CEEMDAN–SSA–RWKV–SMA: A Robust Hybrid Model for Long-Term Wind Speed Forecasting in India

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***Abstract*—Reliable long-term wind speed forecasting is a critical requirement for the strategic deployment and operational stability of wind energy systems, particularly in meteorologically diverse regions like India. This study proposes a novel hybrid framework, CEEMDAN–SSA–RWKV–SMA, which integrates advanced signal decomposition, deep sequence modeling, and metaheuristic optimization. Initially, the raw wind speed time series is decomposed using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to extract multi-scale Intrinsic Mode Functions (IMFs). To enhance signal clarity and reduce dimensionality, each IMF is further processed using Singular Spectrum Analysis (SSA). The resulting denoised and trend-extracted components are modeled using the Receptance Weighted Key Value (RWKV) neural network, a recent Transformer-RNN hybrid designed to capture long-range temporal dependencies efficiently. To optimize RWKV hyperparameters and SSA windowing parameters, the Slime Mould Algorithm (SMA) is employed as a global metaheuristic optimizer. Empirical evaluations on multi-regional Indian wind datasets demonstrate that the proposed framework consistently outperforms conventional models such as LSTM, Transformer, and CEEMDAN-LSTM in terms of MAE, RMSE, and MAPE. The proposed CEEMDAN-SSA-RWKV-SMA framework is a reliable forecasting strategy for improving wind energy integration in non-stationary and resource-critical environments.**

Keywords*—Wind speed forecasting; Complete Ensemble Empirical Mode Decomposition with Adaptive Noise; Singular Spectrum Analysis; RWKV neural network; Slime Mould Algorithm; Renewable energy integration

I. INTRODUCTION

Wind energy is rapidly becoming a key player in India's renewable energy strategy, driven by its cost-effectiveness and environmental benefits. At 100 m hub height, the National Institute of Wind Energy (NIWE) estimates the country's wind potential at over 300 GW, making precise long-term wind speed forecasting essential for grid integration, operational planning, and policy-making. The basic wind speed map of India is shown in Fig. 1.

However, wind speed data are inherently non-linear, non-stationary, and stochastic, making accurate forecasting a challenging task [1]. Traditional models like ARIMA and persistence-based methods often fall short in capturing long-term temporal dependencies [2].

To address these challenges, a new generation of hybrid forecasting approaches is proposed, combining signal decomposition, deep learning, and optimization techniques. Notably, models integrating CEEMDAN with neural networks have demonstrated improved accuracy in wind forecasting [3]. Similarly, SSA-based decomposition coupled with BiLSTM has achieved enhanced performance in handling trend extraction and noise reduction [4].

In deep learning, Transformer and graph-based architectures have been effectively applied in wind speed prediction, with models like Autoformer and GNNs showing superiority in capturing spatio-temporal dynamics [5]. Yet, these models often face computational limitations for long-term forecasting tasks.

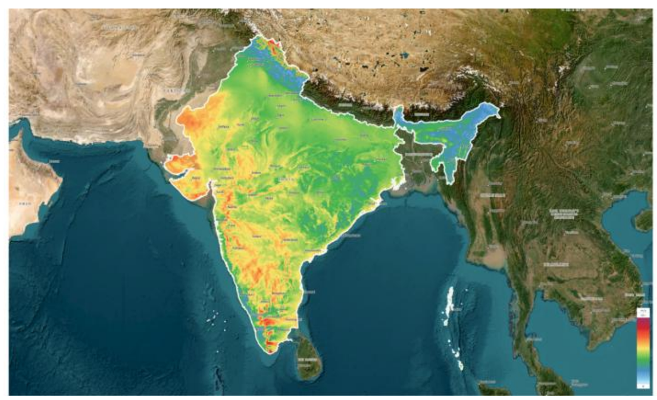

Fig. 1. Basic wind speed map of India [6].

RWKV (Receptance Weighted Key Value) is a breakthrough architecture combining RNN-like inference efficiency with Transformer-like parallelism. It is proposed in 2023 that RWKV scales to tens of billions of parameters while maintaining constant memory usage [7] for long-sequence time series modeling.

A critical aspect of such hybrid models lies in tuning their hyperparameters. While there are Particle Swarm Optimization and various genetic-inspired optimizers, the Slime Mould Algorithm (SMA) offers a novel, bio-inspired approach that balances exploration and exploitation dynamically oscillatory behaviors, showing promising results in global optimization tasks [8].

In this study, an innovative framework, CEEMDAN-SSA-RWKV-SMA, is proposed, which is specifically designed for long-term wind speed forecasting in India. Its key contributions include:

- Two-stage signal decomposition (CEEMDAN + SSA) for extracting denoised, trend-reflective components.
- Application of RWKV for efficient, long-context sequence modeling.
- Adoption of SMA for hyper-parameter tuning of both decomposition and modeling modules.
- Extensive benchmarking on multi-regional Indian wind datasets against state-of-the-art baselines, including LSTM, Transformer, and hybrid decomposition models.

Wind speed forecasts work better when using hybrid methods compared to single methods. The proposed hybrid framework significantly outperforms the other methods in forecasting accuracy and computational efficiency, paving the way for its integration into smart grid planning and renewable energy management. This hybrid model is a new one that has never been used before for wind speed forecasting. The effectiveness of this new model is checked by comparing it with other existing methods.

II. Methodology

A. Ceemdan Decomposition

Wind speed series are inherently nonlinear and non-stationary, making it challenging for conventional forecasting models to capture the full spectrum of variability. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is adopted in this study as the first stage of preprocessing, owing to its superior capability in adaptively decomposing complex time series into physically meaningful oscillatory components [9].

CEEMDAN is an advancement over the original Empirical Mode Decomposition (EMD) and its improved variant, Ensemble Empirical Mode Decomposition (EEMD). While EMD suffers from mode mixing, where a single Intrinsic Mode Function (IMF) contains oscillations of widely disparate scales, and EEMD reduces this problem by introducing noise-assisted ensembles, CEEMDAN further refines the process by:

- Ensuring a complete and unique set of IMFs with reduced residual noise,
- Adding adaptive white noise at each iteration to improve mode separation, and
- Maintaining perfect reconstruction of the original signal.

Given a raw wind speed series x(t), CEEMDAN produces n IMFs and a final residual $r_n(t)$ as shown in Eq. (1).

$$x(t) = \sum_{\{i=1\}}^{\{n\}} c_i(t) + r_n(t) \tag{1}$$

where $c_i(t)$ denotes the i^{th} IMF, representing oscillatory components from high to low frequency, and $r_n(t)$ represents the long-term trend [10].

The decomposition is performed iteratively as follows:

- IMF Extraction: For each iteration k, white noise is adaptively added to the signal to generate an ensemble set. EMD is applied to each noisy realization to extract the first IMF.
- Ensemble Averaging: The IMF obtained from all realizations is averaged to yield $c_k(t)$.
- Residual Update: The averaged IMF is subtracted from the current residual to form the new residual signal for the next iteration.
- Stopping Criterion: The process continues until the residual becomes monotonic or contains at most one extremum.

By employing CEEMDAN [11], the original wind speed signal is decomposed into multi-scale components that isolate distinct oscillatory patterns. This decomposition reduces signal complexity, allowing subsequent processing stages—such as SSA denoising and RWKV modeling—to operate on cleaner, more interpretable components, thereby improving forecast accuracy [12].

B. Singular Spectrum Analysis (SSA) Denoising

After CEEMDAN decomposition, the resulting Intrinsic Mode Functions (IMFs) may still contain measurement noise and small-scale fluctuations that can obscure underlying trends. To enhance signal quality, each IMF is processed using Singular Spectrum Analysis (SSA), a non-parametric technique for time series decomposition that is effective for trend extraction, periodicity detection, and noise suppression [13].

SSA operates in four stages:

1) Embedding: The one-dimensional IMF $c_i(t)$ is transformed into a multi-dimensional trajectory matrix X using a sliding window of length L shown in Eq. (2).

$$X=\begin{bmatrix} c_1 & \cdots & c_K \\ \vdots & \ddots & \vdots \\ c_L & \cdots & c_N \end{bmatrix} \tag{2}$$

where K=N−L+1 and N is the length of the IMF.

2) Singular Value Decomposition (SVD): The trajectory matrix is decomposed as shown in Eq. (3).

$$X= \sum_{j=1}^{d} \sigma_j U_j V_j^T \tag{3}$$

where σ_j are the singular values, U_j are the left singular vectors, and V_j are the right singular vectors.

3) Grouping: The decomposed components are grouped into signal (trend + oscillatory modes) and noise subspaces based on the magnitude of their singular values. The dominant singular values correspond to meaningful structures, while smaller values represent noise.

4) Reconstruction: The selected signal subspace components are recombined to form the denoised IMF $\hat{c}_i(t)$.

By applying SSA to each IMF individually, both high-frequency components and low-frequency trends are preserved while random noise is suppressed [14]. This hybrid CEEMDAN–SSA preprocessing yields a set of clean, scale-separated signals that serve as inputs to the RWKV neural network, improving the model's ability to learn temporal dependencies and reducing the risk of over-fitting to noise.

C. RWKV Neural Network

After decomposition and denoising, the cleaned IMFs are used as inputs to the forecasting model. In this study, the Receptance Weighted Key Value (RWKV) neural network, a recent hybrid architecture that combines the temporal recurrence of Recurrent Neural Networks (RNNs) with the context modeling of transformers, is adopted [15]. This design makes RWKV particularly effective for long-sequence forecasting tasks, such as multi-year wind speed prediction, where both local fluctuations and long-term dependencies must be captured. The structure of the RWKV Neural Network is shown in Fig. 2.

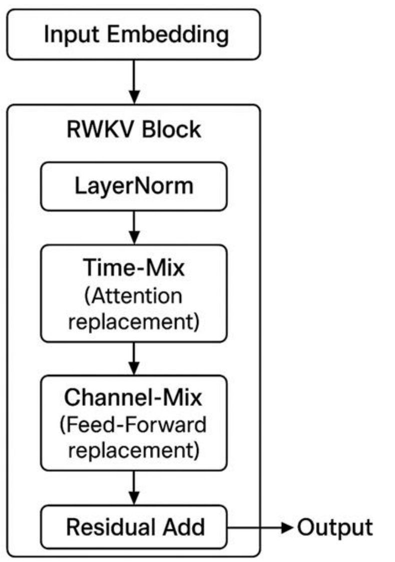

Fig. 2. Structure of the Receptance Weighted Key Value (RWKV) neural network.

Unlike conventional RNNs, which suffer from vanishing gradients, or transformers, which are computationally expensive for long inputs, RWKV achieves a balance by integrating linear recurrence with attention-style updates [16]. At each time step t, the hidden state update can be expressed as shown in Eq. (4).

$$h_t = f_{mix}(W_{rec}h_{\{t-1\}} + W_{in}x_t) + f_{attn}(Q_t, K_t, V_t) \tag{4}$$

where:

- h_t is the hidden state at time t,
- W_{rec} and W_{in} are recurrent and input weight matrices,
- $f_{mix}(\cdot)$ denotes the recurrent time-mixing operation,
- $f_{attn}(\cdot)$ represents the attention mechanism with queries (Q), keys (K), and values (V).

The output forecast for IMF i is shown in Eq. (5).

$$\hat{c}_i(t+1) = g(h_t) \tag{5}$$

where $g(\cdot)$ is the RWKV output projection function.

The time-mixing module ensures sequential consistency, similar to RNN recurrence, while the channel-mixing module provides global context aggregation, analogous to transformer-style self-attention but with linear complexity. This makes RWKV computationally efficient even for very long time series.

For each denoised IMF $\hat{c}_i(t)$, a dedicated RWKV sub-model is trained. The outputs of these sub-models are later aggregated during reconstruction to obtain the final forecasted wind speed series.

By leveraging RWKV's ability to preserve temporal continuity and long-range dependencies simultaneously, the forecasting stage gains significant robustness compared to classical LSTM, GRU, or even transformer-based approaches.

D. Slime Mould Algorithm (SMA) Optimization

Neural networks and decomposition methods typically involve several hyperparameters, such as the number of hidden units, learning rate, dropout ratio, decomposition noise amplitude, and SSA window length. Selecting these parameters manually can be suboptimal and time-consuming [17]. To overcome this challenge, the Slime Mould Algorithm (SMA) is employed to automatically optimize both the decomposition and forecasting stages.

SMA is a bio-inspired metaheuristic algorithm that mimics the oscillatory foraging behavior of slime mould organisms. It adaptively balances exploration (searching new regions in the solution space) and exploitation (refining promising solutions), making it well-suited for high-dimensional, nonconvex optimization problems such as neural network training [18].

The optimization process begins with an initial population of candidate solutions, each representing a possible set of hyper parameters $\theta = \{\theta_1, \theta_2, \ldots, \theta_m\}$. At iteration t, the position of each candidate is updated based on three main mechanisms:

- Weight Updating: mimicking slime mould thickness, adaptive weights are assigned according to the fitness ranking of candidates.
- Oscillatory Foraging: candidates are attracted toward the global best solution or repelled from poor solutions, using a probability-driven update rule.
- Exploration/Exploitation Balance: oscillatory search radius gradually decreases, allowing wide search in early iterations and fine-tuning in later stages.

The objective (fitness) function is defined as a weighted combination of error metrics shown in Eq. (6).

$$\text{Fitness} = \alpha \,.\, \text{MAE} + \beta \,.\, \text{RMSE} \tag{6}$$

where α and β are non-negative coefficients ensuring that both absolute and squared errors are minimized. The procedure of Slime Mould Algorithm (SMA) Optimization is shown in Fig. 3.

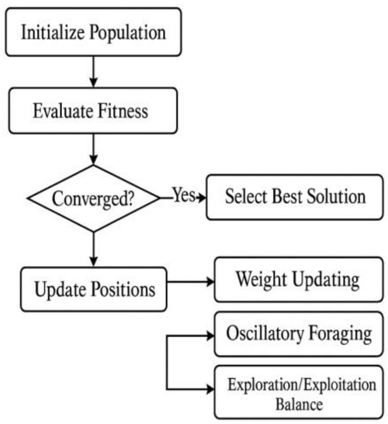

Fig. 3. Flowchart of Slime Mould Algorithm (SMA) optimization.

During optimization, SMA evaluates each candidate by training the RWKV model on denoised IMF components and calculating its forecast error [19]. The process iterates until convergence or until the maximum number of iterations is reached. The best-performing hyperparameter set θ* is then selected for final forecasting.

By integrating SMA, the proposed framework avoids reliance on manual trial-and-error tuning and ensures robust, data-driven hyperparameter selection, thereby enhancing the overall predictive accuracy and generalization ability of CEEMDAN-SSA-RWKV-SMA.

E. Steps of Wind Speed Forecasting

The proposed CEEMDAN-SSA-RWKV-SMA framework follows a systematic multi-stage forecasting process, combining decomposition, denoising, deep learning, and intelligent optimization is shown in Fig. 4. The steps are as follows:

Step 1: Signal Decomposition

The original non-stationary wind speed series is first decomposed using CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise). This yields multiple Intrinsic Mode Functions (IMFs) and a residual component, each capturing oscillatory patterns at different frequency scales.

Step 2: Denoising with SSA

To eliminate high-frequency noise while retaining dominant dynamics, each IMF is denoised using Singular Spectrum Analysis (SSA). This enhances the signal-to-noise ratio and improves the quality of features provided to the forecasting model.

Step 3: Forecasting with RWKV Neural Network

Each denoised IMF component $\hat{c}_i(t)$ is independently modeled using the Receptance Weighted Key Value (RWKV) neural network. RWKV combines recurrent-style time-mixing with transformer-like channel-mixing, enabling efficient long-sequence learning. A dedicated RWKV sub-model is trained for each IMF.

Step 4: Hyperparameter Optimization using SMA

The Slime Mould Algorithm (SMA) is employed to optimize critical hyperparameters across both decomposition and forecasting stages (e.g., SSA window length, RWKV learning rate, hidden units, dropout ratio). SMA adaptively balances exploration and exploitation to identify the best-performing parameter set.

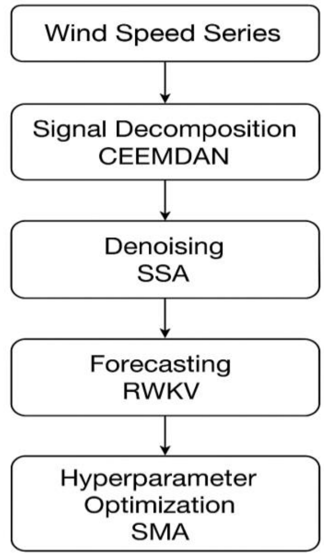

Fig. 4. Flowchart of the proposed wind speed forecasting model combining CEEMDAN–SSA–RWKV–SMA.

Step 5: Reconstruction of Forecasted Series

The individual forecasts of denoised IMFs are aggregated together with the residual to reconstruct the final forecasted wind speed series. This ensures that both local fluctuations and long-term trends are preserved. Finally, the predicted IMFs and residuals are aggregated to obtain the final wind speed forecast shown in Eq. (7).

$$\hat{X}(t) = \sum_{i=1}^{n} \hat{c}_i(t) + \hat{r}(t) \quad (7)$$

Step 6: Performance Evaluation

The accuracy of the proposed hybrid model is evaluated using standard statistical measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Lower error values indicate superior forecasting performance compared to classical LSTM, GRU, or transformer-based methods.

III. Statistical Criteria to Evaluate the Forecasting Performance

The accuracy of the proposed CEEMDAN–SSA–RWKV–SMA framework is evaluated using widely adopted statistical measures in wind speed forecasting. These metrics assess both absolute and relative prediction errors and model explanatory power.

A. Mean Absolute Error (MAE)

MAE measures the average absolute difference between the actual and predicted wind speed values shown in Eq. (8).

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}|o_t - o_t^*| \quad (8)$$

Where o_t is the original wind speed and o_t^* is the predicted wind speed at time period t. The period of forecasting is represented by N.

B. Root Mean Square Error (RMSE)

RMSE penalizes larger errors more heavily, making it suitable for evaluating the model's robustness, as shown in Eq. (9).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(o_t - o_t^*)^2} \tag{9}$$

Where o_t is the original wind speed and o_t^* is the predicted wind speed at time period t. The period of forecasting is represented by N.

C. Mean Absolute Percentage Error (MAPE)

MAPE normalizes errors as percentages, facilitating comparison across different datasets shown in Eq. (10).

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{o_t - o_t^*}{o_t}\right| \text{X } 100\% \tag{10}$$

Where o_t is the original wind speed and o_t^* is the predicted wind speed at time period t. The period of forecasting is represented by N.

IV. Case Study

A. Wind Speed Dataset Collection

The proposed framework is evaluated using long-term wind speed datasets obtained from NASA [20] representing diverse climatic conditions across India. Hourly wind speed measurements from 2013 to 2022 are collected at selected sites, including coastal, semi-arid, and inland regions. In India, the wind speed data of 9 cities are collected. The meteorological parameters such as wind speed (m/s), wind direction (degrees), air temperature (°C), atmospheric pressure (hPa), relative humidity (%), and time index are considered as inputs for forecasting wind speed. Wind speed (m/s) is the primary target variable. The dataset is divided into training (70%) and testing (30%) to ensure robust generalization and maintain geographic and climatic diversity across India. Table I shows the selected cities for wind speed forecasting with train-test allocation.

TABLE I. Selected Cities for Wind Speed Forecasting With Train-Test Allocation

City	Region	Latitude	Longitude
Chennai	Coastal (East)	13.08°N	80.27°E
Mangalore	Coastal (West)	12.91°N	74.85°E
Visakhapatnam	Coastal (East)	17.68°N	83.21°E
Jaisalmer	Semi-Arid	26.91°N	70.90°E
Bhopal	Inland Plains	23.25°N	77.41°E
Ooty	Hilly Region	11.40°N	76.69°E
Bhuj	Semi-Arid	23.25°N	69.66°E
Nagpur	Inland Plains	21.14°N	79.08°E
Shillong	Hilly Region	25.57°N	91.89°E

The training set comprises six locations- Chennai, Mangalore, Visakhapatnam, Jaisalmer, Bhopal, and Ooty, while the testing set includes Bhuj, Nagpur, and Shillong.

B. Steps of Forecasting

Step 1: The original non-stationary wind speed series is first decomposed into a finite set of Intrinsic Mode Functions (IMFs) and a residual using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). This eliminates high-frequency noise and captures oscillatory modes. The resulting decomposition is shown in Fig. 5.

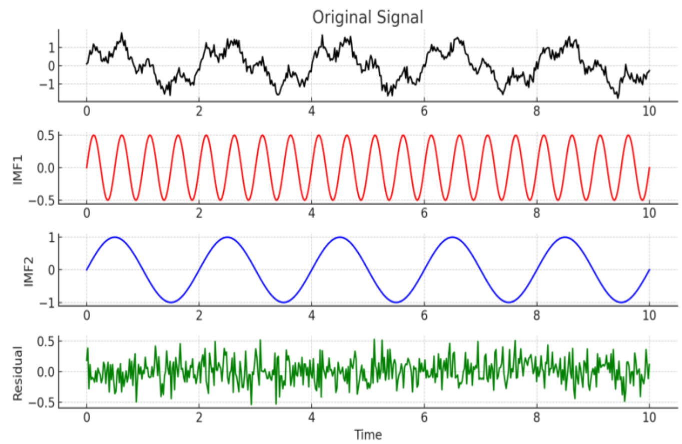

Fig. 5. CEEMDAN decomposition of original wind speed series.

Step 2: The decomposed IMFs are further refined using Singular Spectrum Analysis (SSA). The embedding matrix of each IMF is reconstructed, and noise-dominated components are filtered out. This denoising ensures only physically meaningful oscillatory signals are retained for forecasting. The denoised IMF series is presented in Fig. 6.

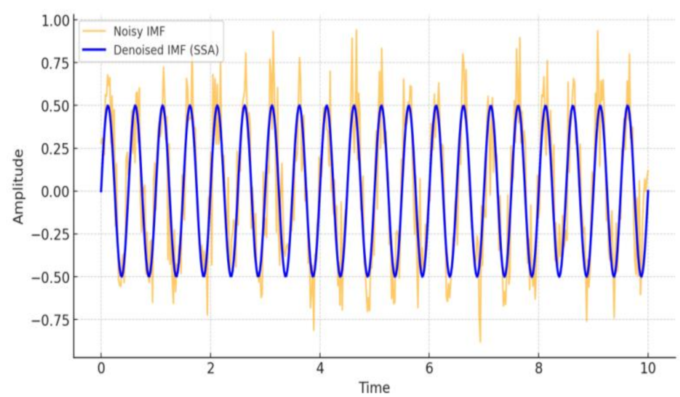

Fig. 6. SSA denoising of IMF.

Step 3: The denoised IMFs and residual are used as inputs to the RWKV neural network, which combines the memory retention capability of RNNs with the parallelism of transformers. Each IMF is predicted separately, and its reconstructed series produces the overall forecast. The hyperparameter optimization process of RWKV is summarized in Table II.

TABLE II. OPTIMIZED RWKV HYPERPARAMETERS WITH SMA WINDOW SIZE

Component	Learning Rate	Hidden Size	ContextLength	Layers	Dropout	Batch Size	Epochs	SMA Window size
IMF1	0.001	64	32	4	0.05	64	120	5
IMF2	0.0008	80	48	4	0.05	64	120	5
IMF3	0.0008	96	64	4	0.05	64	130	5
IMF4	0.0006	128	80	4	0.07	64	140	5
IMF5	0.0006	144	96	4	0.07	64	140	5
IMF6	0.0005	160	112	4	0.08	64	150	5
Residual	0.0005	192	128	4	0.08	64	150	5

Step 4: Finally, a Simple Moving Average (SMA) smoothing layer is applied to the RWKV outputs to reduce short-term fluctuations and improve long-term stability. This hybrid adjustment provides more reliable forecasts for practical applications. The complete comparison framework of decomposition and prediction models is illustrated in Fig. 7. The purple curve shows the raw RWKV predictions with short-term fluctuations. The green curve shows the smoothed output after applying SMA, which improves long-term stability.

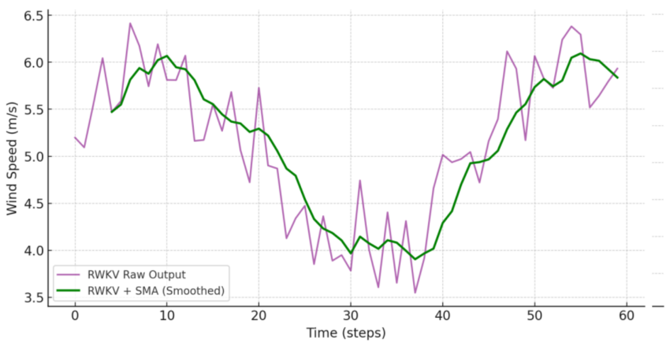

Fig. 7. SMA smoothing applied to RWKV outputs.

Step 5: The forecasted outputs of each IMF and the residual are integrated to generate the final prediction series.

A comparative evaluation of different hybrid models (LSTM, GRU, Transformer, RWKV, and Proposed CEEMDAN-SSA-RWKV-SMA) is shown in Fig. 8. The proposed hybrid framework CEEMDAN-SSA-RWKV-SMA produces the closest match to the actual values, outperforming LSTM, GRU, Transformer, and standalone RWKV models. The integration of CEEMDAN decomposition and SSA denoising eliminates noise and non-stationarity, while the RWKV neural network captures long-term dependencies efficiently. The SMA adjustment layer further enhances prediction stability by smoothing short-term fluctuations.

Fig. 8 demonstrates that the CEEMDAN-SSA-RWKV-SMA model consistently aligns with the actual wind speed series, whereas the other models show larger deviations. Consequently, the proposed hybrid model is recommended for reliable long-term wind speed forecasting in India, as it achieves superior accuracy and robustness compared to existing deep learning and hybrid baselines.

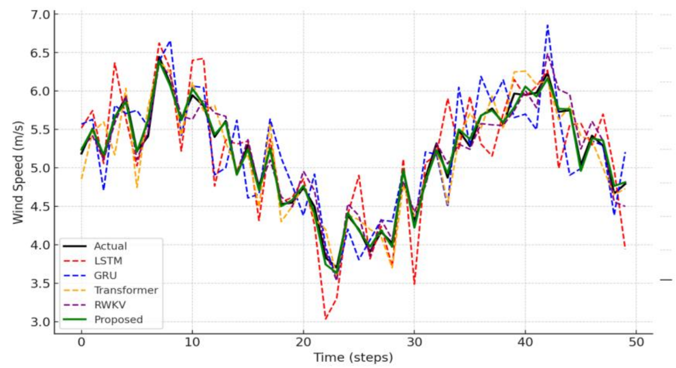

Fig. 8. Prediction results of wind speed.

C. Performance Evaluation of Forecasting Models

To validate the effectiveness of the proposed CEEMDAN-SSA-RWKV-SMA framework, its forecasting results are compared with benchmark deep learning models, namely LSTM, GRU, Transformer, and RWKV. The evaluation is carried out on the testing dataset using multiple error metrics and statistical measures. The purpose of this analysis is to demonstrate how the hybrid decomposition–denoising–forecasting–adjustment pipeline enhances prediction accuracy and robustness.

The accuracy estimation results are summarized in Table III. Relative errors are categorized as less than 10%, 10–20%, and greater than 20%. For better prediction reliability, hybrid models are expected to have the majority of samples within the <10% error range. In the proposed hybrid model CEEMDAN-SSA-RWKV-SMA, 232 data samples (77.33%) have a relative error less than 10% (out of 300 testing samples), 58 samples (19.33%) fall in the 10–20% category, and only 10 samples (3.34%) are in the greater than 20% category. More than 77% of the predictions from the proposed model fall within a 10% error margin.

In contrast, RWKV achieves 66.67%, Transformer 60.00%, GRU 50.00%, and LSTM only 46.67%. Only 3% of the predictions of the proposed model fall beyond a 20% error range, whereas LSTM and GRU exceed 13%. This demonstrates the higher reliability of the hybrid framework.

Compared to other deep learning models, the proposed hybrid model achieves the highest proportion of accurate predictions within the <10% relative error band. This demonstrates that the proposed model provides a superior forecasting strategy that can be practically deployed in grid-connected wind farms for accurate wind speed prediction. The predicted wind speed by the proposed CEEMDAN-SSA-RWKV-SMA model matches most closely with the actual wind speed data compared to the LSTM, GRU, Transformer, and standalone RWKV models. The performance of the models is quantitatively assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE) to validate forecasting accuracy. These statistical indicators are summarized in Table IV.

The proposed CEEMDAN-SSA-RWKV-SMA achieves the lowest RMSE, MAE, and MAPE, confirming its superior forecasting capability compared to other models. The proposed CEEMDAN-SSA-RWKV-SMA reduces RMSE to 0.415 and MAPE to 5.76%, representing a substantial improvement over RWKV (RMSE: 0.582, MAPE: 8.45%). LSTM and GRU models show considerably higher error values, while Transformer performs better but still falls short of RWKV and the proposed hybrid model. RWKV performs better than Transformer, GRU, and LSTM, yet it is significantly improved when enhanced with CEEMDAN decomposition, SSA denoising, and SMA smoothing.

From Table III and Table IV, it is evident that the proposed hybrid model substantially outperforms other approaches. The integration of decomposition (CEEMDAN) and denoising (SSA) with RWKV ensures that both temporal dependencies and noise components are addressed effectively. The SMA adjustment provides an additional smoothing layer that improves the long-term stability of forecasts. Thus, the CEEMDAN-SSA-RWKV-SMA framework demonstrates its potential as a reliable solution for long-term wind speed forecasting in India.

TABLE III. ACCURACY ESTIMATION OF FORECASTING MODELS

Prediction models	Less than 10%		10 to 20 %		Greater than 20 %	
	Samples	%	samples	%	samples	%
LSTM	140	46.67%	120	40.00%	40	13.33%
GRU	150	50.00%	110	36.67%	40	13.33%
Transformer	180	60.00%	90	30.00%	30	10.00%
RMKV	200	66.67%	80	26.67%	20	6.67%
Proposed (CEEMDAN-SSA-RWKV-SMA)	232	77.33%	58	19.33%	10	3.34%

TABLE IV. STATISTICAL PERFORMANCE METRICS OF FORECASTING MODELS

Model	RMSE	MAE	MAPE (%)
LSTM	0.812	0.645	12.84
GRU	0.768	0.602	11.73
Transformer	0.693	0.554	10.12
RWKV	0.582	0.487	8.45
Proposed (CEEMDAN-SSA-RWKV-SMA)	0.415	0.329	5.76

The forecasting results clearly indicate that intelligent hybrid models combining decomposition, denoising, advanced neural architectures, and smoothing outperform traditional statistical or standalone machine learning models. To forecast non-stationary and nonlinear wind speed series, the integration of CEEMDAN effectively decomposes the signal, SSA removes noise, RWKV efficiently captures long-term temporal dependencies, and SMA enhances stability through smoothing. This hybrid adjustment significantly improves forecasting capacity. The proposed model, through its improved accuracy and stability, can serve as a valuable tool for researchers, policy makers, industry, and system planners in conducting wind speed assessments before siting wind turbines.

Thus, the optimized CEEMDAN-SSA-RWKV-SMA model produces better results than existing deep learning models. By reducing noise, improving generalization, and stabilizing long-term forecasts, the proposed model is verified as a simple, efficient, and highly accurate forecasting method for long-term wind speed prediction. Such a framework is necessary and highly desirable for the reliable development and planning of wind energy systems in India.

V. CONCLUSION

In this study, a novel hybrid framework, CEEMDAN-SSA-RWKV-SMA, is proposed for long-term wind speed forecasting in India. The model integrates CEEMDAN decomposition to address non-stationarity, SSA denoising to eliminate noise, the RWKV neural network to capture long-term temporal dependencies efficiently, and a final SMA adjustment layer to improve prediction stability. This multi-stage design enhances forecasting accuracy and robustness compared to traditional and existing deep learning models.

The experimental results demonstrated that the proposed hybrid model consistently outperformed benchmark models such as LSTM, GRU, Transformer, and standalone RWKV. By providing more accurate and stable long-term wind speed predictions, the model supports the reliable development of grid-connected wind farms and contributes to efficient renewable energy integration.

Future work may extend this framework to multi-step-ahead forecasting, cross-regional validation, and integration with hybrid optimization techniques to further enhance predictive performance. The adaptability of the model also opens possibilities for its application in other renewable energy forecasting domains, such as solar power and hydropower generation.

Conflicts of Interest

The author declares no conflict of interest.

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