WindFusion-EW: An Ensemble-Weighted Multi-Model Framework for Ultra-Short-Term Wind Power Forecasting

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ABSTRACT

Ultra-short-term wind power forecasting is an important technical task for supporting stable grid operation and efficient energy dispatch. However, the strong volatility and nonlinear characteristics of the wind limit the performance of conventional single-model forecasting approaches. This paper presents WindFusion-EW, a technical hybrid forecasting framework that combines two-stage signal decomposition with a weighted multi-model ensemble strategy. In this framework, CEEMDAN and Empirical Wavelet Transform (EWT) are sequentially applied to decompose raw wind power time series and extract informative multi-frequency components. Several transformer-based forecasting models are then trained in parallel, and an EnsembleWeighted mechanism dynamically adjusts model contributions based on month-wise validation performance. Experimental results on real-world wind power datasets from France and Turkey show that WindFusion-EW achieves average MAPE values of 1.02% and 1.13%, respectively, outperforming baseline and standalone deep learning models. The results demonstrate that integrating signal processing techniques with adaptive ensemble learning provides an effective and practical solution for ultra-short-term wind power forecasting.

Keywords-CEEMDAN; EWT; Deep Learning; Wind Energy; WindFusion-EW

I. INTRODUCTION

Onshore and offshore wind power is an increasing source of electricity in modern power systems. However, from an operational perspective, the management of wind energy remains challenging due to its inherent variability and uncertainty. The primary operational challenges are not associated with the annual production effort, which is well defined during project development phases, nor simply related to short-term production variability, but with ultra-short-term production variation, which must be actively managed through balancing actions and frequency support mechanisms. Wind power generation may exhibit high variation timescales of tens of minutes, requiring balancing actions to be taken. Based on existing operational experience, such effects increase with growing shares of wind energy in electricity markets and fast-changing weather conditions, where small forecast errors are known to drive corrective actions. On this basis, ultra-short-term forecasting of wind power output, from an operational point of view, focuses on time intervals typically comprising tens of minutes up to several hours ahead. More precise estimations can provide better support during reserve scheduling and avoid meaningless actions. Feasibility studies [1], conducted in Southeast Vietnam and Libya, highlight the impact related to local conditions, average speed, and turbine characteristics, under which both the technical and economic viability of any given project are strongly influenced. These operational experiences support the accurate estimation and forecasting of wind power output.

Research on ultra-short-term wind power forecasting has gradually shifted away from purely statistical formulations toward Deep Learning (DL) and hybrid designs. This transition is motivated not only by the pursuit of improved modeling performance but also by the inherent characteristics of wind power series, which exhibit strong noise, non-stationarity, and multi-scale temporal dynamics. In this context, signal decomposition helps decompose a difficult wind signal into a simpler form that can be easily modeled. Among existing techniques, CEEMDAN [2] has been widely adopted because it reduces mode mixing and produces more stable intrinsic mode functions than earlier EMD variants.

Several studies have explored how CEEMDAN can be combined with learning-based predictors. For example, in [3], CEEMDAN was combined with Empirical Wavelet Transform (EWT) to further reorganize frequency content prior to prediction, reporting improved accuracy compared to single-stage decomposition approaches. Other works extended this idea by introducing a second decomposition layer. In [4], CEEMDAN was integrated with VMD and a GRU predictor, arguing that the separation of the mid- and high-frequency components leads to better short-term forecasts. Similarly, in [5], a frequency-aware framework combined CEEMDAN, VMD, and spectral entropy with a Transformer-GRU architecture, showing that such multi-stage designs are particularly effective for very short horizons (10–30 minutes).

Despite these studies clearly demonstrating the value of decomposition, most of them relied on a single downstream model, implicitly assuming that one architecture can capture all relevant temporal behaviors once the signal is decomposed. At the same time, advances in Transformer-based time-series models have reshaped energy forecasting research. Models such as the Temporal Fusion Transformer (TFT) introduced mechanisms for attention-based temporal modeling and variable selection, offering both performance and interpretability [6]. Autoformer also incorporated auto-correlation and internal decomposition blocks, achieving strong results on long-term forecasting benchmarks [7]. More recently, TimesNet proposed a two-dimensional representation of time series to jointly model intra-period and inter-period patterns [8]. Nevertheless, empirical results across studies suggest that no single Transformer-based model consistently performs best under all wind conditions, particularly when weather patterns change abruptly.

To address this limitation, some studies turned to ensemble methods. In [9], an adaptive ensemble approach dynamically adjusted model weights based on recent forecasting errors, improving short-term adaptability. In [10], it was further demonstrated that dynamic weighting improves both reliability and accuracy in probabilistic forecasting settings. These findings indicate that forecasting performance is inherently time-dependent and that fixed-weight or single-model approaches may fail to capture regime-dependent dynamics effectively. Despite these advances, existing studies typically focus on either improving signal decomposition or improving model fusion, but rarely integrate both within a unified and adaptive forecasting framework. In particular, combining two-stage CEEMDAN-EWT decomposition with adaptive multi-model transformer-based forecasting remains underexplored. This gap is important because decomposition improves signal stability, while adaptive model fusion enables dynamic exploitation of complementary model strengths. Without integrating both aspects, forecasting systems may still suffer from limited robustness under rapidly changing wind regimes.

Motivated by these observations, this study focused on how different modeling choices behave under changing wind conditions. In WindFusion-EW, highly non-stationary wind power series are first stabilized through a CEEMDAN-EWT decomposition so that short-term fluctuations and noise do not dominate the learning process. Multiple Transformer-based models are then trained in parallel, not because any one of them is universally superior, but because their strengths differ across operating regimes. To reflect this variability, model contributions are adjusted over time using month-wise validation errors rather than fixed weights. Tests on real wind power datasets from France and Turkey showed that this combination leads to more stable and consistently lower forecasting errors than conventional baseline approaches.

II. METHODOLOGY

A. Datasets

This study used two different wind farm datasets from France [11] and Turkey [12], both at 10-minute resolution. In the French dataset, the data were collected from one wind turbine located within the region of Haute, with SCADA data given for the electrical, mechanical, and wind-related fields, in order to forecast the active power output. In the Turkish dataset, the fields include operational and meteorological aspects, such as the actual power output, wind speed, wind direction, and theoretical power output.

In both datasets, data processing was performed every month. For each month, the data points were divided in time into 80% for training purposes and 20% for testing. A validation set, which is the final 10% of the training split, was held apart solely for weight estimates in the ensemble calculation.

B. WindFusion-EW Model

Figure 1 shows an overview of the WindFusion-EW model structure. The proposed pipeline focuses on straightforward logic: first, it stabilizes the wind energy signal and then combines various forecasts based on their accuracy, depending on the conditions. The SCADA raw measurements are normalized. The proposed method uses a two-level decomposition process on the series of interest, which represents the target wind farm. The signal is subjected to a processing method called CEEMDAN, which decomposes it into intrinsic mode functions. The signal is then further processed by the EWT method, ensuring that high-frequency variations do not negatively affect the model. After the reconstruction phase, the data is split into training, validation, and testing sets. Several forecasting models are processed in parallel instead of choosing one, due to the realization that different forecasting models have different performances depending on the regimes and periods. The performance of each individual forecasting model is examined on the validation sets with the help of the Mean Average Percentage Error (MAPE). The weights for these forecasting models are adjusted for their performances through the EnsembleWeighted mechanism, whereby the more reliable ones get higher weights, while the less reliable ones get lower weights.

C. Baseline Models

For comparison, a selection of baseline models was chosen to represent a variety of stages in wind power forecasting research. More traditional Machine Learning (ML) approaches, such as Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Random Forest (RF), were chosen as benchmarks, as they are still regularly applied in operational studies. To examine models with a focus on sequence, a Temporal Convolutional Network (TCN) based on dilated convolutions and residuals was applied with the same set of inputs. Hybrid models based on CEEMDAN-EWT-LSTM [3] were also included to determine whether there is a true advantage in the proposed approach.

D. Experimental Setup

All experiments were carried out on a cloud server with an NVIDIA RTX 3090 GPU (with 24 GB of VRAM). The models were developed using Python (PyTorch), including libraries that support time series forecasting, signal decomposition, and data processing. This setup worked well enough to avoid any constraints on training each individual and the ensemble model.

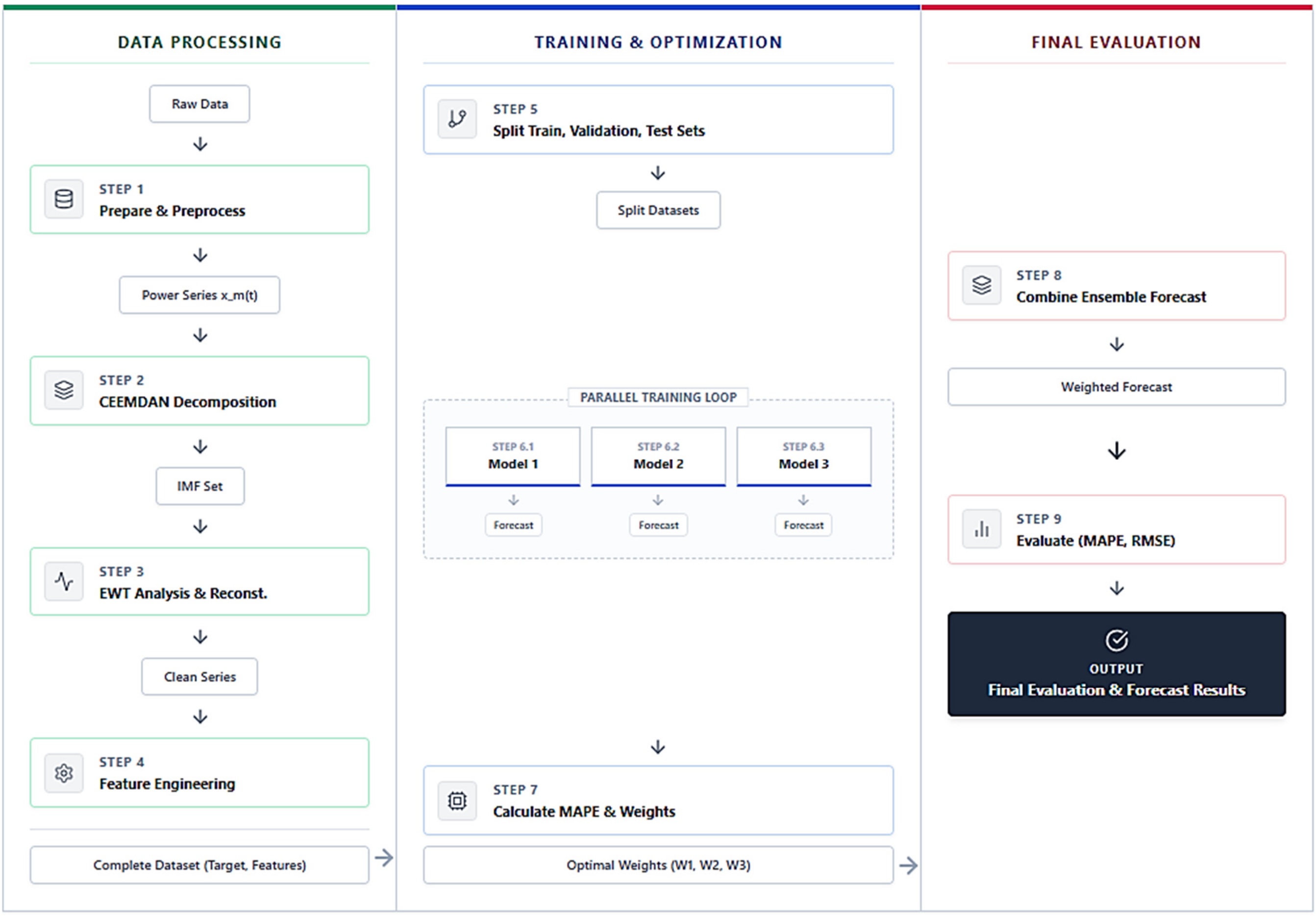


Fig. 1. The overall workflow of WindFusion-EW.

E. Metrics

Forecasting performance was evaluated using MAPE, RMSE, and MAE, which together reflect relative accuracy, sensitivity to large errors, and average deviation. Let N denote the number of test samples, y_t the observed value, and $\hat{y}_t$ the prediction at time step t. To avoid instability when actual power values are close to zero, we did not use the conventional MAPE formulation. Instead, errors were normalized by the installed capacity of the wind turbine, denoted as cap . In practice, cap was set to the monthly $\max(P_{\text{avg}})$. This choice ensured numerical stability and enabled fair comparisons across months and datasets with different power scales:

$$MAPE_{cap} = \frac{100}{N}\sum_{t=1}^{N}\frac{|y_t - \hat{y}_t|}{cap} \qquad (1)$$

RMSE was used to emphasize large forecasting deviations, which are particularly critical in operational settings where sudden errors can trigger costly balancing actions:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \qquad (2)$$

Finally, MAE was used to provide a direct and easily interpretable measure of average prediction error:

$$MAE = \frac{1}{N}|y_t - \hat{y}_t| \qquad (3)$$

III. RESULTS AND DISCUSSION

A. Monthly Performance Analysis of Individual Models

1) France Dataset

Figure 2 shows the monthly MAPE values of the individual forecasting models on the France dataset [11]. The results clearly show that forecasting accuracy changes across months instead of remaining stable over time. This variation is consistent with seasonal wind behavior, where wind patterns become more irregular during transition periods. Classical ML and single-model approaches, including SVR, RF, and standalone LSTM, produce higher errors and larger fluctuations compared to other methods. These models show noticeably worse performance during seasonal transition periods, such as late winter to early spring and early autumn, when wind conditions change more abruptly. Transformer-based models show mixed performance under the same experimental setup. TFT maintains relatively stable accuracy for most months, while Autoformer, N-HiTS, and TimesNet experience larger error variations in several periods. Although some of these models perform well during months with more stable wind conditions, their performance remains inconsistent overall, with clear error increases in certain months. The CEEMDAN-EWT-LSTM model shows more stable behavior throughout most of the year. Its MAPE values remain relatively low even during months with higher wind variability, while several other models exhibit noticeable error increases. This observation indicates that two-stage decomposition helps reduce signal instability and improve the robustness of the model. The results on this dataset confirm that forecasting performance is strongly dependent on temporal conditions, and relying on a single forecasting model may not be sufficient to achieve consistent accuracy.

2) Turkey Dataset

Figure 3 presents the monthly MAPE values for the Turkey dataset [12]. Compared with the France dataset, the error patterns show greater variability across months for almost all models. This behavior reflects the more unstable wind conditions at the Turkish wind farm, as well as the influence of additional input variables such as wind direction and theoretical power output. Similar to the France dataset, the standalone ML and DL models produce higher errors and larger month-to-month variations. Several clear error increases can be observed during winter and seasonal transition periods, when wind speed and direction change more abruptly. The overall magnitude of these variations is also larger than that observed in the France dataset, indicating higher short-term uncertainty. Transformer-based models again show inconsistent performance. Autoformer, N-HiTS, and TimesNet achieve relatively low errors during some stable periods, but their performance deteriorates in other months. These fluctuations suggest that even advanced Transformer architectures may not fully adapt to all wind regimes.

In contrast, the CEEMDAN-EWT-LSTM model demonstrates more stable performance throughout the year. Its MAPE values remain relatively low throughout most months, including periods in which other models experience noticeable error increases. Although slight performance degradation appears in a few months, its overall stability remains higher than that of both classical and Transformer-based models. This result indicates that two-stage signal decomposition helps reduce the impact of signal variability and improves forecasting robustness.

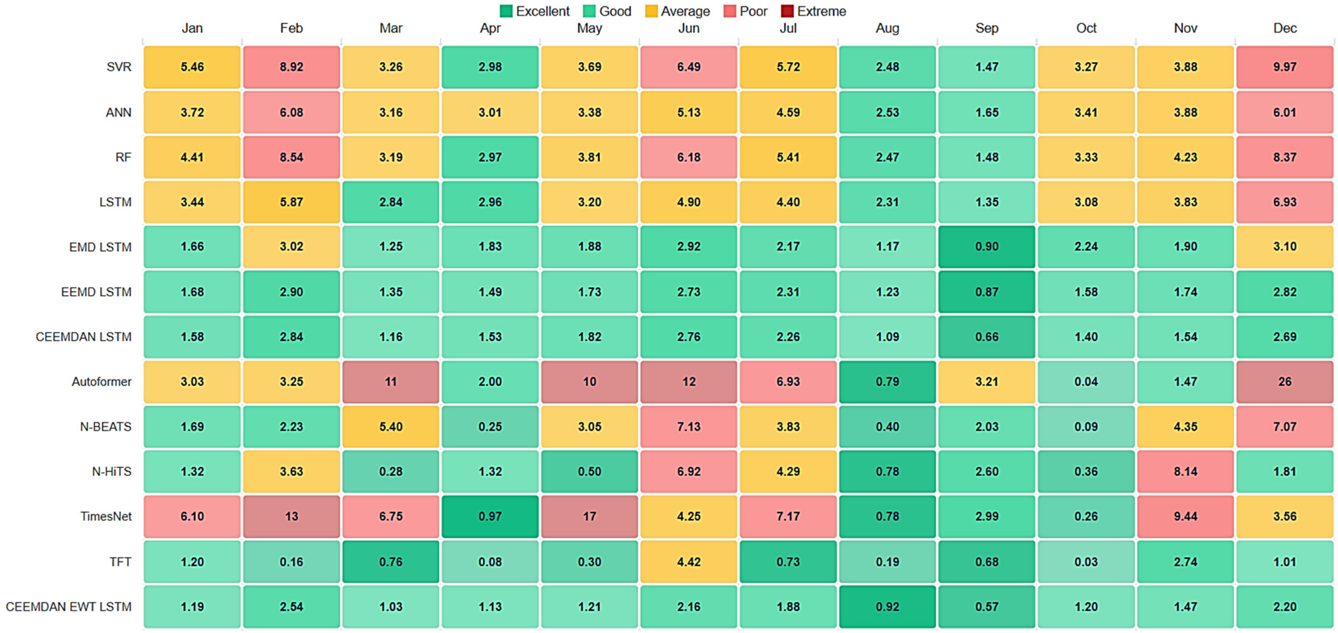
The observations from both datasets show that forecast performance varies depending on temporal conditions and wind regimes. No single model performs best in all situations. Instead, different models show advantages in different periods. Based on this observation, WindFusion-EW was designed to adaptively combine multiple forecasting models using validation-based weighting. Adjusting the model contributions according to their recent performance, the framework maintains stable and accurate forecasting results under changing wind conditions.

B. Average Performance Comparison and Evaluation of the Proposed Model

Tables I and II summarize the average forecasting performance of all models on the France and Turkey datasets, respectively. Unlike the monthly analysis, these tables are used to directly assess the effectiveness of the proposed WindFusion-EW model. For the France dataset, classical ML models produce the largest errors across all metrics, indicating a limited capability to model the noisy and nonlinear characteristics of the SCADA wind power data.

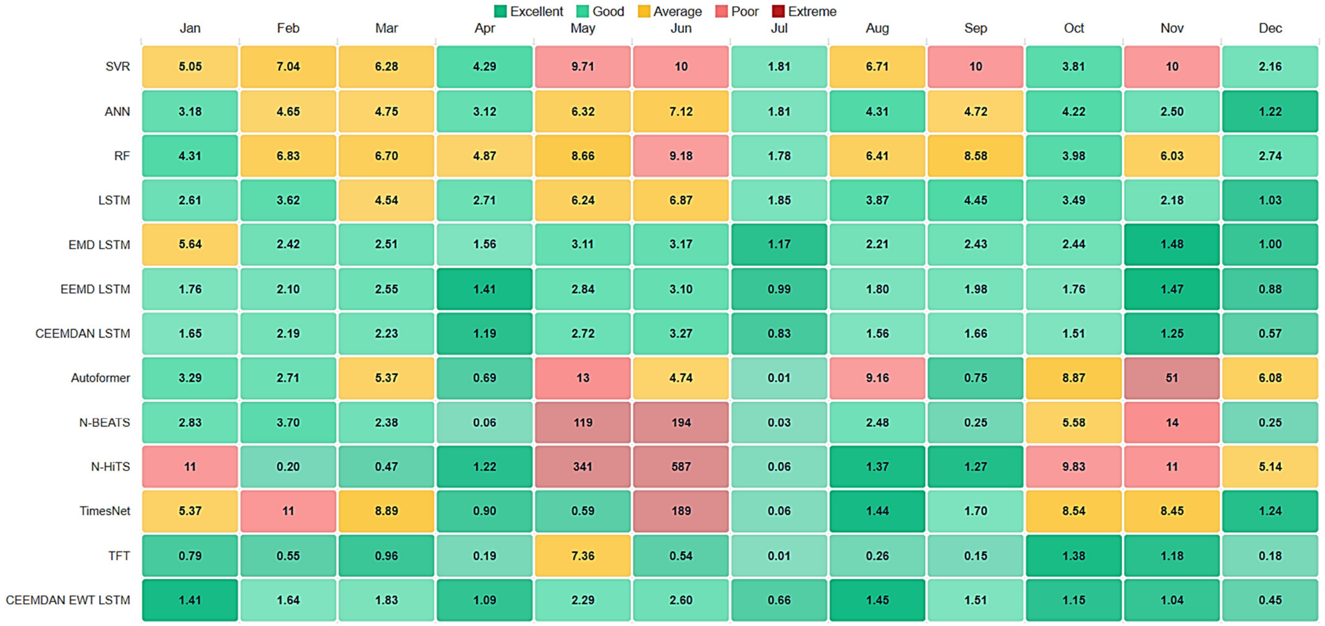
The ANN model yields moderate improvements, but its performance remains inferior to that of sequence-based approaches. Introducing temporal modeling through LSTM leads to a substantial reduction in error, confirming the importance of capturing sequential dependencies in ultra-short-term forecasting. Further improvements are achieved when signal decomposition is applied prior to prediction. Single-stage decomposition models, such as EMD-LSTM, EEMD-LSTM, and CEEMDAN-LSTM, consistently outperform the plain LSTM, with CEEMDAN-LSTM yielding the lowest error among one-stage variants. The benefit becomes more pronounced for the CEEMDAN-EWT-LSTM model, whose average MAPE decreases to 1.16%, accompanied by significantly lower RMSE and MAE. This result demonstrates that refining frequency components through a second decomposition stage provides additional gains beyond standard CEEMDAN preprocessing.

The performance of modern transformer-based architectures varies substantially. TimesNet, Autoformer, and N-HiTS exhibit relatively high average errors on the France dataset, suggesting limited generalization under the given data characteristics and feature configuration. In contrast, TFT achieves a much lower average MAPE of 1.32%, indicating stronger robustness to underlying data variability.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SVR	5.46	8.92	3.26	2.98	3.69	6.49	5.72	2.48	1.47	3.27	3.88	9.97
ANN	3.72	6.08	3.16	3.01	3.38	5.13	4.59	2.53	1.65	3.41	3.88	6.01
RF	4.41	8.54	3.19	2.97	3.81	6.18	5.41	2.47	1.48	3.33	4.23	8.37
LSTM	3.44	5.87	2.84	2.96	3.20	4.90	4.40	2.31	1.35	3.08	3.83	6.93
EMD LSTM	1.66	3.02	1.25	1.83	1.88	2.92	2.17	1.17	0.90	2.24	1.90	3.10
EEMD LSTM	1.68	2.90	1.35	1.49	1.73	2.73	2.31	1.23	0.87	1.58	1.74	2.82
CEEMDAN LSTM	1.58	2.84	1.16	1.53	1.82	2.76	2.26	1.09	0.66	1.40	1.54	2.69
Autoformer	3.03	3.25	11	2.00	10	12	6.93	0.79	3.21	0.04	1.47	26
N-BEATS	1.69	2.23	5.40	0.25	3.05	7.13	3.83	0.40	2.03	0.09	4.35	7.07
N-HiTS	1.32	3.63	0.28	1.32	0.50	6.92	4.29	0.78	2.60	0.36	8.14	1.81
TimesNet	6.10	13	6.75	0.97	17	4.25	7.17	0.78	2.99	0.26	9.44	3.56
TFT	1.20	0.16	0.76	0.08	0.30	4.42	0.73	0.19	0.68	0.03	2.74	1.01
CEEMDAN EWT LSTM	1.19	2.54	1.03	1.13	1.21	2.16	1.88	0.92	0.57	1.20	1.47	2.20

Fig. 2. Performance MAPE per month in the France dataset.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SVR	5.05	7.04	6.28	4.29	9.71	10	1.81	6.71	10	3.81	10	2.16
ANN	3.18	4.65	4.75	3.12	6.32	7.12	1.81	4.31	4.72	4.22	2.50	1.22
RF	4.31	6.83	6.70	4.87	8.66	9.18	1.78	6.41	8.58	3.98	6.03	2.74
LSTM	2.61	3.62	4.54	2.71	6.24	6.87	1.85	3.87	4.45	3.49	2.18	1.03
EMD LSTM	5.64	2.42	2.51	1.56	3.11	3.17	1.17	2.21	2.43	2.44	1.48	1.00
EEMD LSTM	1.76	2.10	2.55	1.41	2.84	3.10	0.99	1.80	1.98	1.76	1.47	0.88
CEEMDAN LSTM	1.65	2.19	2.23	1.19	2.72	3.27	0.83	1.56	1.66	1.51	1.25	0.57
Autoformer	3.29	2.71	5.37	0.69	13	4.74	0.01	9.16	0.75	8.87	51	6.08
N-BEATS	2.83	3.70	2.38	0.06	119	194	0.03	2.48	0.25	5.58	14	0.25
N-HiTS	11	0.20	0.47	1.22	341	587	0.06	1.37	1.27	9.83	11	5.14
TimesNet	5.37	11	8.89	0.90	0.59	189	0.06	1.44	1.70	8.54	8.45	1.24
TFT	0.79	0.55	0.96	0.19	7.36	0.54	0.01	0.26	0.15	1.38	1.18	0.18
CEEMDAN EWT LSTM	1.41	1.64	1.83	1.09	2.29	2.60	0.66	1.45	1.51	1.15	1.04	0.45

Fig. 3. Fig. 3 Performance MAPE per month in the Turkey dataset.

Across all models, WindFusion-EW achieves the lowest error values on all metrics. Compared with the strongest individual model (TFT), the proposed framework further reduces MAPE, RMSE, and MAE, demonstrating that adaptively combining multiple forecasting models yields consistent gains over relying on a single architecture.

On the Turkey dataset (Table II), overall error levels increase for most models due to more volatile wind conditions. Classical approaches again perform poorly, while LSTM-based and decomposition-based models provide improved accuracy. CEEMDAN-EWT-LSTM maintains relatively low errors, confirming the robustness of the two-stage decomposition. However, Transformer-based models exhibit highly diverse behavior, with some architectures suffering severe performance degradation under this dataset. Despite these challenges, WindFusion-EW consistently achieves the lowest average errors across all metrics on the Turkey dataset. This result highlights the ability of the proposed adaptive ensemble framework to effectively handle heterogeneous wind conditions and varying data distributions.

TABLE I. AVERAGE PERFORMANCE ON THE FRANCE DATASET

Model / Method	Avg. MAPE	Avg. RMSE	Avg. MAE
RF	5.43	134.70	92.94
SVR	4.97	147.66	98.43
ANN	4.09	119.80	79.53
LSTM	3.60	77.10	41.07
EMD-LSTM [3]	2.69	66.97	38.34
EEMD-LSTM [3]	2.71	62.87	36.43
CEEMDAN-LSTM [3]	2.55	57.38	34.33
CEEMDAN-EWT-LSTM [3]	1.16	41.07	29.91
TimesNet	6.29	126.40	126.40
Autoformer	6.67	131.80	131.80
N-HiTS	6.02	117.06	117.06
N-BEATS	2.66	53.11	53.11
TFT	1.32	26.52	26.52
WindFusion-EW (Ours)	**1.02**	**20.54**	**20.54**

TABLE II. AVERAGE PERFORMANCE ON THE TURKEY DATASET

Model / Method	Avg. MAPE	Avg. RMSE	Avg. MAE
RF	5.84	346.16	211.29
SVR	6.44	436.70	233.06
ANN	3.99	144.50	121.29
LSTM	3.58	131.05	87.86
EMD-LSTM [3]	2.43	87.86	68.30
EEMD-LSTM [3]	2.43	86.20	62.20
CEEMDAN-LSTM [3]	2.30	68.30	51.61
CEEMDAN-EWT-LSTM [3]	1.43	62.20	51.61
TimesNet	8.73	314.61	314.61
N-HiTS	19.75	714.00	714.00
Autoformer	8.86	319.24	319.24
N-BEATS	80.78	2918.64	2918.64
TFT	1.56	56.18	56.18
WindFusion-EW (Ours)	**1.13**	**40.72**	**40.72**

IV. CONCLUSION

Ultra-short-term wind power forecasting remains challenging due to signal non-stationarity and the inconsistent performance of individual forecasting models. Existing approaches typically address signal decomposition or model prediction separately, limiting robustness under changing wind conditions. To address this gap, this study proposed WindFusion-EW, an adaptive forecasting framework that integrated CEEMDAN-EWT signal decomposition with a dynamically weighted multi-model ensemble. Experimental results on two datasets showed that the proposed model achieved the lowest forecasting errors, with average MAPE values of 1.02% and 1.13%, respectively, outperforming other models. The main contribution is the development of a unified and adaptive framework that combines signal stabilization and dynamic model fusion to improve forecasting accuracy and robustness. Future work will focus on improving computational efficiency for real-time applications.

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