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# An Enhanced Long-Term Wind Speed Prediction Using Dynamic Unified Ensemble Learning and Data Assimilation Techniques: A Case Study in Tamil Nadu, India

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***Abstract: -*** Reliable wind speed prediction is essential for effective grid management since wind energy is a key component of renewable energy generation. However, controlling wind speed just right is no easy feat since the wind flow changes constantly. This paper presents an innovative method for predicting wind speeds in the future. It uses state-of-the-art data assimilation methods and a dynamic unified ensemble learning model. For efficient wind energy planning and monitoring, WSP accuracy is crucial. Data from a single site limited the accuracy of WSPs in previous research. An improved accuracy of long-term wind speed predictions is achieved by the proposed model via the integration of data assimilation and ensemble learning. To increase forecast accuracy, the model uses sophisticated data assimilation methods like the Kalman filter to combine data from many sources. Specifically, the model employs the Stacked CNN + BiLSTM with Data Assimilator (SCBLSTM+DA) technique, which integrates Wind Speed (WS) data from adjacent areas with the CNN + BiLSTM-based Ensemble Learning Model (ELM) and the Four-Dimensional Variational and Ensemble Kalman Filter (4DVar/EnKF) Data Assimilation method. Using real-world wind speed data from nine meteorological stations in Tamil Nadu, India, we find that current prediction models, including both classical statistical and cutting-edge machine learning models, perform better. Further, unlike standalone models, the suggested model shows less susceptibility to changes in prediction time scales. Promising a solution to improve long-term wind speed predictions accuracy, this study has significant consequences for wind energy management and production.

***Keywords:*** Wind energy, long-term wind speed prediction, ensemble learning, data assimilation, Deep learning.

## I. INTRODUCTION

Accurate wind speed forecasting (WSF) is crucial for a diverse array of applications, spanning electricity generation, milling, water pumping, and carbon footprint reduction, to activities like sailing, cargo shipping, kite surfing, and windsurfing. The presence of geographical features such as ridges, escarpments, and hills significantly alter wind speed and direction, leading to bidirectional wind flow in mountainous regions. The interplay of topographic features can result in cumulative impacts, where changes in wind patterns at higher elevations influence those at lower elevations. Understanding the connectivity between similar geographical features, such as bays, is essential for predicting wind speed patterns accurately. While existing WSF methodologies have shown promising results, many previous studies relied on single-location data for modeling, highlighting the need for improved modeling approaches that consider diverse geographical and topographical influences.

The WS being predicted is considered to be connected with the history WS recorded from the same location in these investigations, which exclusively active historical WS data measured at a specific location for forecasting and modelling. As a result, this research ignored the spatial dependence of WS and failed to take into account the Spatial-temporal information close to the given location. Such modelling techniques will restrict WSF's accuracy. In fact, WS in a region exhibits some spatial dependence, which indicates that the WS at one place is connected to the WS at neighbouring locations. Various techniques exist for wind speed measurement across multiple sites, including Model Output Statistics (MOS), Two-Site Correlation models (TSCR), Short-Term Nowcasting Systems (STNS), Sample Cross-Correlation Functions (SCCF), Bayesian Combination Algorithms (BCA), and Neural Networks (NN), with NN emerging as a popular choice in recent years. NNs leverage data patterns and relationships to model complex interactions between inputs and outputs effectively. Additionally, Multi-Layer Perceptron (MLP) models have been utilized for forecasting using reference data. The Extreme Learning Model Based Adaboost Model (ELMBAM) introduced by one study utilized data from 17 automated weather stations to predict short-term wind speed for a single target location. Another study employed a wide range of Machine Learning algorithms within an ensemble learning model (ELM) to assess predictability across different methods and regions. Despite the inherent noise in wind speed prediction, most benchmarked methods exhibit improvements in linear wind-power translations. Notably, the study demonstrates that boosting ensembles offer a cost-effective solution in terms of runtime compared to other Machine Learning algorithms for estimating wind power a day in advance, underscoring their practical utility and effectiveness.

A spatio-temporal model is more complex than other traditional models due to the massive amount of spatial-temporal data and the inclusion of several undefined factors. [12][17][27]. In a few research studies, WS or energy levels have been predicted using spatial-temporal data from a location. The regime switching space-time (RST) model was suggested by [25], and this model took into account all salient WS features, including temporal as well as spatial correlations. The model was enhanced and generalized by [7] because it was only planned for the specified region. Various experimental studies were used to demonstrate the improved

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model's robustness. Utilizing nearby WS data, [13] created Spatio-temporal (multi-channel) Linear Models (SLM) that showed advantages in very short-term WSP. When wind direction is not available at various places, the technique cannot be used due to its complexity.

Numerical Weather Prediction (NWP), which is the primary approach for WSF, often relies on observations that are very precise 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 based on a large amount of geospatial-temporal data is one of the most important procedures involved in NWP. The problem has traditionally been solved using data assimilation (DA), which has been enhanced by applying multiple mathematical-physics models. The objective of data assimilation would be to use observations and long-range forecasts for determining the best possible atmospheric condition and associated uncertainty. Figure 1 depicts the general framework of the DA process. In a sequential time-stepping process called data assimilation, 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.

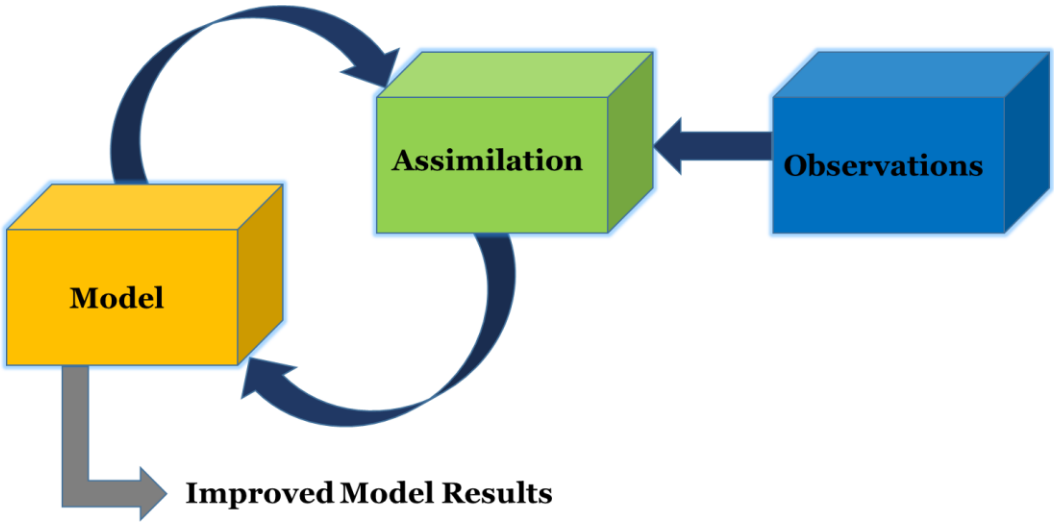



**Figure 1: Data assimilation framework**

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). SAM was primarily utilized in the 1950s, when computers were either unobtainable or in their infancy. Early foundations for data assimilation were SAM. 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 OIM were utilized. The transition from atmospheric DA to VAM, specifically the three- and four-dimensional variational (3D-Vary and 4D-Var) data assimilation, occurred in the earlier years. The 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 chapter describes the spatial-temporal peculiarities 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 WSP operates. The objective of this study is to develop an integrated EML 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. This model takes into account WS measurements obtained from locations in close proximity. The increase in information unavoidably results in a rise in the total quantity of computation, which will also have an effect on the speed of computation. Because of its fast-learning speed and lack of need for iterative weight adjustments, the CNN + BiLSTM Ensemble Learning Model (ELM) is used as a predictor in this investigation. In addition, the ensemble is coupled with the 4DVar/EnKF data assimilation method to correct the ensemble prediction and create accurate forecast results.

### *A. Contributions*

The following are the contributions of our study:

- This paper presents a novel approach for predicting long-term wind speeds using deep ensemble learning techniques combined with data assimilation techniques.
- Development of the Stacked CNN + BiLSTM with Data Assimilator (SCBLSTM + DA) model, which integrates Wind Speed (WS) observations from nearby locations with an Ensemble Learning Model (ELM) based on CNN + BiLSTM architecture, along with the Four-Dimensional Variational and Ensemble Kalman Filter (4DVar/EnKF) Data Assimilation (DA) method.
- Utilization of historical WS data from multiple sites in the proposed model, enabling the exploration of connections between WSs in different regions and addressing the limitations of previous regional-based Wind Speed Forecasting (WSF) models.
- Improvement of the model's stability and predictive performance by employing the 4DVar/EnKF-DA method to address the instability and unreliability of ELM's weights and biases.
- Compared to several state-of-the-art wind speed prediction models, the proposed model exhibits superior accuracy and robustness.

### *B. Paper organization*

The following is the structure of the paper: After the discussion of the related works based on this study in Section 2, which is followed by the explanation of the model to be offered in Section 3, which is followed by the discussion of the experimental research and analysis in Section 4, Following Section 4, the conclusion is presented in Section 5.

## II. II RELATED WORKS

The related works in this study explore various methodologies for wind speed and wind power forecasting. These methodologies leverage techniques such as ensemble learning, neural networks, and data assimilation. Each study aims to improve forecasting accuracy and adaptability through innovative approaches, although their focus, datasets, and validation methods differ. Despite advancements, there are still challenges in generalizing findings across various wind power systems, forecasting horizons, and computation complexity. Consequently, comprehensive and scalable forecasting models are still necessary. Wang, Y et al. [30] described an approach for enhancing accuracy and reliability in short-term wind speed prediction by integrating data denoising techniques, optimization algorithms, and machine learning algorithms. The model emphasizes the importance of optimizing the number of decomposition layers and parameters for improved performance. Through testing on wind speed data from multiple sites, the developed integrated model demonstrated superior performance to traditional models. While the paper suggests further research directions, it does not explicitly address current study limitations.

Quan et al. [31] introduced an ensemble prediction model that integrates various techniques to enhance wind speed forecasting accuracy. It outperforms comparison methods in mean absolute percent errors, and utilizes Variational Mode Decomposition (VMD), Backtracking Search Optimization Algorithm (BBFWA), and ensemble learning. However, the study acknowledges limitations, including the inherent deficiencies of each hybrid model, the trade-off between prediction accuracy and efficiency in ensemble models, Specifically, the time complexity of the proposed model depends on BBFWA parameters and the number of training samples, and the number of decomposition modes in VMD affects the model's performance. Additionally, the paper lacks any declaration of conflicts of interest by the authors. Lee et al. [32] demonstrated the superiority of ensemble learning methods over standalone models in achieving accurate wind energy production predictions. Employing ensemble methods enabled wind power production prediction with significantly higher accuracy than individual models. However, it's worth noting that the study's scope was confined to wind turbines situated in France and Turkey. This could limit the generalizability of the findings to broader geographical regions or different environmental conditions.

Ibrahim et al. [33] introduced the AD-PSO-Guided WOA machine learning algorithm for wind speed ensemble forecasting, showcasing its high accuracy and superior performance compared to other algorithms through rigorous statistical analyses. However, the study's focus solely on wind speed ensemble forecasting potentially limits its generalizability to broader forecasting contexts. Additionally, the utilization of a specific dataset may restrict the algorithm's applicability to other scenarios or geographical locations. Notably, the paper did not explore limitations inherent to the proposed algorithm itself. Consequently, further research is recommended to investigate the algorithm's performance under diverse conditions or in different geographical locations, aiming to enhance its robustness and applicability in real-world forecasting scenarios.

Kadhem et al. [34] introduced a novel method that integrates a Weibull distribution model with an artificial neural network to forecast wind speed data, emphasizing seasonal variations. The approach successfully captured seasonal characteristics of wind speed data across different locations, demonstrating its efficacy in enhancing prediction accuracy. However, the study's findings may be limited in their generalizability beyond specific locations in Malaysia. In addition, the complexity of wind speed forecasting, resulting from random fluctuations and diverse influencing factors, may make the method ineffective. As a result, the study's limitations include its inability to address all factors that influence wind speed predictions. It may affect the reliability and applicability of the proposed method in broader forecasting scenarios. There is a need for further research to address these limitations and improve the robustness of the forecasting approach for a range of geographical regions and environmental conditions.

Zhu et al. [35] introduced a novel method called BLS-EC, based on the BLS neural network, aimed at enhancing wind speed prediction accuracy and generalization compared to existing methods such as ARIMA and RBF. The study focused exclusively on wind speed prediction and did not explore potential applications of the proposed method in other domains. Moreover, the research was constrained to three specific real-time wind speed datasets, potentially limiting the representativeness of the findings across diverse scenarios or locations. While the proposed BLS-EC method demonstrated generalization capabilities in wind speed prediction, further validation may be necessary to ascertain its effectiveness for other types of data or prediction tasks. These limitations underscore the need for future research to explore the broader applicability and robustness of the BLS-EC method across various domains and datasets.

Wang et al. [36] developed an adaptive wind power forecasting model that integrates wind speed-power trend enhancements and ensemble learning, and demonstrated superior accuracy and adaptiveness. As a result, the study's findings can't be generalized to other types of wind power systems since it only focused on a real wind turbine system. Moreover, only certain time intervals (10, 30, 60 minutes) and seasons (10, 30, 60 minutes) were considered when testing the proposed model, namely spring, summer, and autumn. potentially overlooking various forecasting scenarios. Moreover, the study did not address the potential computational complexity or resource requirements associated with implementing the adaptive WPF model in practical settings. This raised concerns about its scalability and feasibility for real-world applications. These limitations highlight the need for further research to validate the model across diverse wind power systems and forecasting conditions. In addition, it is necessary to assess its practical viability and efficiency.

## III PROPOSED METHODOLOGY

The proposed model uses the Stacked CNN + BiLSTM with Data Assimilator (SCBLSTM + DA) model. The SCBLSTM+DA model combines the spatio-temporal dependencies captured by the CNN + BiLSTM-based Ensemble Learning Model (ELM) with real-time observations from nearby locations using the Four-Dimensional Variational and Ensemble Kalman Filter (4DVar/EnKF) Data Assimilation (DA) method. The SCBLSTM+DA model consists of three main components: (1) the CNN + BiLSTM-based ELM, the model uses long short-term memory (LSTM) and convolutional neural networks to capture the spatiotemporal dependence of wind speed; (2) the data assimilator, which assimilates the real-time observations from nearby locations using the 4DVar/EnKF method to improve the accuracy of the prediction; and (3) the stacked architecture, which enhances the model's ability to capture complex spatio-temporal dependencies.

### A. Proposed Stacked Convolutional BiLSTM + DA (SCBLSTM + DA) Forecast Model

In order to create an Ensemble Learning Model (ELM) for WSP, this study used a Stacked Ensemble Model (SEM). The base learners are combined simultaneously inside the SEM. With this method, the base learners independently learn from the training data. The meta-model, which generates output depending on the predictions extracted from base learners, is used to merge the independent learners. Several NN architectures were brought out in the literature to map the non-linear correlation among a system's input and output vectors. This covers MLP, CNN, RNN (such as LSTM), and traditional ML methods (DT and k-NN regression) as well as hybrid models (such as CNN-LSTM and CNN-BiLSTM). Given the previously defined ELM benefit, we use an ensemble learning setting for WSP. In order to develop a WSP ELM setting that is acceptable to the base learners, ML models include MLP, CNN, LSTM, and CNN-BiLSTM. To assess the effectiveness of these models with different meta-learners, several of them are stacked in parallel, individually and collectively. For the base as mentioned above learners, ML models like MetaNetwork [15], Model-Agnostic Meta-Learning [2] and Reptile [17] are tested as meta-learners. For predicting long-term WS, the suggested model applies the stack generalization of the ELM. The proposed design uses MetaNetwork as the meta-learner and several parallel CNN-BiLSTM as the base learner. Even though each of the four CNN-BiLSTM models utilized in this study uses the same design, due to the stochastic nature of the model, they behave differently. The variance in the outputs of the redundant models, however, results in a correct base learner even if the models are redundant. Considering that MetaNetwork is a well-known method, a summary of it is given above. The proposed WSF is depicted in Figure. 2.

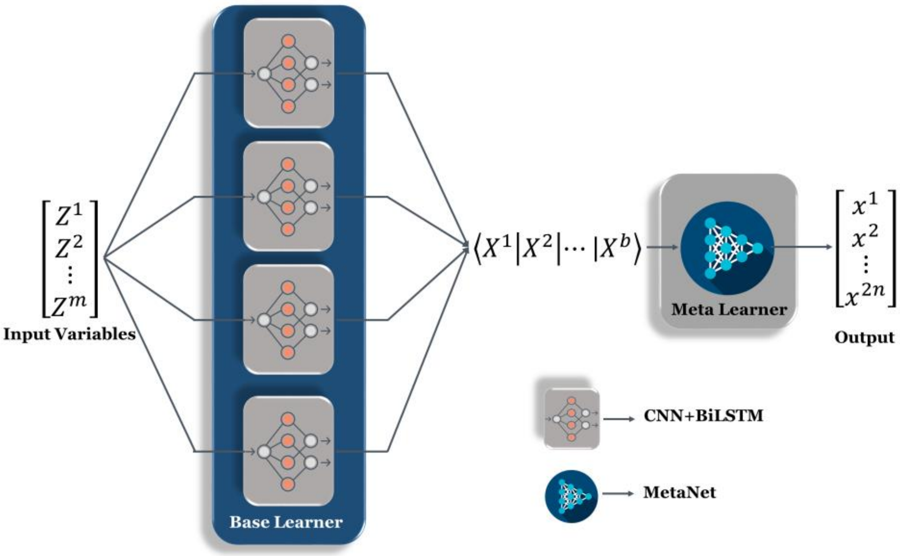



**Figure 2. Proposed deep CNN-BiLSTM framework**

In Figure 2, the proposed method uses measurements with $m \geq 2n$ as inputs for base learners. It is important to understand that the type, location, and target station of measurements all influence the observability of a system. The observability relies on several factors, including the type, location, and target station of measurements. The WS is independently computed by each base-learner and output like a vector through parallel stacking. The meta-learner predicts a final WS and uses the base-learners 'X' output as its input. The Meta-Learner's mapping of prediction and actual WS is acceptably similar. To enhance the results further, the predicted value, along with the observed data, is fed to DAM, which results from the final prediction values, which are exceptionally similar to the actual values. The DA predicted value is updated with the historical data. This ELM, along with DA, is referred to as "Stacked Convolutional BiLSTM + DA (SCBLSTM + DA)" moving forward. The proposed method's flowchart and the algorithm are depicted in Figure 3, and algorithm.

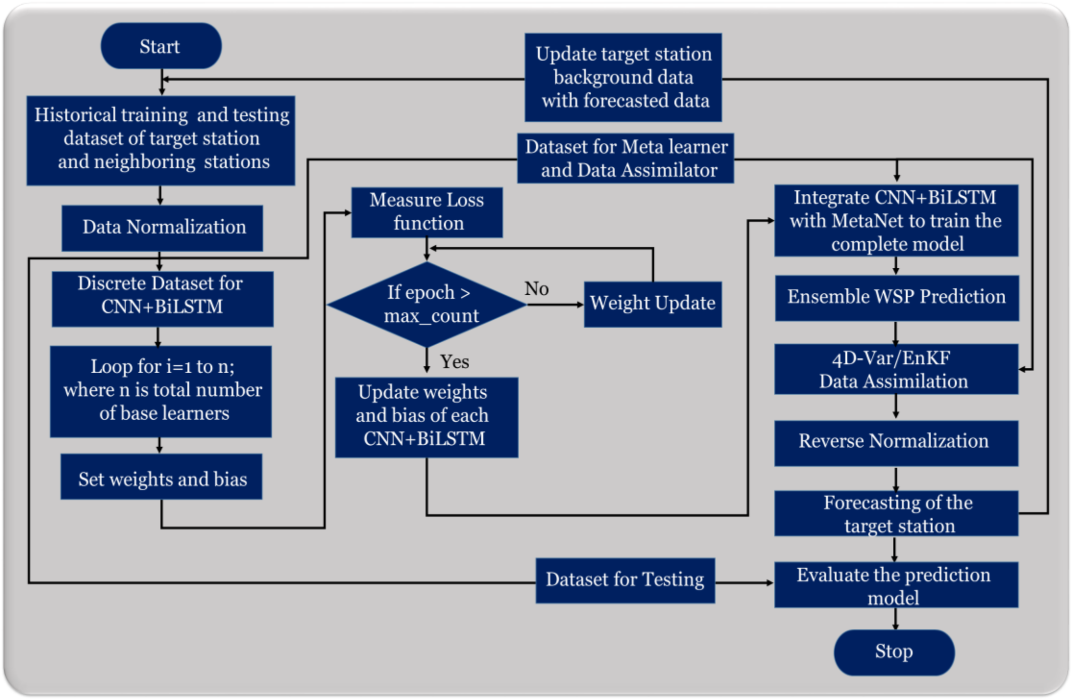



**Figure 3. Flowchart of the proposed (SCBLSTM + DA WSP) model**

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 presence of an entire set of historical measurements and values generated after the DAM are presented in order to train and test the proposed model. A WSF can be planned and controlled using predictable measurements even if some measurements (or) topology changes during the erection process. Accurately predicting missing measurements is crucial to data-driven WSF due to its ability to handle errors, rapid network changes and changes in topology and network features.

**Algorithm 1: SCBLSTM+DA WSF model**

Step 1. Gather and process historical WS data from the target station and nearby stations, and then simultaneously utilize this data along with historical WS data from other stations to construct the model.

Step 2. This equation converts the data used in the modelling into [0, 1], so that the data can be mathematically arrayed with other data with varied dimensions and magnitudes.:

$$Y_t' = \frac{Y_t - Y_{min}}{Y_{max} - Y_{min}} \quad [1]$$

In the above equation, the data before conversion is denoted by 'Yt' and the data after the conversion by $Y_t'$ and the minimum and maximum values of the original dataset are denoted by $Y_{min}$ and $Y_{max}$, respectively.

Step 3. Create ELMs using the CNN-BiLSTM algorithm. The algorithm regulates the weights of various ELMs. This stage involves computing the pertinent errors and updating the weight distributions $D_i, (I = 1, 2, \ldots, T)$ depending on the projected outputs of the ELMs.

Step 4. Calculate the Huber Loss Function (HLF) based on the epoch count and update the weights and bias of each CNN-BiLSTM ensemble learner individually.

Step 5. The ensemble output is created by combining the individual ELM outputs with the MetaNet meta-learner model using connection weights.

Step 6. Apply the 4DVar/EnKF data assimilation model to fine-tune the ELM results

Step 7. The WSF at the target station is obtained by reverse normalizing the DA output value, and this information is then utilized to refresh the target station's historical data.

Step 8. Evaluate the model against various metrics using the test dataset.

## IV EXPERIMENTAL DESIGN

This section outlines the experimental design devised to evaluate and validate the prediction capabilities of the proposed model. It consists of four main components: (1) Target Station, specifying the location or stations where wind speed prediction is the focus; (2) Compared Models, where various existing models or methodologies for wind speed prediction are compared with the proposed model; (3) WSP Time, defining the specific timeframes or periods for which wind speed predictions are made; and (4) Evaluation Indexes for Model Performance, outlining the metrics and criteria used to evaluate the performance of the prediction models. These components collectively facilitate a comprehensive analysis of the proposed model's accuracy, reliability, and effectiveness in predicting wind speeds. This aids in informed decision-making for wind energy planning and management.

### A. Model Performance Evaluation

The proposed WSP model is evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Relative Error (MRE), and Mean Absolute Percentage Error (MAPE). Statistic error criteria are determined by the following formulas:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} (Y_i' - Y_i) \quad [2]$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N} |(Y_i' - Y_i)/\bar{Y}_i| \quad [3]$$

$$\text{RMSE} = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n} (y_i - \tilde{y}_i)^2} \quad [4]$$

$$\text{CC} = \frac{\text{Cov}(y_i, \tilde{y}_i)}{\sqrt{\text{Var}(y_i)\text{Var}(\tilde{y}_i)}} \quad [5]$$

### B. Compared Models

The models compared in Table 1 include two ensemble-based standalone 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, aiming to assess prediction performance. These models are characterized by different methodologies and approaches for wind speed prediction. Input variables are determined using partial auto-correlation and trial-and-error methods, with a partial auto-correction function (PACF) also employed. Due to slight variations in the output of the Ensemble Learning Model (ELM), the experiment is conducted ten times to obtain an average performance measure, ensuring a robust evaluation.

**Table 1: Compared Models**

| Model | | | Author |
|---|---|---|---|
| Standalone Model | Ensemble Based Model | S_ELM#1 | [24] Velusamy et al. 2016 |
| | | S_ELM#2 | [26] Yong et al., 2019 |
| | Hybrid Model | S_Hyb#1 | [9] Hossain et al 2018 |
| | | S_Hyb#2 | [25] Vidya et al.2020 |
| Unified Model | Hybrid Model | ULM#1 | [21] Saeed et al., 2020 |
| | Hybrid Model | BLS-EC#2 | [29] Lingzi Zhuetal.,2020 |

### C. Target Station

In this work, we chose weather stations from Tirunelveli District in the Tamil Nadu state of India (Figure 4). The long-term WSF will help the energy projects to plan their wind turbine installation in locations that could yield better energy. In this work, we chose areas close to western ghat gaps, as these places receive maximum wind throughout the year; out of 19 weather stations (Table 2), 9 stations lay close to the ghat region, as shown in figure 4. The weather station with its longitude and latitude details are listed in Table 2, and the maximum WS and mean speed for each station are listed in Table 3. Our evaluation was conducted at two target stations: Kalakkad and Thenkasi. Kalakkad has a maximum wind speed (WS) of 21.3 kilometers per hour (km/h) and a mean WS of 13.75 km/h, while Thenkasi has a maximum WS of 20.9 km/h and a mean WS of 14.3 km/h. The selection of reference stations depends on the proximity of each target station to its respective reference stations. Table 4 provides detailed information about each target station and its corresponding reference stations.

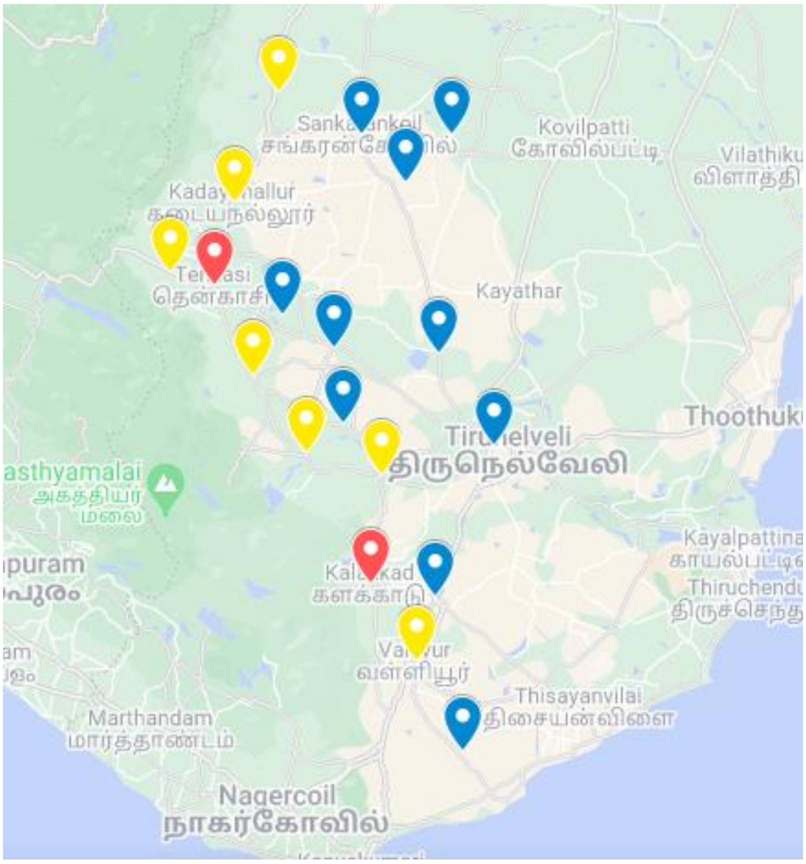



**Figure 4. Location map of the weather station in Tirunelveli district (Red marks are target stations, yellow marks are reference stations)**

**Table 2: Location details of each weather station**

| Station Number | Station | Latitude(°) | Longitude(°) | Elevation(m) |
|---|---|---|---|---|
| 1. | Alangulam | 8.8646356 | 77.4960078 | 128.26 |
| 2. | Ambasamudram | 8.709317 | 77.4529868 | 66.21 |
| 3. | Cheranmahadevi | 8.674728 | 77.565838 | 64 |
| 4. | Kadayam | 8.82134 | 77.374073 | 114 |
| 5. | Kadayanallur | 9.0778543 | 77.3451861 | 196.44 |
| 6. | Kalakadu | 8.5151681 | 77.5505682 | 130.82 |
| 7. | Keelapavoor | 8.913363 | 77.418558 | 126 |
| 8. | Kuruvikulam | 9.177994 | 77.669361 | 131 |
| 9. | Manur | 8.855005 | 77.652181 | 96 |
| 10. | Melaneelithanallur | 9.107793 | 77.600625 | 127 |
| 11. | Nanguneri | 8.4961056 | 77.6464534 | 102.85 |
| 12. | Palayamkottai | 8.720631 | 77.73428 | 51 |
| 13. | Pappakudi | 8.750010 | 77.507566 | 96.51 |
| 14. | Radhapuram | 8.26901 | 77.686538 | 46.62 |
| 15. | Sankarankoil | 9.177797 | 77.535124 | 163 |
| 16. | Shencottai | 8.975113 | 77.249137 | 178.83 |
| 17. | Tenkasi | 8.9590214 | 77.312938 | 163.3 |
| 18. | Valliyoor | 8.401361 | 77.617448 | 95 |
| 19. | Vasudevanallur | 9.239578 | 77.411384 | 183.44 |

**Table 3: WS details for each station**

| Station Number | Station | Max Wind (Km/h) | Mean WS (Km/h) |
|---|---|---|---|
| 1. | Alangulam | 18.9 | 13 |
| 2. | Ambasamudram | 17.1 | 11.9 |
| 3. | Cheranmahadevi | 19.9 | 15 |
| 4. | Kadayam | 17.2 | 12.7 |
| 5. | Kadayanallur | 18.9 | 10.45 |
| 6. | Kalakadu | 21.3 | 13.75 |
| 7. | Keelapavoor | 13.8 | 9.1 |
| 8. | Kuruvikulam | 14.5 | 9.55 |
| 9. | Manur | 18 | 13.5 |
| 10. | Melaneelithanallur | 14.7 | 9.9 |
| 11. | Nanguneri | 19.9 | 11.3 |
| 12. | Palayamkottai | 19.2 | 10.7 |
| 13. | Pappakudi | 15.7 | 11.7 |
| 14. | Radhapuram | 16.6 | 12.6 |
| 15. | Sankarankoil | 16.6 | 12.1 |
| 16. | Shencottai | 19.8 | 13.5 |
| 17. | Tenkasi | 20.9 | 14.3 |
| 18. | Valliyoor | 19.3 | 10.75 |
| 19. | Vasudevanallur | 19 | 13.1 |

**Table 4: Target station and its corresponding reference stations**

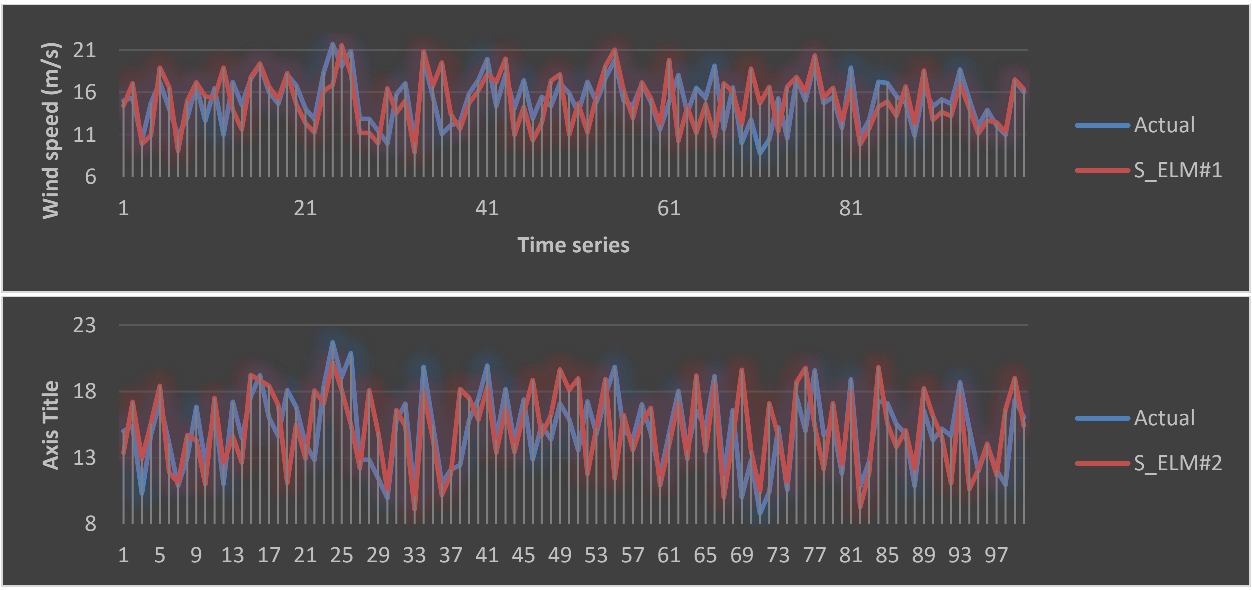
| Target Station | Reference Station | Distance to the Target Station | Max WS | Avg WS |
|---|---|---|---|---|
| Kalakkad | Valliyur | 19.5 km | 19.3 | 10.75 |
| | Cheranmahadevi | 21.1 km | 19.9 | 15 |
| | Nanguneri | 12.2 km | 19.9 | 11.3 |
| Tenkasi | Shencottai | 8.7 km | 19.8 | 13.5 |
| | Kadayanallur | 17.2 km | 18.9 | 10.45 |
| | Kadayam | 17.3 km | 17.2 | 12.7 |

**D. Analysis of Model Comparison**

The following results could be noted and analyzed in the context of the results presented in Tables 5 and Figures 5 and 6. Models like the S_ELM#1 model, S_ELM#1 model, S_Hyb#1 model, and S_Hyb#2 model are stand-alone models which only utilize the Target Station data to create predictions and do not use the WS data from other stations. In addition to using WS data from the TS, Unified models like the ULM#1 model and the proposed model take WS data from both the target and neighbouring 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 hrs to 240 hrs. The MAE, RMSE, and MAPE indexes proposed model, for example, have been reduced by 0.5, 0.05 and 1.15, respectively, in the prediction with Kalakad station as the target, while the Correlation Coefficient Index (CCI) was as close to 1, in comparison to the other model including ULM#1. As for the Thenkasi station, the proposed model achieved 0.28, 0.11 and 0.47 for RMSE, MAE and MAPE, respectively, and the CC was 0.94. Such results demonstrate the drawbacks of stand-alone modelling methods, as well as the high spatial correlations between adjacent wind stations and the usefulness of predictors depending upon spatiotemporal proximity.

**Table 5: 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 |
| | Proposed | 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 |
| | Proposed | 0.2762 | 0.1122 | 0.4683 | 0.9377 |



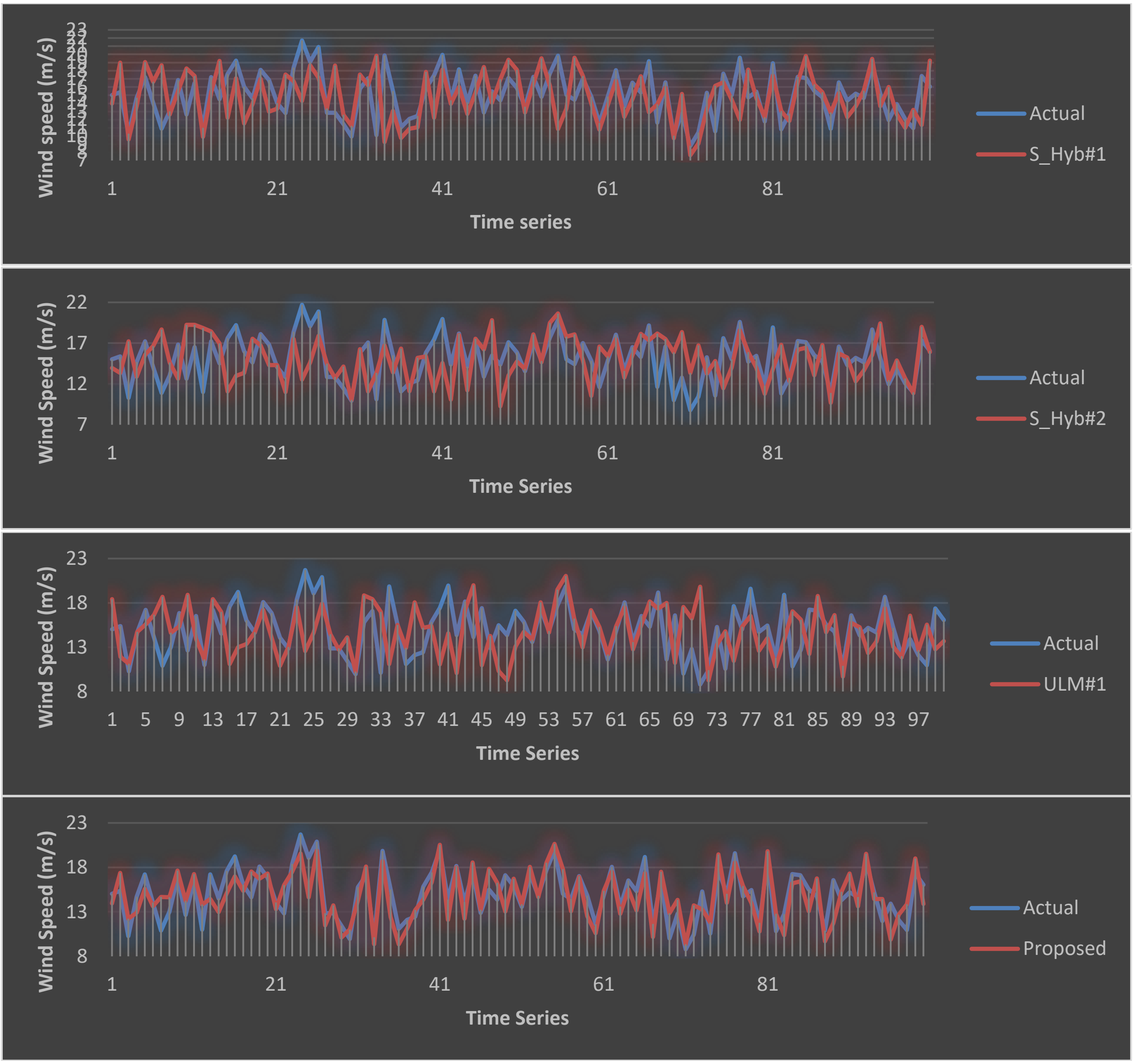
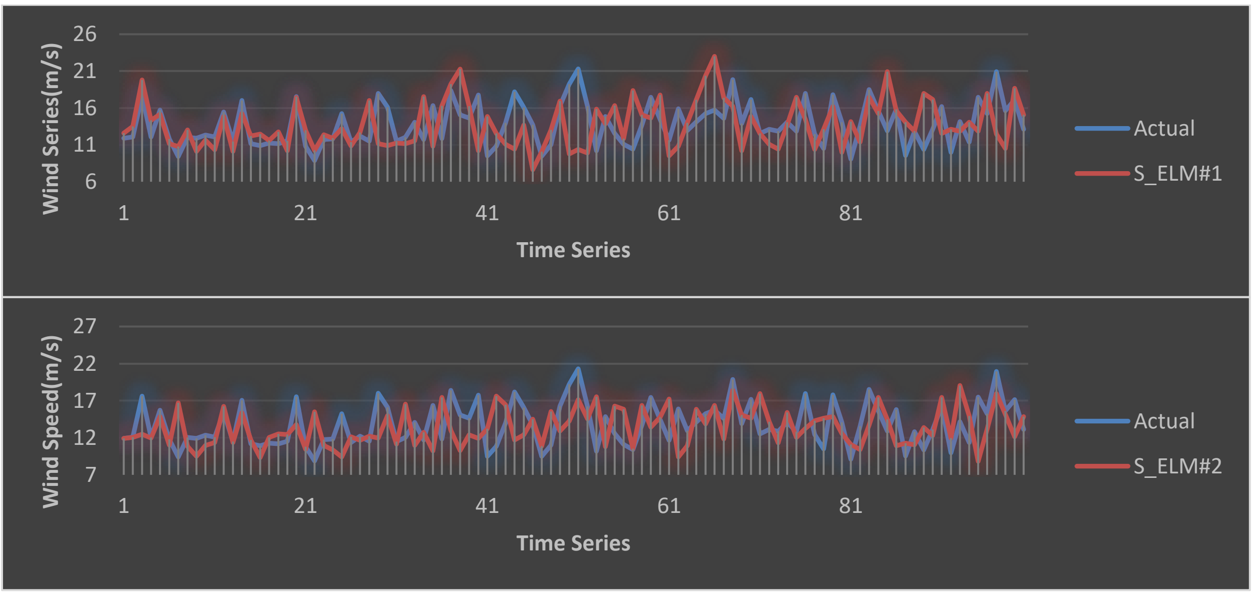



**Figure 5. WSF for Thenkasi station**



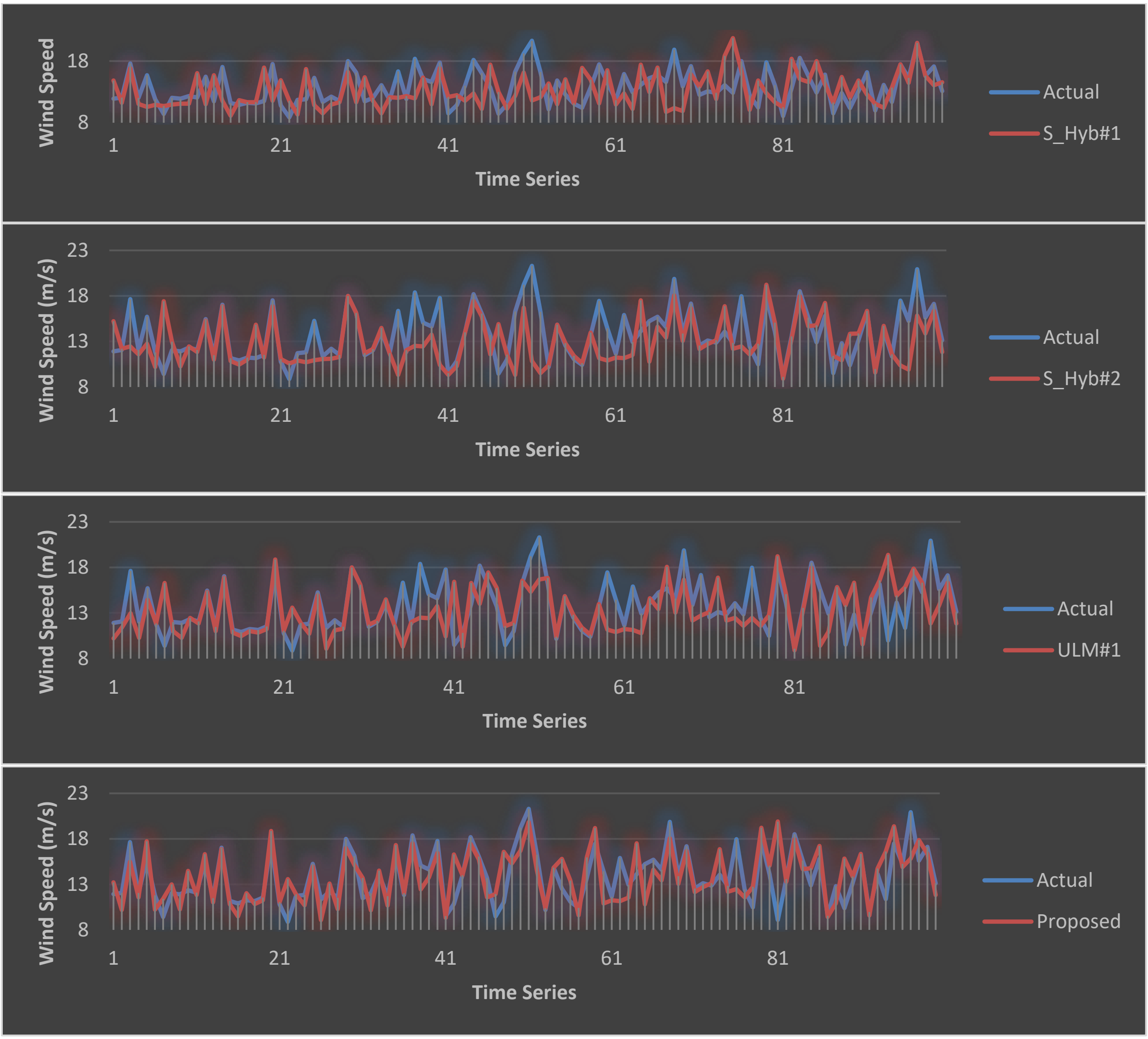



**Figure 6. WSF accuracy for Thenkasi station**

### E. Experiment with IMD Data

This section compares the proposed model with the government forecasting model for real-time forecasts at the Tirunelveli weather substation in Tamil Nadu, India. For reference, we utilized data from Kanyakumari, Sivakasi, and Thoothukudi for this target station. The model was trained using actual recorded data from both the reference and the target station. This data covered from January 1, 2022, to September 31, 2022. Over the following ninety days, at 24-hour intervals, predictions from both the proposed model and the Indian Meteorological Department (IMD) forecast model were contrasted. Figure 7 compares the predictions between the suggested model and the IMD forecast model. The findings indicate that both models produce almost identical predictions.

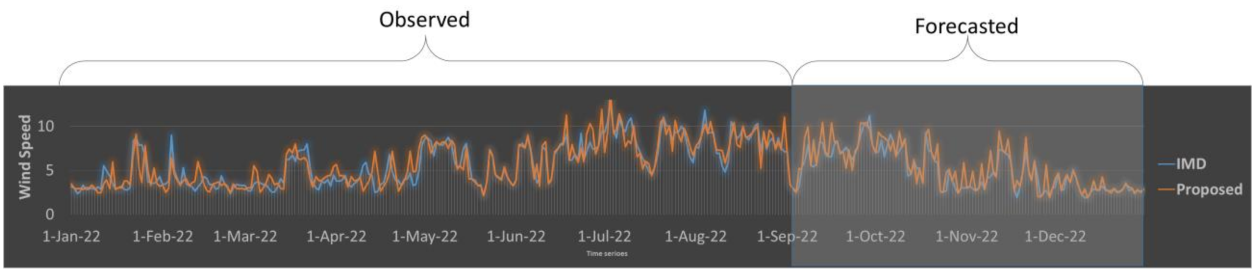



**Figure 7. WSP results 24 hrs in advance for Tirunelveli district**

When predicting performance, data seems to have an advantage. The Unified models provide better prospects than stand-alone models because they fully utilize historical WS from the adjacent stations to enhance WSP at the target station, making up for the stand-alone models' inefficient use of information in WSP. 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 experimentations. This indicates that using the DAM can effectively increase a ML's WSP performance by resolving the instability issue that it was experiencing. The proposed delivers the highest prediction accuracy between those comparable models in the multi-time-scale predictions in the target experiments. The proposed effectively enhances the WSP performance 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.

## V CONCLUSION

The study introduces a novel approach to enhance long-term wind speed prediction by integrating advanced data assimilation techniques with a dynamic unified ensemble learning model. This approach aims to improve prediction accuracy by leveraging data assimilation and ensemble learning methods. Specifically, the proposed SCBLSTM+DA unified model integrates data assimilation with a stacked ensemble consisting of CNN and BiLSTM models. It uses wind speed data from nearby regions. Through experimentation with data collected from nine weather stations in the Tirunelveli region of Tamil Nadu, India, the proposed model is evaluated against other models using various metrics. Focusing on two target stations, the study compares the performance of five models, including the suggested model, standalone models, and a baseline model. Results indicate that the SCBLSTM+DA model outperforms the other models, demonstrating superior predictive power, particularly after incorporating data assimilation. Notably, the proposed model exhibits robustness across different forecast time scales, unlike standalone models. By considering historical wind speed data from surrounding areas, the proposed model effectively enhances wind speed forecasting at target locations. These findings suggest that the proposed approach offers a more efficient and sustainable solution to wind speed prediction, improving grid management and wind energy generation. Moreover, the adaptable nature of the approach suggests its potential to revolutionize various other wind energy applications.

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## References

[1] Bechrakis, D. A., and P. D. Sparis, 2004: Correlation of wind speed between neighboring measuring stations. IEEE Trans. Energy Convers., 19, 400–406.
[2] Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning - Volume 70 (ICML'17). JMLR.org, 1126–1135.
[3] Filik T. Improved Spatio-temporal linear models for very short-term wind speed forecasting Energies, 9 (2016), p. 168
[4] Glahn, H. R., and D. A. Lowry, 1972: The use of model output statistics (MOS) in objective weather forecasting. J. Appl. Meteor., 11, 1203–1211.
[5] Gneiting T., Larson K., Westrick K., Genton M.G., Aldrich E. Calibrated probabilistic forecasting at the stateline wind energy center J. Amer. Statist. Assoc., 101 (2006), pp. 968-979
[6] Graves, A.; Schmidhuber, J. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Netw. 2005, 18, 602–610
[7] Hering A.S., Genton M.G. Powering up with space-time wind forecasting J. Amer. Statist. Assoc., 105 (2010), pp. 92-104
[8] Hoppmann, U., S. Koenig, T. Tielkes, and G. Matschke, 2002: A short-term strong wind prediction model for railway application: Design and verification. J. Wind Eng. Indust. Aerodyn., 90, 1127–1134.
[9] Hossain M, Mekhilef S, Afifi F, Halabi LM, Olatomiwa L, et al. (2018) Application of the hybrid ANFIS models for long-term wind power density prediction with extrapolation capability. PLOS ONE 13(4): e0193772. https://doi.org/10.1371/journal.pone.0193772
[10] Jackson, P. L., and D. G. Steyn, 1994: Gap winds in a fjord. Part I: Observation and numerical simulation. Mon. Wea. Rev., 122, 2645–2665
[11] Li, G., J. Shi, and J. Zhou, 2011: Bayesian adaptive combination of short-term wind speed forecasts from neural network models. Renew. Energy, 36, 352–359
[12] Liu H., Chen C., Tian H., Li Y. A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks Renew. Energy, 48 (2012), pp. 545-556

[13] Maharani, Y. N., S. Lee, and Y.-K. Lee, 2009: Topographical effects on wind speed over various terrains: A case study for Korean Peninsula. Proc. Seventh Asia-Pacific Conf. on Wind Engineering, Taipei, Taiwan, Int. Association for Wind Engineering.
[14] Maroufpoor, Saman & Sanikhani, Hadi & Kisi, Ozgur & Deo, Ravinesh & Yaseen, Zaher. (2019). Long-term modelling of wind speeds using six different heuristic artificial intelligence approaches. International Journal of Climatology. 39. 10.1002/joc.6037.
[15] Munkhdalai T, Yu H. Meta Networks. Proc Mach Learn Res. 2017 Aug;70:2554-2563. PMID: 31106300; PMCID: PMC6519722.
[16] Nawri, N., and R. E. Stewart, 2006: Climatological features of orographic low-level jets within Frobisher Bay. Atmos.– Ocean, 44, 397–413.
[17] Nichol, A., Achiam, J., & Schulman, J. (2018). On First-Order Meta-Learning Algorithms. ArXiv, abs/1803.02999.
[18] Petković D., Nikolić V., Mitić V., Kocić L. Estimation of fractal representation of wind speed fluctuation by artificial neural network with different training algorithms Flow Meas. Instrum., 54 (2017), pp. 172-176
[19] Ravinesh C. Deo, Mohammad Ali Ghorbani, Saeed Samadianfard, Tek Maraseni, Mehmet Bilgili, Mustafa Biazar,
[20] Ripley, B. D., 1996: Pattern Recognition and Neural Networks. Cambridge University Press, 416 pp.
[21] Saeed Samadianfard, Sajjad Hashemi, Katayoun Kargar, Mojtaba Izadyar, Ali Mostafaeipour, Amir Mosavi, Narjes Nabipour, Shahaboddin Shamshirband, Wind speed prediction using a hybrid model of the multi-layer perceptron and whale optimization algorithm, Energy Reports, Volume 6, 2020, Pages 1147-1159, ISSN 2352-4847
[22] Salmon, J. R., and J. L. Walmsley, 1999: A two-site correlation model for wind speed, direction and energy estimates. J. Wind Eng. Ind. Aerodyn., 79, 233–268
[23] Schuster M, Paliwal K. Bidirectional recurrent neural networks. IEEE Trans Signal Process. 1997;45:2673–81. https://doi.org/10.1109/78.650093
[24] Velusamy, Ranganayaki & Deepa, S N. (2016). An Intelligent Ensemble Neural Network Model for Wind Speed Prediction in Renewable Energy Systems. The Scientific World Journal. 2016. 1-14. 10.1155/2016/9293529.
[25] Vidya.S & E. Srie Vidhya Janani (2020) Tabu Search algorithm based general regression neural network for long term wind speed predictions, Automatika, 61:4, 657-669, DOI: 10.1080/00051144.2020.1811571
[26] Yong, Binbin & Qiao, Fei & Wang, Chen & Shen, Jun & Wei, Yongqiang & Zhou, Qingguo. (2019). Ensemble Neural Network Method for Wind Speed Forecasting. 31-36. 10.1109/SiPS47522.2019.9020410.
[27] Zhang Y., Zhao Y., Gao S. A novel hybrid model for wind speed prediction based on VMD and neural network considering atmospheric uncertainties IEEE Access, 7 (2019), pp. 60322-60332
[28] Andrés L. Suárez-Cetrulo, Lauren Burnham-King, David Haughton, Ricardo Simón Carbajo, Wind power forecasting using ensemble learning for day-ahead energy trading, Renewable Energy, Volume 191, 2022, Pages 685-698.
[29] Zhu, L., Lian, C., Zeng, Z. et al. A Broad Learning System with Ensemble and Classification Methods for Multi-step-ahead Wind Speed Prediction. Cogn Comput 12, 654–666 (2020). https://doi.org/10.1007/s12559-019-09698-0
[30] Wang, Y., Zhao, A., Wei, X., & Li, R. (2023). A Novel Ensemble Model Based on an Advanced Optimization Algorithm for Wind Speed Forecasting. Energies, 16(14), 5281.
[31] Quan, J., & Shang, L. (2021). An ensemble model of wind speed forecasting based on variational mode decomposition and bare-bones fireworks algorithm. Mathematical Problems in Engineering, 2021, 1-16.
[32] Lee, J., Wang, W., Harrou, F., & Sun, Y. (2020). Wind power prediction using ensemble learning-based models. IEEE Access, 8, 61517-61527.
[33] Ibrahim, A., Mirjalili, S., El-Said, M., Ghoneim, S. S., Al-Harthi, M. M., Ibrahim, T. F., & El-Kenawy, E. S. M. (2021). Wind speed ensemble forecasting based on deep learning using adaptive dynamic optimization algorithm. IEEE Access, 9, 125787-125804.
[34] Kadhem, A. A., Abdul Wahab, N. I., Aris, I., Jasni, J., & Abdalla, A. N. (2017). Advanced wind speed prediction model based on a combination of weibull distribution and an artificial neural network. Energies, 10(11), 1744.
[35] Zhu, L., Lian, C., Zeng, Z., & Su, Y. (2020). A broad learning system with ensemble and classification methods for multi-step-ahead wind speed prediction. Cognitive Computation, 12, 654-666.
[36] Wang, Y., Xue, W., Wei, B., & Li, K. (2022). An adaptive wind power forecasting method based on wind speed-power trend enhancement and ensemble learning strategy. Journal of Renewable and Sustainable Energy, 14(6).