A COMPARATIVE EVALUATION OF MACHINE LEARNING AND DEEP LEARNING MODELS FOR SHORT-TERM AND MEDIUM-TERM WIND SPEED FORECASTING

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Abstract :

Accurate wind speed forecasting is crucial to increasing the efficiency and reliability of wind generating installations. In order to estimate wind speed in the short and medium term using the main meteorological variables—wind direction, temperature, atmospheric pressure, and relative humidity—the current study compared machine learning (ML) and deep learning (DL) models. A quantitative study methodology was employed, and the accuracy and stability of the forecasting were examined using analytical techniques such descriptive statistics, correlation analysis, and model performance evaluation. This study compared the DL algorithms Long Short-Term Memory (LSTM) and bidirectional LSTM with the ML algorithms Random Forest (RF) and Support Vector Regression (SVR). The findings demonstrated that ML models performed better when used to create fast predictions, whereas DL models were better at reflecting temporal dependencies and nonlinear interactions, producing more accurate and stable forecasts at different horizons. In the renewable energy management, the study identified the significance of the choice of the forecasting models due to the forecasting horizon and the operations conducted.

Keywords : Wind Speed Forecasting, Machine Learning, Deep Learning, LSTM, BiLSTM, Renewable Energy, Time-Series Prediction

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Introduction :

Wind power has become an important phenomenon, as a clean and ecologically friendly source of energy in the shift to renewable energy sources in the world. The rising trend of wind farms has brought forth the need to have precise and trustworthy forecast of wind speed in order to have the best grid integration, energy schedule, and operational plan. It is the stochastic and extremely dynamic character of wind though that renders forecasting a complicated matter that is affected by a variety of meteorological conditions like temperature, pressure, humidity, and the direction of wind. The imprecision of the prediction may cause power imbalance, high costs of functioning and decreased efficiency of renewable energy systems. As such, there is an urgent research interest in creating powerful predictive models that can reproduce nonlinear and time-dependent deviations in the speed of wind among energy analytics.

Traditional statistical methods are helpful for baseline forecasting, but they don't always capture the nonlinear interactions in wind dynamics. ML methods like SVR, Decision Trees, and RF have been used more frequently as computer intelligence advances because they can model complex patterns using past meteorological data. These models have shown good performance in the short-term forecasting situation whereby nearby observations have a strong impact on the wind behavior in the near future. However, the ML models cannot reasonably effectively learn long-term temporal dependencies, which are necessary to medium-term forecasting horizons.

Due to their advanced capacity to extract features and model sequences, DL techniques have emerged as a major substitute for the time-series forecasting challenge in recent years. It has been shown that hybrid neural networks, BiLSTM, and LSTM perform better in the sequential model of wind speed data. Such models are able to approximate both temporary variations and lasting temporal interdependencies and thus the accuracy of predictions made by the model is particularly high when forecasting over long periods. Although these developments are made, DL models are more computationally intensive and require more time to train, and the question arises about how these models can be practically applicable in real-time prediction settings.

A thorough comparison of ML and DL models across a range of forecasting horizons is required, given the growing significance of accurate wind speed prediction in the management of renewable energy sources. While medium-term forecasting aids in maintenance planning and energy market operations, short-term forecasting is focused on short-term operational decisions. The need to determine the best predictive strategy, depending on foretelling time frame, precision, and computation cost, is hence critical in enhancing the dependability of wind energy. In order to address this need, the current study will compare a few ML and DL models to short- and medium-term wind speed forecasts. This will provide empirical data on how well these models performed in a comparative setting and their suitability for use in renewable energy applications.

Literature Review :

Daniel et al. (2020) investigated short-term wind speed prediction using both ML and statistical techniques, and discovered that ML-based techniques, such as Support Vector Machines and RF models, performed better in terms of prediction than more traditional statistical techniques. The study had shown that the nonlinear learning power of ML models permitted them to successfully characterize intricate wind conduct patterns, more so in brief prognostication intervals. It was noted that ML methods considerably decreased forecast error and offered predictive consistency when educated on the past meteorological data, which makes them amenable to operational wind energy control.

Dolatabadi, Abdeltawab, and Mohamed (2020) suggested a bidirectional Long Short-Term

Memory network and discrete wavelet packet transform DL system for wind speed prediction. The results showed that the hybrid design improved prediction accuracy by simultaneously modeling temporal interdependence and dividing wind speed signals into different frequency components. According to the study, the two-way LSTM architecture enhanced the performance of the forecasts for the short-term and medium-term prediction horizons by capturing contextual information both forward and backward. The results demonstrated the value of combining DL frameworks with signal processing techniques to mitigate the stochasticity of wind speed data.

Mora, Cifuentes, and Marulanda (2021) carried out a comparative study of the various DL schemes in short term wind energy prediction and discovered that recurrent neural network schemes and in particular LSTM based models continual out fashioned the shallow ML algorithms. The analysis demonstrated that the DL models had a better generalization ability and efficiency to increasing and decreasing wind speed because they learned in a sequential manner. It was also reported that DL methods produced fewer forecasting errors and were more robust at different meteorological conditions, which highlights their applicability in complicated time-series wind prediction problems.

Singh, Jha, and Gupta (2024) proposed an effective hybrid DL one to increase the accuracy of wind speed estimations and found out that DL frameworks performed better than the conventional ML frameworks in analyzing nonlinear interactions among a variety of meteorological parameters. The authors had shown that the hybrid DL models that fused the feature extraction and the temporal sequences learning yielded more accurate and consistent predictions of wind speed. As it was concluded, more sophisticated DL models presented better stability and predictability of future wind speeds, especially when it was time-dependent over a medium-term horizon and long-term temporal correlations had a considerable impact.

Research Methodology :

The performance of ML and DL models in the short-term and medium-term forecasts of wind speed was compared in this study, which used a quantitative design and an organized methodology. The methodology's objectives were to provide model implementations, systematic data management, and comparative study of the forecasting horizons' prediction accuracy. Consistency on data preprocessing, model training and evaluation processes were stressed in order to ensure reliability and empirical validity of the comparative findings as a tool of forecasting renewable energy using the results.

a. Research Design :

The prediction power of selected ML and DL models was examined and contrasted using a quantitative comparative research design. The design made it possible to compare the most cutting-edge DL architectures with conventional ML algorithms in a methodical manner and objectively evaluate the forecasting accuracy using standardized statistical measures of mistakes.

b. Sample Size and Population :

The study population comprised of past historical wind speed measurements based on the meteorological data applicable in wind energy forecasting. A sample size of 50 observations of wind speed time-series was then chosen in this population and used in purposive sampling to cover various wind conditions across both short-term and medium-term forecasting horizons. The sample used provided a satisfactory variability in the nature of wind which includes velocity, direction, temperature, and humidity, thus facilitating sound comparative model analysis.

c. Data Collection :

Hourly records of wind speed and other associated atmospheric variables were among the secondary data collected from a publicly accessible collection of meteorological and wind energy sources. Temperature, humidity, air pressure, wind direction, and wind speed were among the data gathered and utilized as input features for model training and prediction analysis.

d. Data Collection Tools and Instruments :

Data processing and model implementation in the study were done using computational tools and programming-based analytical environments. Python-based tools like Pandas and NumPy were utilized for data preparation and normalization, and Scikit-learn was used to build ML models like RF and SVR. TensorFlow and Keras were used to create DL models of LSTM and BiLSTM. Standardized model training and evaluation, as well as efficient management of time-series wind data, were made possible by these software applications.

e. Data Analysis :

To verify the model, the acquired data were separated into training and testing samples after being preprocessed by normalization. To guarantee consistency in terms of comparison, the ML and DL models were trained on the same datasets. Performance was predicted using statistical error metrics such as R^2, mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). To ascertain the model's usefulness in the short and medium terms, the short- and medium-term forecasting horizons were evaluated separately.

Results And Discussion :

The R&D section provided a thorough analytical analysis of the wind speed prediction using ML and DL models with respect to the meteorological variables and different forecasting horizons. In the analysis, the distribution properties of wind and atmospheric parameters were analyzed using descriptive statistics, their relationships were examined using correlation evaluation, and the short- and mid-term predictions were made using comparative performance detailing of the selected predictive tools. This thorough explanation aided in developing a shared understanding of how atmospheric change and model design affect predicting accuracy and persistence.

The graphical distribution and descriptive statistics of wind speed and other associated meteorological variables, including wind direction, air temperature, atmospheric pressure, and relative humidity of the air, were based on 50 observations and were shown in Table 1 and. In order to provide a general impression of the data available in the dataset to analyze wind speed prediction, the figure was used to visualize the relative magnitude and dispersion of the variables, while the table summarized the mean, standard deviation (SD), min and max values, and corresponding measurement units.

Table 1: Descriptive Statistics of Wind and Meteorological Variables

Variable	Mean	Std. Deviation	Min	Max	Unit
Wind Speed	6.45	1.82	2.10	10.30	m/s
Wind Direction	182.6	54.3	75.0	298.0	Degrees
Air Temperature	27.4	3.6	19.2	33.8	°C
Atmospheric Pressure	1008.5	4.2	998.1	1016.7	hPa
Relative Humidity	61.2	9.5	40.3	78.6	%

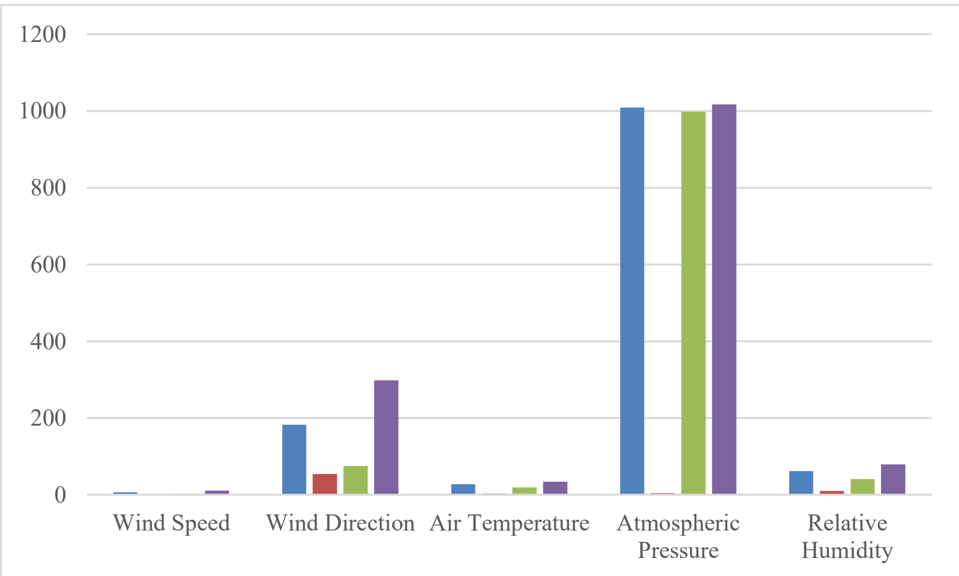

Figure 1: Graphical Representation of Descriptive Statistics of Wind and Meteorological Variables

The average wind speed in the region was 6.45 m/s with a SD of 1.82 and a range of 2.10 to 10.30 m/s, according to the findings, while the average wind direction was 182.6 degrees with a SD of 54.3 and a range of 75.0 to 298.0 degrees. The air temperature ranged between 19.2°C and 33.8°C, with a mean of 27.4°C and a SD of 3.6. With an average, SD, and range of 1008.5, 4.2, and 998.1 to 1016.7 hPa, respectively, the atmospheric pressure was comparatively steady. The relative humidity ranged from 40.3% to 78.6%, having a mean of 61.2% and a SDof 9.5.

Table 2 showed the correlation coefficients between the wind speed and the most important meteorological variables, that is, the wind direction, atmospheric pressure, temperature, and relative humidity. It outlined the degree and direction of relationship between the speed of wind and each of the atmospheric parameters, and the supplementary figure 2 gave a graphical representation of all of these correlation values in order to provide a comparative insight into how each of them is correlated to wind speed.

Table 2: Correlation of Wind Speed with Meteorological Variables

Variable	**Correlation with Wind Speed**
Wind Direction	0.41
Temperature	-0.36
Atmospheric Pressure	-0.28
Relative Humidity	0.33

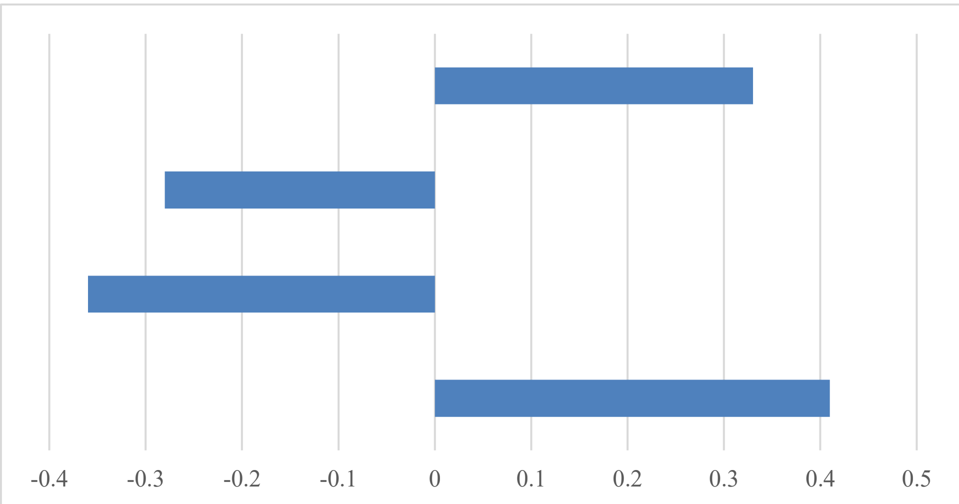

Figure 2: Graphical Representation of Correlation of Wind Speed with Meteorological Variables

The findings revealed that there was a positive relationship between wind speed and wind direction (0.41) and relative humidity (0.33) but a negative association between wind speed and temperature (-0.36) and atmospheric pressure (-0.28). These relationships were proved by the graphical representation that showed positive relationships that were stronger with wind direction, moderate with humidity, and negative with temperature and pressure.

Using assessment metrics like MAE, RMSE, MAPE (%), R^2, and training time in seconds, Table 3 displays the performance of several ML and DL models in short-term wind speed prediction. The Random Forest, SVR, LSTM, and BiLSTM models' predictive and computational performances have been compiled, and figure 3 illustrates the models' relative forecasting performance in relation to the metrics employed.

Table 3: Short-Term Wind Speed Forecasting Performance

Model	**MAE**	**RMSE**	**MAPE (%)**	**R²**	**Training Time (s)**
Random Forest	0.88	1.16	11.9	0.86	3.2
Support Vector Regression	1.02	1.29	13.7	0.82	4.5
LSTM	0.65	0.91	9.1	0.90	12.6
BiLSTM	0.59	0.84	8.3	0.92	15.4

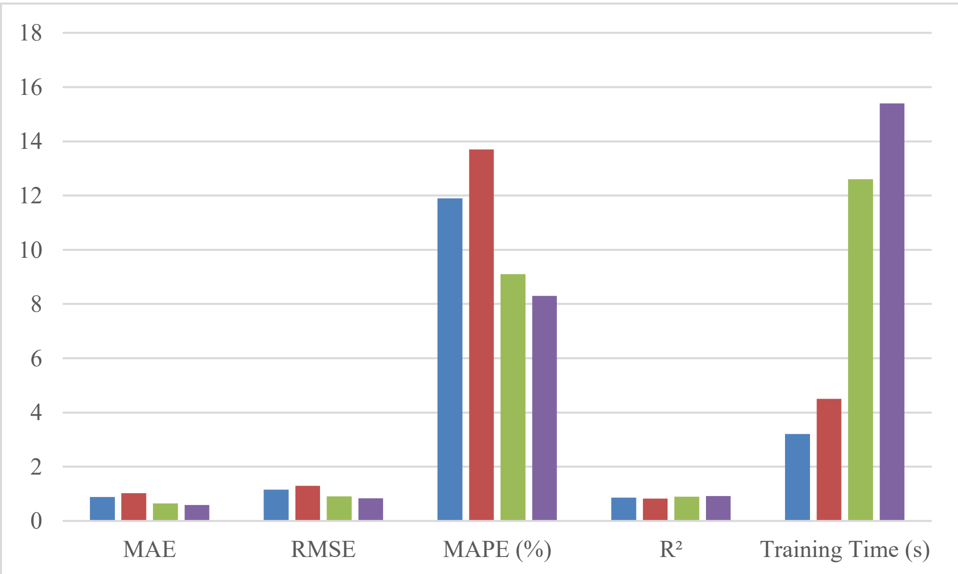

Figure 3: Graphical Representation of Short-Term Wind Speed Forecasting Performance

The findings indicated that, Random Forest had MAE of 0.88, RMSE of 1.16, MAPE of 11.9%, R^2 of 0.86 and 3.2 seconds as training time compared to SVR where MAE was

1.02, RMSE was 1.29, MAPE was 13.7%, R^2 was 0.82 and training time was 4.5 seconds. LMST had a MAE of 0.65, RMSE of 0.91, MAPE of 9.1%, R^2 of 0.90 and a training time of 12.6 seconds, BiLSTM had best predictive power with a MAE of 0.59, RMSE of 0.84, MAPE of 8.3%, R^2 of 0.92 and training time of 15.4 seconds and the graphical illustration showed the high predictive power of DL models over ML models.

Based on evaluation criteria including MAE, RMSE, MAPE%, R^2, and Stability Index, Table 4 displayed the relative effectiveness of ML and DL models in medium-term wind speed prediction. It reported the accuracy and consistency of forecasting of the RF, SVR, LSTM and BiLSTM models and the figure 4 accompanying it gave a graphical representation of the performance of these models in terms of the aforementioned measures.

Table 4: Medium-Term Wind Speed Forecasting Performance

Model	MAE	RMSE	MAPE (%)	R²	Stability Index
Random Forest	1.15	1.48	15.2	0.79	0.81
Support Vector Regression	1.28	1.63	17.4	0.75	0.77
LSTM	0.79	1.08	10.8	0.88	0.89
BiLSTM	0.71	0.99	9.6	0.91	0.92

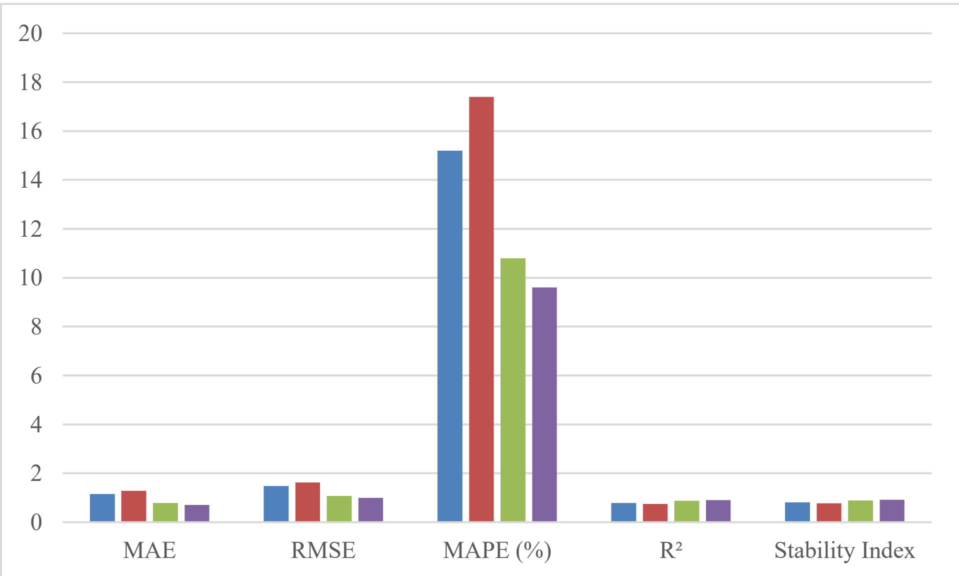

Figure 4: Graphical Representation of Medium-Term Wind Speed Forecasting Performance

The result showed that the MAE of the Random Forest was 1.15, RMSE was 1.48, MAPE was 15.2, R 2 was 0.79 and Stability Index was 0.81, at the same time the SVR had MAE of 1.28, RMSE of 1.63, MAPE of 17.4, R 2 of 0.75 and Stability Index of 0.77. The results of LSTM showed better results, with MAE of 0.79, RMSE of 1.08, MAPE of 10.8, R2 of 0.88, and Stability Index of 0.89, whereas BiLSTM showed the best ones with MAE reminiscent of 0.71, RMSE of 0.99, MAPE of 9.6, R 2 of 0.91, and Stability Index of 0.92, and the graphical representation validated the higher predict.

Overall, the results showed that the meteorological factors were characterized by the observable variability and meaningful relationships with the wind speed that had a significant effect on the forecasting performance. The analysis of comparative models demonstrated that DL models, specifically LSTM and BiLSTM, have always demonstrated lower error rates, increased R^2, and greater stability at both short-term and medium-term horizons, whereas ML models have demonstrated a relatively high error rate but also took shorter time to train. All these findings suggested that DL methods could offer more precise and dependable predictions of wind speed, particularly in the context of medium-term, whereas ML models could serve as inexpensive alternatives to predict wind speed in short-term predictions.

Conclusion :

The researchers used machine and DL models to provide comparative analysis of predicting short-term and medium-term wind speed with the help of meteorological variables and 50 observations. The results indicated that the fluctuation of wind speed was affected by atmospheric conditions like wind direction, temperature, pressure and humidity. The performance measurement showed that DL models, specifically LSTM and BiLSTM, had lower values of MAE, RMSE, and MAPE with higher values of R^2 and stability index, showing a higher accuracy and stability at both forecasting horizons. On the other hand, ML techniques with lower training and processing efficiency, like support vessel regression and random forest, showed higher prediction error. While ML models could be used to predict short-term wind speed, DL models were generally thought to be better suited for medium-term forecasting.

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