



Research Article

Leveraging Bi-LSTM advanced deep learning model for enhanced wind speed prediction

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ABSTRACT

Forecasting of wind speed is essential for the effective design, management, and maintenance of wind energy systems, which are a key component of renewable energy sources. The difficulty of precisely predicting wind speeds is addressed in this study, as wind patterns are often erratic and unpredictable. Four predictive models have been used in this study for comparative analysis. It has been shown that ARIMA model helps to capture temporal dependencies (linear) & the Kalman Filter very efficiently helps to reduce noise in wind speed data. However, non-linear dependencies have been modeled efficiently by LSTM and proposed Bi-LSTM model. Data sets are gathered from two sites encompassing a period of one year, i.e., June 2022 onwards. In comparison to the LSTM, the Bi-LSTM model consistently outperformed the other methods, with higher error rates for the ARIMA and Kalman Filter, a root mean square error of 0.1280 m/s, mean absolute percentage of 0.0531 m/s, symmetric mean absolute percentage error of 0.0108 m/s. Improvement of Bi-LSTM's performance is due to its ability to deal with time-series data (in forward as well as backward directions), that helps it to capture the stronger correlations (temporal) in the dataset of wind speed. This work is novel because it makes use of Bi-LSTM for wind speed prediction, a method not completely explored in the previous research, and it further integrates statistics and deep learning models. The results make demonstration of the fact that Bi-LSTM significantly improves wind speed prediction accuracy, further improving the reliability as well as efficiency of wind energy systems. By demonstrating improved prediction accuracy for a wide range of datasets, this work significantly contributes to the renewable energy systems and highlights the benefits of using advanced deep learning approaches for prediction problems.

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INTRODUCTION

Recently, wind energy has become an important component of the renewable energy sources worldwide. It also

helps to reduce emissions of greenhouse gases and fight climate change. For wind farms to operate as efficiently as possible, grid stability to be maintained, and wind energy systems to be as efficient as possible, it is very essential to

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forecast wind speed in a reliable manner [1]. Wind speed is very difficult to predict on account of its intrinsically stochastic nature and its intricate temporal patterns. Reliable Short-term forecasting of wind speed is very essential so that wind energy becomes more cost-effective, functionally effective, and can be easily incorporated into complex electrical systems. This helps to increase the reliability of the renewable resources and maximize energy output. Several models, have been suggested over time for increasing the precision and dependability prediction of wind speed forecasts [2]. Figure 1 provides a classification of such models.

The nonlinear properties of wind speed are very difficult to be captured by linear models. The deep learning approaches, specifically the Bi-directional LSTM (Bi-LSTM), and Long Short-Term Memory (LSTM) networks, have been implemented to overcome these limitations. These models are effective for wind speed forecasting since they are made to comprehend the extensive temporal dependencies. Table 1 illustrates the most recent studies

made by several scholars in the field of various methods of forecasting, including time scale horizons and descriptions for wind forecasting. Such as persistence forecasting methods used for very short-term predictions [3–5]. NWP methods employed for medium- to long-term forecasts [6–14]. Statistical methods (such as AR, MA, ARMA, ARIMA, SVR, Kalman filtering, and GARCH) used historical wind-speed time-series data for short- to medium-term forecasting [15–34]. Machine learning models, can be applied from short- to long-term forecasting [35–55]. Hybrid approaches is the combination of two or more forecasting techniques, to improve prediction accuracy and robustness [56–80].

Bi-LSTM used here provides a number of significant advantages, particularly the fact that wind speed data typically demonstrates complex temporal correlations. By analysing data in both forward and reverse directions, Bi-LSTM is more effective in identifying these connections and delivering more precise wind forecasts. The Bi-LSTM model considers both past and future data sources, while the traditional approaches use only past data. This is

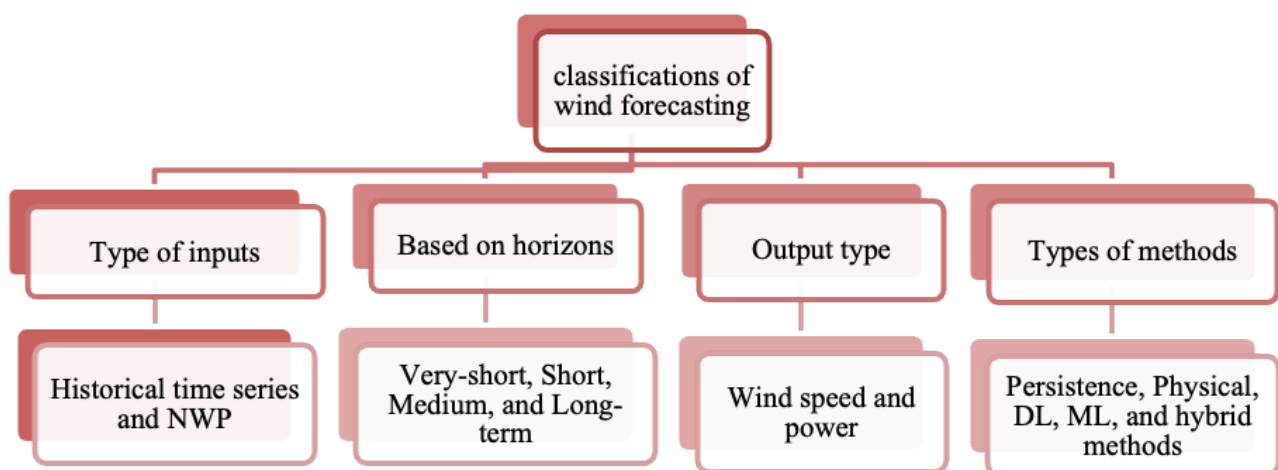


Figure 1. Classifications of wind forecasting based on different categories.

Table 1. Literature of wind forecasting methods with different time scale horizons

Forecasting Method	Description	Applications
Persistence Forecasting [3-5]	Assumes current wind conditions will persist in the near future.	Very short-term forecasts.
Numerical Weather Prediction (NWP) [6-14]	Mathematical models simulate atmospheric conditions using current weather data.	Medium to long-term forecasts (hours to days).
Statistical [15-34] (AR, MA, ARMA, ARIMA, SVR, Kalman, GARCH, etc..)	Use historical wind data and patterns for prediction using statistical and machine learning techniques.	Short to medium-term forecasts (minutes to hours).
Machine Learning Models[35-55] (ANN, RNN, CNN, K-NN, etc..)	Use historical and metrological wind data for prediction using machine learning techniques.	Short to Long-term forecasts (minutes to Days).
Hybrid Approaches [56-80]	Combines methods (e.g., NWP with machine learning) to improve accuracy.	Site-specific forecasts, especially for wind energy.

particularly important for wind speed forecasting, which can be determined by different environmental conditions that occur before and after a specific time point, energy trading, grid stability, and turbine efficiency. Bi-LSTM is a reliable method for wind forecasting. It helps improve renewable energy, supports environmental planning, and reduces weather-related problems. It can use past weather data like wind speed, other weather parameters, and air conditions as input. For time series prediction and renewable energy sources the outcomes of this research play an important role. Some advantages such as reduction in operating expenses, power variation, exploiting storage, accelerating the shift to cleaner energy, and grid integration are delivered by Bi-LSTM forecasting model.

As shown in Table 2, many researchers have used single site data only. The paper is structured as follows: a comprehensive literature review, discussing traditional and machine learning approaches to wind speed prediction, and the objectives of this paper are discussed at first. Further, the paper outlines the methodology, including data collection, model implementation, and performance evaluation. Then the experimental results and a comparison of the performances of the models are presented. Results have been discussed in details and finally the paper is concluded providing the areas for future research. The flow of proposed methodology as shown in Figure 2.

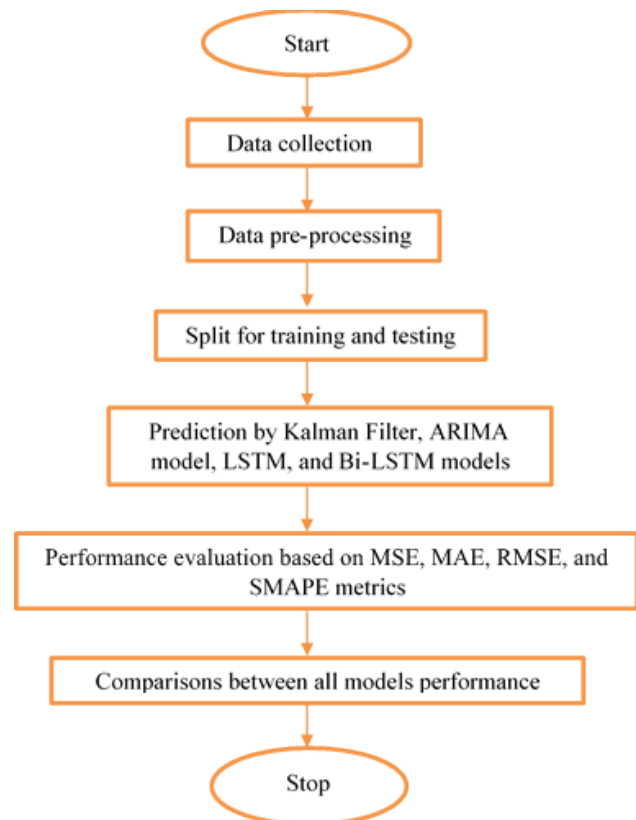


Figure 2. Flowchart of summarizing the methodology.

Table 2. A comparison with past efforts

Ref., Year	Approaches	Strategy	Single Site	Multiple Site with different frequency and geographic location
[12], 2022	Physical Method	NWP	✗	✗
[15], 2018	Statistical Method	ARMA	✗	✗
[24], 2020		ARIMA	✗	✗
[26], 2009		f-ARIMA	✗	✗
[34], 2013		PSO	✗	✓
[35], 2016		WNN	✗	✗
[37], 2009	Intelligent Method	ANN	✗	✗
[39], 2007		RBFNN	✗	✗
[42], 2012		SVM	✗	✗
[46], 2020		SVM	✓	✗
[50], 2023		RNN	✗	✓
[51], 2023	Hybrid Method	ANN	✗	✓
[54], 2010		ARIMA-ANN	✗	✗
[70], 2022		DWT-LSSVM-GARCH	✗	✗
[79], 2018		WT-GA-ANN	✗	✓
[80], 2022	Hybrid Method	CNN-RNN	✗	✓
Proposed Model	Statistical and deep learning methods	Kalman, ARIMA, LSTM, and Bi-LSTM	✗	✓

Objectives

This paper aims to explore and compare Kalman Filter, ARIMA, LSTM as well as Bi-LSTM models for prediction of 1 hour ahead wind speed. Specifically, the objectives are:

1. To implement each model and apply it to wind speed prediction.
2. Performance evaluation and comparison of these models using various statistical metrics.
3. Identification of most accurate and reliable model for wind speed forecasting.

MATERIALS AND METHODS

Data Collection

The data is collected from two sites [81, 82] for a duration from June 2022 to May 2023 and it includes seasonal wind speed time series, recorded at regular interval of one hour. Data is collected for height of 10 meters above the ground. Two different sites have been chosen to collect the data so as to test the reliability of the model in different environments.

Data Pre-processing

Following data Pre-processing techniques are applied on the raw wind speed time series data to make it ready for further analysis:

‘Handling Missing Values’: Due to sensor issues or information communication issues, insufficient data in wind speed datasets is caused. Missing numbers can be restored with help of the techniques like approximation.

‘Standardization’: The wind speed data is normalized so as to verify that each feature is contributing equally. This includes normalizing the data so as to have a mean value of ‘0’ and a standard deviation value of ‘1’, or scaling the data to range of values between 0 and 1.

‘Training-Testing Ratio’: The data set is split into two sets: training and testing sets, each of which is generally used in a ratio of 7:3. This division ensures the training of model on 70 % of data, and its ability to extend is further tested based on a different, unseen 30 % data.

Statistical Methods

Kalman filter

A Kalman filter is optimal & recursive algorithm, which is used for estimating the state of a dynamic system using a series of incomplete (or noisy) measurements over the time. It works by making prediction of the next state and then further making correction of this prediction by making use of new sensor data for minimizing uncertainty.

State-space representation

The Kalman filter is based on a system that is described as state-space model with a state vector describing the system’s current state. A collection of linear equations taking into consideration the system dynamics as well as inputs from outside describes the way in which the state vector changes with time.

Table 3. Mathematical description of Kalman filter

Phase	Mathematical Description
‘State’ Prediction	$[\hat{x}_{k k-1} = F_{k-1} \hat{x}_{k k-1} + B_{k-1} u_{k-1}]$
‘Covariance’ Prediction	$[P_{k k-1} = F_{k-1} P_{k k-1} + F_{k-1}^T Q_{k-1}]$
‘Measurement’ Update	$[K_k = P_{k k-1} H_k^T (H_k P_{k k-1} H_k^T + R_k)^{-1}]$
‘State’ Update	$[\hat{x}_{k k} = \hat{x}_{k k-1} + K_k (Z_k - H_k \hat{x}_{k k-1})]$
‘Covariance’ Update	$[P_{k k} = (I - K_k H_k) P_{k k-1}]$

Recursive estimation

Recursive estimation is used by the Kalman filter in contrast to the batch processing techniques necessitating the processing of every measurement at once. This helps to make it computationally efficient since it uses progressive updating of the state estimate. Two main phases of operation of Kalman Filter are: prediction phase & update phase, for which mathematical description is given in Table 3.

AR (auto regression)

An autoregressive model, often referred to as an AR model, uses relationship between an observation and a certain number of lagged observations to make predictions about future values. The core idea behind an autoregressive model is use of current variable’s value as a linear combination of its past values.

Mathematically, such model of order (p), represented as AR (p), is given by eqn. 1.

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t \quad (1)$$

MA (moving average)

A moving average model (MA) is a forecasting technique using the relationship between an observation and some past forecast errors (residuals) to predict the future values. This model captures short-term patterns and smooths out the random fluctuations in the data. Mathematically, such model (of order q & represented as MA (q)), is given by eqn. 2.

$$Y_t = c + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

ARIMA (auto regression integrated moving average)

The ARIMA model combines AR, Integrated & MA components for capturing features of the time series. The parameters (p, d, q) are estimated from historical data using methods like maximum likelihood estimation where:

Autoregressive component is ‘p’

Differencing (integration) ‘d’

Moving average component ‘q’

The conventional ARIMA models are reliable for wind speed prediction but they may not capture sophisticated patterns or long-term relationship in some time

series. More sophisticated models like Seasonal ARIMA (SARIMA), Vector Auto Regression (VAR), or machine learning models could be concern in some cases.

LSTM

Long Short-Term Memory (LSTM), or LSTM has the ability to store information from previous nodes for a long time, thus, resolving the issue of the ‘vanishing gradient problem’ (of conventional RNNs). LSTM is employed in the forward state, mathematical formulation is given in Table 4. LSTM layers contain memory cells that store information across time steps, controlled by three gates (Fig. 3):

- Input Gate: Input data to be added to ‘memory cell’.
- Forget Gate: Helps in deciding the extent of previous memory to be retained (or discarded).
- Output Gate: Helps to determine the memory cell’s output (to be processed by next layer).

The LSTM network is generally trained by using BPTT and an optimization algorithm such as ‘Adam’ or ‘RMSprop’. The loss function used is generally Mean Squared Error (MSE). Performance of the LSTM model is dependent on a number of hyperparameters, e.g., Number of LSTM units, learning rate, and batch size. After training and evaluation of the model on test set, predictions are compared to the actual wind speed measurements.

Bi-LSTM

Bi-LSTM is designed to capture information of both past and future states in a sequence. Bi-LSTMs are very

effective for situations in which considering context from both directions is essential, such as in NLP. In this network, the input is provided from both the directions. Take note that this is not a form of backward propagation. It is just the input provided from both sides. In a conventional LSTM network, the output is obtained directly from the network, as shown in the Figure 3. The Figure 4. illustrates the structural arrangement of the Bi-LSTM. In a Bi-LSTM, output of both the forward and backward layers at each step is transmitted to an activation layer, whose results are subsequently analyzed. The presented output exhibits the information and correlation between previous and next words [83], as shown in Table 4.

Performance evaluation metrics

Considering critical role of Performance evaluation metrics to ensure the ‘reliability’, ‘accuracy’, and ‘effectiveness’ of the prediction models [84], metrics given in Table 5 are used to make a comparison of various models.

RESULTS AND DISCUSSION

The details of the data used in this study from two different sites (Fig. 5) is already given in section II. Table 6 observes the maximum, minimum, standard deviation, and median of the wind time series, i.e, statistical parameters.

The total number of samples for one year is 8760 (70%: Training, 30%: Testing) which is divided based on the seasons. For prediction, Kalman filter, ARIMA, LSTM, and

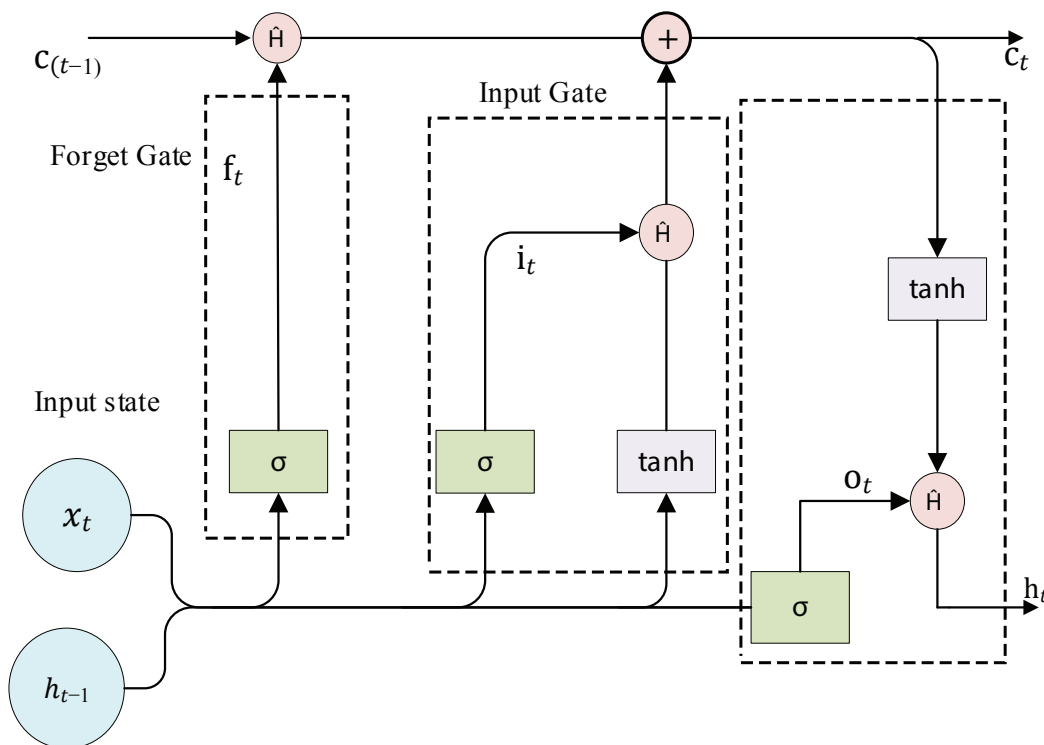


Figure 3. LSTM structure.

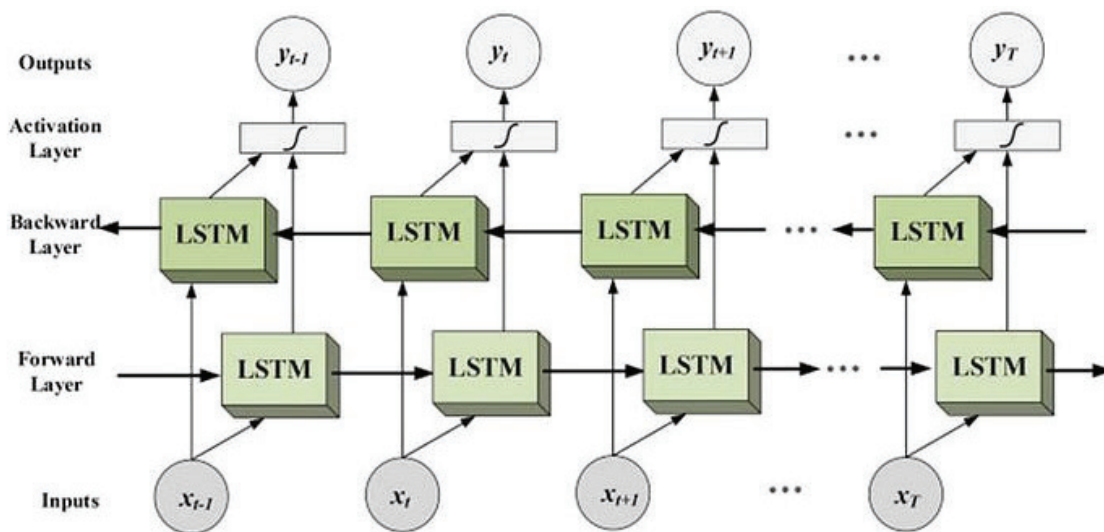


Figure 4. Structure of Bi-LSTM.

Table 4. Mathematical formulation of LSTM and Bi-LSTM [83]

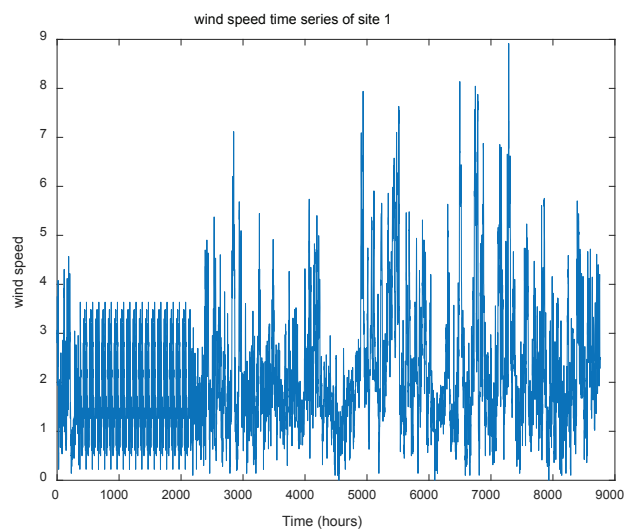
States	Forward State (LSTM), (Bi-LSTM)	Backward State (Bi-LSTM)
Memory cell	$c_t = c_{t-1} * f_t (\tanh(w_c \cdot [x_t, h_{t-1}] + b_c) i_{t-1})$ [83]	$c_t = c_{t-1} * f_t (\tanh(w_c \cdot [x_t, h_{t+1}] + b_c) i_{t-1})$ [83]
Forget gate	$f_t = \sigma(w_f \cdot [x_t, h_{t-1}] + b_f)$ [83]	$f_t = \sigma(w_f \cdot [x_t, h_{t+1}] + b_f)$ [83]
Input gate	$i_t = \sigma(w_i \cdot [x_t, h_{t-1}] + b_i)$ [83]	$i_t = \sigma(w_i \cdot [x_t, h_{t+1}] + b_i)$ [83]
Output state	$o_t = \sigma(w_o \cdot [x_t, h_{t-1}] + b_o)$ [83]	$o_t = \sigma(w_o \cdot [x_t, h_{t+1}] + b_o)$ [83]
Hidden state	$h_t = \tanh(c_{t-1}) * o_t$ [83]	$h_t = \tanh(c_{t+1}) * o_t$ [83]

Table 5. Performance evaluation [84]

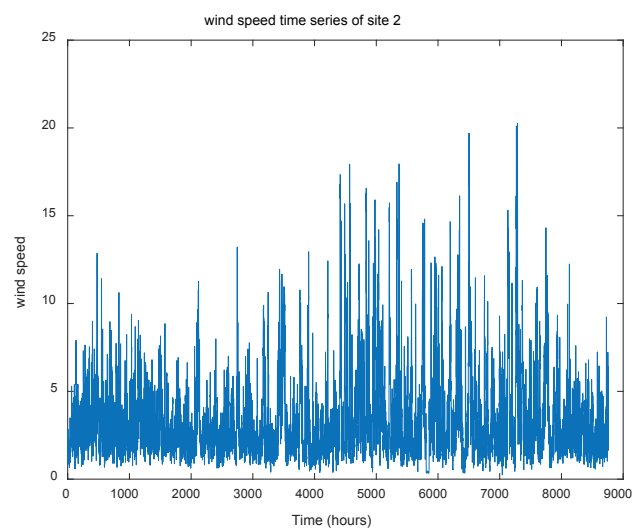
Metrics	Definition	Equation
MSE	Mean Squared Error [84]	$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - X_i)^2$ [84]
MAE	Mean Absolute Forecasting Error [84]	$MAE = \frac{1}{n} \sum_{i=1}^n Y_i - X_i $ [84]
RMSE	Root Mean Squared Error [84]	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - X_i)^2}$ [84]
SMAPE	Symmetric Mean Absolute Percentage Forecasting Error [84]	$SMAPE = \frac{1}{n} \sum_{i=1}^n \frac{ y_i - x_i }{ y_i + x_i /2}$ [84]

Table 6. Statistical parameters for datasets

Statistical parameters	Site 1				Site 2			
	Spring	Winter	Autumn	Summer	Spring	Winter	Autumn	Summer
Max.	8.9157	8.1394	7.1176	4.7854	20.2460	19.7050	13.2176	15.8000
Min.	0	0	0.1414	1.000	0.2536	0.3510	0.3782	0.1800
Std.	2.0125	1.4344	1.0039	0.9972	2.5607	3.3094	1.9486	2.8777
Med.	2.0125	1.9416	1.7464	1.7464	2.7452	3.1101	2.3511	5.3900



5a 'for Site 1'



5b 'for Site 2'

Figure 5. Wind speed time series data.

Bi-LSTM models are used. Traditional (2 techniques) and advanced models (2) employed here are the Kalman filter [85], ARIMA, LSTM, and Bi-LSTM (parameters given in Table 7). Training of the summer season by the Bi-LSTM model, using training data, is shown in Figure 6. The graph shows two lines that represent the performance of an optimization process over multiple function evaluations. 'Min

Observed Objective' (Blue Line) starts at a high value and decreases rapidly at the beginning, levelling off as the function evaluations increase. 'Estimated Min Objective' (Green Line) closely follows the trend of the blue line, indicating a good alignment between the observed and estimated objectives, especially as the function evaluations increase. Both lines converge toward a stable minimum value after around

Table 7. Training parameters of all models

Models	Parameters	Value
ARIMA	p, d, q (AR, differencing, and MA orders)	Values are chosen based on the time series' autocorrelation and partial autocorrelation.
Kalman Filter	State transition matrix (F) [85]	Governs the evolution of the system's state over time.
	Observation matrix (H) [85]	Maps the true state space to the observed space [85].
	Process noise covariance (Q) [85]	Represents uncertainty in the system dynamics.
	Measurement noise covariance (R) [85]	Represents noise in the observations [85].
	Initial state and covariance (x_0, P_0) [85]	Initial guess of the state and its uncertainty [85].
LSTM	Learning Rate	0.0011
	Hidden Units	Number of neurons per LSTM layer (e.g., 50, 100).
	Batch Size	100
	Sequence Length	Length of input time steps per sample (e.g., 10, 20).
	Number of Layers	3
	Epochs	350
	Dropout Rate	0.5
Bi-LSTM	Activation Function	tanh
	Same as LSTM parameters	Learning rate, hidden units, batch size, etc., are similar to LSTM.
	Bidirectional Layers	Processes input sequences in both forward and backward directions.
	Training Complexity	Bi-LSTM requires more computational resources compared to unidirectional LSTM.

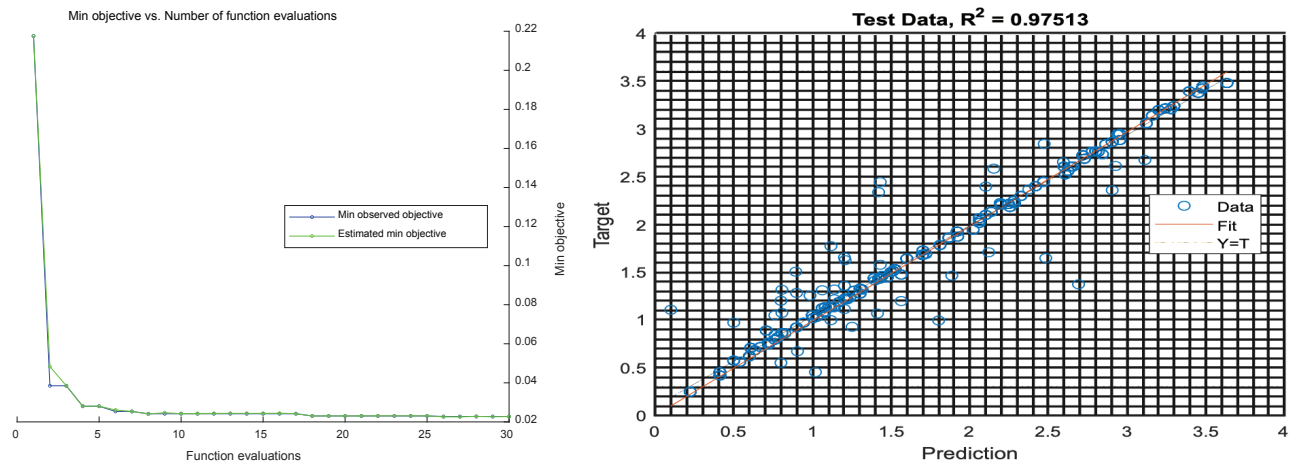


Figure 6. Objective vs. function evaluation and regression curve of summer season from Site 1.

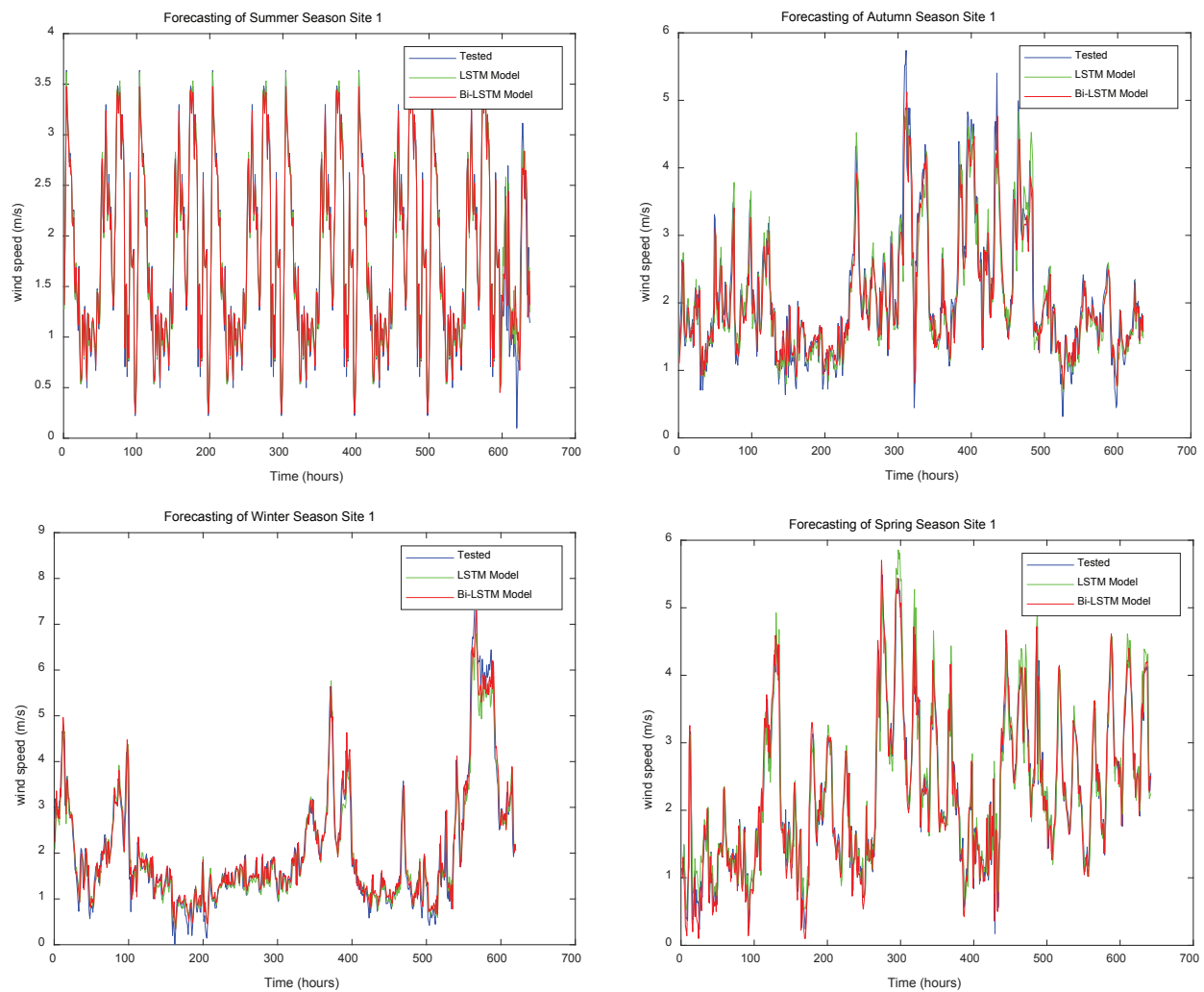


Figure 7. Predictions curve of site 1 from all seasons (Blue (Testing), Green (Predicted by LSTM), Red (Predicted by Bi-LSTM)).

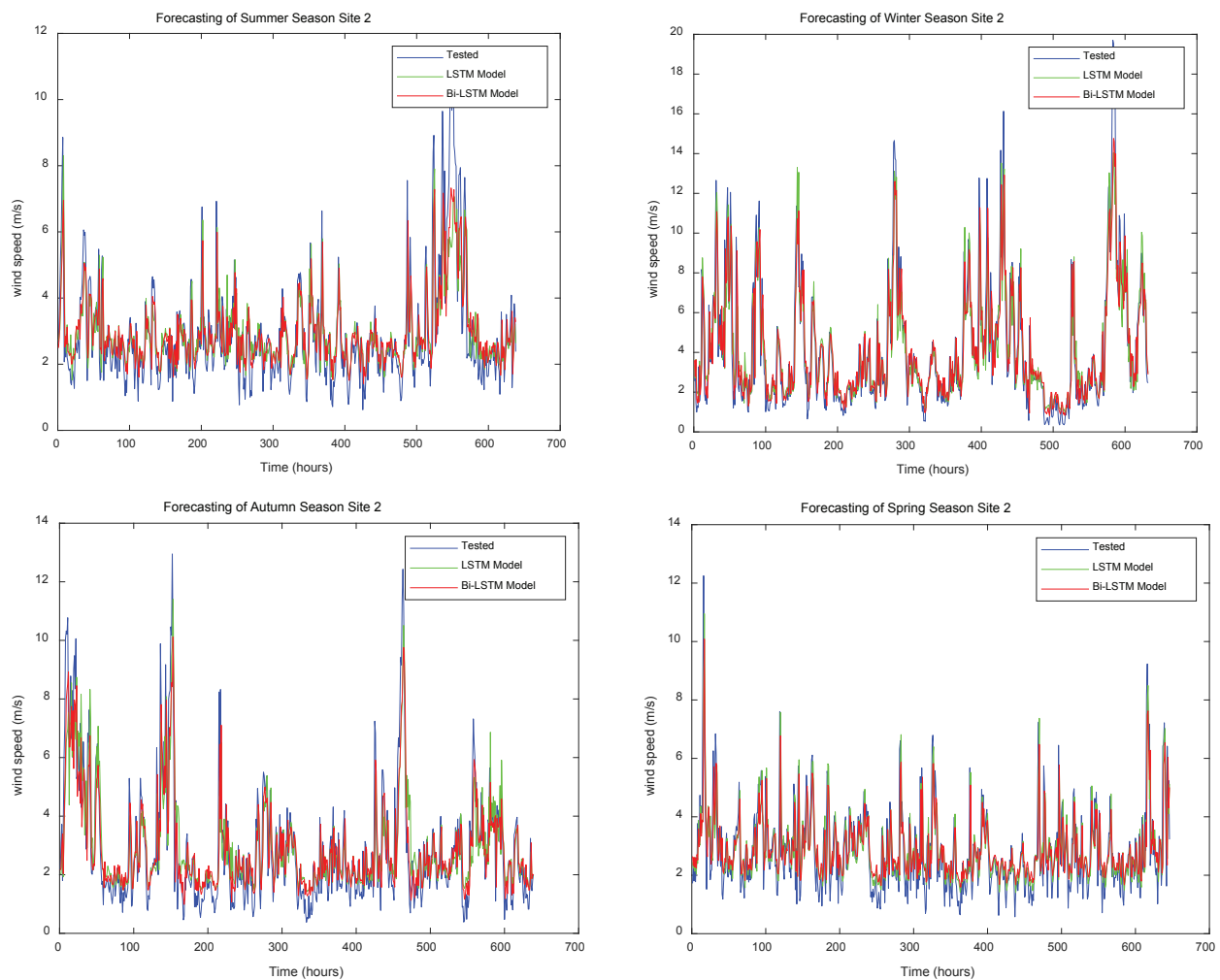


Figure 8. Predictions curve of site 2 from all seasons (Blue (Testing), Green (Predicted by LSTM), Red (Predicted by Bi-LSTM)).

Table 8. Comparison of model's performance for Site 1 (Model '1': Kalman, Model '2': ARIMA, Model '3': LSTM, Model '4': Proposed Bi-LSTM)

Seasons for Site 1	Models	MSE	MAE	RMSE	SMAPE
Summer	'1'	3.6614	1.6980	1.9135	0.4303
	'2'	0.7750	0.7688	0.8803	0.1129
	'3'	0.0255	0.0905	0.1597	0.0170
	'4'	0.0164	0.0531	0.1280	0.0108
Autumn	'1'	4.7028	1.9511	2.1686	0.4255
	'2'	0.8838	0.7187	0.9401	0.0852
	'3'	0.1565	0.2828	0.3956	0.0362
	'4'	0.1413	0.2690	0.3758	0.0350
Winter	'1'	6.2721	2.1019	2.5044	0.4992
	'2'	2.7106	1.4463	1.6464	0.1549
	'3'	0.1380	0.2625	0.3715	0.0389
	'4'	0.1246	0.2518	0.3529	0.0375
Spring	'1'	6.2774	2.2267	2.5055	5.000
	'2'	1.5053	0.9838	1.2297	0.1187
	'3'	0.1846	0.3178	0.4297	0.0461
	'4'	0.1569	0.2850	0.3961	0.0426

Table 9. Comparison of model's performance for Site 2 (Model '1': Kalman, Model '2': ARIMA, Model '3': LSTM, Model '4': Proposed Bi-LSTM)

Seasons for Site 1	Models	MSE	MAE	RMSE	SMAPE
Summer	'1'	3.6614	1.6980	1.9135	0.4303
	'2'	0.7750	0.7688	0.8803	0.1129
	'3'	0.0255	0.0905	0.1597	0.0170
	'4'	0.0164	0.0531	0.1280	0.0108
Autumn	'1'	4.7028	1.9511	2.1686	0.4255
	'2'	0.8838	0.7187	0.9401	0.0852
	'3'	0.1565	0.2828	0.3956	0.0362
	'4'	0.1413	0.2690	0.3758	0.0350
Winter	'1'	6.2721	2.1019	2.5044	0.4992
	'2'	2.7106	1.4463	1.6464	0.1549
	'3'	0.1380	0.2625	0.3715	0.0389
	'4'	0.1246	0.2518	0.3529	0.0375
Spring	'1'	6.2774	2.2267	2.5055	5.000
	'2'	1.5053	0.9838	1.2297	0.1187
	'3'	0.1846	0.3178	0.4297	0.0461
	'4'	0.1569	0.2850	0.3961	0.0426

10–15 function evaluations, suggesting that the optimization process effectively minimizes the objective function.

Prediction by Proposed Model

Figure 7 and 8 provides a performance comparison of the proposed model with LSTM.

Model's Comparison

Tables 8 and 9 indicate the superiority of the proposed model in comparison to others. The results from the experimental analysis indicate that deep learning models, particularly LSTM and Bi-LSTM, significantly outperform traditional models like the Kalman Filter and ARIMA in predicting wind speed. Additionally, the Bi-LSTM model predicts the highest accuracy and has the ability to identify intricate patterns in the data over time. Because of its bidirectional structure, which makes it possible for it to generate dependent variables in both past and future states, the Bi-LSTM model performs the best. Since variation and alterations can occur at any time, this is highly significant when attempting to forecast wind speed.

In comparison to earlier studies using Bi-LSTM for wind speed prediction, this work demonstrates a number of improvements. Improved the addition of more feature engineering techniques, hyper-parameter tuning, and the utilization of larger and more diverse datasets can all lead to greater model performance. In previous studies, for example, inadequate number of datasets and/or inadequate handling of seasonality as well as noise have been the frequent issues. This work addresses these difficulties by use of more reliable designs and/or better pre-processing techniques.

Limitations and Future Work

Although the efficiency of LSTM as well as Bi-LSTM models for wind speed forecasting has been demonstrated here, some limits must be acknowledged, and future research possibilities have to be offered. This study has utilized historical wind speed data from particular locations and for set time periods. Future studies may examine the applicability of proposed models by their applications to a broader range of environments and climates.

Deep learning models (including Bi-LSTM), make use of a large amount of computing resources for training and prediction. Further studies may concentrate on enhancement of these models so as to lower the computational processing demands without decreasing the efficiency. LSTM and Bi-LSTM models are generally considered “black boxes” on account of their complex designs. Enhancing these models' by the use of attention mechanisms may result in crucial insights into the features, thus identifying the features which have more influence on wind speed predictions. Future research may concentrate on developing hybrid approaches which combine the benefits of deep learning methods with statistical methods (such as the Kalman Filter and ARIMA). These models may be capable of making a better tradeoff between computing efficiency, interpretability, and predictability.

CONCLUSION

This paper has determined the capability of the Kalman Filter, ARIMA, LSTM, and Bi-LSTM models for task of wind speed prediction by use of actual wind speed data.

The outcomes have proved that the traditional models like ARIMA and Kalman Filter are beneficial for simple & linear forecasts, the complex, behaviour of the wind speed cannot be effectively handled by them. It has been demonstrated that the Deep Learning models can analyse data in both directions and learn long-term dependencies, thus result in much more accurate predictions. The Bi-LSTM model has been more accurate, resulting in lowest prediction errors which further improves the reliability of electricity grid, thus, making the integration of the renewable energy easier.

The results may be beneficial for various future applications, e.g., basic climate modeling including load prediction for energy systems. The outcomes have demonstrated that Bi-LSTM is the best since because of its capabilities to handle the complex and varied datasets. Although the Kalman Filter and ARIMA are computationally more correct, yet they are less reliable for non-linear dynamics. On account of its versatility, use of Bi-LSTM is preferred for transdisciplinary applications & for forecast of renewable energy, which enhances grid stability. The results of this work may go beyond wind energy prediction and can be used for other sources of renewable energy wherever availability of precise weather and ecological data are essential, including the prediction of solar output or assessing the hydro-power flow. Moreover, since machine learning models are able to handle chaotic & unpredictable time series data, in future, they can be used for wide range of applications, such as time series prediction for financial market evaluation, astronomy, and healthcare. This work further highlights the importance of using the best algorithms available for addressing the global energy challenges and also the importance of collaborating across disciplines for constructing a better as well as more resilient future.

ABBREVIATIONS

AR	Auto- Regressive
ANN	Artificial Neural Network
AI	Artificial Intelligence
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
LSTM	Long-Short Term Memory
Bi-LSTM	Bidirectional Long-Short Term Memory
BPTT	Back Propagate Through Time
CNN	Convolutional Neural Network
DL	Deep Learning
K-NN	K-Nearest Neighbor
MAE	Mean Absolute Error
MA	Moving Average
ML	Machine Learning
MSE	Mean Square Error
NLP	Natural Language Processing
NWP	Numerical Weather Prediction
NREL	National Renewable Energy Laboratory
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network

VAR	Vector Auto Regressive
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SMAPE	Symmetric Mean Absolute Percentage Error

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors certified no conflict of interest.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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