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Comparison of Machine Learning and Deep Learning Models Performance in predicting wind energy

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Abstract

The prediction of wind energy generation is important to enhance the performance and dependability of renewable energy systems due to the rising demand for wind-generated electricity and advancements in wind energy technology competitiveness. This study leverages advanced machine learning (ML) and some other statistical and deep learning based time series forecasting models to enhance the accuracy of wind energy predictions. This comprehensive analysis includes nine ML models—Linear Regression, Random Forests (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), AdaBoost, XGBoost, Support Vector Regression (SVR), and Neural Networks—as well as Four time-series forecasting models—ARIMA, Temporal Convolutional Networks (TCNs), Long Short-Term Memory (LSTM) networks and GRU. Each ML model underwent rigorous cross-validation to ensure optimal performance. The assessment criteria utilized here comprised the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the R^2 Score. It was found that among the nine ML models, Random Forests, GBM and KNN consistently provided superior accuracy and robustness, making them the top choices for wind energy prediction whereas the performance of linear regression, SVM and SVR were very poor for the considered dataset. From the experiment, Random Forest, GBM, and KNN showed the best performance with low MSE values of 0.77, 1.95, and 1.51 respectively, while other models had MSEs above 7.5, with AdaBoost reaching 30. Their RMSEs (0.88, 1.40, 1.23) and MAEs (0.093, 0.73, 0.10) also indicate strong predictive accuracy compared to the rest.In this paper, time series forecasting, TCNs, LSTM and GRU networks showed strong capabilities in capturing temporal dependencies and trends within the wind energy data. Visualization techniques were employed to compare model performances comprehensively, providing clear insights into their predictive power. Therefore, this present study offers a robust framework for researchers and practitioners aiming to leverage machine learning and time series forecasting in the realm of renewable energy prediction.

Keywords: Wind Energy Prediction, Machine Learning, Time Series Forecasting, Evaluation Metrics, Cross-Validation, Renewable Energy.

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1. Introduction

In recent years, there has been a growing focus on incorporating renewable energy sources into the power grid due to environmental concerns and the increasing demand for sustainable energy solutions [1]. Among these sources, wind energy stands out as a promising and rapidly growing contributor to the global energy mix [2-5]. Renewable energy has experienced significant and rapid growth in recent years [1]. According to the GWEC 2024[2] report, in 2023 new installations of renewable energy were 510 GW worldwide which is an increase of nearly 50% compared to 2022. Among these new renewable energy installations, wind energy contributed 117 GW alone to the electricity grid in a single year which shows the remarkable resilience and adaptability of the wind industry [2].Several

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countries, including the United States and China, have implemented a range of regulatory techniques to promote the adoption and expansion of renewable energy [3-6].Wind energy forecasting plays a pivotal role in the management and operation of wind farms, enabling stakeholders to make informed decisions regarding energy production, grid stability, and economic planning [7].Traditional forecasting methods based on physical and statistical models have been prevalent for decades. These methods often rely on meteorological data, historical patterns, and empirical relationships to predict future wind conditions. They are commonly classified into four categories: physical methods, statistical models, artificial intelligence techniques, and hybrid approaches [7-21]. With advancements in soft-computing techniques, AI-based forecasting models often outperform physical methods and statistical approaches, owing to their strong capabilities in data mining and feature extraction [15, 21]. However, with the advent of machine learning (ML) and deep learning techniques, there has been a paradigm shift towards more data-driven and adaptive forecasting approaches. However, predicting renewable energy output accurately is challenging due to the intermittent, chaotic, and unpredictable nature of renewable energy data. Numerous algorithms have been developed and reported in the literature to enhance the accuracy of renewable energy forecasts.

Machine learning models, such as Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and ensemble methods [17,18], have demonstrated their capability to capture complex relationships and nonlinear dynamics inherent in wind speed and power data. In addition to machine learning, deep learning techniques, including Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs), have shown remarkable success in handling temporal dependencies and sequence modelling in wind data. There was some application of deep learning for wind power forecasting and ramp event prediction, emphasizing the effectiveness of recurrent and convolutional neural networks in capturing complex patterns [19]. Some deep learning approaches for wind speed prediction, showcased significant improvements in accuracy compared to traditional methods [22-38].

On the other hand, time series forecasting models such as Autoregressive Integrated Moving Average (ARIMA) [37-41] have been extensively used in wind energy prediction due to their ability to model linear dependencies and seasonality in time series data. Statistical models strive to reveal the mathematical relationships in online time series data of renewable energy, utilizing techniques such as autoregressive moving average, Bayesian methods, Kalman filters, Markov chain models, and grey theory, which have been widely employed. statistical methods for wind power forecasting, underscoring advancements in probabilistic forecasting and their integration into operational systems.

This introduction sets the stage for exploring how ML models and time series forecasting techniques have revolutionized wind energy prediction. It underscores the need for accurate forecasting methods to facilitate the efficient integration of wind energy into the grid, optimize operational strategies, and support sustainable energy initiatives. By leveraging advancements in data science and computational techniques, researchers and practitioners are poised to address the challenges of variability and uncertainty in wind power generation, ultimately contributing to a more reliable and sustainable energy future.

This paper is organized as follows. Section 2 gives previous research work on wind energy forecasting by ML and other Time series forecasting models. In Section 3, Methodology and work plan is presented. We also present the performance matrices by all models and result analysis in Section 4. Finally, conclusions are drawn in Section 5.

2. Literature Survey

Wind power forecasting is crucial for optimizing energy production and grid stability. This survey explores the use of machine learning (ML) and time series models to predict wind power, focusing on their methodologies, advancements, and comparative performance.

Considering statistical approach, Ayua and Emetere [12] evaluated wind energy potential in Yundum and Basse, Gambia, using Weibull and Raleigh distributions to model wind characteristics. Results showed Weibull performs better for Yundum, while Raleigh suits Basse, highlighting both locations' strong wind energy potentials. Sideratos [19] The paper proposes an advanced statistical method using ARIMA models enhanced with Artificial Neural Networks (ANN) to improve short-term wind power forecasting accuracy. Al- Pearre [39] reviewed statistical models for wind speed and power forecasting, focusing on their application and performance in renewable energy systems. Wang et al. [22] reviewed various wind power forecasting models, including physical, statistical, and ML-based approaches, providing insights into their strengths and limitations. Lin et al. [25] proposed a novel hybrid approach combining ML methods for short-term wind speed forecasting, achieving improved accuracy by integrating different modeling techniques. Colak et al. [26] surveyed data mining and ML Zeng techniques for wind power prediction, encompassing decision trees, neural networks, and ensemble methods, discussing their applicability and performance. Wang et al. [28] The paper presents a hybrid wind speed prediction model integrating data preprocessing, multi-objective optimization, and machine learning to enhance forecasting performance. Zeng et al. [29] discussed various ML approaches for wind speed forecasting, including decision trees, random forests, and gradient boosting machines, highlighting their effectiveness in capturing wind dynamics. Zafirakis et al. [27] conducted a comparative study on wind power forecasting methods, focusing on neural networks and support vector machines, evaluating their predictive capabilities and suitability. Li et al. [17] proposed a short-term wind power forecasting model based on SVM optimized with an improved dragonfly algorithm. Their study demonstrated high accuracy in predicting wind power. Zhang et al. [20] reviewed hybrid ML models for short-term wind speed forecasting, discussing combinations of algorithms that enhance forecasting accuracy. Manero et al. [18] conducted a comprehensive literature survey on wind power forecasting using ANNs. They reviewed various network architectures and training methods, highlighting ANNs' effectiveness in this domain. Deng et al. [21] explored deep learning methods, specifically recurrent neural networks (RNNs) and convolutional neural networks (CNNs), for predicting wind power and identifying ramp events demonstrating their applicability and performance. Bali et al. [23] explored deep learning approaches specifically for wind speed prediction, highlighting the effectiveness of these methods in capturing complex patterns. Daniel et al. [30] compared deep learning methods for short-term wind speed forecasting, evaluating the performance of different architectures and their suitability for wind energy applications. For time series-based forecasting Jursa [40] applied ARIMA models for short-term wind power forecasting, demonstrating their utility in capturing temporal patterns and enhancing forecasting accuracy. Yatiyana et al. [41] compares ARIMA and integrated ARIMA models for wind speed and power prediction, highlighting their strengths and weaknesses. Liu et al. [20] investigated TCNs for wind power prediction, showing significant improvements over traditional methods due to their ability to capture long-term dependencies. Longxiang et al. [34] applied LSTM networks for wind power prediction, highlighting their effectiveness in capturing temporal dependencies and improving prediction accuracy. Shahid et al. [36] proposed a hybrid LSTM model for short-term wind power prediction, combining LSTM with other ML techniques to leverage their complementary strengths. Ma et al. [37] The paper proposes a meta learning-based hybrid ensemble model for short-term wind speed forecasting, combining multiple base learners to improve prediction accuracy. So, from the existing literature, it is seen that very few studies are performed to implement advanced machine learning (ML) and other statistical and deep learning-based time series forecasting models to compare and enhance the accuracy of wind energy predictions to effectively utilize the wind power through wind turbines. In this investigation 9 ML models and 4 time-series forecasting models are employed to compare model performances comprehensively, so that clear insights into their predictive power can be achieved.

3. Methodology and Models

This forecasting is long-term forecasting that uses Seventeen years of data collected from Kaggle [42] and the results can be used directly for the planning of energy management. Various environmental factors were taken into consideration for forecasting for better accuracy and results. The dataset consists of 6,574 daily average readings from five weather sensors installed at a meteorological station situated in an open field at an elevation of 21 meters. The data was collected over a span of 17 years, from January 1961 to December 1978.

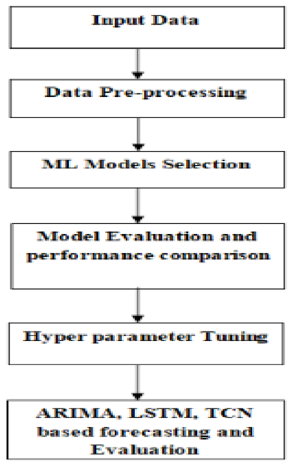

Figure 1. Block diagram of the prediction model.

Workflow of the present work is shown in Figure 1. The first phase of proposed work plan is data collection and this step involves gathering relevant data from Kaggle. In present research work we choose the dataset from Kaggle [40] and calculated Wind power generated daily using the formula (0.5 × ρ × [wind speed (m/s)]^3 × Area), where the value of ρ (density) is considered 1.2 kg/m^3 and area 1m^2. We used this value as a predicted target for our ML models. In second phase, some pre-processing activities like handling missing values, normalizing/scaling features, creating additional features have been performed. After pre-processing in third phase, some popular ML models that are helpful specifically for prediction were implemented (such as Linear Regression, Random Forest, Gradient Boosting Machines, Support Vector Machines, K-Nearest Neighbors, AdaBoost, XGBoost, Support Vector Regression, and Neural Networks). Next in fourth phase the performance of the developed model is tested using various metrics such as accuracy, RMSE, precision, recall, etc. In fifth phase, to improve performance of various ML models, hyperparameter tuning is performed Cross-validation is a robust method for estimating the performance of machine learning models. It helps in reducing bias and variance by partitioning the dataset into multiple subsets and training/evaluating the model multiple times. So it is applied on various models. Finally, in the last phase of the figure1 ARIMA (Autoregressive Integrated Moving Average), LSTM (Long Short-Term Memory) Networks and Temporal Convolutional Networks (TCNs) were chosen for time series analysis of data to create a clear and informative visualization on our dataset, but ARIMA did not perform well on our dataset.

4. Result and Discussion

After experimental analysis it has been found that the models like Linear Regression, SVM and SVR are having very high MSE, RMSE and MAE values as compared to other models.

Table 1. Training and Test Score of evaluation metrics MSE, RMSE and MAE of different ML

	Training Score			Testing Score		
Model	MSE	RMSE	MAE	MSE	RMSE	MAE
Random Forest	0.54	0.73	0.04	2.99	1.73	0.16
Gradient Boosting	0.975863	0.987858	0.618375	3.2966	1.81	0.781
K-Nearest Neighbors	4.45	2.11	0.14	1.57	1.25	0.19
AdaBoost	24.88	8.74	1.89	24.87	8.52	1.5
XGBoost	11.16	6.68	1.4	9.45	5.62	1.36
Neural Network	0.9758	0.987	0.618	1.2	1.09	0.28

Here in the Table 1 these evaluation metrics (MSE, RMSE, MAE) values are shown for some of the efficient models (out of nine only six can be moderately considered) for our dataset. From table 1it is clearly visible that four model's (Random Forest, Gradient Boosting, Neural Network, KNN) performances were good during training and Testing.

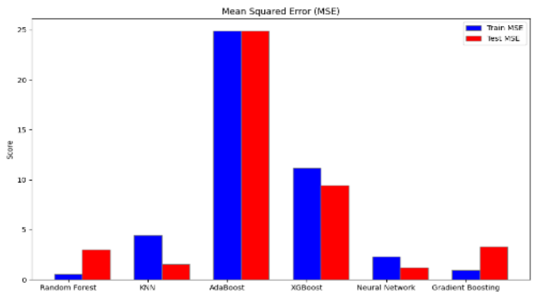

Figure 2. Train and Test MSE of all selected models.

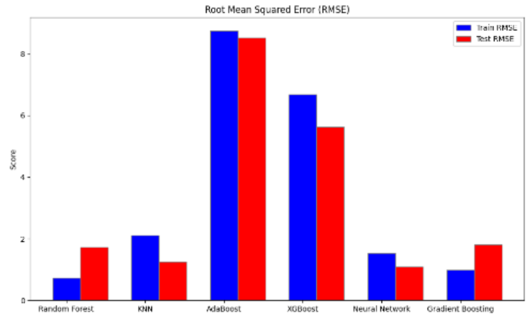

Figure 3. Train and Test RMSE of all selected models.

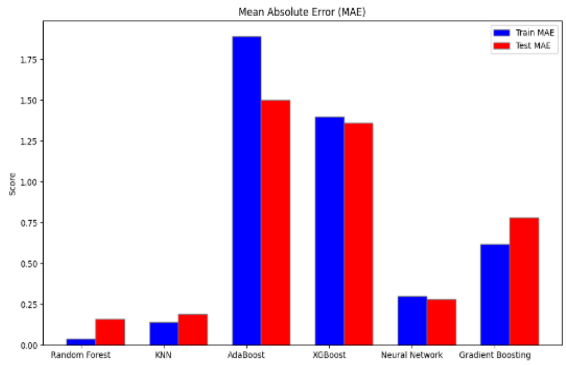

Figure 4. Train and Test MAE of all selected models.

Figures 2, 3 and 4 finally show the train and test MSE, RMSE and MAE respectively. It is clearly found that Random Forest, Gradient Boosting, Neural Network and KNN performances were good during training and testing in respect to their evaluation metrics values.

Table 2. Cross Validation of evaluation metrics MSE, RMSE and MAE of different ML models

Model	MSE	RMSE	MAE
Random Forest	0.770082	0.877543	0.0928
Gradient Boosting	1.9536	1.3977	0.7253
K-Nearest Neighbors	1.511	1.2293	0.1000
AdaBoost	30.87	8.52	4.679
XGBoost	7.45	5.014	0.9328
Neural Network	9.13222	3.09	2.28

From table 2, it has been found that the performance of the Neural Network got worse during cross-validation. From the above table it is clear that Random Forest consistently performed well across all cross-validation folds, indicating that it has low variance and high stability in predicting wind

energy. The low error metrics suggest that the model captures the underlying patterns effectively. Gradient Boosting and KNN showed moderate performance in cross-validation, with slightly higher errors compared to Random Forest.
As the models like Linear regression, SVM and SVR did not give a good output in respect to evaluation metrics they went for hyper parameter tuning but then also they are not suitable for predicting wind energy for our dataset.
In the last phase of this study, popular Statistics based and deep learning-based forecasting models are applied for predicting wind energy like ARIMA, LSTM, GRU and TCN.
LSTM and GRU come under RNN whereas TCN comes under CNN. But out of these Four, ARIMA model did not perform well on the dataset whereas LSTM and TCN suited well for predicting the energy generated corresponding to Wind speed.

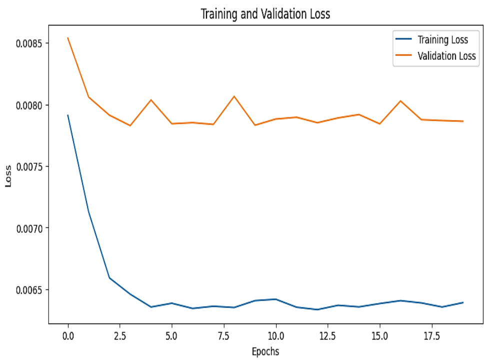

Figure 5. Training and Validation loss by LSTM model

Figure 6. Training and Validation loss by TCN model

Figure 7. Training and Validation loss by GRU model

Fig 5, 6 and 7 represent training and validation loss by LSTM, TCN and GRU deep learning model. Here it has been found that training loss is low but high validation loss for all three models. The low training loss suggests that the model has effectively learned to fit the training data, but the high validation loss indicates its inability to generalize well. It indicates that the model is overfitting.

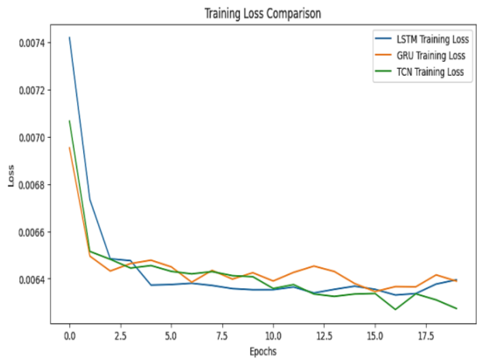

Figure 8. Training loss comparisons for all models

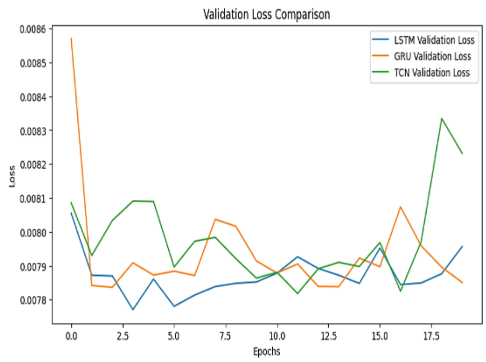

Figure 9. Validation loss comparisons for all models

Figures 8 and 9 represent combined Training and Validation loss for all models respectively. From figure 8,

It has been found that during training the performance of TCN was best as training loss for this model gradually decreases as compared to other models. From figure 9 it can be concluded that, validation loss for LSTM model is consistent throughout the testing process.
Another additional experiment is conducted using a dataset collected from [43] for the Kurnool City (Andhra Pradesh), India, covering the years 2021 to 2025 to evaluate the performance of the considered models. Our validation efforts were focused on all models that were used for previous dataset like Random Forest, Gradient Boosting Machines (GBM), K-Nearest Neighbors (KNN), SVR, AdaBoost and XGBoost, but for this recent dataset also the previous top three performing models like—Random Forest, Gradient Boosting Machines (GBM), and K-Nearest Neighbors (KNN) performed well. Each model was retrained using the new dataset, and their performances were evaluated using MSE, RMSE, MAE and R^2 score.

Table 3. Evaluation metrics MSE, RMSE and MAE of three best performing ML models considering new dataset

ML Models	MSE	RMSE	MAE	R^2
Random Forest	5.345	2.312	0.261	0.9994
Gradient Boosting Machines (GBM)	9.092	3.015	0.726	0.9989
K-Nearest Neighbors (KNN)	12.496	3.535	0.515	0.9985

In table 3 a comparative analysis is shown to evaluate the performance of three machine learning models—Random Forest, Gradient Boosting Machines (GBM), and K-Nearest Neighbors (KNN)—using common regression metrics. The Random Forest model achieved the best performance with the lowest MSE (5.345), RMSE (2.312), MAE (0.261), and highest R^2 (0.9994), indicating excellent predictive accuracy. Compared to GBM and KNN, it consistently outperformed across all metrics.

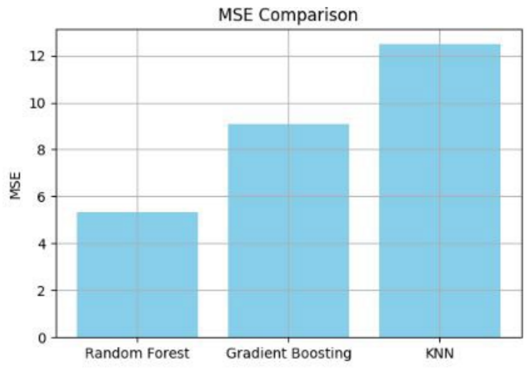

Figure 10. MSE comparison of three different ML models

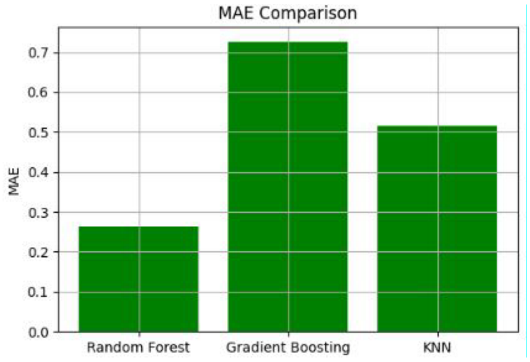

Figure 11. MAE comparison of three different ML models

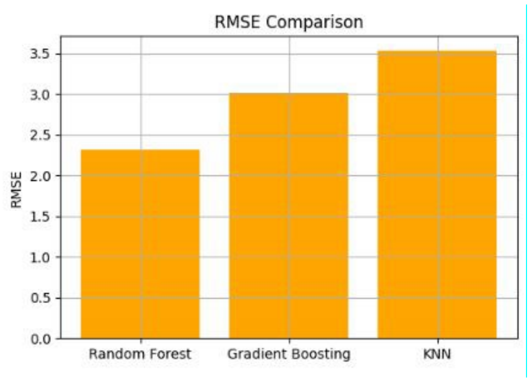

Figure 12. RMSE comparison of three different ML models

Figures 10-12 demonstrate that all three models retained high predictive accuracy and stability, validating their effectiveness on independent data from a different geographical and temporal setting. This confirms the generalizability and robustness of the selected models for wind energy prediction tasks across different regions and time spans.

4.1. Sensitivity analysis

To ensure the robustness of the model, sensitivity analysis [44, 45] has been performed for the high performing models (RF, GBM and KNN) considering the recent dataset for the Kurnool City (Andhra Pradesh), India, covering the years 2021 to 2025 [43].

As wind speed is an influential parameter for wind power generation, here for our experimental purpose wind speed is used as input feature and power as target variable. Each of the models is trained on the original data. Then the wind speed values were changed by +10%. Without performing cross validation, the prediction change is finally measured and MSE, RMSE, MAE are computed.

Table 4. Sensitivity analysis results

Model	MSE (actual)	MSE (+10 %)	RMSE (actual)	RMSE (+10 %)	MAE (actual)	MAE (+10 %)
Random Forest	5.345	5.347	2.312	2.312	0.261	0.262
Gradient Boosting	9.092	9.092	3.015	3.015	0.726	0.726
KNN	12.496	12.498	3.535	3.535	0.515	0.516

Table 4 represents the comparison of model performance metrics before and after perturbing wind speed by +10%. The performance metrics remained nearly constant after perturbing the input feature (wind speed) by 10%. This indicates a high degree of robustness in all three models, particularly Random Forest and Gradient Boosting. This robustness suggests that these models are not sensitive to small variations in input data, which is a desirable property in real-world applications where sensor readings or input data may have slight variations or noise.

In addition to ML model validation, deep learning-based time series forecasting methods are applied like—Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Temporal Convolutional Networks (TCNs)—to the new dataset. Training and Validation loss for each model was calculated.

Figure 13. Training and validation loss for LSTM model

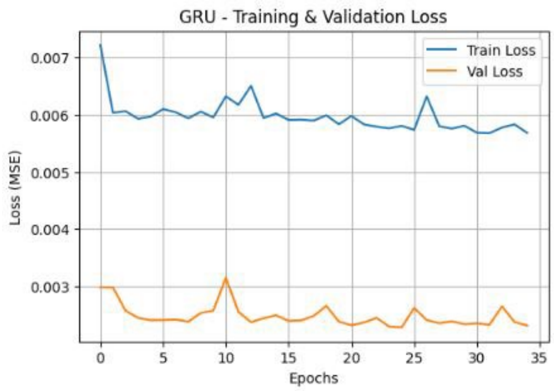

Figure 14. Training and validation loss for GRU model

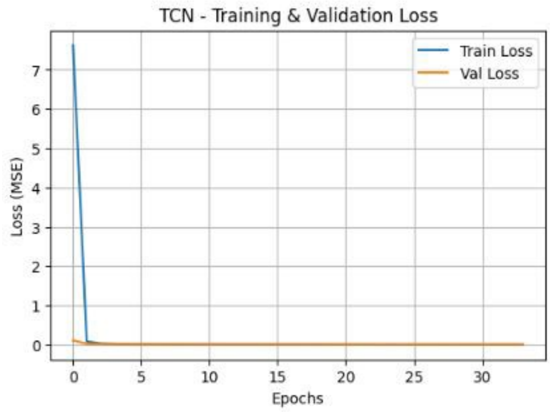

Figure 15. Training and validation loss for TCN model

In figure 13 it is seen that LSTM model showed good convergence with the validation loss remaining consistently lower than the training loss. In case of figure 14, it can be noticed that GRU Model exhibited a similar pattern to the LSTM, with decreasing training and validation losses, and the validation loss staying below the training loss.

Further in figure 15 it is found that TCN Model demonstrated a very rapid decrease in both training and validation loss in the initial epochs, converging to very low and stable values with minimal gap between them.

Table 5. Comparison of Model Performance Based on Validation Loss, Stability, and Overfitting Risk

Model	Validation Loss	Stability	Risk of Overfitting
GRU	Moderate (~0.0025-0.003)	Moderate	Mild

LSTM	Lower (~0.0022–0.0024)	High	Low
TCN	Very low	Very high	Very High

Among all models shown in Table 5, overall LSTM is best because

- It offers low and stable validation loss, reasonable training loss, and balanced learning.
- TCN might appear better numerically, but the sharp drop and near-zero loss raise concerns.
- GRU is acceptable but underperforms compared to LSTM.

5. Conclusions

This research highlights the significant impact of advanced machine learning and time series forecasting models on improving the accuracy and reliability of wind energy predictions, which is vital for meeting the increasing demand and enhancing the competitiveness of wind power generation. By evaluating nine different machine learning models and three-time series forecasting models through thorough cross-validation and multiple evaluation metrics, we identified the most effective approaches. Our results indicate that Random Forests, Gradient Boosting Machines (GBM), and K-Nearest Neighbours (KNN) consistently achieved the highest levels of accuracy and robustness, making them the most suitable choices for wind energy prediction. Conversely, Linear Regression, Support Vector Machines (SVM), and Support Vector Regression (SVR) performed poorly on the dataset. From sensitivity analysis it is noticed that for practical applications in wind energy systems, such robust models can contribute significantly to stable and reliable power output forecasting, supporting effective energy planning and grid management. In the realm of time series forecasting, both Temporal Convolution Networks (TCNs) and Long Short-Term Memory (LSTM) networks excelled in capturing temporal dependencies and trends within the wind energy data, demonstrating their strong predictive capabilities. In summary, this study provides a solid framework for utilizing machine learning and time series forecasting to improve wind energy predictions. The findings offer valuable insights and guidance for researchers and practitioners dedicated to enhancing the efficiency and reliability of renewable energy systems.
Future works can explore using real-time and more diverse data sources to make models even more accurate. Combining different machine learning and deep learning models might also boost performance. Future study may also include the incorporation of explainable AI (XAI) frameworks to enhance transparency and interpretability, which is critical for real-world deployment and decision-making by energy providers.

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