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WindForecastX: a dynamic approach for accurate long-term wind speed prediction in wind energy applications

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Abstract

Wind energy is a vital renewable energy source, and accurate Wind Speed Prediction (WSP) plays a key role in optimizing wind energy production and managing power grids effectively. However, predicting Wind Speed (WS) remains a significant challenge due to the inherently complex and dynamic behavior of wind flow. This paper introduces WindForecastX, an innovative approach that improves prediction accuracy by leveraging a dynamic unified ensemble learning model combined with advanced data assimilation techniques. The ability to accurately predict WS is vital for wind energy planning and monitoring. The accuracy of WSP has been limited because previous studies predominantly relied on data from a single location to develop models and predictions. The proposed WindForecastX model combines the strengths of ensemble learning and data assimilation techniques to enhance long-term WSPaccuracy. WindForecastX utilizes a Stacked Convolutional Neural Network (CNN) and bidirectional long short-term memory (BiLSTM) with a Data assimilation (SCBLSTM + DA) model, Adaptive Wind Speed Assimilation and Quality (AWAQ) incorporating WS observations from nearby locations. By leveraging these advanced techniques, including the Kalman filter, WindForecastX assimilates data from multiple sources to enhance the accuracy of WSP. To evaluate WindForecastX, we utilize real-world wind speed data collected from nine meteorological stations in the Tirunelveli district of Tamil Nadu, India. These stations are used for training and testing, with two stations designated as target stations for WSP. The results demonstrate that WindForecastX outperforms existing WSPmodels. Furthermore, WindForecastX exhibits reduced sensitivity to changes in the prediction time scale compared to standalone models, enhancing its reliability.

Keywords Windenergy · Windspeed Prediction · Long-Termprediction · Ensemblelearning · Dataassimilation · Deep Learning

1 Introduction

A wide range of applications, including generating electricity, milling grain, pumping water, reducing carbon footprints, sailing, powering cargo ships, kite surfing, and windsurfing, depend on accurate Wind Speed Prediction (WSP) (Qin and Stewart 2020; Zhang et al. 2024). Here, due to the topographic channeling, wind direction could be bidirectional in areas with high mountains (Christakos et al. 2020; Hao et al. 2024). It is expected that there will be a cumulative impact when evaluating differences in wind patterns across undulating and hilly terrain (Moreno et al. 2024). This means that changes in wind patterns atop one ridge or hill may influence those atop hills and ridges that are below (Jiang et al. 2024). As a result, it is essential to have an understanding of how bays are similar to one another andconnected,and the likelihood of WSP circumstances between them. Even while the current WSP

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methodologies have obtained good performance results, most previous research studies on WSP relied on data from a single location to paradigm models, whether single models (or) well-liked hybrid models (Wang et al. 2024; Li et al. 2024).

The Wind Speed (WS) being predicted is considered to be connected with the historical data of the WS recorded from the same location, which exclusively active historical WS data measured at a specific location for forecasting and modeling (Bommidi et al. 2023; Pang and Dong 2024). As a result, the spatial dependence of WS was ignored and failed to take into account the Spatial–temporal information close to the given location. Such modeling techniques will restrict WSPaccuracy (Wang et al. 2023; Du et al. 2024).

There are a few techniques for measuring winds with one site utilizing data from another. Model Output Statistics (MOS) (Steininger et al. 2023), Two-Site Correlation models (TSCR), Short-Term Nowcasting Systems (STNS) (Nguyen and Bae 2020), Sample Cross-Correlation Functions (SCCF) (Wang et al. 2022a, b), Bayesian Combination Algorithms (BCA) (Chen 2023), has become the standard option. By searching for patterns and relationships among data, a Neural Network (NN) is applied to model complex relationships among inputs and outputs (Jiang et al. 2022). Using reference data, a Multi-Layer Perceptron (MLP) (Feng et al. 2020) introduced the Extreme Learning Model Based Adaboost Model (ELMBAM), which used data from 17 automated weather-related stations to predict short-term WSP for one target location (Wu and Ling 2024). To evaluate the levels of predictability of various methods and regions, (Pham et al. 2022) utilized a wide range of Machine Learning algorithms in their Ensemble Learning Model (ELM). Compared to other Machine Learning (ML) algorithms for estimating WSP a day in advance, their study and practical findings demonstrate boosting results.

A spatiotemporal model is more complex than other traditional models due to the massive amount of spatial–temporal data and the inclusion of several undefined factors (Abbasi et al. 2021). In a few research, WS or energy levels have been predicted using spatial–temporal data from a location. The Regime-Switching Space–Time (RST) model (Zhang et al. 2022a, b), and this model takes all salient WS features into account, including temporal as well as spatial correlations. Various experimental studies were used to demonstrate the improved model's robustness. Utilizing nearby WS data, (Isensee et al. 2020) created Spatiotemporal (multi-channel) Linear Models (SLM) that showed advantages in very short-term WSP. When the wind direction is not available at various places, the technique cannot be used due to its complexity (Apata and Oyedokun 2020).

Numerical Weather Prediction (NWP), which is the primary approach for WSP, often relies on observations that are very accurate in both space and time. But the exact condition of its actuality cannot be assessed in any way. As a result, figuring out how to get an appropriate starting condition assessment is one of the most important procedures involved in NWP. The problem has traditionally been solved using DA, which has been enhanced by applying mathematical models of multi-physics. The objective of data assimilation uses observations and long-range forecasts to determine the best possible atmospheric condition and associated uncertainty. In a sequential time-stepping process called DA, a prior model forecast is compared to recently acquired observations, the model state is then modified to reflect the observations, the new forecast is started, and so on. This procedure's update stage is commonly referred to by the term "analysis", and the "background" refers to the short model forecast that was developed to generate the analysis.

The Simple Analysis Method (SAM), Optimal Interpolation Method (OIM), and Variational Analysis Method (VAM) stages have features mainly related to the evolution of Data Assimilation Methodology (DAM). Here, the SAM was primarily utilized in the 1950s when computers were either unobtainable or in their infancy. The early foundation for Data Assimilation (DA) was SAM. The statistical factors were added to the environment of DA in the 1960s and 1970s. Some types of OIM were utilized for DA observations and incorporated into forecast models based on those factors. In numerous operational centers across the world, these OIMs were utilized. The transition from atmospheric DA to VAM, specifically the three- and four-dimensional variational (3D-Vary and 4D-Var) DA, occurred in the earlier years. Theth 3D-Vary and 4D-Var techniques recommend optimally blending observations and background information to provide the best approximation of the model's initial state. This method has numerous uses in NWP, in addition to its extensive use in the assimilation of atmosphere and ocean. Rather than concentrating just on the speed-up for DA due to a modified NN, this paper describes the spatial–temporal peculiarity of hybrid DAM based on Multi-Layer Perceptron (MLP) in an exploratory manner.

Many methodologies have recently been implemented to make deterministic forecasts of future WS states using advanced learning models. This is still relevant today, but the use of NN ensemble forecasts has transformed the way WSPoperates. The study involves developing an integrated Ensemble Learning Model (ELM) for long-term WSP that incorporates data from the target station as well as locations in the surrounding area. The accuracy of their forecasts for a target station is the focus of this model, which was developed with that goal in mind. In account, this model takes WS measurements obtained from locations nearby. The increase in information unavoidably results in a rise in the total quantity of computation, which will also affect the speed of computation. Because of its fastlearning speed and lack of need for iterative weight adjustments, the CNN + BiLSTM ELM is used as a predictor in this investigation.

1.1 Novelty

The novelty of the work is depicted as follows.

- Dynamic Unified Ensemble Learning Model: WindForecastX is a dynamic ensemble learning model that combines multiple algorithms to improve the accuracy of wind speed predictions. Unlike traditional approaches that rely on single models, the ensemble approach aggregates the strengths of multiple predictive models, making it more adaptable to different wind patterns and enhancing generalization across a range of prediction scenarios.
- Integration of Stacked CNN and BiLSTM: The model uniquely integrates two powerful deep learning architectures: Stacked Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN component effectively captures spatial features from the wind speed data, while the BiLSTM network handles the temporal dependencies, allowing the model to learn both short-term and long-term wind patterns. This combination enables the model to adapt to complex wind flow dynamics, making predictions more precise and reliable.
- Data Assimilation for Improved Forecasting (SCBLSTM + DA): One of the most innovative aspects of WindForecastX is its use of Data Assimilation (DA) techniques, particularly the Kalman Filter and the Adaptive Wind Speed Assimilation and Quality (AWAQ) method. Data assimilation integrates multi-source data from nearby meteorological stations, improving the prediction accuracy by considering spatial correlations between stations. This approach effectively mitigates the limitations of traditional models that only rely on data from a single location. The assimilation of real-time observations from nearby stations allows the model to correct for errors, smooth predictions, and account for unexpected changes in wind behavior, which significantly enhances WSP accuracy.
- Enhanced Long-Term Prediction Accuracy: WindForecastX's ability to make long-term predictions is an important advancement. Previous models have often struggled with long-term accuracy due to the sensitivity of wind predictions to changing weather conditions. WindForecastX leverages its ensemble learning framework and data assimilation approach to reduce this sensitivity, providing more reliable forecasts over extended time periods. This makes it a valuable tool for long-term wind energy planning, grid management, and wind turbine placement optimization.

1.2 Contributions

The major contribution of this paper is illustrated as follows.

- Development of WindForecastX: This paper introduces WindForecastX, a novel wind speed prediction model that combines Stacked Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The model is designed to enhance the accuracy and reliability of wind speed forecasting by leveraging the strengths of CNN for spatial feature extraction and BiLSTM for capturing temporal dependencies in wind speed data.
- Integration of Data Assimilation Techniques: WindForecastX integrates advanced data assimilation techniques, specifically Kalman Filtering, to refine wind speed predictions. This approach assimilates observations from multiple Reference Stations (RS) to improve the accuracy of predictions at the Target Stations (TS), accounting for spatial and temporal variations in wind patterns.
- Real-World Validation Using Meteorological Data: The proposed model is evaluated using real-world wind speed data from nine meteorological stations located in the Tirunelveli district of Tamil Nadu, India. These stations provide diverse data on wind speed patterns and serve as the basis for model validation. Two of these stations were specifically designated as Target Stations (TS), and the others were used as Reference Stations (RS). The experimental results show that WindForecastX significantly outperforms existing models in terms of prediction accuracy, reliability, and robustness.
- Enhanced Prediction Accuracy and Reduced Sensitivity: The proposed model demonstrates improved prediction accuracy with a reduction in both Mean Relative Error (MRE) and Mean Bias Error (MBR), outperforming state-of-the-art models such as EEMD-LSTM-LSSVM, VMD-GNN-TFC, BiLSTM-A, and TFT. Additionally, WindForecastX exhibits reduced sensitivity to changes in the prediction time scale, making it more reliable in dynamic wind environments compared to standalone models.

1.3 Research questions

The following research questions are to be analyzed.

1. How do hybrid models that combine traditional statistical methods with machine learning algorithms compare to standalone models?
2. How effective is the adaptive learning mechanism in updating prediction models with new data for maintaining accuracy over extended periods?
3. What are the specific modeling approaches needed to ensure accurate predictions at different temporal resolutions?

1.4 Significance of Contribution

The significant contributions are obtained below.

- Proposal of a novel approach, WindForecastX, for enhancing long-term wind speed prediction.

- Integration of a dynamic unified ensemble learning model to enhance the wind speed predictionaccuracy.
- Utilization of advanced data assimilation techniques, including the Kalman filter, to assimilate data from multiple sources and enhance prediction accuracy.
- Overcoming the limitations of previous studies by utilizing wind speed observations from nearby locations, expanding the model's applicability beyond a single data source.
- Development and utilization of the Stacked CNN + BiLSTM with SCBLSTM + DA model, for improved prediction performance.
- Analysis of the WindForecastX model using real-world wind speed data from multiple meteorological stations, providing practical insights into its performance.

The efficient and reliable operation depends on accurate long-term wind speed predictions. Traditional methods for forecasting wind speed often suffer from high uncertainty and limited adaptability to dynamic environmental conditions, leading to suboptimal energy production and increased operational costs. This challenge is particularly pronounced in regions like the Tirunelveli district of Tamil Nadu, India, where wind patterns exhibit significant variability due to local climatic and geographical factors. The existing methodologies are inadequate in providing accurate and reliable forecasts, resulting in inefficiencies in energy production and increased operational costs. Traditional models often fail to capturethecomplex as well as dynamic nature of wind speed, leading to predictions with high uncertainty. Existing approaches struggle to adapt to changing environmental conditions and geographical variations, reducing their effectiveness in diverse regions. The proposed model employed various metrics was taken to compute the wind speed prediction, the proposed model gains the values with greater effectiveness results than the existing models which can show the greater effectiveness of the results.

The remaining sections of the paper arearranged as follows, Sect. 2 elaboratesonthe related surveys of the various authors with their research gaps. Section 3 presents the details about the proposed WindForecastXmodel, and the experimental results for the prediction of wind speed are presented in Sect. 4. At last, Sect. 5 discussed the conclusion.

2 Related works

The prediction of wind speed is a critical challenge in various industries, including renewable energy, aviation, and meteorology. Over the years, significant advancements have been made in developing analytical models and methodologies aimed at improving the accuracy and reliability of wind speed forecasts. These advancements have largely been driven by the integration of Machine Learning (ML) techniques, as well as traditional physical models and ensemble approaches.

2.1 Machine learning approaches for wind speed prediction

Machine Learning (ML) techniques have gained considerable attention in recent years due to their ability to uncover complex patterns in wind speed data. Several studies have explored the use of neural networks (Blanchard and Samanta 2020), support vector machines (Zheng et al. 2023), and random forests (Ali et al. 2023) to predict wind speed. These models typically rely on historical wind data, along with meteorological factors like temperature, pressure gradients, and geographical features, to improve forecasting accuracy. In particular, deep learning models have shown promise for wind speed prediction. Cai et al. (2020) introduced a Multi-Task Gaussian Process (MTGP) regression model, which demonstrated significant improvement in forecast accuracy. However, despite its potential, the MTGP method faced challenges in terms of computational efficiency. To address this, Qian et al. (2021) proposed a two-layer Attention-based Long Short-Term Memory (2Atts-LSTM) model, which outperformed baseline models in short-term wind speed prediction. Nevertheless, this approach was limited by the complexity of training the model. Similarly, ensemble methods have been explored to enhance the robustness of wind speed forecasts. For instance, Genget al. (2020) developed a hybrid Principal Component Analysis (PCA) and LSTM network model, which minimized dimensionality and optimized the learning rate to improve prediction accuracy. This method was found to outperform traditional models in terms of prediction reliability and efficiency. In contrast, Zhang et al. (2022a, b) proposed a more intricate ensemble model involving multiple techniques, including Time-Varying Filter-based Empirical Mode Decomposition (TVFEMD), Random Forest, and Bi-directional LSTM. While this method increased data stability and improved accuracy, the prediction time was notably longer.

2.2 Traditional and hybrid approaches

In addition to machine learning, physical models grounded in fluid dynamics principles continue to play an important role in wind speed forecasting. Computational Fluid Dynamics (CFD) simulations and numerical weather prediction models are commonly used to simulate wind patterns at various altitudes and locations (Castorrini et al. 2023). These models offer valuable insights into the physical behavior of wind, though they often require substantial computational resources and can struggle to account for all relevant variables. Hybrid models that combine machine learning and physical principles have also been developed to leverage the strengths of both approaches. For example, Yan et al. (2022) presented a hybrid model that analyzed wind speed data across various time scales, extracting both nonlinear and linear features for improved prediction accuracy. However, the model's inability to integrate diverse periodic feature types limited its effectiveness. Furthermore, Wang et al. (2022a, b) used a Multi-point-AdaBoost-Extreme Learning Machine (ExLM) approach, incorporating data from multiple meteorological stations to predict multi-time-scale wind speeds. While the method showed promising results with an efficiency of 78.2%, it still struggled with prediction accuracy in certain instances.

2.3 Uncertainty estimation and probabilistic forecasting

Uncertainty in wind speed forecasts is a critical consideration, especially for applications in renewable energy where prediction errors can have significant financial and operational implications. Recent research has focused on probabilistic forecasting methods to estimate uncertainty alongside predicted wind speeds. Fan et al. (2023), Ai et al. (2023), and Du et al. (2024) have explored various probabilistic approaches, which provide a range of possible wind speeds and associated probabilities, thereby enabling more informed decision-making. Kosana et al. (2022) introduced an innovative Reinforcement Learning-based model (OMS-QL), using Q-Learning for online dynamic selection of the optimal forecasting model. This approach significantly outperformed traditional methods, providing better prediction accuracy in dynamic scenarios. Nevertheless, the model's limitations in predicting wind speed accurately highlight the ongoing challenges in this field.

2.4 Recent advances and future directions

Despite these advancements, many of the proposed models still face challenges in terms of real-world applicability and accuracy. For instance, Li et al. (2020) developed a method to separate nonstationary short-term residual and stationary long-term baseline components to improve accuracy, but the model has yet to be fully implemented in practical settings. Similarly, Lawal et al. (2021) combined 1D CNN and BLSTM networks for short-term wind speed prediction, achieving an efficiency of 67.4%, though the performance of the hybrid network was not always optimal. Furthermore, Tümse et al. (2022) employed an adaptive neuro-fuzzy inference system (ANFIS) and other neural network models to estimate wind turbine output power. While ANFIS showed better performance, it required significant time and resources. This highlights the trade-off between model complexity and computational efficiency that many researchers face in developing practical forecasting systems.

A summary of related works for the various authors under various approaches is illustrated in Table 1.

2.5 Research gap and the need for a novel technique

The research gap in wind speed prediction techniques arises from the limitations of traditional approaches in accurately forecasting wind speed for wind energy monitoring. These traditional methods struggle with the nonlinear nature of wind speeds, which depend on various factors related to the surrounding environment. Predicting parameters that are influenced by weather conditions in real-time systems is challenging.

Based on the literature review provided, several advanced techniques have been explored for predicting wind speed, each with its strengths and limitations. However, there remains a research gap in achieving consistently accurate and robust predictions, particularly under varying environmental conditions and over different time scales. Key challenges identified include:

- Nonlinear Nature of Wind Speed: Existing approaches struggle to capture the complex, nonlinear relationships that affect wind speed, such as changes in weather conditions and environmental factors.
- Integration of Multiple Variables: Effective wind speed prediction requires integrating various climate variables like air pressure, temperature, and geographical factors, which influence wind patterns.
- Performance in Real-World Applications: Many advanced models show promising results in validation settings but may fail to perform adequately when deployed in real-world scenarios due to their complexity or computational inefficiencies.

The identified research gap, a novel technique could focus on:

- ***Integrated Ensemble Approaches:*** The developed model combines the strengths of various forecasting models to enhance prediction accuracy and reliability.
- ***Feature Engineering and Selection:*** The feature selection can be implemented to effectively capture relevant climatic and geographical factors impacting wind speed variability.
- ***Real-Time Adaptability:*** The designed model is employed to change the condition of the environment and also incorporate continuous learning mechanisms to enhance the prediction accuracy over time.
- ***Computational Efficiency:*** Computational efficiency of the model is ensured by optimizing the real-time applications, and balancing accuracy with practical deployment constraints.

Table 1 Summary of Related Works

Author	Techniques	Uses	Merits	Demerits
Li et al. (2020)	Nonstationary short-term residue and stationary long-term baseline	Gain ultra-short-term wind speed forecasts	Increase forecast accuracy	Failed to be implemented in the real world
Cai et al. (2020)	MTGP regression model	Locate the intended turbine position by mapping the numerical predictions	Less computational efficacy	Large-scale offshore wind farm on the real-world data
Qian et al. (2021)	2Atts-LSTM	Identify short-term wind speed	Enhanced effectiveness	Lacks in training a more complicated framework
Wang et al. (2022a, b)	Multi-point-AdaBoost- ELM	Enhance target location prediction	Improved performance	Cannot predict the wind speed accurately
Yan et al. (2022)	SARIMA model	Gain information on wind speed	Greater accuracy	Fails to integrate various periodic feature types
Geng et al. (2020)	PCA and LSTM	Predict the speed of wind	Effectively predict the wind speed	Consuming more time
Zhang et al. (2022a, b)	TVFEMD-RF-CNN-ISCA-BiLSTM method	Enhance the stability of the wind data	Enhanced performance	More prediction time
Kosana et al. (2022)	OMS-QL method	Identify wind speed	Improved efficiency	Failed to predict the wind speed accurately
Lawal et al. (2021)	Hybrid 1D CNN and BLSTM network	Accurate short-term wind identification	Predict wind speed	Performance of the prediction is not good
Yang and Yang (2020)	BRR-EEMD	Identify the wind speed	Accurately predict the speed of wind	More time for consumption
Bilgili et al. (2007)	ANNs	Predict the speed of wind	ANNs model was effective	Consumed more time
Bilgili and Sahin (2010)	LR, NLR, and ANN methods	Predict wind speed	ANN was more effective than the LR and NLR models	More time consumption
Tümse et al. (2022)	ANFIS, ENN, and FNN	Predict the speed of wind	Better Effectiveness	Required additional time, labor, and measurement expenses
Ozbek et al. (2022)	ANFIS with Grid Partition	Efficient in predicting wind speed	Enhanced Efficiency	More consumption time

3 Proposed methodology

In this section, we introduce WindForecastX, which includes Cache-MLP, a hybrid model designed to improve long-term wind speed prediction via historical data as well as real-time updates. This section provides the background information on Cache-MLP, the Backtracked-Multi Layer Perceptron (MLP), Convolution Neural Network (CNN), and Bi-directional LSTM (BiLSTM) Architecture. In the proposed WindForecastX approach, the integration of advanced data assimilation techniques. Traditional methods often suffer from limitations such as reliance on data from single locations and difficulty in capturing the dynamic nature of wind flow. WindForecastX addresses these challenges by leveraging the SCBLSTM + DA model, which combines Stacked CNN and BiLSTM with a Data Assimilator. This model integrates observations from multiple nearby meteorological stations, utilizing a CNN + BiLSTM-based ELM in conjunction with 4DVar/EnKF for data assimilation.

The 4DVar/EnKF method plays a crucial role by assimilating data from various sources into the prediction framework. It continuously updates the model's initial conditions and parameters based on observed wind speed data, thereby improving the model's predictive accuracy over time. By assimilating real-time observations from multiple stations, WindForecastX enhances its capability to capture local wind patterns and variations. This approach not only outperforms traditional statistical models and existing machine learning approaches but also demonstrates reduced sensitivity to changes in prediction time scales, thus enhancing its reliability for wind energy planning and grid management applications. The comprehensive evaluation using real-world data from multiple meteorological stations validates WindForecastX's effectiveness in improving wind speed prediction accuracy and reliability for practical implementation in renewable energy systems. The following subsections provide a summary of the mentioned techniques.

3.1 The Cache-MLP

The Cache-MLP is an innovative hybrid model that combines traditional multilayer perceptrons (MLPs) with caching mechanisms to efficiently process and utilize wind speed data (Huang et al. 2020). The idea for Cache-MLP was born out of the necessity to effectively manage large datasets and the temporal nature of wind speed variations (Huang et al. 2021). In operational systems, an analysis cycle is a procedure by which a first estimate (X_b) is made using short-term projections, and the knowledge of fresh observations (y_o) is integrated to produce an analysis field X_a.The optimal weight (ω), as in Eq. (1), is specified in 4D-Var (or) EnKF and may be determined by solving a DA problem.

$$x_t^a = x_t^b + \omega * \left(y_t^o - h\left(x_t^b\right)\right) \tag{1}$$

In order to optimize the "analytical field," the Cache-MLP keeps the training data set, which includes initial predictions and observations. To account for the flow-dependency of environmental elements, it is preferable to use information from at least the five steps before to the current time $\left(X_a t5, X_a t1\right)$ while attempting to predict $\varepsilon X_a \varepsilon$ at a time t. The Cache-MLP then resolves the DA by Eq. (2) optimization problem.

$$x_t^a = \sum_{i=0}^{5} \omega_{t-i} x_{t-i}^b + \sum_{i=0}^{5} v_{t-i} y_{t-i}^o + bias \tag{2}$$

For $\left(X_b, y_o\right)$, correspondingly, w and v represent weight matrices. The tendency of the weights is represented by employing the *bias* term. Figure 1 (a) & (b) depicts the Cache-MLP's structure.

3.2 The Backtracked-MLP

Multilayer Perceptrons (MLPs) (Grum 2023) are widely used for various prediction tasks due to their ability to model nonlinear relationships. Researchers have combined pure Var and ensemble DA approaches using a wide range of techniques in traditional hybrid DA methods, and the experimental proof has increased the "analysis field". The Backtracked MLP, which draws its inspiration from a hybrid, utilizes the output of Cache-MLPs that have been trained as its training data set. Figure 1 (a) & (b) depicts the Backtracked-MLP's structure.

The following is an explanation of the operating steps.

1. The training sets of the Cache-MLP-NNs will be revisited, with particular attention given to train the data.
2. Assist in the optimization of the "analytical fields" by updating the 4D-Var chunks
3. A Backtracked-MLP shares a structure with Cache-MLP, and empirical tests were used. Last but not least, the formula used by the hybrid DAM to determine $\varepsilon X_a \varepsilon$ can be expressed in Eq. (3), Eq. (4), and Eq. (5).

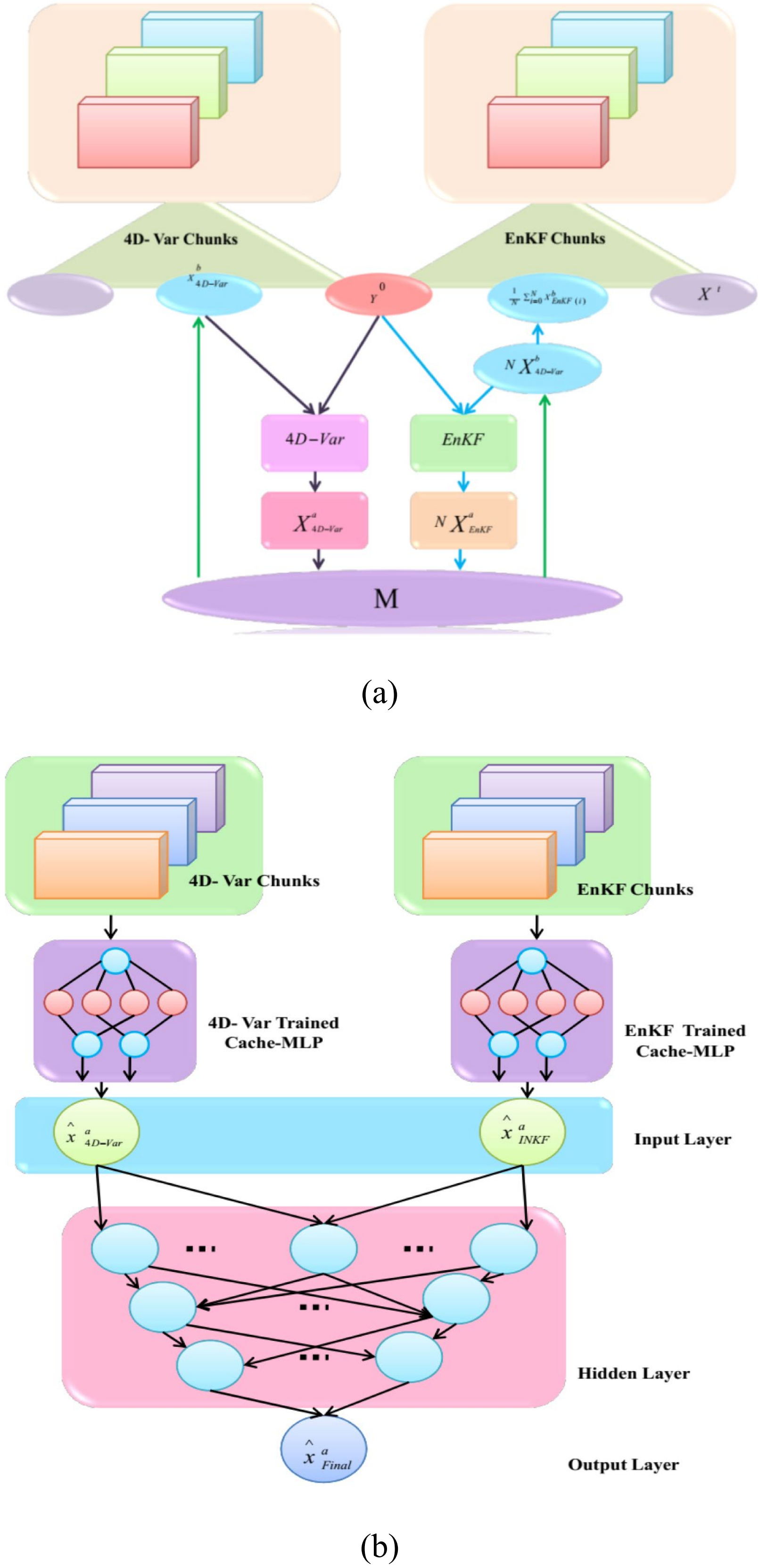
$$\hat{x}_{4\mathrm{Dvar}}^a = CacheMLP\left(4D\mathrm{var}\left(x_i^b, y_i^o\right)\right) \tag{3}$$

$$\hat{x}_{EnKF}^a = CacheMLP\left(EnKF\left(x_i^b, y_i^o\right)\right) \tag{4}$$

$$x_t^a = BacktrackedMLP\left(\hat{x}_{4D-Var}^a, \hat{x}_{EnKF}^a\right) \tag{5}$$

where, $i \in [t-5, t]$.

Fig. 1 Backtracking MLP model for (**a**) Stage 1 and (**b**) Stage 2



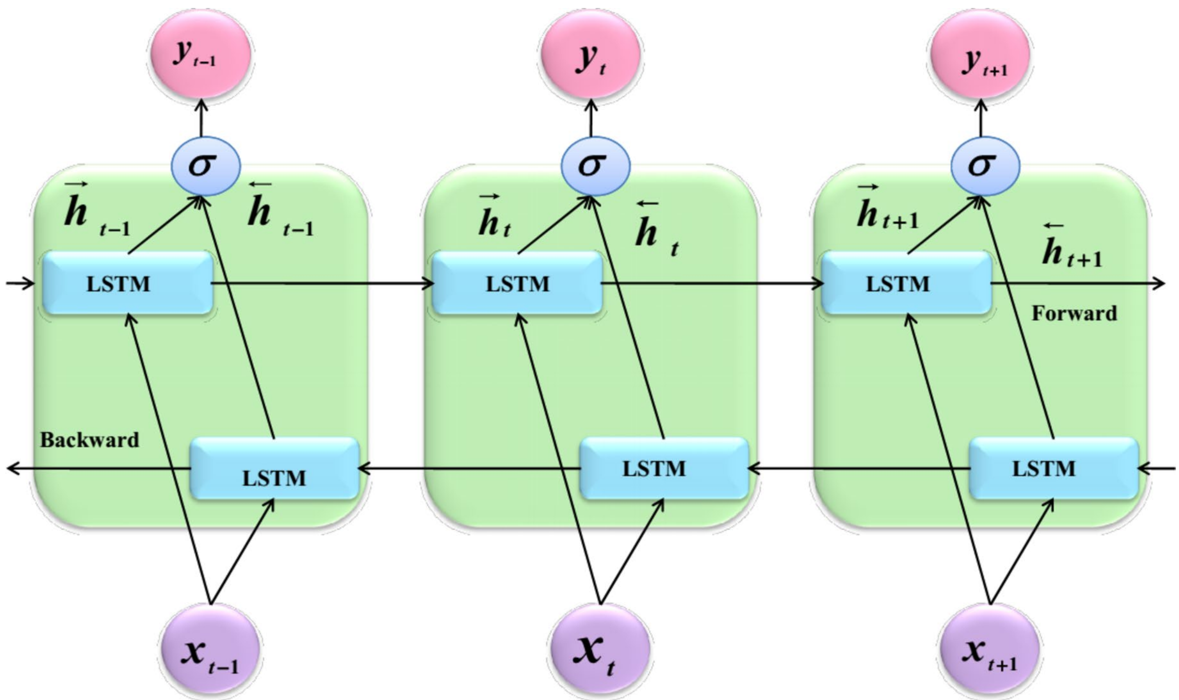


Fig. 2 Schematic representation of a bidirectional LSTM model (Apaydin et al. 2020)

3.3 Convolutional neural network (CNN)

The target and reference station databases of incoming solar and Wind Energy (WE) are the source for CNN's model parameters. The convolution layer and ReLU (Rectified Linear Unit) are in the initial procedure. The input solar and wind databases are processed using a convolution layer. To identify the specific feature, a feature map is produced by performing a convolution process. To introduce nonlinearity into the model, ReLU activation is used.

In the CNN layer, element-by-element calculations are done with the help of the activation function named Rectified Linear Unit (ReLU). The ReLU's job is to look at a feature map and change any negative numbers to zeros. ReLU makes training and calculations go faster. The layer that comes after the convolution layer is called the pooling layer. The purpose of this layer is to make the feature smaller in size. Max pooling and convolution together give a position-independent way to find features. Similarly, the Max pooling layer is robust against fluctuations and perturbations. The classification procedure receives the combined output of the convolution and max pooling layers.

3.4 Bi-directional LSTM (BiLSTM) architecture

BiLSTM-NNs were suggested in the research to improve the functionality and learning speed (Rezaei et al.2023). Figure 2 depicts the BiLSTM model (Apaydin et al. 2020), which enables us to take into account both the past and future context of source codes. Lastly,h_t^f and h_t^b are joined to provide the output "y_t".W_{xh}^f,W_{hh}^f,W_{xh}^b,W_{hh}^b,W_{hy}^f, and W_{hy}^b represents the weights of the hidden layer to the output gates.b_h^f,b_h^b, and b_y indicates the vectors.ThisEquation (6), Eq. (7), and Eq. (8) are used to implement the BiLSTM model:

$$h_t^f = \mathrm{Re}LU\left(W_{xh}^f 0.17\mathrm{em}x_t + W_{hh}^f h_{t-1}^f + b_h^f\right) \tag{6}$$

$$h_t^b = \mathrm{Re}LU\left(W_{xh}^b x_t + W_{hh}^b h_{t+1}^b + b_h^b\right) \tag{7}$$

$$y_t = W_{hy}^f h_t^f + W_{hy}^b h_t^b + b_y \tag{8}$$

3.5 Hybrid CNN + BiLSTM model

The proposed WindForecastXmodel uses the Stacked CNN + BiLSTM with Data Assimilator (SCBLSTM + DA) model. Kalman filters aid in estimating uncertain information and smoothing noisy data by determining the actual underlying state. Widely employed in signal processing and sensor fusion, they enhance measurements and diminish noise. Before inputting data into the CNN + BiLSTM model, implement the Kalman filter to minimize noise and enhance measurements. Kalman filters utilize past states and present measurements to estimate the accurate data state, particularly beneficial for refining noisy signals or sensor measurements. Employ the Kalman-filtered data as input for the CNN, allowing it to extract hierarchical features. CNN layers can be tailored to acquire noise-resistant features and adapt to data variations. The CNN layers' output, post-Kalman filtering, can be input into the BiLSTM network. BiLSTM models effectively capture temporal dependencies and patterns in data sequences, offering advantages for sequential data following Kalman filtering. Merge results from CNN and BiLSTM models trained on Kalman-filtered data. Apply ensemble techniques such as averaging, stacking, or voting to combine predictions. Consider the computational complexity of Kalman filters for real-time applications. The SCBLSTM + DA model consists of three main components: (1) the CNN + BiLSTM-based ELM, which captures the spatiotemporal dependencies of wind speed using CNN and LSTM networks; (2) the data assimilator, which assimilates the real-time observations from nearby locations using the 4DVar/EnKF method (3) the stacked architecture.

The Machine learning Guided Particle display (MLPD) assimilation of the wind database is processed by CNN using the Convolution layer. To identify the specific feature, a feature map is prepared by performing a convolution operation. The CNN layer uses the activation function to perform element-wise calculations.

Max pooling and average pooling are the two different types of pooling. The position invariant feature extraction is produced by using max pooling and convolution. Overfitting is decreased by max pooling's use of fewer parameters during the Feature Extraction (FE)phase.The recommended hybrid CNN-BiLSTm Model's specific processing steps are;

Step 1: Gathering wind data from geographical location, Eq. (9)

$$PWP = \left\{ WP_{1,1}, WP_{1,2}, WP_{1,3}, ..., WP_{1,T} \right\} \tag{9}$$

Step 2: Involves validating the data obtained for the DL model on a scale of 0 to 1.

Step 3: A 3-D matrix structure is created from the homogenized data. Data validation would also confirm that the scale of the information is comparable.

Step 4: With a filtration system of size s_z, the homogenized data set is rapidly sent to the 1-D convolution layer. Therefore, Eq. (10) determines the weight at the time t.

$$W_{Wp(t)} = F_k^{Sz-1} * F_k^{Sz} * n_c^{Sz-1} * n_c^{Sz} \tag{10}$$

and bias being defined as $B_{kt} = nS_{zc}$.

Step 5: The output of WPF, a one dimensional (1-D) convolutional layer's output, is computed by Eq. (11)

$$C(t) = W_{wp(t-1)} * A_{wp(t-1)} + B_t^k \tag{11}$$

wherein $Awp(t-1)$ signifies the activation function of the wind systems, Eq. (12)

$$A_{wp(t)} = G(C(t)) \tag{12}$$

wherein the nonlinearity inside the activation functions relating to time t is represented by $G(c(t))$.

Step 6: A convolution layer's input parameters are transmitted into the max pooling layer, where moderate-dimension FE is carried out, Eq. (13)

$$Mx_H * Mx_W * n_c = \left(\frac{Mx_H - F}{WP} + 1 \right) * \left(\frac{Mx_W - F}{WP} + 1 \right) \tag{13}$$

wherein Mx_H and Mx_W signifies the height and width of the matrix.

Step 7: The max pooling layer generates information for the BiLSTM layer. The information must be stored in the memory module is also decided by the memory controller, Eq. (14)

$$p_t = \sigma\left(W_i \left[GM_{t-1}, X_t \right] + B_t^k \right) \tag{14}$$

Step 8: The sole control of deciding which historical state data must be rejected, Eq. (15)

$$GM_t = \sigma\left(W_f \left[GM_{t-1}, X_t \right] + B_t^k \right) \tag{15}$$

A tanh non-linear activation factor within the tanh activation stack introduces non-linearity into the system, Eq. (16)

$$C\prime(t) = \tanh\left(W_c \left[GM_{t-1}, X_t \right] + B_t^k \right) \tag{16}$$

Step 9: The data is retained when the input state remains the same, andremoved by the FG Eq. (17)

$$C(t) = GM_{t-1} * C_{t-1} + P_t * C\prime(t) \tag{17}$$

Step 10: The layer state is determined by an Output Gate (OG). Equation (18) and Eq. (19). Data from the Left Gate (LG) and Right Gates (RG) are accepted by BiLSTM.

$$A_{(t)} = \sigma\left(W_0 \left[GM_{t-1}, X_t \right] + B_t^k \right) \tag{18}$$

$$h_{(t)BiLSTM} = h_{(t)} * h_{(t)} \tag{19}$$

3.6 Meta learner model (MLM)

In this section, Metanetworks and theProposedStacked Convolutional BiLSTM + DA (SCBLSTM + DA) Forecast Model are explained as follows.

3.6.1 Meta networks

Meta Networks, often known as MetaNet, is an MLM with a model and training process created for rapid generalization among tasks (Dokur et al. 2022) "Fast weights" are essential for MetaNet's rapid generalization. Typically, stochastic gradient descent is used to update the weights in NNs, and this procedure is known to be slow. Using one NN for predicting the parameters of added NN is one technique to accelerate learning; the resulting weights are known as "fast weights". Loss gradients were being utilized in MetaNet as metainformation to feed models that learn fast weights. In NN, predictions are extracted by combining fast and slow weights. Algorithm 1 presents the functionality of the adopted MetaNet model:

Algorithm 1: MetaNet

Step 1: At every time step t, sample an inputs' random pair like the support set S, $S, (X'_i, y'_i)$ and (X'_j, y_j). For $t = 1,...,K$, let $X_{(t,1)} = X'_i$ and $X_{(t,2)} = X'_j$.

Step 2: Calculate a loss for representation learning using $L_t^{emb} = 1_{y'_i = y'_j} \log P_t + \left(1 - 1_{y'_i = y'_j}\right) \log(1 - P_t)$ where $P_t = \sigma\left(W \left| f_\theta\left(X_{(t,1)}\right) - f_\theta\left(X_{(t,2)}\right)\right|\right)$

Step 3: Let the task-level fast weights: $\theta^+ = F_w\left(\nabla_\theta L_1^{emb},....,L_T^{emb}\right)$ be computed.

Step 4: Go through the examples in the S support set for Next and calculate the fast weights.

Step 5: A probability distribution $P(\hat{y}_i \mid X_i) = g_\phi(X_i)$ and the loss can be cross-entropy

Step 6: Compute the example-level fast weights and extract the task's metainformation (loss gradients) using $\phi_i^+ = G_v\left(\nabla_\phi L_i^{task}\right)$

Step 7: Next, in the $value$ memory M's i^{th} location, store ϕ_i^+.

Step 8: By applying slow and fast weights: $r'_i = f_{\theta,\theta^+}(X'_i)$, the support sample is encoded into a task-specific input denotation

Step 9: Next, into "key" memory R's i^{th} location, store r'_i.

Step 10: Lastly, it seems to be time to build the training loss by applying the test set $U = \{X_i, y_i\}_{i=1}^{L}$ Begins with $L_{train} = 0$.

Step 11: Encode the test sample into a task-specific input denotation: $r_j = f_{\theta,\theta^+}(X_j)$.

Step 12: The fast weights are assessed through the presentation to denotations of support set samples inside memory R. An attention function is based on your decision. Here MetaNet uses Cosine Similarity (CS), $a_j = \text{cosine}(R, r_j) = \left[\frac{r'_1.r_j}{\|r'_1\|.\|r_j\|},....,\frac{r'_N.r_j}{\|r'_N\|.\|r_j\|}\right], \phi_j^+ = Soft\max(a_j)^T M$

Step 13: Update the training loss: $L_{train} \leftarrow L_{train} + L^{task}\left(g_{\phi,\phi^+}(X_i), y_i\right)$

Step 14: Update each of the parameters (θ, ϕ, w, v) using L_{train}.

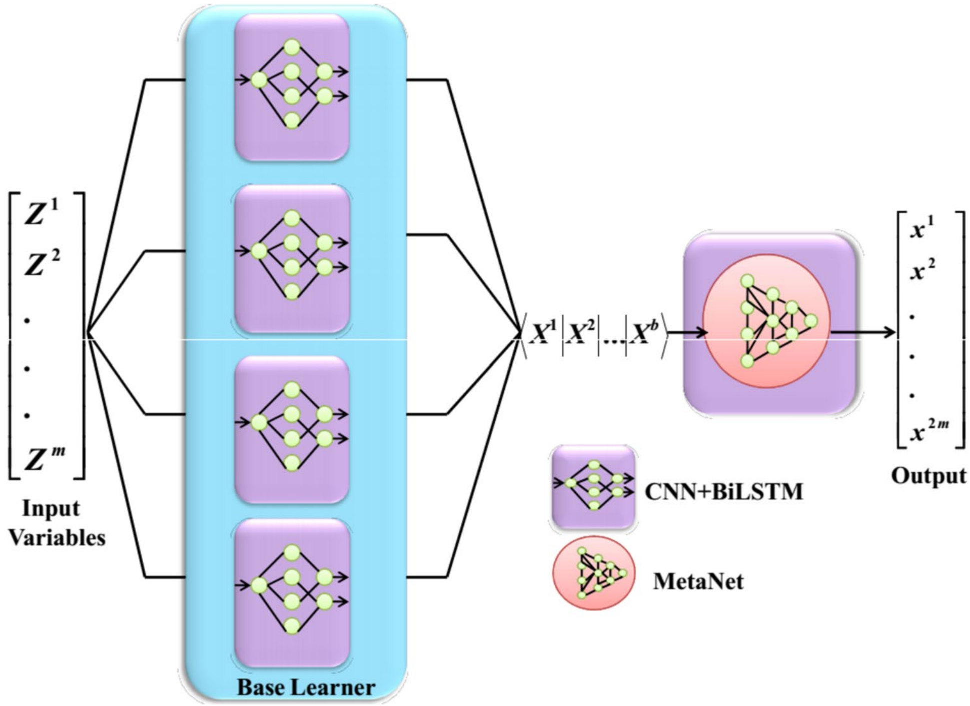


Fig. 3 Deep CNN-BiLSTM architecture

3.7 Proposed stacked convolutional BiLSTM + DA (SCBLSTM + DA) forecast model

To create an Ensemble Learning Model (ELM) for wind speed prediction (WSP), this study employs a Stacked Ensemble Model (SEM). In this framework, base learners are combined simultaneously, with each base learner independently learning from the training data. The meta-model, which generates output based on the predictions from these base learners, merges their individual predictions. The base learners include a variety of machine learning models such as Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) like Long Short-Term Memory (LSTM), traditional machine learning methods like Decision Trees (DT) and k-Nearest Neighbors (k-NN) regression, as well as hybrid models. Given the benefits of ensemble learning, this study utilizes ensemble learning for wind speed prediction (WSP), testing several machine learning models including MLP, CNN, LSTM, and CNN-BiLSTM as base learners to create an optimal ELM framework.

To evaluate the effectiveness of these models with different meta-learners, multiple models are stacked both in parallel and sequentially. For the base learners, machine learning models such as MetaNetwork, Model-Agnostic Meta-Learning (Meta-Learning) (Chen et al. 2020), and Reptile (Shah and Shroff 2021) are tested as meta-learners.

The proposed model for long-term wind speed prediction applies stack generalization of the ELM, with MetaNetwork acting as the meta-learner and several parallel CNN-BiLSTM models as base learners. While the four CNN-BiLSTM models in this study share the same architecture, their stochastic nature leads them to behave differently. As a result, even if the models are redundant, their outputs will diverge, creating variability in their predictions. This variance helps in constructing more accurate base learners.

Since MetaNetwork is a widely recognized meta-learning technique, we provide a summary of it above. The proposed Wind Speed Prediction (WSP) model architecture is shown in Fig. 3.

The measured data are used as inputs to the base learners in the proposed model. The meta-learner effectively maps the predicted wind speed to the actual observed values. To improve the predictions further, the predicted wind speed, along with the observed data, is passed through a Data Assimilation Model (DAM), which fine-tunes the predictions to closely match the actual values. The final predicted values are updated with historical data, refining the model's predictions over time. This ensemble method, combined with data assimilation, is referred to as "Stacked Convolutional BiLSTM + Data Assimilation (SCBLSTM + DA)" in subsequent sections of the paper.

The flowchart and algorithm for the proposed method are shown in Fig. 4 and Algorithm 2, respectively.

Algorithm 2: SCBLSTM + DA WSP model

Step 1: Gather and process historical WS data

Step 2: The data are normalized and converted to $[0,1]$

Step 3: Create ELMs using the CNN-BiLSTM algorithm.

Step 4: The CNN-BiLSTM regulates the weights of various ELMs by using the weight distributions $D_i, (I = 1,2,...,T)$

Step 5: Calculate the Huber Loss Function (HLF) based on the epoch count

Step 6: Update weights and bias of each CNN-BiLSTM ensemble learner

Step 7: The ensemble output is created by combining the individual ELM outputs with the MetaNet meta-learner model using connection weights.

Step 8: Apply the 4DVar/EnKF data assimilation model to fine-tune the ELM results.

Step 9: The WSP at the target station is obtained by reverse normalizing the DA output value.

Step 10: Evaluate the model against various metrics using the test dataset.

The loss function utilized is Huber loss. This quantity is obtained experimentally by examining the training of ML model error settling over a period of 200 epochs for the proposed work. The predictable measures could be used for planning the location of future windmill erection and control of the WE system at the time of real-time operation of the proposed WSP, even if some measurements are missing (or) the topology is changing. The acceptable level of error, also known as the threshold, that indicates convergence or satisfactory model performance, depends on the error metrics relevant to your specific model and problem. The 200 epochs for our wind speed prediction problem are employed to avoid overfitting. The North East Monsoon—Weather Data dataset has temporal dependencies and wind dynamics, so longer training may lead to overfitting. Limiting epochs to 200 helps balance capturing long-term patterns while reducing overfitting risks. Training deep learning models for large datasets like wind speed prediction can be computationally demanding. Therefore, capping epochs at 200 optimizes convergence within a reasonable timeframe, optimizing computational resource utilization. These metrics could include mean squared error, cross-entropy loss, and others. For example, if the error falls below the predefined threshold before reaching 200 epochs, the training process can be stopped early. This is because further iterations may not significantly improve the model's performance. Because it allows for managing errors, rapid changes in the network, and changes in topology and network features, accurately predicting missing measurements is crucial for the data-driven WSP.

Time complexity

The execution time of any developed approach can be accessed by evaluation of its time complexity. The time complexity is the order of $O(N^2)$ and $O(N\log N)$ for the maximum and minimum value of the objective function. Also, the time complexity is calculated by updating the process of decision variables. The time complexity is in the order of $O(N \times d)$.

Therefore, the total time complexity is estimated as,

$$O(CNN - BiLSTM) = O\left(m\left(N^2 + n \times d\right)\right) = O\left(m\left(N^2 + m \times N \times d\right)\right) \tag{20}$$

The maximum iteration is indicated as m the iteration number N and the decision variable is d

4 Experimental design

In this section, an experimental design is implemented in evaluating and confirming the prediction performances of the WindForecastX model. There seem to be four sections: Target Station, Compared Models, and WSP Time for model performance.

4.1 Experimental setup

WSP of the proposed WindForecastX model was performed using MATLAB R2018a software with 1.10 GHz Intel(R) processor on the Windows 11 64-bit operating system.

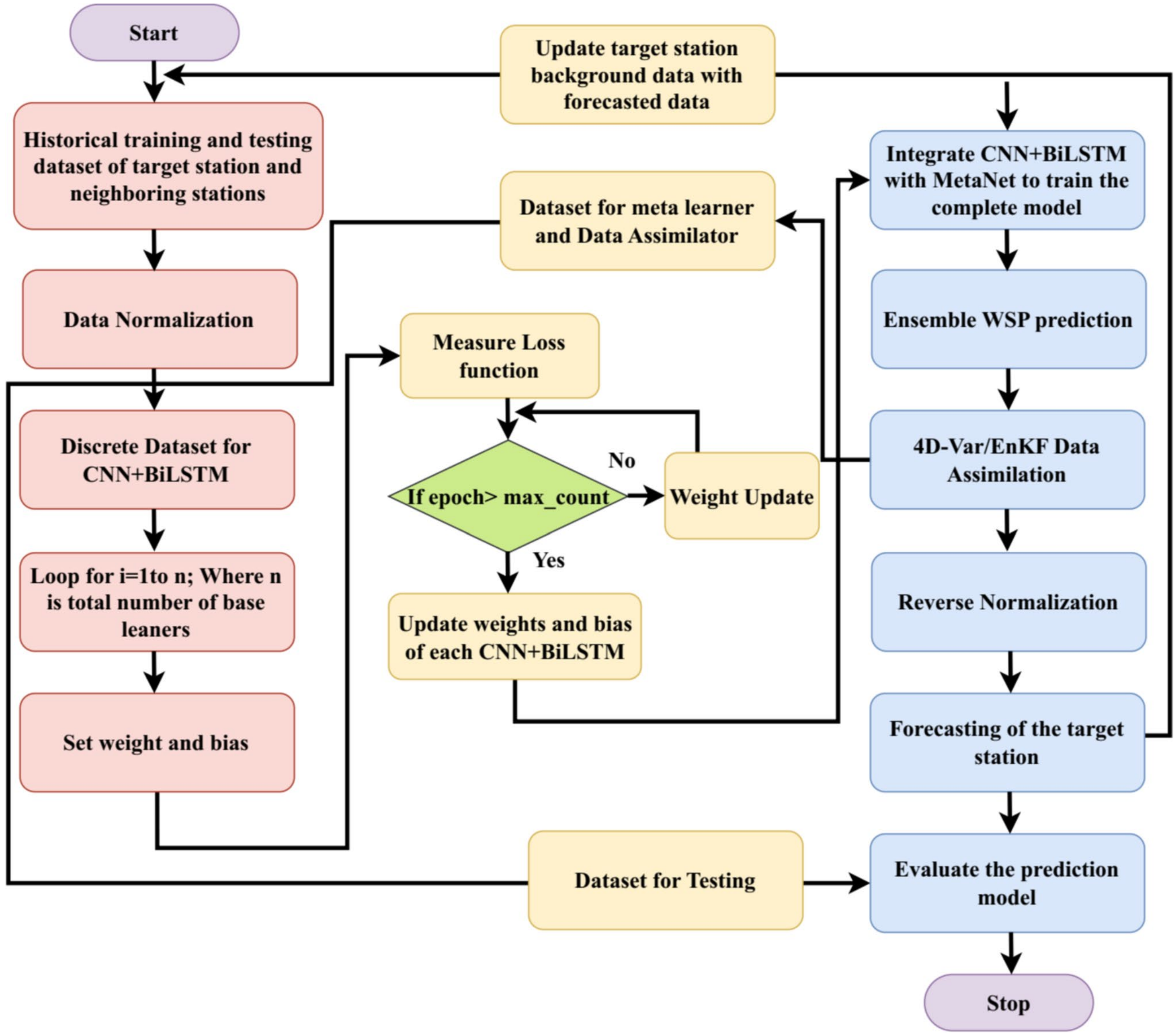


Fig. 4 Workflow of the proposed WindForecastX Model

4.2 Dataset description

Northeast Monsoon – Weather Data datasets (https://www.kaggle.com/datasets/santhoshkumarv/north-east-monsoon-weather-data-tamilnadu) compile extensive atmospheric information to forecast future weather conditions. The dataset, gathered from both IoT devices and local weather stations, focuses on analyzing atmospheric changes over time. It includes data recorded at five-minute and one-hour intervals, suitable for 70% for the training, 20% for testing, and 10% for the validation ratios.

4.3 Indexes for model performance evaluation

The formulas for the statistical error criterion are depicted in the following:

Mean Absolute Error (MAE)

The MAE is computedusing

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left(Y'_i - Y_i\right) \tag{21}$$

N signifies the number of data, Y_i and Y'_i represents the actual value and the predicted values.

Table 2 Compared Models

Model			Author
Standalone Model	Ensemble Based Model	S_ELM#1	Ranganayaki and Deepa (2016)
		S_ELM#2	Yong et al. (2019)
	Hybrid Model	S_Hyb#1	Hossain et al. (2018)
		S_Hyb#2	Li et al. (2011); Vidya and Srie Vidhya Janan (2020)
Unified Model	Hybrid Model	ULM#1	Samadianfard et al. (2020); Saeed et al. (2020)
	Hybrid Model	BLS-EC#2	Zhu et al. (2020)
Proposed Model		WindForecastX	

Mean Absolute Percentage Error (MAPE)

The equation for MAPE is shown in Eq. (22).

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\left(Y'_i - Y_i\right)/\overline{Y_i}\right| \tag{22}$$

Root Mean Square Error (RMSE)

The RMSE computes the predictive accuracy

$$RMSE = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widetilde{Y}_i\right)^2} \tag{23}$$

Correlation Coefficient (CC)

The CC is a statistical measure which is computed by,

$$CC = \frac{Cov\left(Y_i, \widetilde{Y}_i\right)}{\sqrt{Var\left(Y_i\right)Var\left(\widetilde{Y}_i\right)}} \tag{24}$$

4.4 Compared models

The models taken for comparison are listed in Table 2. Two ensemble-based stand-alone models (S_ELM#1, S_ELM#2), two standalone hybrid models (S_Hyb#1, S_Hyb#2), one Unified MLP-based learning model (ULM#1),and the proposed model are analyzed for comparison. Following is a description of these models. A Partial Auto-Correction Function (PACF) (Weiß et al. 2023), as well as Trial-And-Error Methods (TAEM), are used for setting the input variables.

4.5 Target station

In this work, we chose weather stations from Tirunelveli District in the Tamil Nadu state of India (Fig. 5) (https://www.kaggle.com/datasets/santhoshkumarv/north-east-monsoon-weather-data-tamilnadu). Table 3 presents the locations and wind speed details of various weather stations in the Tirunelveli District of Tamil Nadu, India, providing crucial data for wind energy analysis and forecasting. The table includes information on station numbers, geographic coordinates (latitude and longitude), and elevations of the stations, along with their recorded maximum wind speeds (Max Wind) and mean wind speeds (Mean WS). These details are essential for understanding the wind conditions at different locations in the district, which is important for both energy generation and wind pattern analysis. The stations are categorized as Weather Stations (WS), Reference Stations (RS), and Target Stations (TS). Weather Stations (WS) are general observation stations that provide basic wind speed data but are not directly used in wind forecasting models. Reference Stations (RS) are stations selected to assist in predicting the wind speed at Target Stations (TS). The Target Stations (TS) are those for which wind speed predictions are made based on data from the nearby Reference Stations (RS). For example, Kalakkad is a Target Station (TS), and it uses Kadayam and Kadayanallur as its Reference Stations (RS), which are located 18.5 km and 25 km away, respectively. In the table, the Reference Stations for each Target Station are listed along with their respective distances. This is crucial because the accuracy of wind speed predictions at the Target Station depends on the proximity and similarity of wind conditions at the Reference Stations. For instance, Tenkasi, a Target Station (TS), relies on Radhapuram (32.5 km away) and Shencottai (27.8 km away) as its Reference Stations. These distances help assess the degree of correlation between the wind conditions at the reference and target locations, with closer distances typically indicating more similar wind patterns. Overall, Table 3 serves as a comprehensive reference for understanding the spatial arrangement of weather stations in the district and the relationships between Target and Reference Stations, thereby aiding in more accurate wind speed forecasting for energy planning and other applications.

The weather data used in Fig. 5 is employed to analyze wind patterns, seasonal variations, and average wind speeds. Gaps in the Western Ghats accelerate wind flow, making them ideal for wind energy projects. Placing weather stations near these gaps ensures accurate data collection for

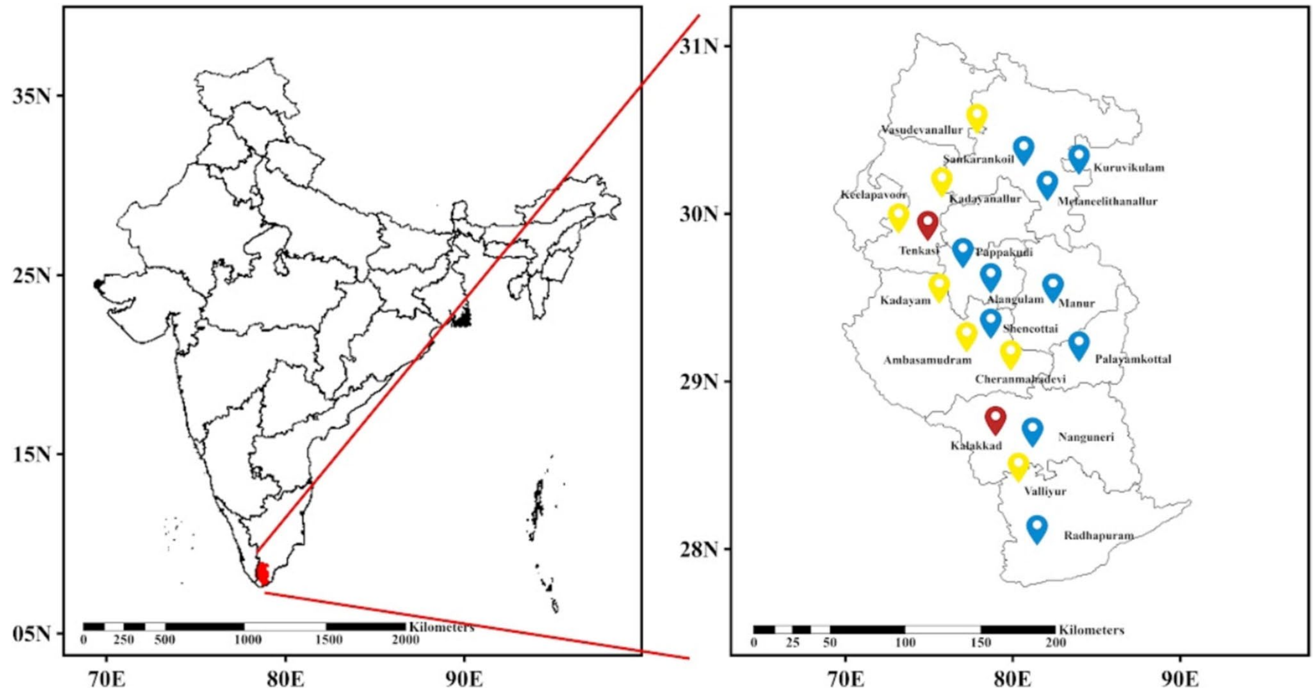


Fig. 5 Quality map of the weather station in Tirunelveli district (Red marks are target stations, yellow marks are reference stations, and blue marks are nearby weather stations)

Table 3 Location and Wind Speed (WS) Details of Weather Stations and Their Reference Stations (RS)

Station No	Station	Latitude (°)	Longitude (°)	Elevation (m)	Max Wind (Km/h)	Mean WS (Km/h)	Ref. Station (RS)/ Target Station (TS)	Reference Station(s) (RS) and Distance (Km)
1	Alangulam	8.864	77.496	128.26	18.9	13	WS	N/A
2	Ambasamudram	8.709	77.452	66.21	17.1	11.9	WS	N/A
3	Cheranmahadevi	8.674	77.565	64	19.9	15	RS	Alangulam (14.8 km)
4	Kadayam	8.821	77.374	114	17.2	12.7	RS	Cheranmahadevi (11.5 km)
5	Kadayanallur	9.077	77.345	196.44	18.9	10.45	RS	Kadayam (13.6 km)
6	Kalakkad	8.515	77.550	130.82	21.3	13.75	TS	Kadayam (18.5 km), Kadayanallur (25 km)
7	Keelapavoor	8.913	77.418	126	13.8	9.1	WS	N/A
8	Kuruvikulam	9.177	77.669	131	14.5	9.55	WS	N/A
9	Manur	8.855	77.652	96	18	13.5	WS	N/A
10	Melaneelithanallur	9.107	77.600	127	14.7	9.9	WS	N/A
11	Nanguneri	8.496	77.646	102.85	19.9	11.3	RS	Kadayam (22.3 km), Kalakkad (28 km)
12	Palayamkottai	8.720	77.734	51	19.2	10.7	WS	N/A
13	Pappakudi	8.750	77.507	96.51	15.7	11.7	WS	N/A
14	Radhapuram	8.269	77.686	46.62	16.6	12.6	WS	N/A
15	Sankarankoil	9.177	77.535	163	16.6	12.1	WS	N/A
16	Shencottai	8.975	77.249	178.83	19.8	13.5	RS	Nanguneri (24.4 km), Kalakkad (39.5 km)
17	Tenkasi	8.959	77.312	163.3	20.9	14.3	TS	Radhapuram(32.5 km), Shencottai (27.8 km)
18	Valliyur	8.401	77.617	95	19.3	10.75	RS	Sankarankoil (45.3 km), Pappakudi (33.2 km)
19	Vasudevanallur	9.239	77.411	183.44	19	13.1	WS	N/A

Table 4 Analysis using reference database based upon statistical criteria

Target Station	Model	RMSE (m/s)	MAE (m/s)	MAPE (%)	CC
Kalakkad	S_ELM#1	0.1554	0.8939	9.2654	0.7204
	S_ELM#2	0.2793	0.7124	7.2676	0.7521
	S_Hyb#1	0.3376	0.7969	3.0135	0.8169
	S_Hyb#2	0.0676	0.6453	1.3736	0.8265
	ULM#1	0.0661	0.6305	1.3419	0.8512
	WindForecastX	0.0569	0.5431	1.1561	0.9072
Tenkasi	S_ELM#1	0.6128	1.2810	5.5598	0.8092
	S_ELM#2	0.8261	0.7173	1.3328	0.7720
	S_Hyb#1	0.8919	0.6494	0.9603	0.7478
	S_Hyb#2	0.3282	0.1333	0.5565	0.8265
	ULM#1	0.3206	0.1302	0.5436	0.8512
	WindForecastX	0.2762	0.1122	0.4683	0.9377

identifying optimal sites for wind turbine installations. This helps minimize risks and enhance energy production efficiency. Using wind energy reduces dependence on fossil fuels, contributing to sustainable development goals and promoting economic growth. This study focuses on utilizing weather data from the Tirunelveli District, specifically near the Western Ghats gaps, to optimize wind energy project planning.

4.6 Analysis of model comparison

The following results could be noted and analyzed in the context of the results presented in Table 4, Figs. 6 and Fig. 7. Models like the S_ELM#1 model, S_ELM#2 model, S_Hyb#1 model, and S_Hyb#2 model are stand-alone models that only utilize the Target Station data to create predictions and do not use the WS data from other stations. In time series data, "actual" refers to observed values of the variable, like wind speed. Comparing actual and predicted values can show how well a model performs. The x-axis is labeled "Days," representing each day in the time series. In addition to using WS data from the Target Station (TS), Unified models and the proposed model take WS data from both the target and neighboring stations into account for WSP. The two unified models outperformed the above-mentioned stand-alone models for the data of two target stations for the prediction from 24 to 240 days. The MAE, RMSE, and MAPE indexes are reduced by 0.5 m/s, 0.05 m/s, and 1.15%, respectively, in the prediction with Kalakad station as the target, while the CC was as close to 1, in comparison to the other model including ULM#1. As for the Thenkasi station, the proposed model gains 0.28 m/s, 0.11 m/s, and 0.47% for RMSE, MAE, and MAPE, respectively, and the CC was 0.94.Such results demonstrate the drawbacks of stand-alone modeling methods, as well as the high spatial correlations between adjacent wind stations and the usefulness of predictors depending upon spatiotemporal proximity.

Table 5 highlights the performance of the WindForecastX model compared to other recent forecasting models. The WindForecastX model demonstrates the best performance in both MRE (0.125) and MBR (0.251), indicating it is both more accurate and less biased in its predictions than the other models. The EEMD-LSTM-LSSVM, VMD-GNN-TFC, BiLSTM-A, and TFT models have higher MRE and MBR values, demonstrating comparatively lower accuracy and higher bias.

- Mean Relative Error (MRE): Measures the average relative difference between predicted and actual values, providing an indication of the model's overall accuracy. Lower MRE values indicate better prediction accuracy.
- Mean Bias Error (MBR): Measures the average bias (or systematic error) of predictions. A smaller MBR (closer to 0) indicates that the model's predictions are more unbiased.

A recent review of the existing models like the Mesoscale eddy Model (Boopathi and Mohanty 2024), Multiple linear regression Model (Sulca et al. 2024), and Precipitation Indices Model (Islam et al. 2024) were taken to compare with the WindForecastX model. The performance of the existing model and the proposed model is illustrated in Table 6. The Table shows that the proposed WindForecastX model shows superior results.

The Cross-validation accuracy for the proposed and the recent review of the existing models are illustrated in Fig. 8. The existing models such as EEMD-LSTM-LSSVM, VMD-GNN-TFC, BiLSTM-A, and TFT were taken to compare

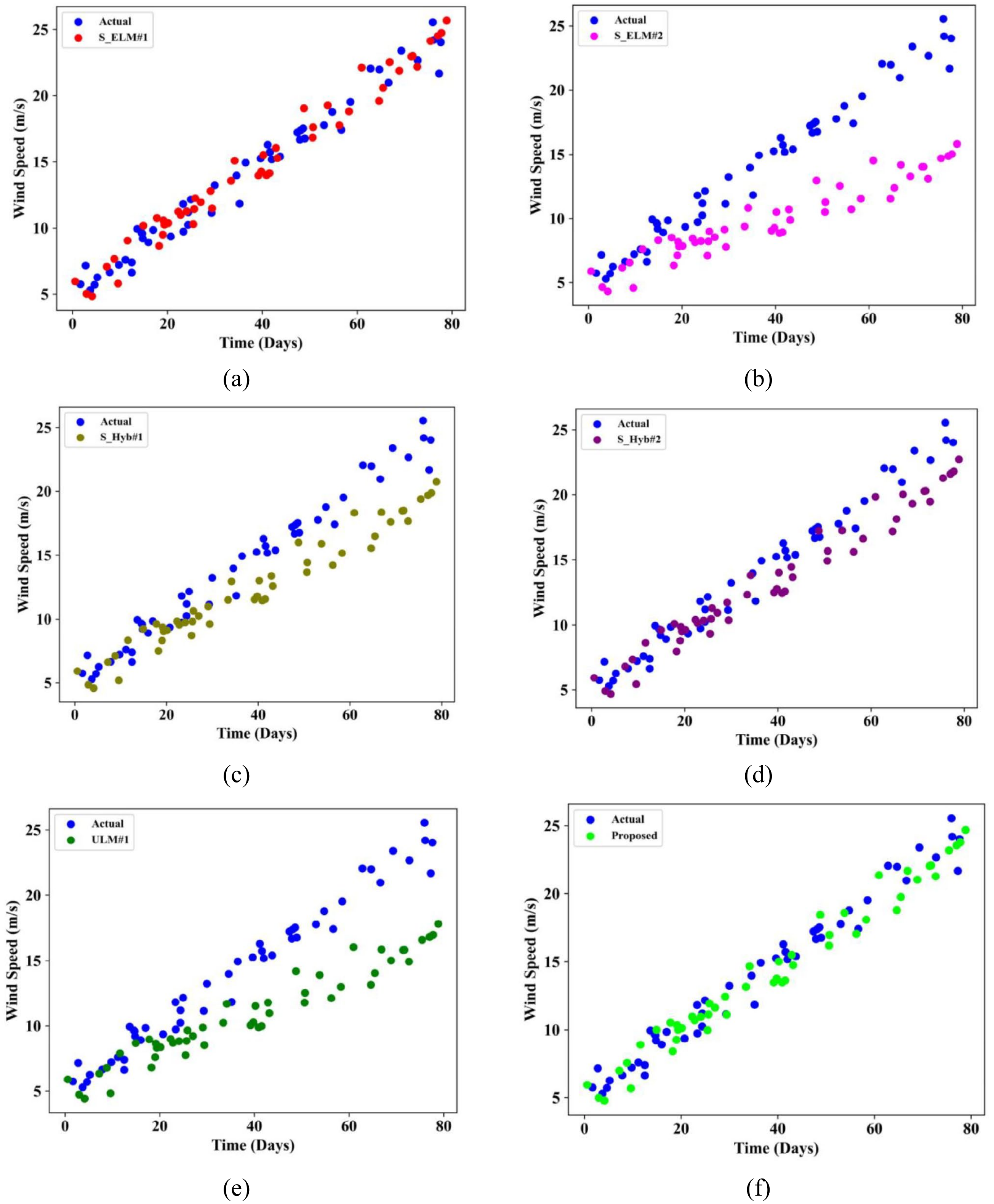


Fig. 6 Analysis of WSP in Kalakad station for (a) S_ELM#1 (Ranganayaki and Deepa (2016) (**b**) S_ELM#2 (Yong et al. (2019)) (**c**) S_Hyb#1 (Hossain et al. (2018)) (**d**) S_Hyb#2 (Li et al. (2011); Vidya and Srie Vidhya Janan (2020)) (**e**) ULM#1 (Samadianfard et al. (2020); Saeed et al. (2020)) and (**f**) WindForecastX Models

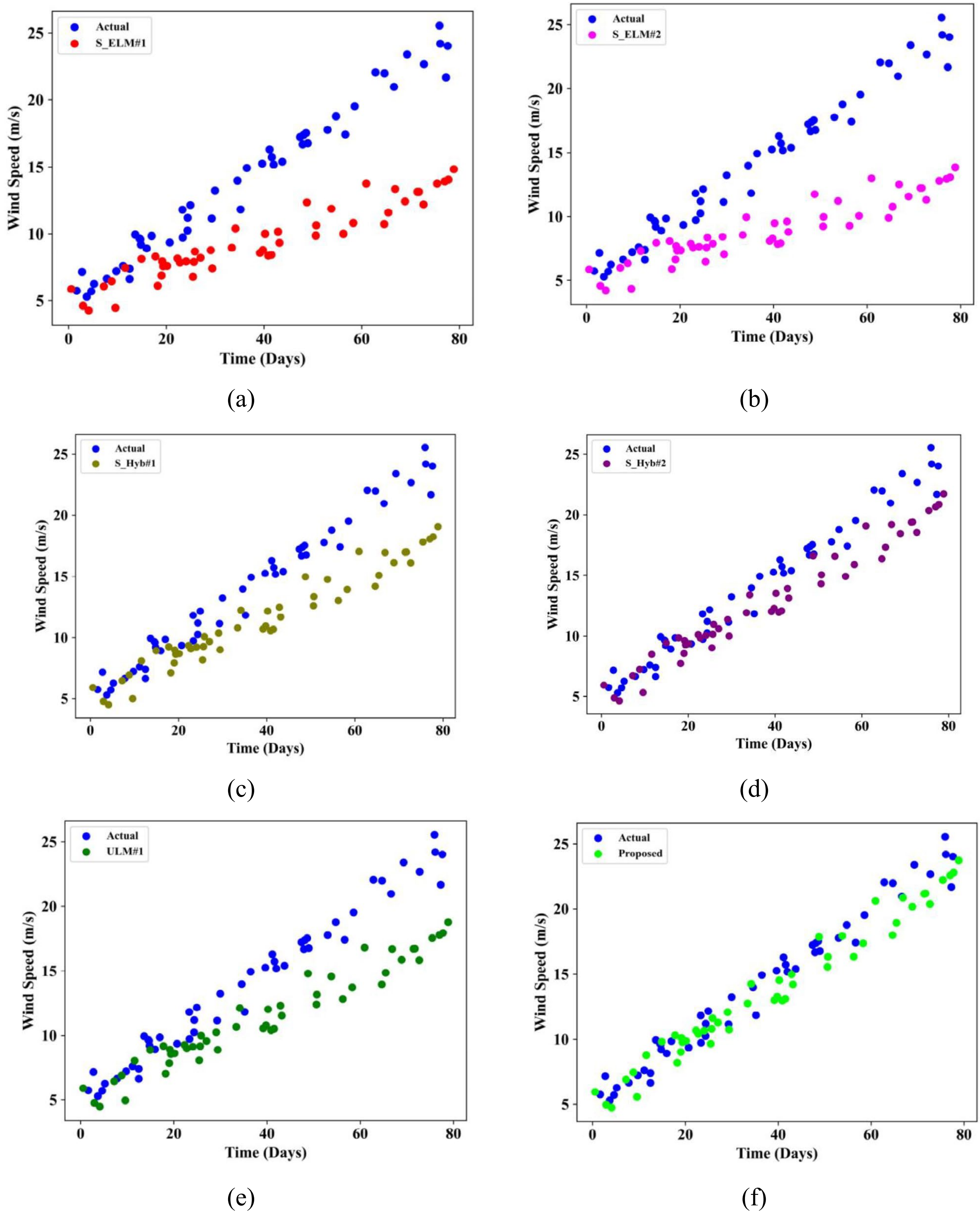


Fig. 7 Scattering plot analysis of WSP in Thenkasi station for (**a**) S_ELM#1 (Ranganayaki and Deepa (2016)) (**b**) S_ELM#2 (Yong et al. (2019)) (**c**) S_Hyb#1 (Hossain et al. (2018)) (**d**) S_Hyb#2 (Li et al. (2011); Vidya and Srie Vidhya Janan (2020)) (**e**) ULM#1 (Samadianfard et al. (2020); Saeed et al. (2020)) and (**f**) WindForecastX Models

Table 5 Analysis of MRE and MBR for the proposed and the Recent review of the related works

Techniques	Mean Relative Error (MRE) (%)	Mean Bias Error (MBR) (-)
WindForecastX	0.125	0.251
EEMD-LSTM-LSSVM	0.562	0.676
VMD-GNN-TFC	0.875	0.753
BiLSTM-A	0.632	0.826
TFT	0.971	0.843

Table 6 Analysis of Northeast Monsoon for the Proposed and the recent review of the Related works

Techniques	Performance (%)
WindForecastX (Proposed)	98.54%
Mesoscale eddy Model (Boopathi and Mohanty 2024)	83.61%
Multiple Linear Regression Model (Sulea et al. 2024)	72.54%
Precipitation Indices Model (Islam et al. 2024)	76.87%

with the proposed WindForecastX approach. The analysis of the Cross-validation is employed with the Folds from one to five, From this Figure obtains that the existing model gains the lower cross-validation accuracy but the proposed WindForecastX approach gains the higher cross-validation accuracy for five folds.

4.7 Experiment with IMD data

Theproposed model is compared with the Government's real-time forecast model for the Tirunelveli weather substation of Tamil Nādu, India. For this target station, we employed a dataset from Kanyakumari, Sivakasi, and Thoothukudi as the reference dataset. The proposed model is compared with the Indian Meteorological Department (IMD) forecast model for the next 90 days for 24-h intervals. The following Fig. 9 shows the prediction comparison of the wind speed based on the time series of days between the proposed model and the IMD forecast model. The results show that RMSE, MAE, and MAPE is 0.0569 m/s, 0.5431 m/s, and 1.1561% in comparison with the prediction of the IMD model.

When predicting the effectiveness the leveraging data gives Unified models an edge over stand-alone models. This compensates for the inefficiencies of stand-alone models, which do not fully utilize such information. The S_Hyb#2 model predicts more accurately than the Hyb#1 model. In addition, compared to the ULM#1 model, the proposed model displays lower forecast error in these experiments. This indicates that using the DAM can effectively increase an ML's WSPperformance by resolving the instability issue that it was experiencing. The proposed delivers the highest prediction accuracy between those comparable models. The proposed effectively enhances the WSPperformance of the model by entirely using the WS data given by its nearby stations and by creating a powerful predictor using the 4DVar/EnKF algorithm.

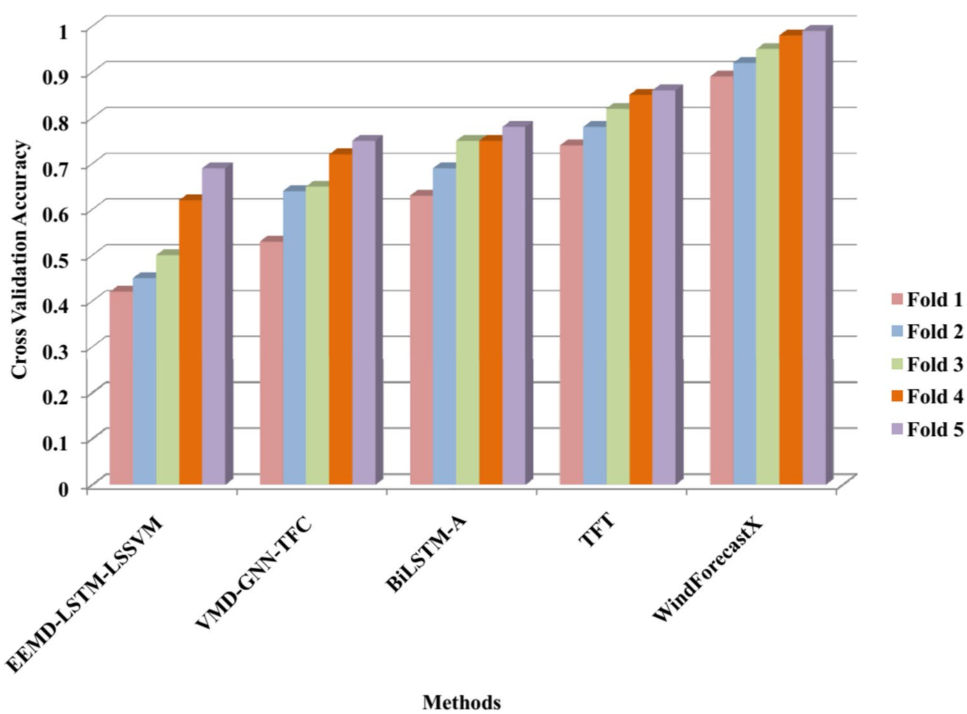


Fig. 8 Cross Validation Accuracy Analysis

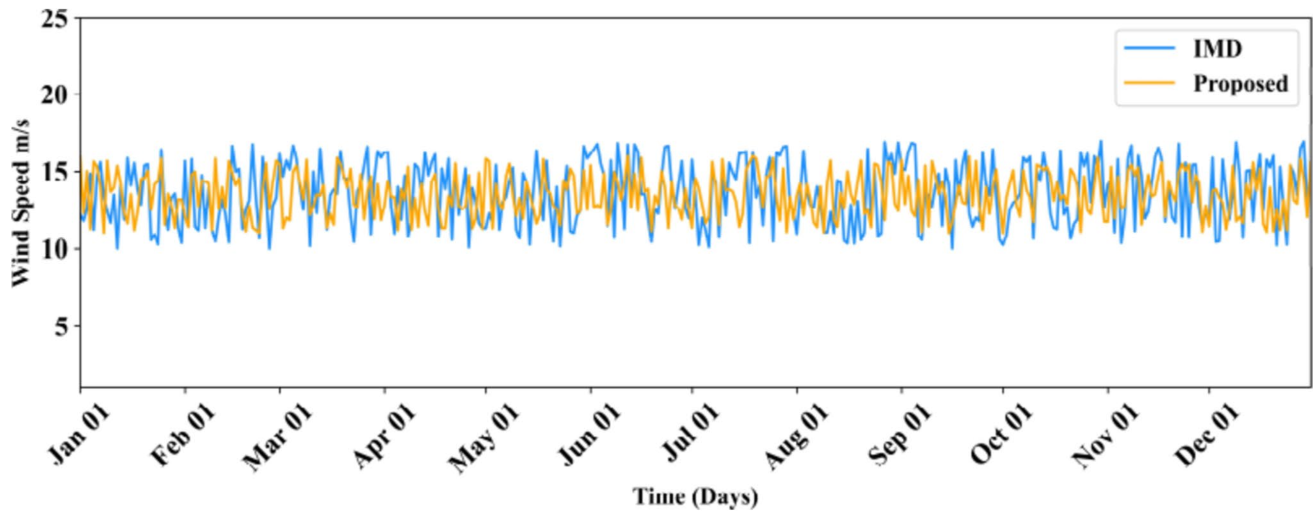


Fig. 9 WSP results in 24 h in advance for Tirunelveli district

During the implementation of the WindForecastX model in the Tirunelveli district of Tamil Nadu, India, several specific challenges and considerations arose. One of the primary challenges was related to the availability and quality of meteorological data from the selected stations. Ensuring the consistency and reliability of data inputs from these stations was crucial for the accuracy of the model predictions. This required rigorous data cleaning, preprocessing, and quality assurance measures to mitigate any potential biases or inaccuracies in the input data.Another challenge was the localization of the model to suit the specific geographical and climatic conditions of the Tirunelveli district. While the model showed promising results in this region, adaptation to different geographical locations and diverse climate conditions would require careful calibration and validation. Factors such as terrain characteristics, local wind patterns, and seasonal variations could significantly impact the performance when applied elsewhere.In terms of scalability and adaptability, the WindForecastX model exhibits potential due to its modular architecture and integration of ensemble learning with data assimilation techniques. The use of 4DVar/EnKF allows the model to assimilate data from multiple sources, which enhances its capability to capture local variations and adapt to different environmental conditions. However, scalability would depend on the availability of sufficient data and computational resources to handle larger datasets and more complex geographical regions.To ensure broader applicability across different locations, further validation and adaptation of the model would be necessary. This includes collecting and integrating data from additional meteorological stations in diverse regions to train and fine-tune the model parameters effectively. Continuous monitoring and validation against ground truth observations would also be essential to assess and improve the model's performance under varying climatic conditions and geographical contexts. Overall, while WindForecastX shows promise in enhancing wind speed prediction accuracy, its scalability and adaptability to different locations.

The Nomenclature list of the symbols is illustrated in Table 7.

4.8 Discussion

In this study, this paper proposes a WindForecastX, a hybrid model that combines Stacked Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) with Data Assimilation (DA) techniques to enhance the accuracy of wind speed prediction (WSP). The model was evaluated using data from nine meteorological stations in the Tirunelveli district of Tamil Nadu, India, with a particular focus on the Kalakkad and Tenkasi stations. The following discussion delves into the research questions posed at the outset of this work.

4.9 Hybrid models vs. standalone models

4.9.1 How do hybrid models that combine traditional statistical methods with machine learning algorithms compare to standalone models?

The comparison between the proposed WindForecastX model (a hybrid ensemble model) and standalone models (both traditional statistical and machine learning-based) reveals significant improvements in prediction accuracy. Hybrid models, like SCBLSTM + DA, integrate the strengths

Table 7 Nomenclature for all Symbols

Symbols	Description
(X_b)	short-term projections
(y_o)	fresh observations
X_a	analysis field
(ω)	optimal weight
t	time
w and v	weight matrices
bias	the tendency of the weights
b_h^f, b_h^b, and b_y	vectors
$W_{xh}^f, W_{hh}^f, W_{xh}^b, W_{hh}^b, W_{hy}^f$, and W_{hy}^b	weights of the hidden layer to the output gates
$Awp(t-1)$	activation functions of the wind systems
$G(c(t))$	nonlinearity of the activation function
Mx_H and Mx_W	matrix's height and width
S	support set
m	iteration number N
N	the number of data
d	decision variable
Y_i and $Y_i\prime$	actual value and the predicted values

of ensemble learning and data assimilation, leading to better generalization, especially in complex, dynamic conditions like wind speed forecasting. Standalone models, whether statistical or machine learning-based, tend to underperform as they fail to capture the multi-dimensional dependencies in wind speed data. The inclusion of multi-source data—from local meteorological stations and other sensors that further strengthens the hybrid model, as it considers broader contextual information.

Thus, the hybrid model's superior performance supports the hypothesis that combining traditional methods with advanced machine learning techniques can yield more accurate and robust predictions.

4.10 Effectiveness of adaptive learning mechanism

4.10.1 How effective is the adaptive learning mechanism in updating prediction models with new data for maintaining accuracy over extended periods?

The adaptive learning mechanism in WindForecastX enabled by Data Assimilation (DA) proved highly effective in maintaining the accuracy of predictions over extended periods. By continuously incorporating real-time wind speed data from multiple meteorological stations, the model adapts to changing wind patterns, ensuring it remains accurate even as environmental conditions evolve. This adaptability is particularly beneficial for long-term wind speed forecasting, where dynamic updates are essential for maintaining prediction precision over time.

The results indicate that the data assimilation approach is crucial for improving the model's resilience and performance as it adjusts to new data, keeping the prediction model up to date without retraining the entire system. The mechanism ensures that prediction errors do not accumulate over time, maintaining reliable performance in both the short and long term.

4.11 Modeling approaches for different temporal resolutions

4.11.1 What are the specific modeling approaches needed to ensure accurate predictions at different temporal resolutions?

For accurate predictions at different temporal resolutions, WindForecastX combines ensemble learning, data assimilation, and temporal modeling (via CNN and BiLSTM). The stacked CNN effectively captures short-term temporal dependencies in wind speed data, while BiLSTM handles long-term temporal dependencies, making the model suitable for both short-term and long-term forecasting. This combination allows the model to adjust to the temporal characteristics of wind speed data, ensuring accuracy at various prediction horizons.

For hourly predictions, the model can focus on more immediate wind speed patterns, leveraging the short-term capabilities of the CNN. For daily, monthly, or yearly predictions, the model can consider longer-term trends and dependencies, which are captured effectively by the BiLSTM layers. Therefore, the SCBLSTM + DA model ensures that wind speed predictions are precise and reliable, irrespective of the temporal resolution required.

5 Conclusion

In this paper, we proposed an SCBLSTM + DA unified data model to enhance the accuracy of the long-term WSPat the target location. The proposed WindForecastX model integrates the CNN and BiLSTM-based stacked ensemble with the DAM and fully exploits the WS near the target area. The proposed WindForecastX model is evaluated using data from nine meteorological stations in the Tirunelveli district of Tamil Nadu, India, and compared to other models using various metrics. Two of these stations were chosen as target stations for WSP. For comparison and analysis, five models and several metrics are employed. The findings of WindForecastXdemonstrate that the SCBLSTM + DA significantly outperforms all four standalone models and the one unified model in terms of performance. Adopting the DAM significantly improved the stacked ensemble's prediction ability. Considering the historical WS at nearby places, the proposed model can effectively enhance the WSPat target locations and is, therefore, more promising than conventional standalone modeling techniques. From the experimental results, the metrics were taken to evaluate the wind speed prediction, for the Kalakkad station the theproposed model gains the values as 0.0569 m/s, 0.5431 m/s, 1.1561%, and 0.9072. Also, for the Tenkasi station, these metrics attain as 0.2762 m/s, 0.1122 m/s, 0.4683%, and 0.9377. The findings indicate that WindForecastX is better than current wind speed prediction models, offering substantial benefits to the efficiency and sustainability of wind energy production and grid management. WindForecastX is versatile across various wind energy applications and guarantees to transform the approach of assembling and managing wind energy.In the future, by adding new features, such as atmospheric pressure and ambient temperature, the model could be improved further. Another crucial strategy that is required in the investigation to enhance prediction performance is the use of data clustering.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflicts of interest The authors have no conflicts of interest to declare.

Human and animal rights This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Consent to participate Not applicable.

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