Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
July 2024 5(7), 708–718

EVALUATING THE PERFORMANCE AND ACCURACY OF AI TECHNIQUES IN WIND SPEED FORECASTING

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DOI
10.29121/shodhkosh.v5.i7.2024.4335

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

The effectiveness of many artificial intelligence systems in predicting wind speed is investigated in this work. Enhancing prediction accuracy and reliability for renewable energy management is the aim. Our analysis disproves the first theory that suggests complicated models perform better. Rather, we have shown that more straightforward methods, such as Random Forest regressors and XGBoost, consistently outperform their more complex equivalents. With a mean average percentage error of 6% and a prediction accuracy of almost 94%, these models exhibit remarkable precision, explaining roughly 91% of the variability in the data (R squared). Furthermore, they demonstrate computational efficiency, leading to faster processing times as compared to more complex models. Our study emphasises how important it is to carry out realistic model selection and empirical testing for wind speed predictions. This advances the strategies for managing renewable energy sources. This paper demonstrates the enhanced predictive capabilities of AI techniques, improving wind speed prediction accuracy and dependability. Thus, it facilitates making well-informed choices on the usage of renewable energy.

Keywords: Wind Speed Forecasting, Ai Techniques, Predictive Accuracy, Renewable Energy Management, XG Boost, Random Forest

1. INTRODUCTION
1.1. WIND ENERGY GLOBAL AND INDIAN CONTEXT

Throughout recent years, India has seen an enormous expansion in how much power produced from wind power projects (Yousuf, 2019). India's wind power plants are now adding more than 25,000 MW of capacity. Most Indian governments are developing new wind energy regulations to entice developers of wind farms. Developers of wind farms seek long-term agreements that reduce the risk of their investments. A problematic feature of a renewable grid is minute-by- minute wind energy generation that equates to hour- by-hour changes to satisfy consumer demand.

By 2020–30, it is predicted that the global demand for fossil fuels would increase to 20%. By lowering total producing costs and risk, wind penetration contributes to a nation's energy portfolio diversification. If energy authorities support wind technology, wind turbines can generate competent power. They must carry a thorough coverage that covers all expenses and hazards related to it. The distinct features of wind energy technology allow it to effectively mitigate the techno-economic risks that are inherent in projects. By include wind in their portfolios, utilities and other energy providers are able to better match the demand and preferences for power and improve the country's energy supply structure. The cost of wind energy is determined by wind resources, including their availability, frequency, and blowing speed (Yang Z.

&., 2018). The cost of producing wind energy includes the cost of capital equipment as well as depreciation and operation and maintenance. Now that significant obstacles have been removed, projects involving wind turbines to generate power are both possible in India and beyond.

The yearly energy output per square metre area swept by the rotating turbine blades is known as specific yield. The annual production of a typical wind turbine at 7 m/s wind speed is around 1100 KWH per square metre. In other words, when wind speed doubles, power creation increments multiple times. Nonetheless, power in the breeze fluctuates with temperature and level, which thus impacts air thickness (Li, 2010). This is how electricity is created by a wind turbine. Since summer wind has a lower density than winter wind, more wind power is produced in the winter at the same wind speed. The physical topography, the site's terrain, the diurnal fluctuation, general climatic conditions of the area, and other factors all affect the behaviour and structure of wind at different sites.

- **Weather forecasting**

The most common way of assessing the situation with the climate for a particular region utilizing a few meteorological variables is known as weather conditions guaging. Data in regards to the situation with the climate at some random time is accumulated to make weather conditions conjectures. For meteorologists and researchers, precise weather conditions foreseeing has shown to a troublesome embrace (Bou-Rabee, 2020). Each part of life, including power age, the travel industry, air terminal frameworks, mining, and farming, relies upon climate data. In horticulture, weather conditions gauges help ranchers pursue the ideal choices to increment crop yields. Consistent climate information is important for air terminal and maritime frameworks to identify quick changes in the climate. For wind ranches to direct the activity of their breeze turbines during the age of wind power, exact breeze speed conjecture is fundamental. Precise meteorological information is important for mining organizations to screen the World's outside ceaselessly. Day to day, week by week, month to month, or yearly weather conditions anticipating becomes significant on the grounds that it can all the more precisely address the pattern of the changing environment and proposition opportune and compelling natural data for choices made at the miniature administration level.

Because of the improvement of environment perception strategies like satellite meteorological perception, as well as the quick expansion in how much climate information, weather conditions determining has now entered the time of large information (Godinho, 2021). Exact climate expectation is past the capacities of conventional PC knowledge calculations. Additionally, weather conditions estimating and environment forecast might be made more exact and fruitful with the improvement of profound learning calculations and appropriate information perception draws near. Consequently, it's a good idea to deal with enormous datasets utilizing profound learning strategies so they can learn and make expectations all the more precisely founded on verifiable information. Brain network layers are utilized in profound gaining methods to find and concentrate huge examples from datasets. Precise extraction of undeniable level dynamic data from Huge Information might be accomplished utilizing brain networks with profound structures. The utilization of profound learning in weather conditions estimating has been prodded by its effective application in a few fields, which is an essential progression for the meteorological area. For weather conditions anticipating undertakings, profound learning structures, for example, Long Transient Memory Organizations and Intermittent Brain Organizations have demonstrated to be trustworthy models.

Contingent upon the boundary to be expected, guaging models might be named temperature expectation models, wind speed forecast models, precipitation expectation models, dew point expectation models, etc. Each expectation model makes a gauge for a specific boundary in light of verifiable information. In light of various meteorological variables, temperature determining models try to gauge an area's most minimal, greatest, or normal temperature. While the base temperature gauge is subject to overcast cover around evening time, the most noteworthy temperature figure is reliant upon daylight during the day.

Farming relies intensely upon the capacity to expect temperature. Ahead information on the weather conditions helps ranchers in going with the ideal decisions to further develop crop development. For ranchers, the exorbitant temperature is dependably a significant issue since it will truly hurt the two plants and animals. The ideal temperature for plant improvement ought to be available. Crop harm might emerge from low temperatures. In this way, in agribusiness, temperature-based conjecture is significant.

Like this, wind speed expectation strategies are intended to foresee wind speed. Since wind has involves in various fields, including power creation, farming, industry, maritime frameworks, and the marine climate, wind speed expectation is a significant errand (Maroufpoor, 2019). Air travels through the breeze from high strain to low tension, and the distinction in tension between the two is utilized to quantify wind speed. The breeze speed ascends couple with the distinction. Among the best sustainable power sources is wind energy. Carbon dioxide outflows from customary energy sources, like petroleum products, are the essential driver of an Earth-wide temperature boost. Sustainable power sources are less expensive, contamination free, interminable, and ecologically useful than regular energy sources. Using wind energy productively advances reasonable turn of events. Populace development, industrialization, and urbanization are the principal drivers of the expanded requirement for sustainable power sources. The age of wind power expanded altogether somewhere in the range of 2001 and 2018. Assuming the accessible breeze speed is more noteworthy than the cut-in speed of the breeze turbine, then wind power creation can be expanded. A slight change in wind speed will bring about a bigger breeze power since wind power and wind speed are cubic related. Accordingly, wind ranches require steady wind speed checking. For the breeze turbine to work appropriately and to create the most wind power conceivable, wind speed anticipating is vital.

How much precipitation that a specific spot gets throughout some undefined time frame is known as quantitative precipitation. Both the flood checking framework and the horticulture area rely upon exact downpour gauges. Frozen water or fluid that gathers in the climate and drops to Earth is called precipitation. Ranchers will track down this climate boundary helpful in settling on conclusions about collecting, splashing, and water system.

The weight that air applies on Earth's surface is known as air pneumatic force, and it changes with level. As level increments, air pressure brings down. The dew point demonstrates how much water fume in the air and has a higher worth when this fixation is higher. The two plants flourishing in districts with moderate precipitation and abandon plants require dew point for legitimate turn of events. Stickiness alludes to how much dampness in the lower's air that is fundamental for photosynthesis, fertilization, leaf advancement, and monetary creation. One of the hazardous contaminations in the lower air is ozone. How much ozone present in the climate uncovers what it means for people, plants, and other living things. The effect of tropospheric ozone on the climate and human wellbeing can be moderated by determining and overseeing ozone focuses.

- **Wind power forecasting**

As wind power turns out to be increasingly more coordinated into power organizations, the meaning of wind power determining have expanded continuously. said that reducing the requirement for energy and reserve power balance is a key use for wind power forecasting. This would lead to lower wind power integration costs, lower emissions from balancing power plants, and higher wind power value. Since many wind farms are situated in isolated locations, wind power projections are also necessary for assessing system security and operating the grid.

2. LITERATURE REVIEW

Domínguez-Navarro (2023) As per the info model sort, pre-and post-handling techniques, fake brain network model, expectation skyline, strides ahead number, and assessment metric, this study assesses and arranges the estimating models that have been used lately (Domínguez-Navarro, 2023). The discoveries of the review show that by understanding the future breeze speed values, counterfeit brain organization (ANN)- based models might give exact breeze determining and pivotal data about the exact area of planned breeze use for a power plant.

Hao, Y., Yang, W., and Tian, Z. (2022) With its benefits for the economy, society, and climate, wind speed guaging is crucial for the creation of wind power (Hao,2022). Regardless, earlier exploration has frequently overlooked the commitment of big information for mixture models. An inventive group model that combines man-made consciousness strategies with blended recurrence models has been made. The model preprocesses the first wind speed information, considering clamor concerns and recognizing significant features. As sub-models, it additionally incorporates blended recurrence models and man- made brainpower. The model's mean outright rate blunders are 4.4286%, 6.6154%, 5.2740%, and 3.8682%, showing great anticipating execution.

Li, T., Xu, Y., Yang, Q., Huang, G., (2023) Experimental wavelet change is utilized in the EWT- ARIMA-LSSVM-GPR-DE-GWO strategy, a progressive short-term breeze speed forecast method, to break down wind speed signals into numerous characteristic mode capabilities (Li T. X., 2023). The DE-GWO strategy is utilized related to an assortment of forecast models, including as ARIMA, LSSVM, and GPR, to improve hyperparameters in this methodology. The methodology becomes effective in coordinating breeze power into the network since it exhibits uncommon precision and stability, especially at high non-fixed breeze speeds.

Y. Hao, W. Yang, and K. Yin (2023) to increment gauge viability, this work makes a profound learning combination model in light of blended recurrence demonstrating (Y. Hao, 2023). It utilizes a blended recurrence demonstrating module with four blended information testing and four AI models, as well as an information preprocessing module to revamp low-and high-recurrence wind speeds. The model guarantees precision and improves foreseeing execution by utilizing ideal sub-models in light of an assessment file. Four trials and discussions show how the model further develops wind speed figures, speeds up the improvement of low-carbon urban communities, and improves metropolitan energy organizations.

Wang, J., Zhang, L., Liu, Z., Huang, X., (2024) A clever estimating structure for wind speed guaging in savvy lattices is introduced in this paper. To catch the characteristic properties of wind speed groupings, the structure combines variational mode disintegration and solitary range examination in two phases of

information handling (Wang, 2024). The loads of expectation groupings are determined utilizing a multi-objective streamlining procedure. As per the exploratory outcomes, the proposed system performs better compared to past benchmark correlation models, which makes it a suitable choice for wind speed determining and a compelling instrument for overseeing power matrix activity.

Alonso-Pérez, S., Galarza, (2023) The extended consumption of petroleum products and their hindering impacts on exhaust outflows have incited the review to research the use of wind turbines as an answer for the issue of electric interest. Despite the fact that breeze speed might be utilized to gather wind energy, its flighty conduct makes effective usage troublesome (Alonso-Pérez, 2023). The reason for the review is to determine whether the exactness of present breeze speed expectations for the following 10 minutes can be improved by coordinating AI strategies with time-recurrence decay of wind speed information. With a root mean square blunder of 0.34 m/s and a deviation beneath 0.1% in 62% of the approval data set, the made breeze speed forecaster beat benchmark models by 51.5% in terms of exactness.

Chevallier, J., Zhao, S., Wang, Y., Yang, P., (2023) Utilizing a crossover technique, the exploration proposes a half breed insightful structure for short- term hourly wind speed expectation. Three stages make up the structure: result enhancement, information forecast, and sign pre-handling. Obstruction data is dispensed with in the initial step, normal data that is disguised is removed in the subsequent stage, and lingering data is recuperated in the third stage through blunder adjustment. Sotavento wind homesteads' verifiable hourly wind speed information is utilized to survey the structure's exhibition (Chevallier, 2023). As indicated by the outcomes, de-noising functions admirably for catching genuine examples however could affect the exactness of short-term expectations. While utilizing the deconstruction approach rather than single models, it is worked on by 52.84% to gauge execution. To determine in the event that mistake change is important, a disorder test is required. The system beats past models in catching convoluted properties for different short-term hourly wind speed time series.

Al-Sumaiti, V. K. Saini, and R. Kumar (2023) For shrewd matrix applications, this study offers an exhaustive evaluation of learning-based short-term determining models (Al-Sumaiti, 2023). Besides, the review looks at a few guaging models for wind speed estimating, for example, measurable, half and half, physical, and vulnerability examination models. Three general classifications — traditional AI, high level AI, and probabilistic learning — are utilized to bunch the learning-based models. 41 particular models are utilized in this work to expect wind speed. The dataset used for this situation study was accumulated from the Jodhpur, India area. There are 8759 examples in the dataset, each with five features: temperature, dew point, tension, stickiness, and wind speed. Occasional effects are likewise remembered for this expectation. Trial of the model's exactness have considered both individual and different attributes in the info information. In view of coefficient of relapse and blunder files, the presentation of these 41 learning-based models is analyzed. It has been noticed that these models' exhibition changes as per occasional varieties. Future proposals are likewise illustrated in light of the models' appraisal.

Paramasivan, S. K., and Subbiah, S. S. (2023) expecting wind energy requires expecting wind speed. Precise breeze speed determining is a better approach to effectively control the ascent in energy interest (Paramasivan, 2023). The essential objective of this work is to address non-linearity, overfitting, the scourge of dimensionality, and vulnerability to upgrade wind speed guaging execution. Boruta feature selection is utilized to address overfitting issues and the scourge of dimensionality. Bi-directional Long Short Term Memory (Bi-LSTM), which depends on profound learning, is utilized to deal with the non- linearity and vulnerability issues. This work proposes the BFS-Bi-LSTM, a Bi-LSTM with Boruta feature selection, to upgrade wind speed estimating execution. Utilizing Boruta wrapper feature selection (BFS), the model concentrates appropriate features from the meteorological factors for wind speed expectations.

3. RESEARCH METHODOLOGY

In this research, we investigate the procedure for assessing AI models' forecast accuracy for wind speed. This evaluation relies heavily on the utilization of historical wind speed data, which serves as the foundation for the training, testing, and validation of AI systems' predicting abilities. Importing the dataset is the initial step towards doing a comprehensive analysis.

- **Dataset Description**

The dataset contains crucial information regarding wind speed observations over a certain time period and is often stored in a CSV (Comma Separated Values) format. Once the dataset has been imported, special attention is given to the data structure, where the date column is identified as the 'Unnamed: 0' column. For the investigation to ensure appropriate temporal representation, this column has to be imported as a datetime object.

The initial step after importing the wind speed data file is to look for duplicate entries. The duplicated() method in Python's pandas module is used to determine which rows are copies of the ones that came before them. Following investigation, it was discovered that the dataset had 23,039 instances of duplicate entries. To fix this duplication, a decisive action is taken to eliminate the duplicate entries from the Data Frame. The drop_duplicates() method is used to successfully eliminate these duplicate entries. As a result, 95,185 unique entries are added to the Data Frame, ensuring the uniqueness of every observation.

- **Model Architecture**

The hearty engineering of the Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) model takes into account point by point time series examination and estimating. Each component that makes up its structure is necessary to recognise the underlying dynamics and patterns in the data. At the core of it is the autoregressive (AR) component, which mainly describes the relationship between the present data and their historical values, especially within the same season. This component (represented by the parameter 'p') provides insight into the intrinsic temporal dependencies of the time series data. Furthermore, the integrated component, denoted by 'd' and 'D,' facilitates the transformation of the data into a stable series using differencing, so contributing to the assurance that the data is appropriate for study. The model incorporates a moving average (MA) component, denoted by the parameter 'q', to take into consideration the impact of prior forecast mistakes on the current observations. This component aids in accounting for abrupt changes or shocks in the data that the autoregressive component is unable to explain.

- **XGBoost (Extreme Gradient Booster)**

An inclination helping strategy that utilizes slopes in light of choice trees is called Outrageous Angle Supporting, or XGBoost. It makes short, fundamental choice trees iteratively. Each tree is known as a "frail student" in view of its serious predisposition. XGBoost starts by building the least complex, introductory tree, which has low execution. Hence, it creates another tree, this one educated to expect exercises that the principal tree, a sluggish student, couldn't do. The strategy produces students that are progressively more awful, every one of them revising the past tree before the halting condition is satisfied, like the quantity of trees (assessors) that should be created.

Figure 1

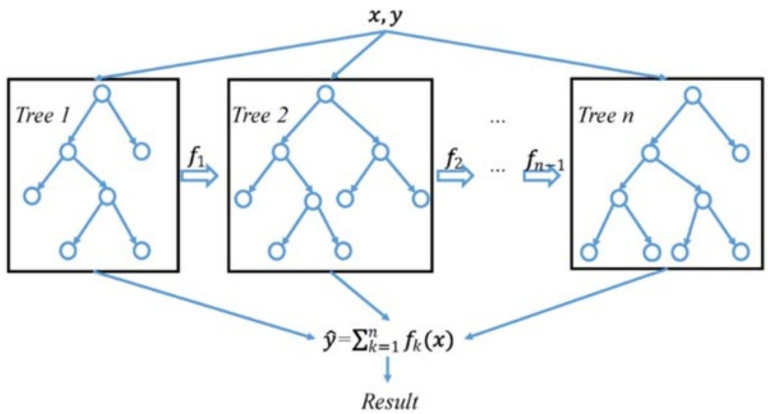

Figure 1 XGBoost Architecture

- **Random Forest Algorithm**

As a result of its versatility and usability, the Irregular Woods Calculation is frequently used to tackle issues with both relapse and grouping. The principal advantage of the technique is its capacity to deal with complex datasets and limit over fitting, which makes it a powerful instrument for an assortment of AI expectation undertakings. The Arbitrary Timberland Calculation's ability to deal with informational collections including both ceaseless factors — like those in relapse and downright factors — like those in order is one of its key highlights. It performs better in assignments including relapse and order. The objective of this instructional exercise is to give an exhaustive handle of irregular woods' activity and tell the best way to apply it to an order task.

Figure 2

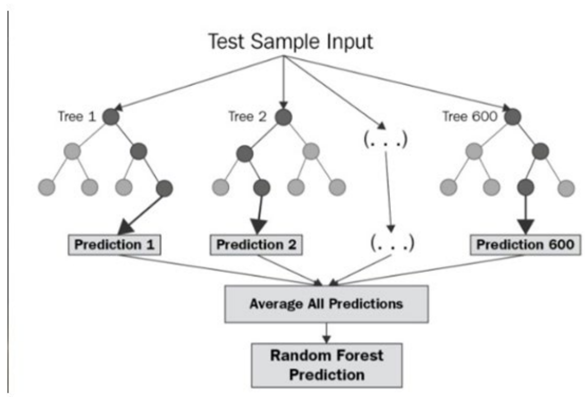

Figure 2 Random Forest Algorithm Model Architecture

- **Long Short-Term Memory (LSTM) Recurrent neural networks (RNNs) utilize a specific**

kind of engineering known as long short-term memory, or LSTM. Its will probably manage the issue of long-term reliance in grouping forecast issues. A superior form of the recurrent neural network (RNN) engineering called Long Short-Term Memory (LSTM) was made explicitly to all the more actually address successive information and its perplexing linkages than ordinary RNNs. The cell is comprised of four layers that cooperate to deliver the cell state and the result. After then, at that point, these two articles are moved to the following secret layer. Three strategic sigmoid entryways and one tanh layer make up a LSTM, though RNNs have only one neural net layer that utilizes the tanh initiation function. Information flow has been limited by the use of cell gates. They determine the precise amount of data that will be needed by the next cell and pinpoint the data that needs to be deleted. The final values often lie between 0 and 1, where 0 denotes that no things were accepted and 1 denotes that all items were included.

Figure 3

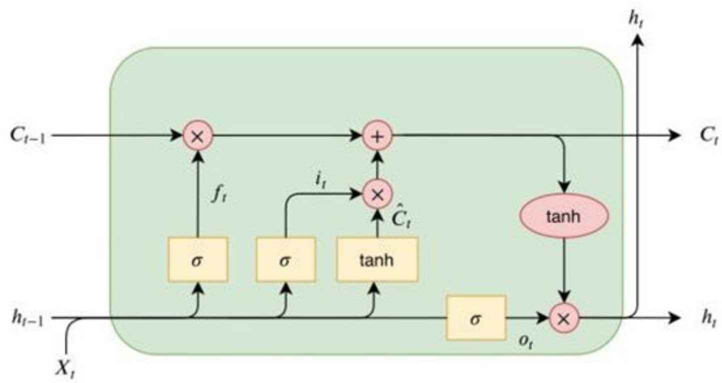

Figure 3 LSTM Architecture

- **Measuring Scales**

Simple statistical techniques to intricate machine learning algorithms can be used in these models. Comparing these models' performances using several metrics, such R-squared (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), is a well known technique for surveying these models.

R-squared (R^2): This measurement works out the percentage of the reliant variable's variety that can be anticipated in view of the autonomous factors. On a size of 0 to 1, 1 signifies an optimal match. The R2 equation is:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

where SStot is the absolute amount of squares and

SSres is the amount of squared residuals.

Root Mean Squared Error (RMSE): The average disparity between the normal and noticed values is estimated by the Root Mean Square Error (RMSE). It gives an indication of the correctness of the model; lower numbers mean greater performance. The RMSE formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE): The average absolute difference (MAE) between the noticed and projected values is determined. Rather than RMSE, it is less vulnerable to exceptions. The MAE equation is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Mean Absolute Percentage Error (MAPE): The percentage difference between the expected and actual values is measured by MAPE. It is especially helpful when comparing models' performances on various scales. The MAPE formula is:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

These measurements are employed to evaluate and contrast forecasting model performance.

4. RESULTS

It is crucial to recognise that, despite the SARIMAX model's exceptional performance metrics when trained and assessed on the complete dataset, over fitting may have inflated the model's findings for wind speed predictions. To address this problem, we do out-of- sample forecasting, which yields less favourable results for estimating the following 15 days.

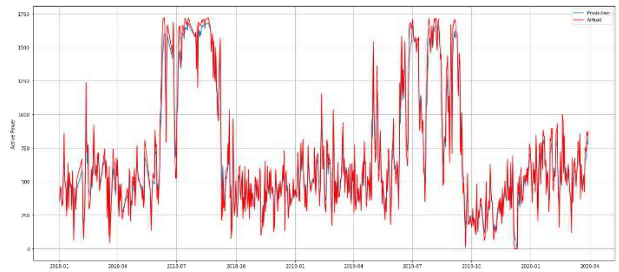

Figure 4 SARIMAX results

We had difficulties while analyzing the findings of the previous two phases, in which we trained the SARIMAX model on datasets that spanned 733 days and 600 days, respectively. The predicting results did not meet our expectations.

Figure 5

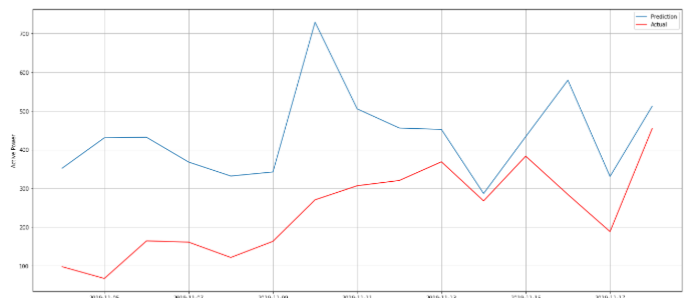

Figure 5 SARIMAX results

We decided against pursuing the third strategy, which would have required predicting using two-thirds of the training data, in light of these subpar outcomes. We have decided to look at alternative models in order to see if we can provide a more accurate prediction. This move is characteristic of our devotion to painstakingly assessing and working on our strategies to ensure the accuracy and constancy of wind speed estimates.

Figure 6

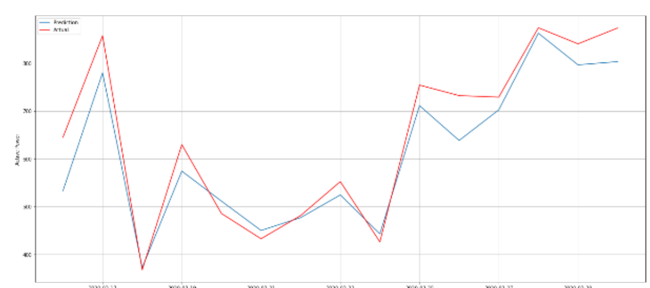

Figure 6 XGBoost Results

Wind Speed measurements were used as the input (X) and Active Power values as the output (y) for training the XGBoost model. We used all available data for training, with the exception of the last 15 days, which were reserved for testing. By using this technique, it was ensured that the model was not evaluated using data from its training set. Following evaluation, the XGBoost algorithm demonstrated significantly improved performance over previous models. As the graph below shows, there was a high level of agreement between the XGBoost model's predictions and the actual results. With an impressive R-squared of 0.91, the model demonstrated a strong correlation between the observed and predicted values. Besides, it is vital that there was an extensive diminishing in both the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) when contrasted with past preliminaries, demonstrating that the model is precise in determining wind speed.

Figure 7

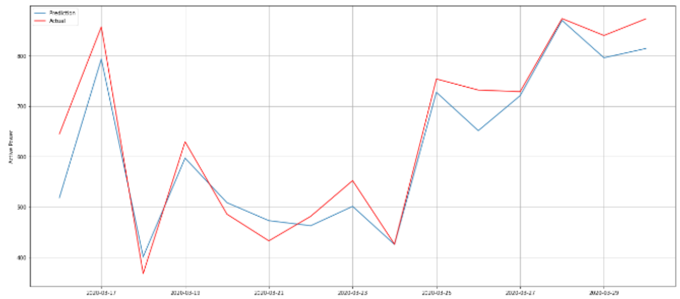

Figure 7 Random Forest Regressor Results

We then investigated the possibilities of a Random Forest regressor, using a process akin to that of the XGBoost model. With all available data, with the exception of the latest 15 days set aside for testing, we trained the model using Wind Speed values as input (X) and Active Power values as output (y).

The use of an LSTM (Long Short-Term Memory) model was then explored. In contrast to earlier methods, a distinct process was needed to prepare the data for the LSTM. In this case, X_train and y_train were built in distinct ways. Using data from several previous rows, the LSTM predicted the future Active Power value instead than depending just on a single prior row. Given the dataset's underlying monthly pattern, we chose to use 35 rows of previous data in this case to inform the forecast for the next 15 values.

Figure 8

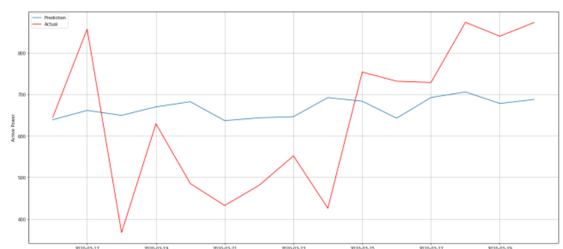

Figure 8 LSTM Results

The apparent seasonal trends in the data led us to believe that a SARIMA model would be the most productive when we first started this investigation. Nevertheless, the SARIMA model did not perform as well as expected, therefore our expectations were not fulfilled. In a similar vein, we anticipated that the LSTM neural network would perform well in capturing the intricate connections present in the data. Our results, however, disproved this theory because the LSTM model did not provide acceptable outcomes either.

Table 1 Consolidated Results

Method	R-Squared	RMS	MAE	MAP
SARIMA X (733 days training)	-1.89	225.06	96.86	0.34
SARIMA X (600 days training)	-3.26	195.04	227.7 1	1.26
Extreme Gradient	0.906	42.07	52.95	0.062

Boost (XGBoost)				
Random Forest Regressor	0.915	40.54	50.99	0.064
LSTM	-0.19	162.71	187.76	0.30

The following fifteen days' power production was accurately predicted by both the Random Forest and XGBoost regressors, with an accuracy rate of about 94% and a mean average percentage error of 6%. Moreover, these models were able to account for and capture the underlying patterns and dynamics within the dataset, as seen by their capacity to explain over 91% of the variation in the data (R squared). Notably, compared to other strategies, both methodologies produced these outstanding outcomes in a noticeably shorter amount of time.

5. CONCLUSION

Our research has produced insightful information on how well various modeling techniques predict wind speed while evaluating the functionality of AI systems. Remarkably, less complex methods such as Random Forest regressors and XGBoost surpassed initial expectations and consistently produced accurate predictions with a high degree of precision. These discoveries underline that it is so critical to do reasonable tests and select a model for wind speed expectation in view of a useful methodology. Our study demonstrates the improved predictive capabilities of various AI approaches, which further advances approaches to renewable energy management. In the end, this results in wind speed estimates that are more accurate and reliable, enabling informed decision-making.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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