the Gradient Boosting Regressor reduces overfitting to improve generalization. The process of fine-tuning strikes a careful balance between preventing undue adaptation to noise in the training data and capturing complex patterns [9][12].Using validation datasets, the prediction performance of the model is rigorously assessed to make sure it is reliable outside of the training set. The Gradient Boosting Regressor is proven to be a reliable method for predicting wind power production in a variety of scenarios by this thorough evaluation [15].Gradient Boosting Regressor's strength essentially comes from the way its ensemble technique combines the predictive capacity of several decision trees to produce a reliable and accurate model. Gradient Boosting Regressor is now positioned as a powerful and priceless tool in the continuous quest for effective and sustainable wind energy generation.

3.5 XGBoost

A key component in forecasting wind power output from datasets including past data is the XGBoost Regressor. By carefully analyzing factors such as temperature and wind speed, the model finds important traits and ranks them. Using a gradient boosting architecture, XGBoost builds a group of decision trees that together identify complex correlations and patterns in the dataset [21].In order to minimize overfitting and guarantee the model's flexibility to a variety of situations, regularization techniques are essential to the training process. By fine-tuning the hyperparameters, the model becomes more predictive across a range of situations. The model's ability to handle missing data with resilience in the face of real-world dataset issues is noteworthy.

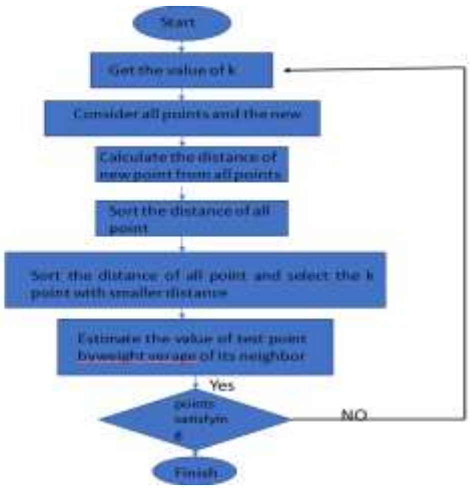


After being trained, the XGBoost Regressor performs exceptionally well, yielding precise estimates for wind power output in fresh, untested data. The ensemble's capacity to fully account for the interdependencies across environmental factors is the reason for its forecasting brilliance [7][11][14].

Strict assessment protocols, frequently incorporating validation datasets, guarantee the correctness and dependability of the model in real-world scenarios. Moreover, XGBoost offers insightful information on feature significance, which promotes a better comprehension of the variables affecting wind power projections. To put it simply, the XGBoost Regressor proves to be a formidable friend in the fight for sustainable and effective wind power generation. Its intelligent ensemble approach, flexibility in a range of environments, and perceptive interpretability make a substantial contribution to increasing the efficiency of energy production and developing renewable energy solutions [16][17].

3.6 KNN

Using historical datasets, the K-Nearest Neighbors (KNN) Regressor plays a crucial role in wind power production prediction. KNN is a non-parametric, instance-based learning method that works well in situations where there are complicated and non-linear correlations between variables since it makes predictions based on how similar data points are. Using the historical dataset, the algorithm starts a closest neighbor search to find data points that are similar to the input characteristics [19][20]. The selection of the parameter 'k,' which denotes the count of closest neighbors taken into account, is crucial as it affects the equilibrium between the flexibility and resilience of the model. KNN provides a localized method that captures fluctuations within smaller portions of the dataset by calculating the average or weighted average of the target values of the k-nearest neighbors. Its capacity to adjust to non-linear interactions fits very nicely with the complex dynamics involved in predicting wind power. The selection of distance metrics, such as Manhattan or Euclidean distance, has a major impact on prediction accuracy as well as the measurement of data point similarity. When working with missing data, the KNN Regressor exhibits a relative resilience, effectively imputing missing values by taking surrounding occurrences into account [11][12][13]. Even though KNN is usually regarded as a "black-box" model, its predictions may be understood, particularly when looking at the closest neighbors. The algorithm's performance is rigorously evaluated using validation datasets, and practical implementations depend heavily on the algorithm's scalability for handling bigger datasets [21] .



4. Evaluation Metrics

Evaluating the error of model for forecasting of wind power output

Evaluating the forecasting of wind power output typically involves comparing the forecasted values with the actual or observed values. One common metric used for evaluating the accuracy of forecasts is the Mean Absolute Error (MAE) or Root Mean Square Error (RMSE). These metrics measure the average magnitude of errors between predicted values and actual values.

4.1 Mean Absolute Error (MAE):

MAE measures the average absolute differences between forecasted and observed values. The formula is:

$$\frac{1}{n}\sum_{i=1}^{n} |\ forecast - actual\ |$$

Where:

n is the number of observations.

forecast represents the forecasted value for observation i.

actual represents the actual or observed value for observation i.

4.2 Root Mean Square Error (RMSE):

RMSE is a measure of the differences between predicted values and observed values, giving more weight to larger differences. The formula is:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(forecast - actual)^2}$$

Where:

n is the number of observations.

forecast represents the forecasted value for observation i.

actual represents the actual or observed value for observation i.

4.3 Mean Absolute Percentage Error (MAPE):

MAPE measures the average percentage difference between forecasted and observed values. The formula is:

$$\frac{1}{n}\sum_{i=1}^{n} |\ \frac{forecast - actual}{actual}\ | \times 100\%$$

Where:

n is the number of observations.

forecast represents the forecasted value for observation i.

actual represents the actual or observed value for observation i

4.4 Mean Absolute Percentage Error (MAPE

Mean Absolute Error (MAE) is a metric used to measure the average absolute differences between predicted values and actual values. It provides a straightforward and easy-to-interpret measure of the model's accuracy.

$$\frac{1}{n}\sum_{i=1}^{n} |\ \frac{\text{forecast} - \text{actual}}{\text{actual}}\ |$$

4.5R-squared (R2

R-squared (R2) is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variables in a regression model. It is often used to assess the goodness of fit of a regression model.The formula for R-squared is:

$$\mathbf{R^2 = 1 - \frac{SSR}{SST}}$$

Where:

($\mathbf{R^2}$) is the R-squared value.

SSR is the sum of squared residuals (the sum of the squared differences between the predicted values and the actual values).

SST is the total sum of squares (the sum of the squared differences between each data point and the mean of the dependent variable).

5. Results

The evaluation results highlight distinct characteristics of each regression model. The Decision Tree, XGBoost, GradientBoostingRegressor, and Random Forest models showcase remarkable precision, capturing the underlying patterns in the data with minimal errors. These models not only exhibit low mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) values but also achieve high R2 scores, indicating a close fit to the actual data.

In contrast, the Support Vector Machine (SVM) model, while performing reasonably well, shows a relatively higher level of error across the metrics, suggesting a less precise fit. The KNN Regressor, although providing reasonable predictions, has higher error rates compared to the top-performing models. Meanwhile, the Linear Regressor aligns itself with the high-performing ensemble methods like XGBoost and Random Forest, showcasing a robust fit and predictive accuracy.So,Decision Tree, XGBoost, Gradient Boosting Regressor, and Random Forest models emerge as standout performers, demonstrating superior predictive capabilities. The linear regression model also proves to be a strong contender. The SVM model, while competent, lags slightly behind in terms of precision. The KNN Regressor, while acceptable, shows a comparatively higher degree of error. These insights can guide the selection of an appropriate regression model based on the specific requirements and trade-offs in the given context.

Method	MSE	RMSE	MAE	MAPE	R2
Decision Tree	80.00	8.9444	5.41879	5.4187	0.999
XGBoost Regressor	38.7684	6.2264	4.3180	2.7558	0.999
SVM	85.11	92.36	70.97	5.319	0.912
GradientBoostingRegressor	55.8127	7.4707	5.4216	2.75586	0.999
Random Forest	27.0780	5.2036	2.9678	2.7558	0.9995
KNN Regressor	88.41	221.107	139.414	89.7959	0.93561
Linear Regressor	38.7684	6.22643	4.3180	2.75586	0.9995

6. Conclusion:

This paper delves into the imperative task of prognosticating wind turbine power output employing machine learning-based forecasting models, an essential endeavor for orchestrating grid efficiency and stability amid the capricious nature of wind speed. The inquiry scrutinizes a myriad of methodologies, accentuating the salience of statistical and machine learning approaches, particularly spotlighting hybrid network models. Underscoring the exigency for precision in wind power projections, especially in the pursuit of ambitious objectives like Net Zero Emissions by 2050, the paper elucidates challenges in grid stability concomitant with the amalgamation of renewable sources, underscored by the imperative for avant-garde forecasting models.

The comprehensive literature scrutiny illuminates extant studies, showcasing a gamut of machine learning paradigms such as Support Vector Regression, Regression Tree, Random Forest, and Artificial Neural Networks. It accentuates the pivotal role of meteorological data and the exploration of sophisticated data pre-processing techniques within the milieu of model development. The methodological exegesis expounds upon an array of machine learning models, encompassing Decision Tree, Support Vector Machine, Random Forest, Gradient Boosting Regressor, XGBoost, and K-Nearest Neighbors, painstakingly expounding upon their robust attributes. The evaluative metrics section delineates criteria inclusive of Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and R-squared, revealing nuances in model efficacy. In summation, this scholarly endeavor contributes erudite insights, furnishing a meticulous analysis of wind power forecasting methodologies, models, and evaluative metrics to inform judicious decision-making in the realm of renewable energy.

References

1. Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., ... & Nenadic, G. (2019). Machine learning methods for wind turbine condition monitoring: A review. Renewable energy, 133, 620-635.

2. Yousuf, M. U., Al-Bahadly, I., & Avci, E. (2019). Current perspective on the accuracy of deterministic wind speed and power forecasting. IEEE Access, 7, 159547-159564.

3. Rashid, H., Haider, W., & Batunlu, C. (2020, September). Forecasting of wind turbine output power using machine learning. In 2020 10th International Conference on Advanced Computer Information Technologies(ACIT) (pp. 396-399).IEEE.
4. R., Shi, X., Liang, J., & Dang, J. (2021). Feature selection and hyper parameters optimization for short-term wind power forecast. Applied Intelligence, 1-19.
5. Wang, Y., Zou, R., Liu, F., Zhang, L., & Liu, Q. (2021). A review of wind speed and wind power forecasting with deep neural networks. Applied Energy, 304, 117766.
6. Lydia, M., & Kumar, G. E. P. (2021). Machine learning applications in wind turbine generating systems. Materials Today: Proceedings, 45, 6411-6414.
7. Dolatabadi, A., Abdeltawab, H., & Mohamed, Y. A. R. I. (2020). Hybrid deep learning-based model for wind speed forecasting based on DWPT and bidirectional LSTM network. IEEE Access, 8, 229219-229232.
8. Kariniotakis, G. N., Stavrakakis, G. S., & Nogaret, E. F. (1996). Wind power forecasting using advanced neural networks models. IEEE transactions on Energy conversion, 11(4), 762-767.
9. Quan, H., Srinivasan, D., & Khosravi, A. (2013). Short-term load and wind power forecasting using neural network-based prediction intervals. IEEE transactions on neural networks and learning systems, 25(2), 303-315.
10. Dolatabadi, A., Abdeltawab, H., & Mohamed, Y. A. R. I. (2020). Hybrid deep learning-based model for wind speed forecasting based on DWPT and bidirectional LSTM network. IEEE Access, 8, 229219-229232.
11. Yousuf, M. U., Al-Bahadly, I., & Avci, E. (2019). Current perspective on the accuracy of deterministic wind speed and power forecasting. IEEE Access, 7, 159547-159564.
12. Lydia, M., & Kumar, G. E. P. (2021). Machine learning applications in wind turbine generating systems. Materials Today: Proceedings, 45, 6411-6414.
13. Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. Renewable energy, 37(1), 1-8.
14. Lei, M., Shiyan, L., Chuanwen, J., Hongling, L., & Yan, Z. (2009). A review on the forecasting of wind speed and generated power. Renewable and sustainable energy reviews, 13(4), 915-920.
15. Netsanet, S., Zhang, J., Zheng, D., Agrawal, R. K., & Muchahary, F. (2018, February). An aggregative machine learning approach for output power prediction of wind turbines. In 2018 IEEE Texas Power and Energy Conference (TPEC) (pp. 1-6). IEEE.
16. Liu, M., Qiu, P., & Wei, K. (2019, November). Research on wind speed prediction of wind power system based on GRU deep learning. In 2019 IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2) (pp. 1699-1703). IEEE.
17. Barber, S., Hammer, F., & Tica, A. (2022). Improving site-dependent wind turbine performance prediction accuracy using machine learning. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering, 8(2), 021102.
18. Chrimes, D. (2023). Using decision trees as an expert system for clinical decision support for COVID-19. Interactive Journal of Medical Research, 12(1), e42540.
19. Lanjewar, M. G., Parab, J. S., & Shaikh, A. Y. (2023). Development of framework by combining CNN with KNN to detect Alzheimer’s disease using MRI images. Multimedia Tools and Applications, 82(8), 12699-12717.
20. Cinyol, F., Baysal, U., Köksal, D., Babaoğlu, E., & Ulaşlı, S. S. (2023). Incorporating support vector machine to the classification of respiratory sounds by Convolutional Neural Network. Biomedical Signal Processing and Control, 79, 104093.
21. Kromer-Edwards, C., Castanheira, M., & Oliveira, S. (2023, June). Using feature selection from xgboost to predict mic values with neural networks. In 2023 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.
22. Yao, L., Li, W., Zhang, Y., Deng, J., Pang, Y., Huang, Y., ... & Lee, T. Y. (2023). Accelerating the Discovery of Anticancer Peptides through Deep Forest Architecture with Deep Graphical Representation. International Journal of Molecular Sciences, 24(5), 4328.
23. Emon, I. S., & Rahman, M. (2023). Media interestingness prediction in imagecleffusion 2023 with dense architecture-based ensemble & scaled gradient boosting regressor model. In Experimental IR Meets Multilinguality, Multimodality, and Interaction, CEUR Workshop Proceedings, CEUR-WS. org, Thessaloniki, Greece.
24. Kreuzberger, D., Kühl, N., & Hirschl, S. (2023). Machine learning operations (mlops): Overview, definition, and architecture. *IEEE Access*.