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Article

Comparative Analysis of Various Machine Learning and Deep Learning Models for Wind Power Forecasting in Tamil Nadu, India

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Abstract

Reliable wind forecasting is the key to enhance the reliability and efficiency of renewable energy systems. In this research, a detailed comparison of various machine learning (ML) and deep learning (DL) methods are provided for prediction of wind energy based on wind speed, which is real-world measurements gathered at five major sites in Tamil Nadu through the repository of the Iowa State University. A dataset of about 12,900 records was utilized to train and test ML and DL models. Conventional ML algorithms- random forest, decision tree, K-nearest neighbors, AdaBoost, XGBoost, multilayer perceptron were used for prediction of wind energy which showed good Predictive results. Some of the DL models that were tested include convolutional neural networks, recurrent neural networks, temporal convolutional networks, long short-term memory (LSTM) and Bidirectional LSTM (BiLSTM). The BiLSTM was the best with the smallest errors (mean squared error train: 0.0087, test: 0.0093; root mean square error train: 0.0932, test: 0.0963; mean absolute error train: 0.0081, test: 0.0093) and which had the highest R^2 = 0.986. Statistical Friedman test is also conducted by nonparametric methods to evaluate all applied DL model's performance. Out of every experiment made, the result indicated that the capability of BiLSTM is best suitable in forecasting power on various wind speed for geographically different areas of Tamil Nadu.

Keywords

Energy generation, Renewable energy, Wind speed, Machine learning, Deep learning

Article History

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1. Introduction

The renewable energy output should be estimated accurately and it is one of the pillars of modern power system planning and operation. Wind, solar, and hydro are renewable sources that help in the decarbonization [1]. Despite the fact that these resources are renewable, they pose a source of problems because of their variability to grid stability and reliability. According to the Global Wind, proper forecasting will be required to ensure balance among supply and demand, minimize fluctuation of power as well as maximize use of the available resources [1]. In addition to stability, predictability reduces the cost of backup power generation, increases the efficiency of energy storage systems and advances the overall functioning performance [2-5]. Through proper forecasting of high- and low-demand times, operators have the option to fine-tune plan generation schedules, switch demand response systems and operation of storage systems more effectively- providing stable supply of power even when the renewable generation is fluctuating [5]. In addition to this, enhanced prediction leads to less reliance on fossil fuels thus minimizing greenhouse gases emissions. Environmental emission is a factor that is becoming more and more important in the world. The renewable energy capacity is focused on in policies of energy [5]. Renewable energy capacity is global expanding at a record pace. According to the Global Wind Energy Council (GWEC) 2024 report [1], by 2023, the new renewable installations were 510 GW representing a nearly 50% upsurge out of 2022. Wind energy has reached 117 GW alone, which is very impressive power in wind industry. Countries (United States and China) have adopted various policy frameworks to hasten the implementation of renewable energy fields [4-7]. However, such large-scale variable energy sources of power cannot be integrated unless accurately and effectively forecasted. Moreover, excess renewable energy generated at the time of low demand can be stored and utilized in the future, which contributes to another efficiency increase and lower operational cost [8-11]. Physical and statistical models are considered as the traditional forecasting methods to predict the renewable generation by using the meteorological and historical data [12-15]. They are autoregressive integrated moving average (ARIMA), Kalman filters, Bayesians, Markov chain, and grey theory, which have been effective in modelling linear dynamics and providing probabilistic predictions [16-19]. Nevertheless, they frequently pose a challenge to predictive power particularly with nonlinear dynamics and chaotic variations found in wind power data because of the advent of machine learning (ML) and deep learning (DL) [20-23]. Support vector machines (SVM), artificial neural networks (ANNs), and ensemble models (e.g., random forest (RF), XGBoost) are some of the ML algorithms that have been shown to show a lot of promise in nonlinear modelling of wind datasets [24-27]. Equally, DL models such as long short-term memory (LSTM) networks and temporal convolutional networks (TCN) have achieved the ability to identify temporal patterns and long-term relationships in time-series data [28-31]. ARIMA time series models are still extensively used in the forecasting of wind energy because they can identify the linear dependence and seasonality [32-35]. Other statistical methods, such as Bayesian, Kalman filter, Markov, and grey theory models are still being used to make probabilistic forecasts and apply it to real-world energy management systems [36-39]. To sum up, the effective integration of renewable into the grid, operational efficiency improvement, and long-term sustainability will never be possible without the proper forecasting of wind energy [40-43]. The convergence of the progress of statistical techniques, ML, and DL is enabling researchers and power system operators to deal with the problem of variability and uncertainty during wind generation, and the future of energy is becoming more reliable, more efficient, and more sustainable.

Figure 1 shows the five wind-monitoring regions in Tamil Nadu considered for developing the wind energy prediction model. Here our study uniquely evaluates six ML and five DL architectures under identical conditions, providing a new regional benchmark for wind forecasting accuracy.

This paper is a detailed and systematic discussion about the wind energy forecasting with the applications of both ML and DL models approaches depending on the real-world examples of wind speed in 5 important areas of Tamil Nadu, India. The main contributions of the work can be summed up as follows:

(1) Here a unified experimental framework is developed to compare six ML models and five DL models under the same conditions of wind data in the real world. (2) It sets a regional wind energy forecasting standard in five major wind prone areas of Tamil Nadu. (3) Advanced DL models, such as convolutional neural networks (CNN), recurrent neural networks (RNN), TCN, LSTM, and BiLSTM are contrasted with standard ML models to point out their comparative forecasting performance. (4) BiLSTM model is reported to be the best predictor with the lowest errors in prediction and the largest coefficient of determination (R^2). (5) A nonparametric Friedman statistical test is used to prove the comparative effectiveness of DL models. (6) The results are important to the practical implications of grid operators and policymakers to improve the integration, reliability, and efficiency of renewable energy.

This paper has the following structure: Section 2 presents a review of the past works concerning the prediction of wind energy based on the use of ML and time series models. Section 3 refers to the working plan and methodology. Section 4 gives the performance measures of the various models and discusses the results. Lastly, Section 5 reveals the conclusions and future scopes of this present investigation.

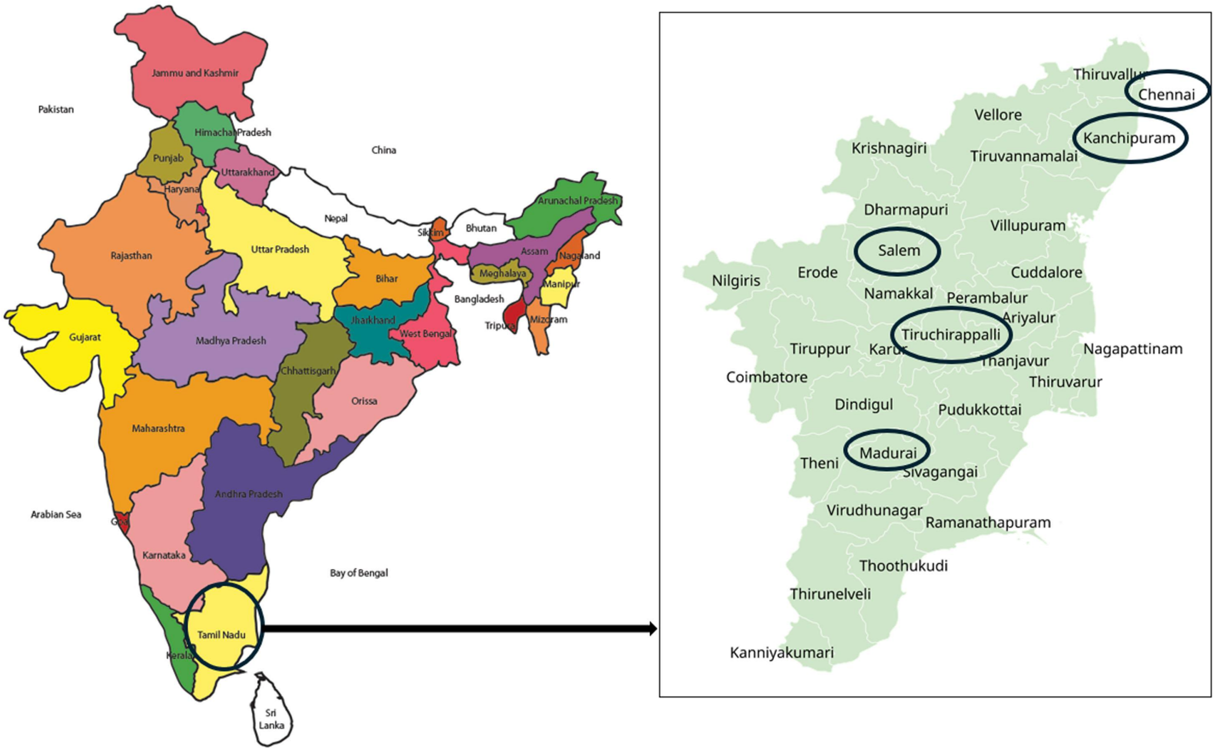

Figure 1. Map of Tamil Nadu showing the five selected regions used for wind data collection in the energy prediction study.

2. Literature Survey

The forecasting of wind power is crucial in the optimization of power generation and stability of the grid. Researchers have experimented with a vast array of techniques over the years, with both conventional statistics and more sophisticated ML and DL methods, in order to increase the accuracy of forecasts.

The literature survey in Table 1 provides an organized overview of existing research in wind speed prediction, enabling quick comparison of methods and outcomes. This foundation helps position the current study within the broader body of work. Early investigations, such as the work of Ayua and Emetere [8], focused on understanding local wind characteristics to assess regional wind potential, laying the foundation for subsequent forecasting studies. Alongside these efforts, statistical time-series approaches remained vital, with Sideratos et al. [15] demonstrating that hybridization of classical ARIMA models with artificial neural networks (ANNs) could enhance short-term wind speed prediction accuracy by compensating for linear model limitations. As forecasting requirements became more complex, comprehensive reviews by Pearre and Swan [35] and Wang et al. [18] systematically compared statistical, physical, and ML approaches, highlighting that while physical and statistical models offer interpretability, they struggle with nonlinear and nonstationary wind characteristics. These reviews collectively emphasized the growing relevance of ML-based techniques, such as decision trees (DT), neural networks (NN), ensemble learning, and support vector-based models—for capturing the essential nonlinearities present in wind datasets. Empirical evidence supporting the superiority of ML approaches has been provided through multiple experimental studies. Colak et al. [22], Ye et al. [25] and Zafirakis et al. [23] independently demonstrated that ML models exhibit strong capabilities in recognizing complex wind patterns, outperforming conventional statistical methods under varied climatic situations. Beyond standalone ML techniques, hybrid and ensemble strategies have gained traction. Lin et al. [21] and Zhang et al. [16] showed that combining multiple ML algorithms significantly improves forecasting accuracy, while Li et al. [13] further enhanced support vector machine (SVM) performance through optimization using the dragonfly algorithm. Consistently, Manero et al. [14] confirmed the robustness of ANN-based models across different wind forecasting applications. Recent advancements in deep learning (DL) have further reshaped wind forecasting research by enabling more effective modeling of temporal dependencies. Architectures such as LSTM, RNN, CNN, and TCN have proven particularly suitable for time-series wind data. Studies by Deng et al. [17], Bali et al. [19] and Daniel et al. [26] reported superior performance of DL models in ramp event detection and short-term prediction accuracy. These findings were extended by Shahid et al. [32] and Ma et al. [33], who demonstrated that hybrid and ensemble DL frameworks can achieve even higher predictive accuracy compared to single-model implementations.

Despite the rapid advancement of ML and DL techniques, traditional statistical models have not become obsolete. Jursa and Rohrig [36] and Yatiyana et al. [37] showed that ARIMA-based models remain competitive for short-term linear forecasting tasks, particularly when computational simplicity and interpretability are prioritized. However, while individual studies have compared selected models, systematic and unified comparisons across classical statistical models, ML algorithms, and modern DL techniques remain limited. Addressing this gap, another study conducts a structured comparison of six ML algorithms and four time-series models to evaluate their relative predictive capabilities for wind energy forecasting. This approach responds directly to the need identified in prior surveys, including the work of Rakshit and Sengupta [38], who highlighted the growing dominance of ML and DL models—such as random forests (RF), gradient boosting, and ANNs—over traditional approaches in wind data forecasting. Similarly, Rajaperumal and Christopher Columbus [39] emphasized that conventional models struggle with nonlinear and temporal complexities, whereas RF, XGBoost, LSTM, and stacking ensembles benefit from advanced feature engineering and hyperparameter optimization. Further regional evaluations support these conclusions. Hossain et al. [40] evaluated multiple ML models for wind prediction in Dhaka, identifying polynomial regression as the most accurate model, followed closely by RF, albeit with higher computational cost. Altork et al. [41], using NWTC meteorological data, observed that linear regression achieved superior performance compared to SVM and Fine Tree models, suggesting that hybrid modeling frameworks could yield further improvements. Complementary findings were reported for Moroccan wind farms, where RNN models outperformed SVMs in capturing daily wind variations to support grid operation and energy trading [42]. More sophisticated hybrid approaches, including Markov, CA-Markov, SVR, and LSTM-Wavelet models, were investigated by Mokarram and Pham [43], achieving notable improvements in noise reduction and forecasting accuracy. Habib and Hossain [44] further demonstrated that DL models supported by strategic feature engineering can significantly reduce prediction errors, achieving a mean absolute error (MAE) of 8.76 compared to conventional methods. Comparative benchmarking by Abdelsattar et al. [45] revealed that Extra Trees was the most effective ML model, while ANN ranked highest among DL approaches in terms of predictive accuracy. Finally, Ibrahim and Altun [46] reaffirmed the strength of LSTM networks in retaining temporal dependencies for wind power prediction.

All these earlier investigations have a common emphasis on highlighting the role of the Intelligent ML and DL frameworks, which replace the use of traditional statistical forecasting approaches. All these studies collectively highlight how the traditional statistical forecasting is being replaced by intelligent and data-driven ML and DL frameworks. These models are better able to represent nonlinearities and temporal dynamics, and fit more to the complex conditions in the real world, and can greatly improve grid reliability, maintenance planning, and energy market participation. Finally, the trend towards data-driven forecasting is going to make the contemporary power systems more accurate, efficient, and sustainable.

Table 1. Literature survey summary table.

Method Used	Key Findings	Ref.
Weibull & Rayleigh distributions	Improved wind characterization for Gambia.	[12]
ARIMA, ANN	Enhanced short-term wind forecasting.	[19]
ML forecasting	Identified complex wind patterns.	[26]
ML forecasting	Long-term monitoring data analysis.	[29]
ANN & SVR	Accurate wind generation forecasting.	[27]
Hybrid ML	Improved short-term forecasting.	[25]
Hybrid model	Higher short-term accuracy.	[20]
SVM, Dragonfly Algorithm	Optimized SVM for wind prediction.	[17]
ANN review	Validated ANN robustness.	[18]
Genetic LSTM	Higher accuracy via hybrid DL.	[36]
Meta-ensemble hybrid	Enhanced short-term accuracy.	[37]
ARIMA, evolutionary algorithm	Effective for short-term linear data.	[40]
ARIMA	Reliable short-term forecasting.	[41]
ML vs DL comparison	ML/DL outperform traditional models.	[42]
ML/DL, ensemble	Higher accuracy via feature engineering.	[43]
Multiple ML models	Polynomial Regression best; RF competitive.	[44]
Linear Regression (LR), SVM, Trees	Linear Regression most accurate.	[45]
Artificial intelligence (AI) models	RNN best for daily variation.	[46]
Hybrid SVR/LSTM/Markov	High noise-reducing efficiency.	[47]

3. Methodology

This paper has undertaken wind energy forecasting with wind-speed data from 5 important locations (Kanchipuram, Madras, Madurai, Salem and Trichi) in Tamil Nadu, collected from the Iowa State University repository since 2018 [47]. It was directed towards forecasting the energy production of both vertical axis wind turbines (VAWTs) and horizontal axis wind turbines (HAWTs). The methodology was systematic and comprised of data collection and pre-processing which involves treatment of missing values and scaling of features [38]. Most previous studies have focused only on short-term wind prediction or used limited datasets. In this work, we use real-time wind data from five major regions of Tamil Nadu to provide a more practical and local view of wind forecasting. Our study compares total fourteen different ML and DL models to find the most accurate and reliable approach. By combining traditional and modern techniques, a clearer idea is provided of how these models perform in real-world conditions. This helps in improving the accuracy and stability of wind power prediction for regional energy planning.

3.1 Data Preprocessing

To ensure reproducibility and consistency across all experiments, a uniform data preprocessing pipeline was applied prior to model training and evaluation. Initially, the raw wind dataset was inspected for missing or incomplete records. All rows containing missing values were removed to maintain data integrity and to avoid introducing bias through imputation, given the moderate dataset size and the availability of sufficient complete samples. For traditional ML models, no explicit feature normalization was applied. This choice was motivated by the nature of the selected algorithms, such as tree-based models (DT, RF, AdaBoost, and XGBoost), which are inherently scale-invariant, and K-nearest neighbors (KNN), for which distance sensitivity was addressed through model-specific parameter tuning rather than global scaling. In contrast, for DL models, standard normalization was performed to improve training stability and convergence speed. Specifically, the input features were normalized to a common scale prior to training, which helps ensure stable gradient updates and prevents dominance of features with larger numerical ranges during backpropagation. After preprocessing, the cleaned dataset was divided into training and testing subsets using an 80:20 split, where 80% of the data was used for model training and 20% for independent testing. This split was consistently maintained across all ML and DL experiments to enable a fair and unbiased comparison of model performance.

ML algorithms were then implemented in the following step to understand the optimized prediction model using the models of the RF, SVR and DT [42,43]. Besides, time-series prediction of wind energy output was applied using more advanced DL methods, such as CNN, RNN, TCN, LSTM, and BiLSTM.

3.2 Machine Learning Models

3.2.1 RF

RF is a learning algorithm that uses a large number of DT in the training phase, and averages their prediction (in regression) or votes the majority of the DT (in classification). Every tree is conditioned on a separate bootstrapped sample of the original data, and a random sample of features is chosen any time a split is made. This twin randomness is also a great help in reducing variance and it minimizes overfitting (unlike a single DT). RF is also popular as a benchmark model in wind-energy forecasting research generally because of its stability, ease of tuning, and high generalization levels.

3.2.2 DT

DT is a supervised learning algorithm, which models decision-making logic by a hierarchical tree. The model recursively divides the data depending on the values of features by impurity metrics (Gini index or entropy or variance reduction). The decision rule is denoted by each internal node and the result of the prediction is denoted by each leaf node. DTs are very interpretable, and thus, they are appealing in the explanation of the role of single meteorological parameters on the speed of winds. They are able to automatically shape nonlinear relationships and interactions among variables without scaling features.

3.2.3 KNN

KNN is a non-parametric, instance-based learning algorithm that gets used as a method of prediction using the top k most similar samples in the training data set. Distance metrics such as Euclidean, Manhattan or Minkowski distance are normally used to measure similarity. The speed of the wind is predicted by taking an average of the results of the chosen neighbors. KNN works well with local similar patterns in wind-speed, like in the case of stable weather. It does not involve a definite training period and this is simple conceptually. Its performance however is very sensitive to the selection of k, distance metric and scaling of feature.

3.2.4 Adaptive Boosting

Adaptive Boosting (AdaBoost) is an ensemble method of learning that uses a combination of many weak learners usually shallow DT to create a powerful predictor model. The algorithm is an iterative one in which there is an increased weighting of samples which are misclassified in earlier iterations. Later learners pay more attention to the hard cases that eventually results in a gradual accuracy improvement. AdaBoost is effectively applied in wind-speed forecasting to drive up the performance of the prediction process, which focuses on the complex and uncommon wind patterns that are frequently overlooked by the traditional models. It is quite effective in eliminating bias and enhancing model expressiveness. AdaBoost is however sensitive to noisy data and outliers which may have disproportionately large weights. When using AdaBoost on meteorological data it is therefore imperative that proper preprocessing and noise handling should be performed.

3.2.5 Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is an effective gradient-boosting model, which is designed to form DT in series through the optimization of a regularized objective function. In comparison with classic boosting, XGBoost uses L1 and L2 regularization, shrinkage, column subsampling, and more complex tree-pruning algorithms to ensure overfitting, as well as, to enhance generalization. To predict wind-speed, XGBoost is helpful in modeling nonlinear relationships among and complex interactions of meteorological variables. It is very well suited to real-time and large-scale wind-energy applications because of its capability to process missing data and large data sets. The XGBoost has been widely reported as one of the most effective ML models in the literature concerning wind-speed prediction because of its high accuracy and fast calculation.

3.2.6 Multilayer Perceptron

Multilayer perceptron (MLP) is a feedforward artificial neural network that consists of an input layer, one or more hidden layers and an output layer. The neurons perform a weighted average of inputs and then a nonlinear activation function, including ReLU, sigmoid or tanh. Backpropagation and gradient-based optimization are used in minimization of prediction error to train the network. MLP can learn complicated nonlinear mappings between meteorological data and the wind speed. Despite the fact that it does not explicitly model the temporal dependencies, it is also capable of making accurate predictions on the scenario where historical wind-speed values are provided as feature inputs. MLP performance is determined by the network structure, activation functions and the size of training data. As an appropriate baseline DL architecture (so far), MLP is capable of offering predictive power on the task of forecasting wind-speed with the use of adequate data and appropriate regularization.

3.3 Deep Learning Models

3.3.1 CNN

CNNs are DL designs that were initially used in image processing but are currently being used in time-series forecasting. Convolutional filters are the elements of CNNs that help them obtain local patterns and trends of input sequences. The weight sharing and pooling operations decrease the quantities of the parameters and enhance the computation effectiveness. CNNs are effective in short-term dependence on temporal variations and local changes in wind behavior in wind-speed forecasting. They are especially applicable to understand spatial-temporal correlations where the data of more than one sensor or station are at hand. Stable training and lower over fitting are also observed in CNNs than in fully connected networks and therefore fit high-dimensional meteorological data.

3.3.2 RNN

RNNs are used when the model is required to work with sequential data, using the hidden state that passes information over time. This form of feedback enables RNNs to identify time-based dependencies of time-series data. RNNs are useful in predicting the wind speed because of the sequentiality of wind changes. Nonetheless, vanishing and exploding gradients afflict the standard RNNs, and make them constraint when it comes to long-term dependency learning. Although such difficulties exist, RNNs present a structural backbone of more complicated recurring networks like LSTM and gated recurrent unit (GRU).

3.3.3 LSTM

LSTM is a unique form of RNN architecture that is used to resolve the vanishing gradient issue. The LSTM networks are very effective in both short-term variability and long-term variability of wind-speed data. The reason why they are considered as one of the most popular models in wind-speed forecasting is their stable learning behaviour and capability to remember the historical information which may be relevant. The LSTM models are always more effective in comparison with traditional ML models, particularly in long-horizon prediction.

3.3.4 BiLSTM

BiLSTM is a variation of LSTM, which works in both forward and backward directions to work with the input sequence. The structure allows the model to use both past and future time steps. BiLSTM is more efficient in capturing complex temporal dependencies compared to unidirectional models in the aspect of wind-speed forecasting. Availability to the future context enables the network to enhance the accuracy of prediction especially when used in offline forecasting. BiLSTM models have been shown to be more effective at capturing irregular changes in patterns of wind and sudden changes.

3.3.5 TCN

TCN is a sequence modeling architecture based on convolution, which uses causal and dilated convolution to make long-range temporal dependencies. Causal convolutions make sure that the prediction of a specific time step only depends on the current and historical inputs, and they maintain temporal causality. TCNs operate in parallel and, therefore have a higher training speed and gradient stability than RNN-based models. Dilation enables TCNs to obtain a wide receptive field to use fewer layers.

3.4 Evaluation Metrics

Error metrices such as mean squared error (MSE), RMSE, MAE and R^2, were used to evaluate a model's performance. The performance of all the models was evaluated using matrices like accuracy, precision, recall, and F1-score [38,39]. This was a methodological procedure that ensured that a detailed study was done for the choice of the most performing model.

There is the need to evaluate wind power forecasting models to understand the correctness of all performing models.

3.4.1 MSE

The MSE is actually the mean of the square differences between the predicted and actual values. It is an effective measure of model accuracy. Essentially, the low MSE value implies that the model is more accurate and does not produce major forecasting errors [39].

$$MSE= \frac{1}{n}\sum_{i=1}^{n} (x_i\text{-}y_i)^2 \qquad (1)$$

Where x_i is the original value, y_i is the anticipated value.

3.4.2 MAE

The MAE measures the average size of the prediction errors. It offers a model's overall accuracy by taking the mean of the absolute differences between the predicted and actual values. Unlike squared-error metrics, MAE treats all deviations equally, making it a clear and reliable indicator of how close the forecasts are to real observations [39].

$$MAE= \frac{1}{n}\sum_{i=1}^{n} |x_i\text{-}y_i| \qquad (2)$$

Where x_i is the original value, y_i is the anticipated value.

3.4.3 RMSE

The RMSE is calculated by taking the square root of the MSE.The model's best predictions are considered by lower RMSE [39].

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i\text{-}y_i)^2} \qquad (3)$$

Where x_i is the original value, y_i is the anticipated value.

3.4.4 R²

The R^2, reflects how well a model captures the variability in the observed data. A value close to 1 indicates a strong fit, meaning the model enlightens most of the variation in the actual results and effectively represents the underlying shapes in the data.

$$R^2=1-SST/SSR \qquad (4)$$

Sum of squared residuals (SSR) measures the total squared differences between the anticipated values and the original observed values, indicating the unexplained error in the model.

Total sum of squares (SST), instead, signifies the overall variance in the dependent variable, showing how much the data varies around its mean [39].

The performance of various models was evaluated with the help of various metrics such that RMSE, MAE, MSE, and R^2. The statistical nonparametric Friedman test assists in ascertaining whether the performance that we witnessed is valid or not [48,49].

Different DL models have been tested in this research employing identical wind energy datasets that were gathered along five geographically different areas. The Friedman statistical test is hence used to statistically compare the relative performance of such models.

3.5 Hyperparmeter Selection

To ensure a fair and consistent comparison across all DL architectures, identical training configurations were adopted for the CNN, RNN, LSTM, TCN, and BiLSTM models. The Adam optimizer was employed for all experiments with a fixed learning rate of 0.001, owing to its adaptive learning capability and stable convergence behaviour in both sequential and CNN. The batch size was set to 16, and the models were trained for 20 epochs, which was found sufficient to achieve convergence while mitigating the risk of overfitting on the available dataset. Regarding activation functions, Tanh activation was used in the recurrent layers of the RNN and BiLSTM models to effectively model temporal dependencies, whereas ReLU activation was applied in the CNN, LSTM, and TCN layers to promote faster convergence and alleviate vanishing gradient issues. These hyper parameter choices were kept constant across all DL models to maintain experimental uniformity and ensure the reliability of comparative performance evaluation.

3.6 Statistical Performance Test

In this work, several ML and DL models were evaluated using the same wind speed data collected from five regions of Tamil Nadu. Since every model was tested on the same datasets under identical conditions, the performance results are naturally related rather than independent. The Friedman statistical test was therefore chosen because it is well suited for this type of comparison. Instead of relying on the absolute error values, the test ranks the models on their forecasting accuracy and then examines whether the differences in these rankings are statistically meaningful. An additional advantage of the Friedman test is that it does not require assumptions about data normality, which is important because forecasting error measures such as MAE and RMSE often do not follow a normal distribution. This makes the test robust and reliable for practical wind energy forecasting studies. The Friedman test [48] will, therefore, be suitable and a viable procedure in establishing statistically significant differences in the performance of the evaluated DL models when it comes to forecasting their performance.

Mathematical formulation of the Friedman test:

$$X_F^2 = \frac{12N}{K(K+1)} R_J^2 \text{-} 3N\,(k+1) \qquad (5)$$

Where J =1 to k, R_j is the average rank of the j^{th} model across all datasets, k is the number of models being compared, N is the number of datasets or experimental runs.

The computed statistic X_F^2 approximately follows a chi-square distribution with k-1 degrees of freedom. A statistically significant result indicates that at least one forecasting model performs significantly differently from the others. In this study, the Friedman test is used to validate the superiority of the BiLSTM model over other DL architectures in wind energy forecasting.

4. Result and Discussion

For this experiment, wind data from Tamil Nadu, India were considered. The data are real-world measurements obtained from the Iowa State University repository [47]. The wind energy forecasting models in this study were trained using a combined dataset comprising five wind-monitoring sites across Tamil Nadu. As a result, the analysis emphasizes overall model robustness and predictive capability at the regional level, rather than site-specific optimization. Therefore, no single site can be identified as the most optimal location based solely on the present results. In the present study, the proposed ML and DL models were evaluated using daily average wind speed data collected from five influential regions of Tamil Nadu since 2018.

According to the findings in Table 2, BiLSTM model has the lowest values of MSE, RMSE and MAE, and highest values of R^2 indicating that it has better predictive accuracy and generalization ability.

The performance of TCN and CNN is also high as they are good at capturing the complex temporal dependencies with high R^2 values. RNN offers consistent performance, which is a bit less precise as compared to TCN and BiLSTM. LSTM represents a relatively bigger error values, yet predictive ability is not bad. On the whole, the findings show that BiLSTM and TCN are the most efficient models used in the regression prediction of wind energy to provide correct predictions with the minimal error.

Table 2. DL model (CNN, RNN, TCN, LSTM, and BiLSTM) evaluation metrics.

Model	MSE (Training)	MSE (Testing)	RMSE (Training)	RMSE (Testing)	MAE (Training)	MAE (Testing)	R^2 (Training)	R^2 (Testing)
CNN	0.023	0.0243	0.1516	0.156	0.0135	0.0151	0.9653	0.9636
RNN	0.0244	0.0263	0.1563	0.1621	0.0196	0.0224	0.9632	0.9607
TCN	0.0188	0.0166	0.1372	0.1289	0.0128	0.0127	0.9716	0.9752
LSTM	0.0531	0.0386	0.2305	0.1965	0.0303	0.0239	0.9199	0.9422
BiLSTM	0.0087	0.0093	0.0932	0.0963	0.0081	0.0093	0.9869	0.9861

Figure 2 shows the MSE performance of the five DL models like CNN, RNN, TCN, LSTM and BiLSTM–in both training and testing stages. From the graph, it can be observed that BiLSTM exhibits the lowest MSE in both training and testing, indicating superior generalization and prediction accuracy. When compared to the others, LSTM, however, has the highest MSE in both cases, which indicate a possible overfitting or inefficient learning of the data patterns. CNN and RNN models are satisfactory where very near training and testing MSE is observed indicating stable but not optimal results. TCN gives comparatively lower values of MSE than CNN and RNN, reflecting good temporal modelling ability. In general, the comparison shows that BiLSTM is the best model to reduce prediction error, which is important in minimizing prediction error.

Figure 3 shows the Root Mean Squared Error (RMSE) of five DL architectures, namely CNN, RNN, TCN, LSTM, and BiLSTM during the training as well as during testing phases. From the graph, it can be seen that BiLSTM has the least MSE in the training and testing phases which reflects the best generalization and accuracy of prediction.

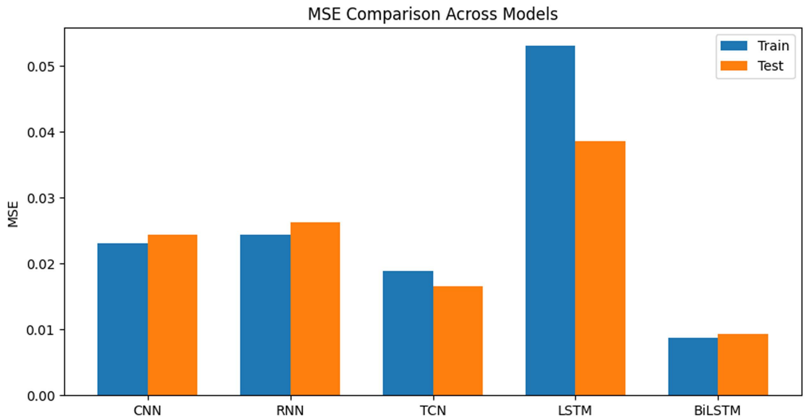

Figure 2. MSE Comparison across all CNN models.

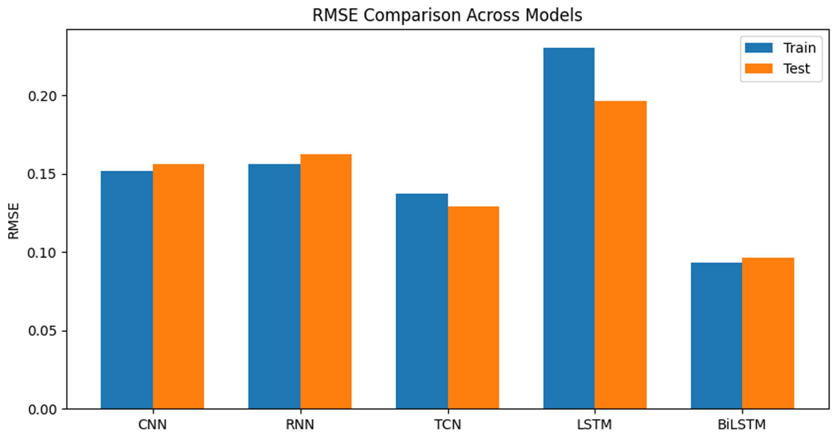

Figure 3. RMSE comparison across all CNN models.

Figure 4 presents the MAE of five DL models–CNN, RNN, TCN, LSTM, and BiLSTM in both training and testing phases. From the graph, it can be observed that BiLSTM exhibits the lowest MAE in both training and testing, indicating superior generalization and prediction accuracy.

Figure 5 shows that all models achieve high R^2 values, indicating strong predictive performance. Among them, BiLSTM demonstrates the highest R^2 for both training and testing, confirming its superior accuracy and generalization. LSTM has slightly lower R^2 values, while CNN**,** RNN, and TCN maintain consistently high and comparable performance levels. Overall, BiLSTM proves to be the most reliable model in capturing data variance effectively.

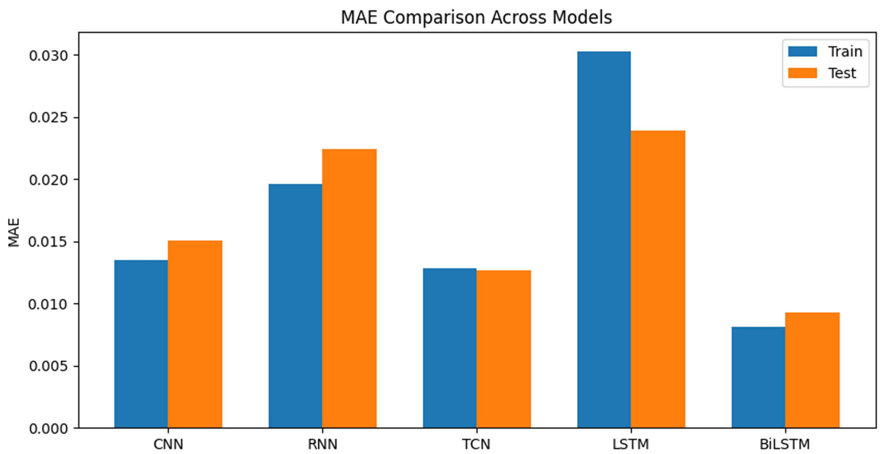

Figure 4. MAE comparisons across all CNN models.

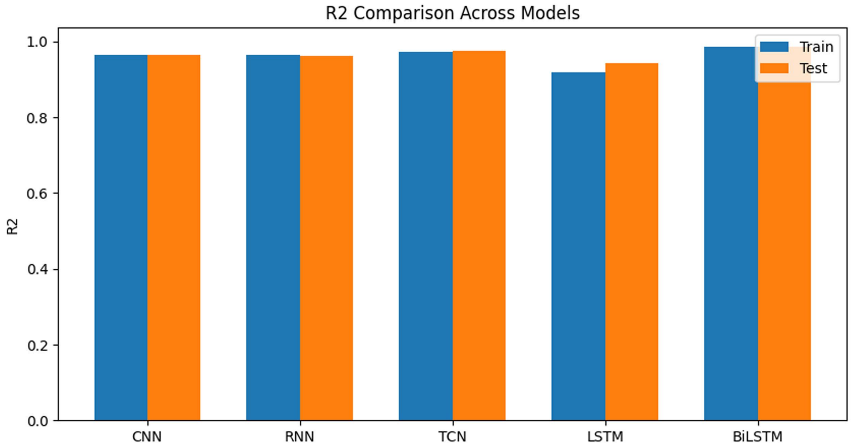

Figure 5. R^2 comparison across all CNN models.

The MAE distribution depicted in figure 6 is represented in box plots. BiLSTM has the least and most consistent MAE which proves that it is strong. The Friedman statistical test also confirms that BiLSTM performance is also statistically significant.

BiLSTM model has not been used in wind energy prediction in the past. Our experimental findings show that it achieves better results than any other DL model analyzed in this paper. As the assessment of different ML and DL models makes it clear, it is evident that all of those algorithms had a very high level of performance in the wind data of Tamil Nadu, which indicates a good data learnability and consistency. Ensemble techniques like RF, Gradient boosting machine (GBM), KNN are among the ML models and the AdaBoost, and XGBoost had almost flawless accuracy with minimal errors, which represented their strength in the ability to capture the nonlinear wind patterns. DL models also provided good performance, as the BiLSTM has become the most precise model. BiLSTM effortlessly acquires past and future dependencies in time-series data. Models like TCN and CNN also demonstrated competitive accuracy and stability, in which they are able to capture temporal and spatial relationships. RNN and LSTM, though a little less accurate, nevertheless were shown to be reliable. The findings of our research are in line with most recent research like Rakshit and Sengupta [42], who claimed that ensemble learning models RF, GBM, KNN and DL (LSTM, TCN) are better than traditional techniques in wind prediction activities. The similarity between these results is close and strengthens the validity of our findings and proves the fact that the high performance of the BiLSTM model is justified.

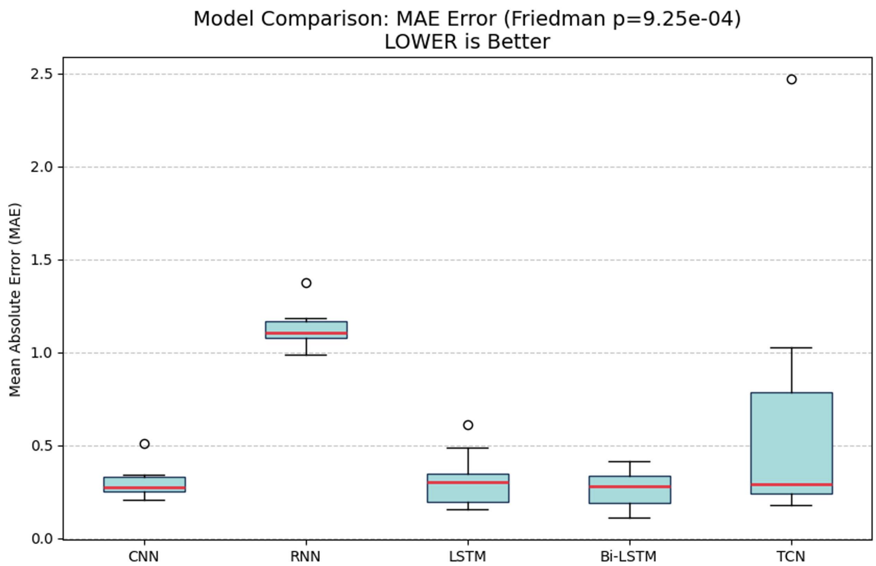

Figure 6. Precision-recall with highlighted agreement analysis across all models.

5. Conclusions and Future Work

In this paper, a detailed comparison of the earning of ML and DL models in real-time prediction of wind energy based on the data in 5 major regions of Tamil Nadu, India, is presented. The classical ML algorithms RF, DT, KNN, AdaBoost, XGBoost and MLP had close to perfect classification performance, which implied high data learnability. BiLSTM was the most effective model of DL as it showed the lowest MSE, RMSE, and MAE values, and the largest amount of R2. This is validating its high capacity to embrace both the short- and long-term temporal dependencies.

TCN and CNN also reported consistent and dependable performances hence are applicable to real-time forecasting. The statistical superiority of the BiLSTM model was further established by the statistical Friedman test that is nonparametric.

Moreover, in this study investigation on five regions of Tamil Nadu was done which may restrict the model's performance to generalize across states, extreme weather conditions or diverse geographical terrains. Other meteorological variables including humidity, temperature, pressure also affect wind speed which are not studied in the present research, and this may have constrained predictive precision in conditions of changing climate. Increased length of time interval, more meteorological parameters and expansion of the dataset for geographically different areas of India or other parts of the world will be used to affirm robustness of the models. Future work will include spatial mapping of site-specific wind power forecasts to better capture regional variability across Tamil Nadu.

Creating hybrid or ensemble DL models–CNN-BiLSTM, TCN-BiLSTM or attention-enhanced architectures- can also make predictive strength better. Integrating explainable artificial intelligence (XAI) methodologies such as shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME) will be necessary in terms of further interpretability and support on decision-making in the business environment. Lastly, implementation of the most effective models, especially BiLSTM and TCN, into a real-time wind monitoring and forecasting system, which is IoT-enabled, can contribute to the planning of renewable energy and optimization of the grid in Tamil Nadu and elsewhere.

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Data Availability Statement

The data is available in https://mesonet.agron.iastate.edu/.

Author Contributions

Saswati Rakshit: Conceptualization, methodology, investigation, data analysis, validation, formal analysis, writing-original draft. Anal Ranjan Sengupta: Conceptualization, writing-original draft, writing-review and editing.

Conflict of Interest

The authors declare that they have no conflict of interest.

Generative AI Statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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