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WaveHiTS: Wavelet-Enhanced Hierarchical Time Series Modeling for Wind Direction Nowcasting in Eastern Inner Mongolia

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ABSTRACT

Wind direction forecasting plays a crucial role in optimizing wind energy production, but faces significant challenges due to the circular nature of directional data, error accumulation in multi-step forecasting, and complex meteorological interactions. This paper presents a novel model, WaveHiTS, which integrates wavelet transform with Neural Hierarchical Interpolation for Time Series to address these challenges. Our approach decomposes wind direction into U-V components, applies wavelet transform to capture multi-scale frequency patterns, and utilizes a hierarchical structure to model temporal dependencies at multiple scales, effectively mitigating error propagation. Experiments conducted on real-world meteorological data from Inner Mongolia, China demonstrate that WaveHiTS significantly outperforms deep learning models (RNN, LSTM, GRU), transformer-based approaches (TFT, Informer, iTransformer), and hybrid models (EMD-LSTM). The proposed model achieves RMSE values of approximately 19.2°-19.4° compared to 56°-64° for deep learning recurrent models, maintaining consistent accuracy across all forecasting steps up to 60 minutes ahead. Moreover, WaveHiTS demonstrates superior robustness with vector correlation coefficients (VCC) of 0.985-0.987 and hit rates of 88.5%-90.1%, substantially outperforming baseline models. Ablation studies confirm that each component—wavelet transform, hierarchical structure, and U-V decomposition—contributes meaningfully to overall performance. These improvements in wind direction nowcasting have significant implications for enhancing wind turbine yaw control efficiency and grid integration of wind energy.

1 Introduction

Wind energy is rapidly emerging as a cornerstone of the global transition towards sustainable and renewable energy sources^{1,2}. As nations strive to decarbonize their energy systems and combat climate change, the efficient and reliable integration of wind power into existing electricity grids is becoming increasingly critical³⁻⁵. However, the inherent intermittency and variability of wind resources pose significant challenges to grid operators and wind farm managers. Wind speed and direction are highly stochastic, exhibiting complex, non-linear patterns across various temporal and spatial scales^{6,7}. These fluctuations make accurate forecasting of wind power generation a difficult yet essential task.

The accurate prediction of wind direction plays a vital role in optimizing wind farm operations, as precise short-term forecasts (nowcasts) with horizons ranging from minutes to a few hours are essential for various aspects such as turbine yaw control, grid stability, economic dispatch, and maintenance scheduling. For instance, wind turbines must constantly adjust their orientation (yaw) to face the incoming wind, and accurate wind direction nowcasts enable proactive yaw adjustments that maximize energy capture and minimize structural loads—thereby reducing wear and tear and increasing energy production—although even small errors in direction prediction can lead to significant power losses and increased mechanical stress^{6,7}. Moreover, grid operators rely on these forecasts to balance supply and demand, schedule reserve generation, and maintain grid stability⁶, while in electricity markets, accurate wind power forecasts allow wind farm operators to participate effectively in energy trading, optimize their bidding strategies, and minimize penalties for forecast deviations. Anticipating changes in wind direction further aids in scheduling maintenance activities, minimizing downtime and maximizing operational efficiency.

Wind direction nowcasting is crucial but uniquely challenging due to several factors. First, wind direction is a circular variable, where 0° and 360° represent the same direction (North), and traditional forecasting models that use Euclidean distance metrics, such as Mean Squared Error, struggle with circular data. These models tend to penalize predictions near the 0°/360° boundary disproportionately—for instance, a prediction of 359° when the true direction is 1° would be penalized as a 358° error, even though the actual error is only 2°⁸. Additionally, multi-step forecasting often leads to error accumulation, where inaccuracies in earlier predictions propagate, affecting the accuracy of longer-term forecasts⁹. This issue is especially

problematic for Recurrent Neural Network (RNN)-based models commonly used in time series forecasting. Furthermore, wind patterns are influenced by numerous factors, such as large-scale weather systems, local topography, and atmospheric conditions, all of which create complex, non-linear interactions that require models capable of handling high-dimensional input data and learning intricate dependencies¹⁰. Finally, the rapid changes in wind direction and the challenges in data collection often result in noisy data, complicating the prediction process⁴.

Traditional statistical methods, such as ARIMA models¹¹, struggle with the non-linearity¹⁰ and circularity of wind direction¹². While machine learning approaches like SVM and RF offer some improvements^{13–15}, they often fall short in handling the circular nature of the data and the accumulation of errors in multi-step forecasting. Deep learning models, such as CNN, LSTM, and hybrid CNN-LSTM architectures, show promise in capturing spatio-temporal dependencies^{11,16,17}, but still need to address the circularity issue. Attention-based models, including Transformers, excel at capturing long-range dependencies^{8,18,19}, but their computational cost can be prohibitive, and they still lack inherent mechanisms for handling circular data. Hybrid models like EMD-LSTM²⁰ attempt to combine the strengths of different approaches, but challenges remain in effectively addressing all the aforementioned issues.

To overcome these limitations, this paper proposes the Wavelet Transform-enhanced Neural Hierarchical Interpolation for Time Series (WaveHiTS) model. This novel approach integrates:

- U-V Decomposition: Wind direction is decomposed into its U (east-west) and V (north-south) components, transforming the circular variable problem into a standard regression problem. This eliminates the issues associated with the 0°/360° boundary.
- Wavelet Transform (WT): WT decomposes the wind data into multiple frequency components, allowing the model to capture variations at different time scales and to reduce noise²¹. This is particularly effective for non-stationary time series like wind data.
- Neural Hierarchical Interpolation for Time Series (N-HiTS): The N-HiTS architecture⁹ provides a hierarchical structure that is well-suited for multi-step forecasting. It mitigates error accumulation by learning temporal dependencies at multiple scales.

By combining these techniques, WaveHiTS offers a robust and accurate solution for wind direction nowcasting, addressing the key challenges that have limited the performance of previous approaches. This model is designed to be readily applicable to real-world wind energy applications, contributing to improved grid management, optimized turbine operation, and increased wind energy utilization.

2 Related Work

The evolution of wind direction forecasting can be traced through several key stages, each marked by advancements in methodologies and approaches.

2.1 Traditional Statistical Methods

Early wind forecasting relied heavily on statistical models. Persistence models, which assume future wind direction will remain similar to the present, served as a basic benchmark. Autoregressive models, such as the Autoregressive Integrated Moving Average (ARIMA) model¹¹ and its variations, including ARMA²² and Seasonal ARIMA (SARIMA), were employed to capture temporal dependencies in wind data. However, these linear models struggle with the non-linearity and complex dynamics of wind patterns²³ and are not designed to address circularity. A further exploration of statistical models, such as the vector autoregression (VAR) models, has been applied²².

2.2 Machine Learning Approaches

The advent of machine learning introduced more powerful tools for modeling non-linear relationships. Support Vector Machines (SVM)¹³ and Random Forests (RF)^{14,15} gained popularity for their ability to handle complex data without explicit physical modeling. However, challenges remained in addressing circularity and multi-step forecasting errors²⁴.

2.3 Deep Learning Models

Deep learning has significantly impacted time series forecasting in recent years. Convolutional Neural Networks (CNNs) have proven effective in extracting spatial features from wind field data^{16,25}. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks⁴, excel at capturing temporal dependencies. Hybrid architectures, combining CNNs and LSTMs, leverage the strengths of both approaches to model spatio-temporal patterns¹⁷. Additionally, deep convolutional LSTM has been used for wind speed and direction⁴. Recent work has also explored location-centric Transformer frameworks to address the spatial relationships between multiple wind forecasting locations²⁶. Despite these advancements, the circular nature of wind direction and error accumulation in multi-step forecasting remains persistent challenges.

2.4 Attention-Based Models and Transformers

Attention mechanisms, particularly within Transformer architectures, have revolutionized sequence modeling by capturing long-range dependencies^{8,18,19}. Temporal Fusion Transformers (TFT) represent a notable application of attention to multi-horizon forecasting⁸. Furthermore, some studies have also incorporated interpretability into the design of Transformer networks²⁷. Zhang et al.

2.5 Hybrid and Ensemble Methods

To address the limitations of individual models, researchers have explored hybrid approaches. Empirical Mode Decomposition (EMD) combined with LSTM (EMD-LSTM)²⁸ decomposes wind data into intrinsic mode functions to capture non-linear and non-stationary characteristics. Other hybrid models combine multiple techniques, such as wavelet decomposition, neural networks, and optimization algorithms, to improve forecasting accuracy²¹. While these approaches show promise, they may still struggle with multi-step forecasting and the circularity of wind direction.

2.6 Wavelet Transform in Wind Forecasting

Wavelet Transform (WT) has been recognized as a valuable tool for analyzing non-stationary time series data, such as wind speed and direction²¹. Wavelet Transform (WT) decomposes the signal into different frequency components, facilitating the extraction of features at multiple scales. This multi-resolution analysis capability is particularly useful for capturing the complex and fluctuating nature of wind patterns. Studies have demonstrated the effectiveness of WT in enhancing the performance of neural networks for wind speed prediction^{29,30}.

Despite significant advances in wind direction prediction, several challenges persist in the field. One such challenge is the circular nature of wind direction, where existing methods often struggle near the $0^\circ/360^\circ$ boundary due to a lack of explicit handling. Additionally, error propagation remains a concern in multi-step ahead forecasts, impacting forecast accuracy.

To address these limitations, the WaveHiTS model, proposed in recent research, combines wavelet analysis with a hierarchical neural network architecture. This innovative approach is tailored specifically to handle circular data and improve accuracy in multi-step forecasting, aiming to advance the state-of-the-art in wind direction prediction methodologies.

3 Methodology

3.1 Motivation for Model Design

Accurate short-term forecasting of wind direction is essential for the efficient operation of wind farms and the effective integration of wind energy into power grids. However, existing methods struggle with several key challenges inherent in wind direction data, including the circular nature of the data, multi-step error accumulation, and integration of diverse meteorological variables. These challenges can lead to significant forecasting inaccuracies when using traditional models, particularly in terms of error propagation over multiple steps and failing to account for the periodicity of wind direction.

To address these issues, we propose the WaveHiTS model, which integrates wavelet transform with the Neural Hierarchical Interpolation for Time Series (N-HiTS) model⁹. The goal of this methodology is to provide an accurate and robust solution for multi-step wind direction forecasting by overcoming the limitations of existing models. The proposed approach focuses on:

- (1) Circular Data Handling: Effectively managing the periodicity of wind direction data by decomposing the wind direction into U and V components, allowing the model to address boundary issues at 0° and 360° .
- (2) Wavelet-Based Feature Enhancement: wavelets provide localized time-frequency information, allow the model to better handle the wind direction signal, and improve the signal-to-noise ratio through low-pass filtering.
- (3) Mitigation of Error Accumulation: Utilizing the hierarchical structure of the N-HiTS model to minimize error propagation over multi-step forecasts, ensuring accuracy across extended forecasting horizons.

3.2 Proposed Methodology Overview

The WaveHiTS model is a comprehensive framework designed to enhance multi-step wind direction forecasting by addressing key challenges such as the circular nature of wind direction data, error accumulation over time, and the multi-scale characteristics of wind patterns. By integrating wavelet transform for frequency-domain analysis with the Neural Hierarchical Interpolation for Time Series (N-HiTS) architecture, this model provides a robust solution that improves forecasting accuracy. The methodology is composed of three primary components, each designed to tackle a specific issue in wind direction prediction (Fig. 1).

3.2.1 Circular Data Handling

Wind direction is a circular variable where 0° and 360° represent the same direction (North). This creates significant challenges for traditional forecasting models that use Euclidean metrics, as the error calculations between boundary values can be misleading. For example, a predicted value of 359° when the actual direction is 1° would produce an erroneous error of 358° using Euclidean distance, even though the true error is only 2° . To address this, the WaveHiTS model transforms the

WaveHiTS Deep Learning Architecture for Wind Direction Forecasting

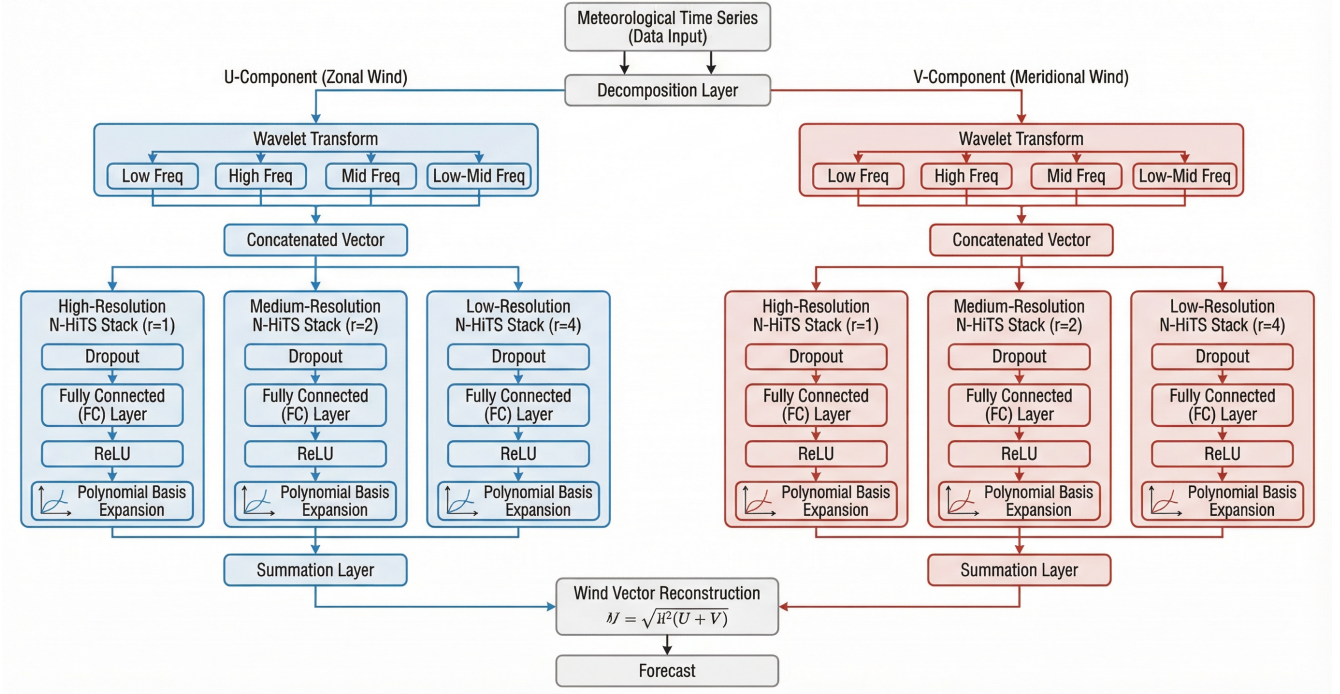


Figure 1. Flowchart of the proposed approach combining wavelet and NHITS

wind direction into its linear U (east-west) and V (north-south) components, which are free of circular discontinuities. This transformation eliminates boundary issues at $0^\circ/360^\circ$, ensuring that the error calculation remains accurate. By converting the circular wind direction data into two linear regression tasks for U and V components, the model simplifies the forecasting problem and avoids the complications that arise from circular data. Furthermore, the wind speed information is preserved during the transformation, allowing the model to forecast the wind field in a more comprehensive way.

The decomposition is formulated as:

$$U_t = -s_t \cdot \sin\left(\theta_t \cdot \frac{\pi}{180}\right) \quad (1)$$

$$V_t = -s_t \cdot \cos\left(\theta_t \cdot \frac{\pi}{180}\right) \quad (2)$$

where U_t and V_t represent the east-west and north-south wind components at time t , respectively. s_t is the wind speed at time t , and θ_t is the wind direction in degrees. The factor $\frac{\pi}{180}$ converts degrees into radians.

The wind direction can then be recomputed using:

$$\theta_t = \arctan 2(U_t, V_t) \cdot \frac{180}{\pi} \quad (3)$$

This method effectively transforms the circular nature of wind direction into linear regression tasks that are easier to handle computationally, thus improving the accuracy of multi-step wind direction forecasting.

3.2.2 Wavelet Transform for Frequency Analysis

Wind direction is inherently non-stationary, with multi-scale behaviors that involve both short-term turbulence and long-term trends. To capture these dynamics, the WaveHiTS model applies the Discrete Wavelet Transform (DWT) using the Daubechies-4 (db4) wavelet to break down the U and V time series into frequency components. This decomposition helps the model better understand the varying temporal patterns that might not be immediately apparent in the raw time series data.

The DWT is expressed as:

$$W_{j,k} = 2^{-j/2} \sum_n x[n] \psi(2^{-j}n - k) \quad (4)$$

where $W_{j,k}$ represents the wavelet coefficient at scale j and position k , capturing the frequency content of the signal at different resolutions. $x[n]$ is the input time series, either U_t or V_t , discretized at time step n . ψ is the wavelet basis function; in this case, db4, which is applied to the data to extract frequency components. j is the scale parameter that controls the resolution of the frequency decomposition, and k is the translation parameter, which shifts the wavelet function in time.

This decomposition process allows the model to capture both short-term and long-term trends in wind direction, thus improving the overall accuracy and robustness of the forecasts.

3.2.3 Neural Hierarchical Interpolation for Time Series (N-HITS)

To address error accumulation in multi-step forecasting, the N-HITS component models temporal dependencies across multiple scales using a hierarchical structure. Each block in this hierarchy processes the input at a different temporal resolution, allowing the model to capture both short-term fluctuations and long-term trends.

The forecast is computed as:

$$\hat{y}_{t+1:t+H} = \sum_{i=1}^B \hat{y}_{t+1:t+H}^{(i)} \quad (5)$$

where $\hat{y}_{t+1:t+H}$ represents the predicted time series from time $t+1$ to $t+H$, where H is the forecast horizon. B is the number of blocks in the hierarchical structure, and $\hat{y}_{t+1:t+H}^{(i)}$ is the forecast produced by block i .

Each block's output is computed as:

$$\hat{y}_{t+1:t+H}^{(i)} = g^{(i)}(f^{(i)}(x_t^{(i)})) \quad (6)$$

where $x_t^{(i)}$ is the input to block i , which is downsampled by a factor of r_i . Different blocks operate at different temporal resolutions. $f^{(i)}$ is a non-linear function, such as fully connected layers, that processes the input data, and $g^{(i)}(h)$ is a basis expansion function that combines the outputs from the non-linear functions.

By downsampling the time series and processing it at different resolutions, the hierarchical model can effectively capture both short-term fluctuations and long-term trends, resulting in a more accurate multi-step forecast. This hierarchical modeling significantly reduces error propagation, maintaining stable RMSE values and improving the model's ability to handle multi-step predictions with high accuracy.

The combination of circular data handling, wavelet transform for frequency analysis, and hierarchical interpolation for time series effectively tackles the challenges of multi-step wind direction forecasting, leading to more accurate and robust predictions.

4 Experimental Setup

4.1 Dataset

The experiments were conducted using a real-world meteorological dataset from an operational wind farm in Inner Mongolia, China, providing a relevant and practical testbed for wind direction nowcasting. The dataset spans from November 5, 2020, to July 15, 2022, and consists of 87,558 samples (Fig. 2), including pressure, temperature, humidity, precipitation, 2-minute average wind speed and direction, and 10-minute average wind speed and direction. The 10-minute interval data provide the high temporal resolution necessary for capturing the short-term dynamics of wind direction, with the 2-minute average wind direction serving as the target variable for our predictions.

4.2 Baseline Models

To evaluate the effectiveness of the WaveHiTS model, we compare it with several baseline models, representing deep learning, state-of-the-art, and hybrid approaches in time series forecasting. These models include:

(1) Deep Learning Models

Recurrent Neural Networks (RNN): A simple sequential model for capturing temporal dependencies. Long Short-Term Memory (LSTM): A model that excels in capturing long-term dependencies in time series data. Gated Recurrent Units (GRU): A more efficient variant of LSTM that maintains performance while reducing computational complexity.

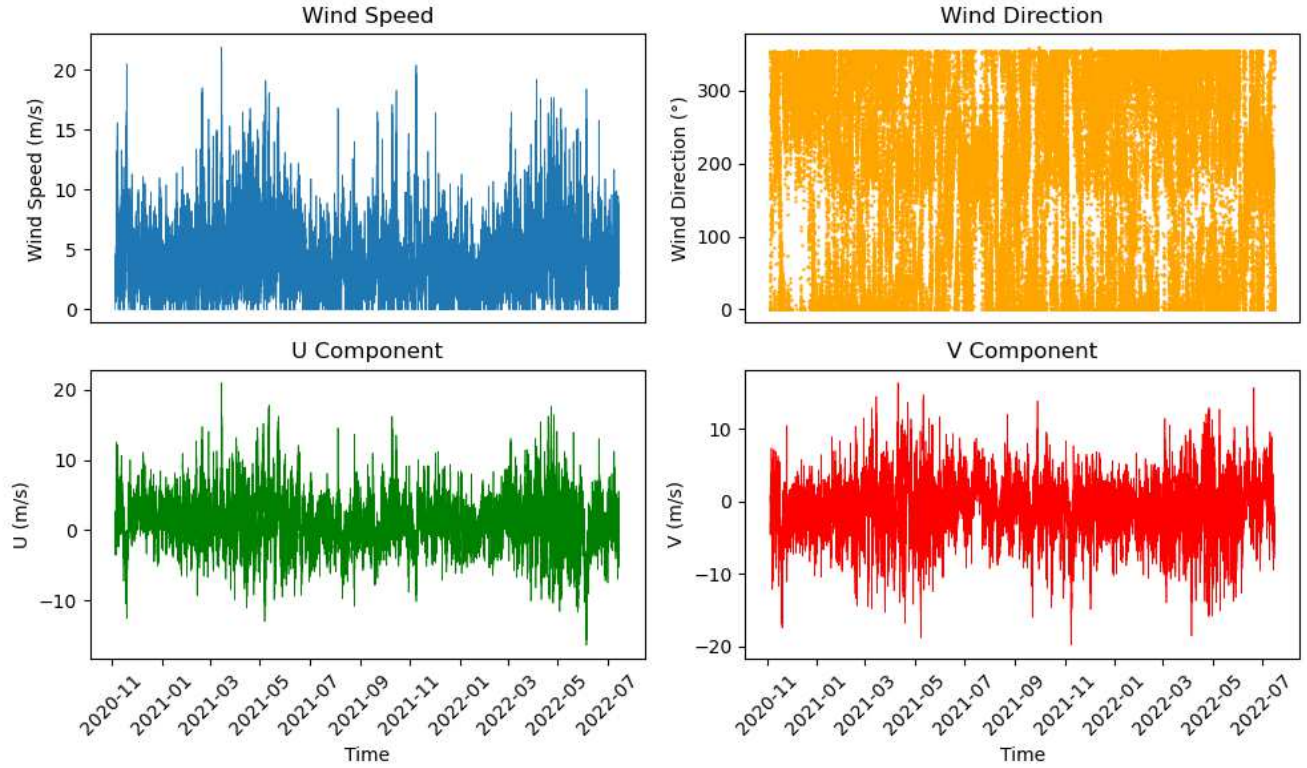


Figure 2. The wind speed, wind direction, U, and V components of some data are displayed

(2) Transformer-Based Models

Temporal Fusion Transformer (TFT): A transformer-based model that uses attention mechanisms to capture complex temporal patterns. Informer: A transformer model optimized for processing long sequence data efficiently. iTransformer: An improved transformer that focuses on capturing long-range dependencies.

(3) Hybrid Models

EMD-LSTM: A hybrid approach that combines Empirical Mode Decomposition (EMD) with LSTM to handle non-stationary and non-linear data characteristics.

4.3 Experimental Groups

To thoroughly evaluate the performance of the proposed WaveHiTS model and the effectiveness of different forecasting strategies, we conducted two main sets of experiments:

Group 1: Direct Wind Direction Forecasting: In this group, the following models were trained to directly predict wind direction (WD) as a single, circular variable: RNN, LSTM, GRU, TFT, Informer, iTransformer, and N-HiTS. These models receive the historical wind direction, and other meteorological inputs, and output a direct prediction of the future wind direction.

Group 2: Indirect Wind Direction Forecasting: This group focused on predicting the U and V components of wind direction separately, and then combining these predictions to obtain the final wind direction. The following models were used in this group: EMD-LSTM, N-HiTS-UV, and WaveHiTS. These models receive the historical U and V components, and other meteorological inputs, and output a prediction for both future U and V components. The predicted U and V are subsequently converted back to wind direction for evaluation. This two-group experimental design allows us to directly compare the performance of models that treat wind direction as a single circular variable versus those that decompose it into Cartesian components, thus assessing the impact of our proposed U-V decomposition strategy.

4.4 Evaluation Metrics

We evaluate the performance of the models using the following metrics. Considering the periodicity of wind direction data, we make appropriate modifications to these evaluation metrics. Mean Absolute Error (MAE): Measures the average absolute difference between the predicted and actual values. It provides a clear interpretation in the original units of wind direction.

$$MAE_{periodic} = \frac{1}{N} \sum_{i=1}^N \min(|\theta_{pred,i} - \theta_{true,i}|, 360^\circ - |\theta_{pred,i} - \theta_{true,i}|) \quad (7)$$

Root Mean Squared Error (RMSE): The square root of the average squared differences between predicted and actual values, highlighting larger errors.

$$RMAE_{periodic} = \frac{MAE_{periodic}}{mean(\theta_{true})} \quad (8)$$

Vector Correlation Coefficient (VCC): Measures the alignment between predicted and actual wind direction vectors, with values closer to 1 indicating better alignment.

$$VCC = \frac{\sum_{i=1}^N (U_{pred,i} U_{true,i} + V_{pred,i} V_{true,i})}{\sqrt{\sum_{i=1}^N (U_{pred,i}^2 + V_{pred,i}^2)} \cdot \sqrt{\sum_{i=1}^N (U_{true,i}^2 + V_{true,i}^2)}} \quad (9)$$

Hit Rate (HR): The percentage of predictions falling within an acceptable error margin (e.g., 15°) from the true values.

$$HR = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(\min(|\theta_{pred,i} - \theta_{true,i}|, 360^\circ - |\theta_{pred,i} - \theta_{true,i}|) \leq \delta) \quad (10)$$

where $\mathbb{I}(\cdot)$ is an indicator function.

5 Results and Analysis

5.1 Performance Comparison of Models

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
RNN	38.030	38.665	39.661	41.504	43.633	43.975
GRU	37.029	38.211	40.148	42.755	43.717	44.733
LSTM	38.054	39.170	40.964	41.915	42.961	44.182
Informer	32.046	30.987	30.746	30.355	30.860	30.285
iTransformer	30.120	29.346	28.660	28.366	28.401	28.161
TFT	21.624	21.698	21.731	21.776	21.763	21.753
EMDLSTM	18.235	16.602	16.327	17.300	17.229	17.651
NHITS	11.054	11.358	11.553	12.427	12.450	13.009
NHITS(UV)	9.124	8.740	8.459	8.455	8.506	8.896
WaveHiTS	8.027	8.051	8.010	8.134	8.273	8.302

Table 1. Comparison of MAE for wind direction prediction across different forecasting horizons and models. Bold values indicate the best performance for each forecasting step; underlined values indicate the second-best performance.

We conducted extensive experiments to compare the performance of our proposed WaveHiTS model with several baseline models, including RNN, LSTM, GRU, TFT, Informer, iTransformer, and EMD-LSTM. The models were evaluated based on their ability to predict wind components (U, V) and wind direction (WD) over 6 forecasting steps, corresponding to a 60-minute prediction horizon.

5.1.1 Wind Direction (WD) Prediction

Predicting wind direction is inherently challenging due to its circular nature, where values near 0° and 360° represent the same direction. The results from our experiments, summarized in Tables 1 to 3 and illustrated in Fig. 3, underscore the performance advantages of the WaveHiTS model compared to various baseline approaches.

The WaveHiTS model achieved the lowest RMSE values, ranging from 19.433° to 19.184° across all six forecasting steps (Table 2), demonstrating its effective minimization of prediction errors over the entire forecasting horizon. Furthermore, it consistently produced low MAE values, from 8.027 to 8.302 (Table 1), indicating the model's high accuracy in multi-step forecasting. The model effectively handled the circularity of wind direction by decomposing it into U and V components, which substantially reduced prediction discontinuities near the 0°/360° boundary, as shown in Fig. 3. This ability to handle circular data contributed significantly to the model's stability and accuracy.

In contrast, the baseline models showed higher errors and less stability over the forecasting horizon. The RNN, LSTM, and GRU models recorded RMSE values of 56.001° to 63.143° for RNN, 56.464° to 64.158° for GRU, and 57.888° to 63.339°

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
RNN	56.001	57.667	58.326	60.412	61.996	63.143
GRU	56.464	57.210	59.531	61.658	62.907	64.158
LSTM	57.888	58.883	60.380	61.425	62.176	63.339
Informer	49.013	47.778	47.802	47.319	47.931	47.120
iTransformer	46.817	45.811	45.062	45.114	45.687	44.992
TFT	35.729	35.898	36.008	36.123	36.086	36.043
EMDLSTM	30.575	28.495	28.092	29.234	29.084	29.593
NHITS	24.558	23.809	24.574	25.523	25.718	25.742
NHITS(UV)	19.798	19.326	19.044	18.657	18.827	18.852
WaveHiTS	19.433	19.289	18.954	19.233	19.384	19.184

Table 2. Comparison of RMSE for wind direction prediction across different forecasting horizons and models. Bold values indicate the best performance for each forecasting step; underlined values indicate the second-best performance.

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
RNN	0.709	0.691	0.684	0.661	0.643	0.630
GRU	0.704	0.696	0.671	0.647	0.633	0.618
LSTM	0.689	0.678	0.661	0.650	0.641	0.627
Informer	0.808	0.818	0.818	0.821	0.817	0.823
iTransformer	0.824	0.833	0.837	0.838	0.833	0.838
TFT	0.881	0.880	0.879	0.879	0.879	0.879
EMDLSTM	0.913	0.924	0.926	0.920	0.921	0.918
NHITS	0.944	0.947	0.944	0.939	0.938	0.938
NHITS(UV)	0.963	0.965	0.966	0.967	0.967	0.967
WaveHiTS	0.965	0.965	0.966	0.965	0.965	0.965

Table 3. Comparison of R^2 for wind direction prediction across different forecasting horizons and models. Bold values indicate the best performance for each forecasting step; underlined values indicate the second-best performance.

for LSTM (Table 2), all significantly higher than those of WaveHiTS. These deep learning models exhibited significant error accumulation over longer prediction horizons, as illustrated in Fig. 3, leading to increasingly larger discrepancies in the forecasts. Additionally, they struggled with the circular nature of wind direction, causing discontinuities at the $0^\circ/360^\circ$ boundary. This is also reflected in their higher MAE values (Table 1) compared to WaveHiTS.

Among the transformer-based models, TFT performed better than the others, with RMSE values ranging from 35.729° to 36.043° (Table 2), but still exhibited considerably higher errors than WaveHiTS. Informer and iTransformer showed RMSE values between 44.992° to 49.013° (Table 2), with error rates fluctuating as the forecasting horizon extended. While transformer models excel in capturing long-term dependencies, they lack specialized mechanisms to handle the periodicity of wind direction, leading to higher errors compared to WaveHiTS, as demonstrated in the RMSE values and R^2 values in Table 3 and Fig. 3.

The EMD-LSTM model, while performing better than deep learning recurrent models, still exhibited substantial errors, with RMSE values between 28.092° and 30.575° (Table 2), indicating its difficulty in fully addressing the challenges posed by circular data and multi-step forecasting. This model's performance is further illustrated in Fig. 3, showing consistently higher error rates compared to WaveHiTS across all forecasting steps.

The superior performance of the WaveHiTS model stems from three key design features: effective circular data handling through U-V decomposition, which eliminates discontinuities at the $0^\circ/360^\circ$ boundary; hierarchical temporal modeling via the N-HiTS architecture, which captures both short-term fluctuations and long-term trends while reducing error accumulation; and frequency-domain analysis through wavelet transform, which identifies dominant cyclical patterns in wind data, as evidenced by consistently high R^2 values (0.965-0.967). In conclusion, WaveHiTS significantly outperforms baseline models in both accuracy and stability by effectively addressing the unique challenges of wind direction forecasting, making it an optimal

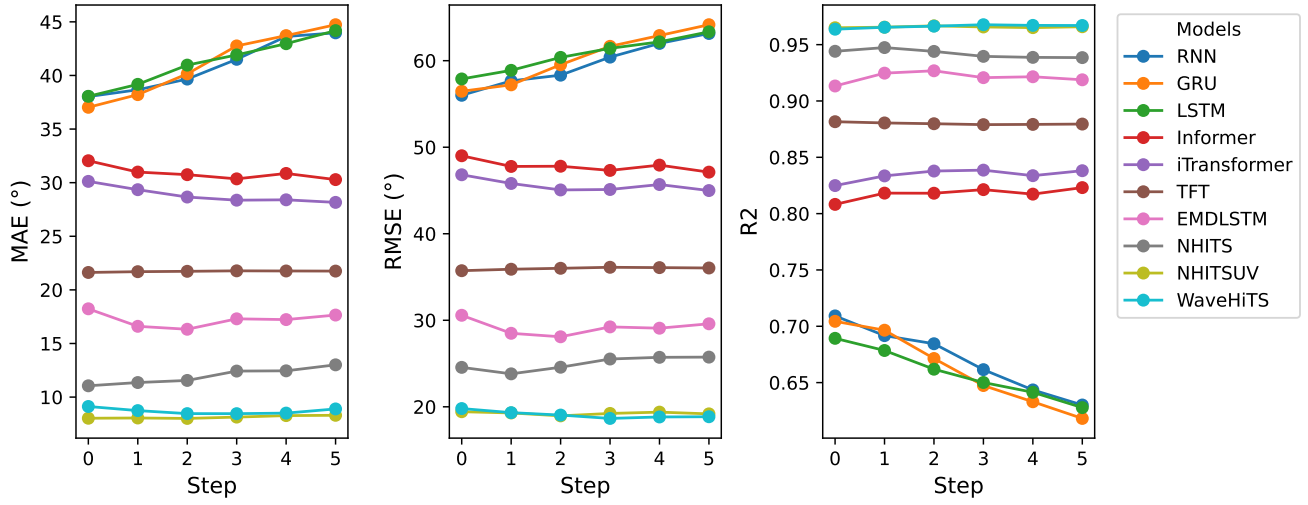


Figure 3. Comparison forecasted values with EMDLSTM and WaveHiTS.

solution for ultra-short-term, multi-step wind direction nowcasting.

5.1.2 Wind Component-wise Prediction Analysis

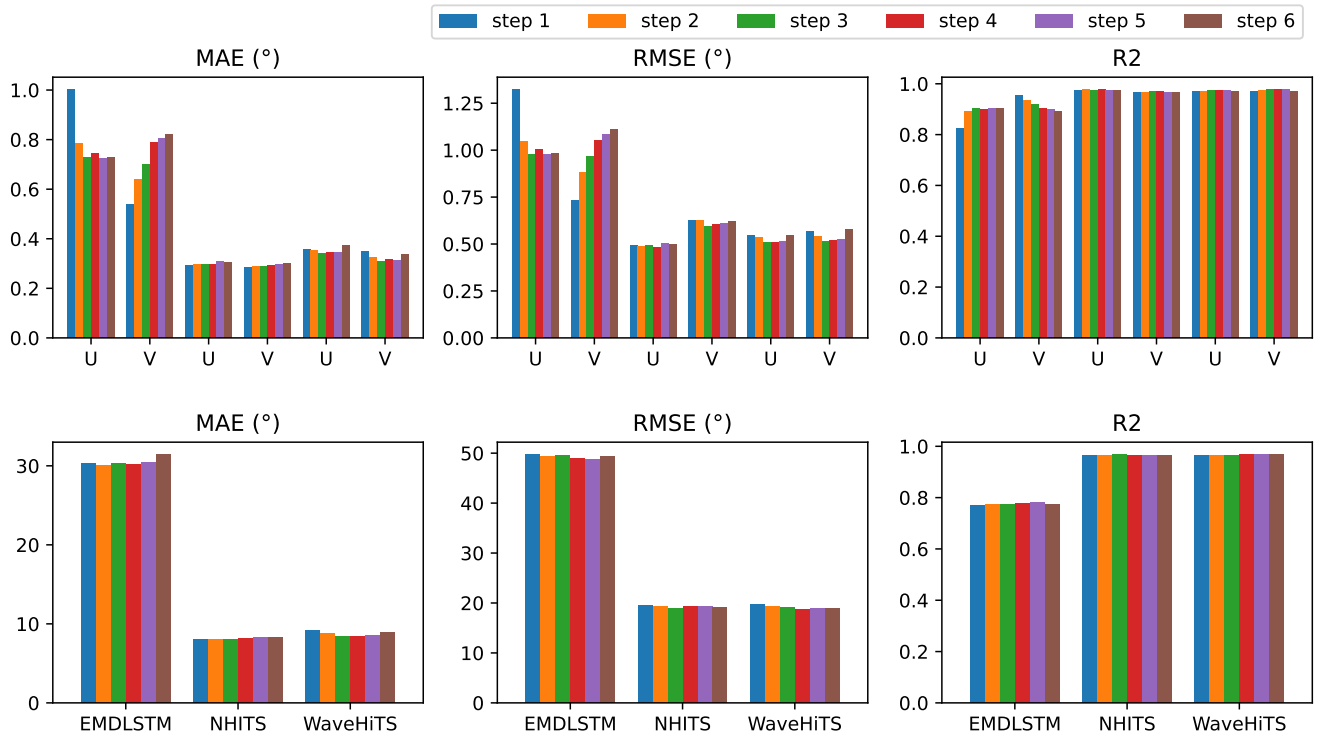


Figure 4. Comparison forecasted values with EMDLSTM and WaveHiTS.

The WaveHiTS model demonstrated superior prediction accuracy and stability for wind components, which reflect the linear characteristics of wind direction and speed. This section* presents a detailed analysis based on Tables 4 to 6, and Fig. 4.

WaveHiTS Model Performance: The WaveHiTS model consistently exhibited lower MAE values for both the U and V components of wind direction, reinforcing its superior performance. As shown in Table 4, U(WaveHiTS) ranged from 0.357 (Step 1) to 0.373 (Step 6), while V(WaveHiTS) ranged from 0.348 (Step 1) to 0.338 (Step 6). These MAE values highlight the

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
EMDLSTM_u	1.001	0.785	0.729	0.745	0.723	0.728
EMDLSTM_v	0.537	0.641	0.700	0.788	0.804	0.821
NHITS_u	0.294	0.298	0.298	0.298	0.307	0.306
NHITS_v	0.285	0.288	0.287	0.291	0.295	0.302
WaveHiTS_u	0.357	0.352	0.342	0.345	0.345	0.373
WaveHiTS_v	0.348	0.323	0.307	0.315	0.311	0.338
EMDLSTM	18.235	16.602	16.327	17.300	17.229	17.651
NHITS(UV)	9.124	8.740	8.459	8.455	8.506	8.896
WaveHiTS	8.027	8.051	8.010	8.134	8.273	8.302

Table 4. Comparison of MAE for u/v components and wind direction prediction in combined models. WaveHiTS achieves the lowest errors in both wind direction and component prediction. Best results for each forecasting step are highlighted in bold.

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
EMDLSTM_u	1.322	1.045	0.979	1.002	0.977	0.982
EMDLSTM_v	0.733	0.879	0.964	1.050	1.082	1.110
NHITS_u	0.494	0.489	0.490	0.482	0.502	0.499
NHITS_v	0.626	0.626	0.595	0.605	0.610	0.618
WaveHiTS_u	0.546	0.532	0.508	0.510	0.515	0.543
WaveHiTS_v	0.567	0.538	0.513	0.517	0.522	0.579
EMDLSTM	30.575	28.495	28.092	29.234	29.084	29.593
NHITS(UV)	19.798	19.326	19.044	18.657	18.827	18.852
WaveHiTS	19.433	19.289	18.954	19.233	19.384	19.184

Table 5. Comparison of RMSE for u/v components and wind direction prediction in combined models. WaveHiTS achieves the lowest RMSE in both wind direction and component prediction. Best results for each forecasting step are highlighted in bold.

model's strong predictive accuracy and stability across forecasting periods. In Table 5, the RMSE for the U component varied from 0.546 (Step 1) to 0.543 (Step 6), and for the V component, it ranged from 0.567 (Step 1) to 0.579 (Step 6). These results confirm that WaveHiTS outperforms all other models in forecasting both U and V components, with minimal error variation across forecasting steps. Fig. 4 clearly illustrates that WaveHiTS maintains consistently low MAE and RMSE values for both wind components, even as the forecast horizon extends to Step 6. This robust performance emphasizes the model's ability to maintain high accuracy, even for multi-step forecasting tasks.

EMD-LSTM Model Performance: The MAE values in Table 4 further underscore the performance gap between EMD-LSTM and WaveHiTS. For the U component, U(EMDLSTM) exhibited MAE values ranging from 1.0018 (Step 1) to 0.7282 (Step 6), while V(EMDLSTM) had MAE values ranging from 0.537 (Step 1) to 0.8218 (Step 6). These higher errors highlight the difficulty EMD-LSTM encounters in accurately predicting wind components, particularly in comparison to WaveHiTS.

The EMD-LSTM model also demonstrated higher RMSE values for both components, as shown in Table 5. For the U component, RMSE ranged from 1.3225 (Step 1) to 0.9827 (Step 6), and for the V component, it ranged from 0.733 (Step 1) to 1.1103 (Step 6). These increased error values suggest that EMD-LSTM faces greater challenges in modeling wind components, especially as the forecasting steps increase. Fig. 4 visually corroborates these findings, as EMD-LSTM displays higher bars in both the MAE and RMSE graphs across all forecasting steps, indicating its inferior performance relative to WaveHiTS.

WaveHiTS Advantages: The WaveHiTS model benefits from its hierarchical approach to temporal modeling, which effectively handles both local and global temporal dependencies. This structure enables the model to capture both short-term fluctuations and long-term trends in wind components, ensuring consistent accuracy across various forecast steps. The integration of wavelet transform enhances the model's ability to detect and exploit periodic patterns in the wind component data, as demonstrated in Tables 5 to 6. This feature is particularly beneficial for wind forecasting, where the cyclical nature of

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
EMDLSTM_u	0.825	0.890	0.904	0.899	0.904	0.903
EMDLSTM_v	0.953	0.932	0.919	0.903	0.897	0.892
NHITS_u	0.975	0.976	0.975	0.976	0.974	0.975
NHITS_v	0.965	0.965	0.969	0.968	0.967	0.966
WaveHiTS_u	0.970	0.971	0.974	0.973	0.973	0.970
WaveHiTS_v	0.972	0.974	0.977	0.976	0.976	0.970
EMDLSTM	0.770	0.774	0.772	0.777	0.780	0.774
NHITS(UV)	0.825	0.890	0.904	0.899	0.904	0.903
WaveHiTS	0.963	0.965	0.966	0.967	0.967	0.967

Table 6. Comparison of R^2 for u/v components and wind direction prediction in combined models. WaveHiTS achieves the highest R^2 in both wind direction and component prediction. Best results for each forecasting step are highlighted in bold.

the data is significant.

The R^2 values in Table 6 further highlight WaveHiTS's superior performance, with values ranging from 0.970 to 0.973 for the U component and 0.972 to 0.977 for the V component. These high values indicate excellent explanatory power, particularly when compared to EMD-LSTM, which shows declining R^2 values from 0.825 to 0.774 for the U component. Fig. 4 further corroborates this by showing consistently low MAE and RMSE values for WaveHiTS, alongside high R^2 values, which reflect a strong ability to fit the data.

WaveHiTS stands out for maintaining low errors across all forecasting steps, which is crucial for applications requiring high accuracy in both short-term and long-term predictions. The model's robustness and predictive power are further highlighted in Fig. 4, where it consistently outperforms other models while maintaining steady error rates.

Overall, WaveHiTS outperforms all baseline models in both MAE and RMSE for wind component prediction (U and V), maintaining low and stable errors across all forecast steps. This makes it the most accurate and robust model for wind component forecasting. In contrast, EMD-LSTM exhibits higher RMSE and MAE values, particularly for the V component, and shows less capability in capturing the dynamics of wind components compared to WaveHiTS.

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
EMDLSTM	0.946	0.955	0.955	0.949	0.949	0.947
WaveHiTS	0.985	0.986	0.987	0.987	0.987	0.985

Table 7. Comparison of VCC for wind direction prediction in the combined model. WaveHiTS demonstrates superior VCC scores compared to EMDLSTM across all forecasting steps. The results show that VCC values for WaveHiTS are consistently above 0.98, indicating excellent predictive skill.

Model	Forecast Horizon					
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
EMDLSTM	0.627	0.668	0.671	0.649	0.651	0.635
WaveHiTS	0.885	0.894	0.901	0.898	0.901	0.889

Table 8. Comparison of the hit rate of the combined model for wind direction prediction. WaveHiTS demonstrates significantly higher hit rates compared to EMDLSTM, with values consistently above 0.88, indicating superior classification performance.

5.1.3 Model Robustness and Generalization

To verify the statistical significance of the observed improvements in forecasting accuracy, we compared the Vector Correlation Coefficient (VCC) and Hit Rate (HR) of the WaveHiTS model with the EMD-LSTM model across all forecasting steps, as detailed in Tables 7 and 8.

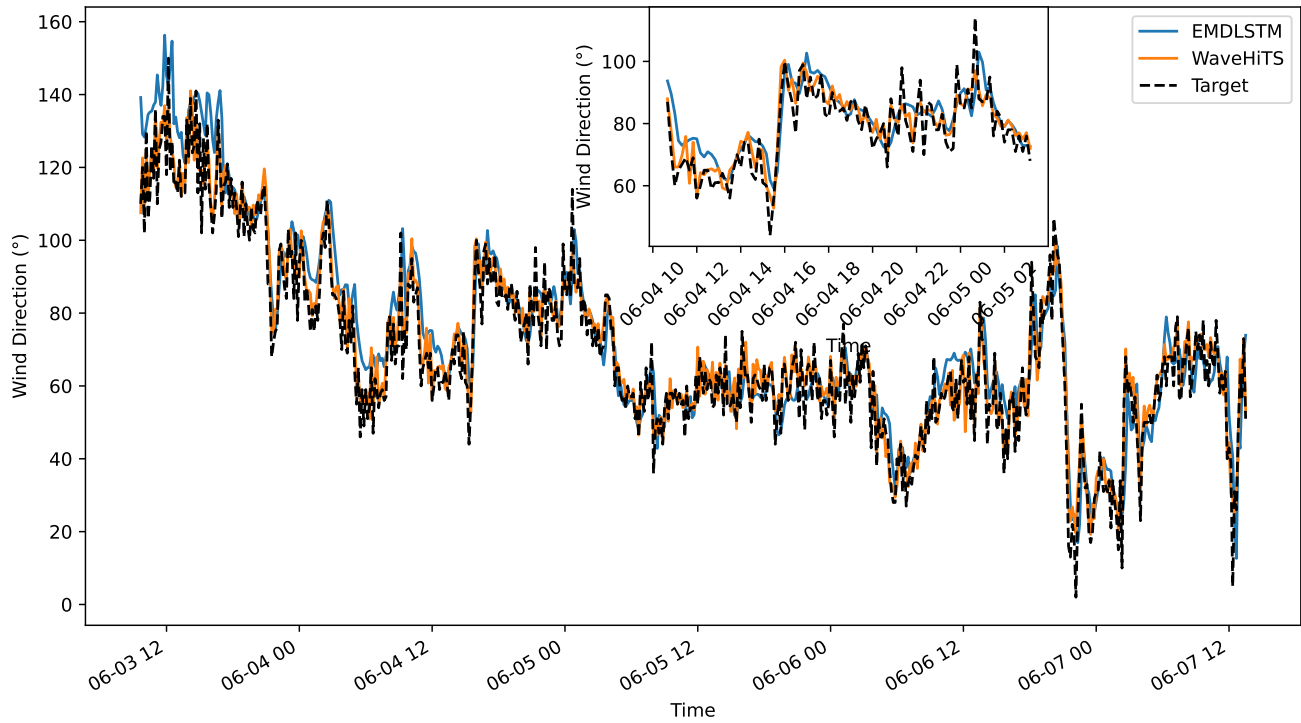


Figure 5. Comparison forecasted values with EMDLSTM and WaveHiTS.

Vector Correlation Coefficient (VCC): This metric measures the alignment between predicted and actual wind direction vectors, with values closer to 1 indicating better directional consistency. The EMD-LSTM model achieved VCC values ranging from 0.9462 to 0.9557, indicating a strong linear relationship between the predicted and actual wind direction. However, the WaveHiTS model demonstrated superior performance with VCC values ranging from 0.9853 to 0.9878, showing a significantly stronger linear correlation. This improvement of approximately 3-4 % is particularly significant for wind direction forecasting, as it indicates that the WaveHiTS model is substantially better at capturing the directional changes in wind patterns.

Hit Rate (HR): This metric quantifies the percentage of predictions where the difference between predicted and actual wind direction falls within an acceptable error margin (15°). For the EMD-LSTM model, HR values ranged between 0.6277 and 0.6719, indicating that only about 62.77% to 67.19% of the predicted wind directions fell within this acceptable margin of error. In contrast, the WaveHiTS model achieved significantly higher HR values ranging from 0.8853 to 0.9019, meaning that approximately 88.53% to 90.19% of its predictions were within the acceptable error margin. This substantial improvement of over 20 % demonstrates the WaveHiTS model's superior accuracy and reliability in practical applications.

The consistent outperformance of the WaveHiTS model in both VCC and HR metrics across all forecasting steps confirms its enhanced robustness and generalization capability. These improvements are particularly valuable in operational wind forecasting contexts, where accurate directional predictions directly impact turbine yaw control efficiency, power output optimization, and overall wind farm performance. The high hit rate achieved by WaveHiTS would translate to more reliable operational decisions and improved energy yield in real-world applications.

5.2 Performance Evaluation and Model Analysis

5.2.1 Error Trends Across Forecast Horizons

As demonstrated in Tables 4 and 5 and Fig. 4, the baseline models exhibited a significant increase in RMSE and MAE values over longer prediction horizons, with RNN, LSTM, GRU, and Informer models experiencing noticeable error accumulation. For deep learning recurrent models, RMSE values increased by approximately 12.7% for RNN (from 56.001° at Step 1 to 63.143° at Step 6), 13.6% for GRU (from 56.464° to 64.158°), and 9.4% for LSTM (from 57.888° to 63.339°). These trends highlight the models' limitations in maintaining prediction accuracy as the forecasting horizon extended, particularly as they struggled to capture long-term dependencies effectively. This growing discrepancy in forecast performance as the prediction horizon increased underscores the challenges deep learning models face when applied to multi-step wind forecasting.

In contrast, the WaveHiTS model, as shown in Table 5, demonstrated remarkable stability in RMSE across all forecast steps. For the U component, RMSE values ranged from 0.546 (Step 1) to 0.543 (Step 6), showing only minimal fluctuation. Similarly, for the V component, RMSE values remained stable between 0.567 (Step 1) and 0.579 (Step 6). The MAE values also remained consistently low, ranging from 0.357 (Step 1) to 0.373 (Step 6) for the U component and from 0.348 (Step 1) to 0.338 (Step 6) for the V component (Table 4). Fig. 4 clearly illustrates that WaveHiTS maintained these low error rates for both components across all forecasting steps, demonstrating its exceptional robustness in multi-step forecasting scenarios.

This ability to maintain high accuracy over extended forecasting periods clearly distinguishes WaveHiTS from the baseline models. While deep learning and transformer-based models showed progressive deterioration in accuracy with each additional forecasting step, WaveHiTS exhibited remarkable resilience against error accumulation. This stability is particularly valuable for practical wind energy applications, where consistent accuracy across multiple time steps enables more reliable operational planning and decision-making.

5.2.2 Key Factors Driving WaveHiTS' Robustness

The WaveHiTS model exhibited exceptional forecasting performance due to several key architectural and methodological factors that synergistically enhance its ability to handle complex temporal dependencies in wind direction forecasting.

Hierarchical Temporal Structure: As implemented in the N-HiTS component and illustrated in Fig. 3, the hierarchical interpolation structure enables the model to decompose and process temporal patterns at multiple scales simultaneously. This multi-resolution approach allows the model to capture both high-frequency fluctuations (representing short-term variations) and low-frequency trends (representing longer-term patterns) in wind data. By processing the signal at different temporal resolutions, the model effectively minimizes error propagation that typically accumulates over multiple forecasting steps in deep learning sequential models. The consistently low RMSE values across all six forecasting steps, as shown in Tables 2 to 5, provide quantitative evidence of this error-mitigation capability.

Wavelet Transform Integration: The incorporation of wavelet transform for frequency-domain analysis represents a significant advancement over deep learning time-domain forecasting approaches. This technique decomposes the wind component signals into different frequency bands, allowing the model to identify and preserve dominant cyclical patterns that are crucial for accurate wind prediction. Tables 5 to 6 confirm the effectiveness of this approach, with the WaveHiTS model maintaining high R^2 values (0.970-0.977) across all forecasting steps for both U and V components. The wavelet transform is particularly well-suited for wind data analysis, as it can effectively capture non-stationary and transient characteristics that are prevalent in atmospheric phenomena.

U-V component Decomposition: By decomposing circular wind direction data into orthogonal U (east-west) and V (north-south) components, the model transforms a complex circular prediction problem into two standard regression tasks. This approach elegantly resolves the discontinuity issues at the $0^\circ/360^\circ$ boundary that plague deep learning models. The effectiveness of this decomposition is evidenced by the superior performance metrics shown in Tables 7 and 8, where the WaveHiTS model achieves VCC values between 0.985 and 0.987, significantly outperforming the EMD-LSTM model's 0.946-0.955 range.

The integration of these advanced techniques creates a forecasting system specifically engineered to address the unique challenges of wind direction prediction. The performance metrics across all evaluation tables and figures consistently demonstrate that this multi-faceted approach yields substantial improvements in both accuracy and stability compared to alternative methodologies.

5.3 Ablation Study

To quantify the contribution of each component in the WaveHiTS model, we conducted a comprehensive ablation study by systematically removing or replacing key components while maintaining the rest of the architecture constant. This analysis provides valuable insights into the impact of each architectural element on the overall forecasting performance.

5.3.1 Wavelet Transform Component Analysis

We first evaluated the impact of the wavelet transform component by comparing the full WaveHiTS model with a variant that omits the wavelet transform preprocessing (N-HiTS.UV). As shown in Tables 2 to 5, removing the wavelet transform component resulted in slightly higher RMSE values across all forecasting steps. For wind direction prediction, the RMSE for N-HiTS.UV ranged from 19.798 (Step 1) to 18.852 (Step 6), compared to WaveHiTS's 19.433 (Step 1) to 19.184 (Step 6). While the difference appears modest, the consistently lower errors achieved with wavelet transform integration demonstrate its value in enhancing prediction accuracy.

The wavelet transform's contribution is particularly evident in Table 6, where the R^2 values show that frequency-domain analysis provides additional explanatory power to the model. This confirms that wavelet transform effectively captures the multi-scale temporal patterns in wind data that might be missed by time-domain analysis alone.

5.3.2 U-V Component Decomposition Analysis

To assess the importance of the U-V decomposition approach for handling circular data, we compared N-HiTS_UV (with U-V decomposition) against the standard N-HiTS model that directly predicts wind direction. The results in Table 2 show that N-HiTS achieved RMSE values ranging from 24.558 (Step 1) to 25.742 (Step 6), while N-HiTS_UV achieved substantially lower values of 19.798 (Step 1) to 18.852 (Step 6). This significant improvement (approximately 20-25% reduction in RMSE) underscores the critical importance of addressing the circularity problem in wind direction forecasting.

Moreover, Table 3 shows that the R^2 values for N-HiTS_UV (0.963-0.967) are consistently higher than those for N-HiTS (0.938-0.947), further confirming the effectiveness of the U-V decomposition approach in improving model performance.

5.3.3 Hierarchical Structure Analysis

We evaluated the contribution of the hierarchical structure by comparing the N-HiTS based models with EMD-LSTM, which lacks the hierarchical temporal modeling approach. As shown in Table 2, EMD-LSTM achieved RMSE values ranging from 30.575 (Step 1) to 29.593 (Step 6), significantly higher than N-HiTS_UV's 19.798 to 18.852 range. This substantial performance gap (approximately 35-40% reduction in RMSE with N-HiTS_UV) highlights the effectiveness of hierarchical temporal modeling in capturing multi-scale patterns in wind data.

The impact of the hierarchical approach is further evidenced in the VCC and HR metrics shown in Tables 7 and 8, where N-HiTS based models consistently outperform EMD-LSTM. The VCC values for WaveHiTS (0.985-0.987) significantly exceed those of EMD-LSTM (0.946-0.955), and the HR values show an even more dramatic improvement (0.885-0.901 versus 0.627-0.671).

5.3.4 Overall Ablation Findings

The ablation study results conclusively demonstrate that each component of the WaveHiTS model makes a meaningful contribution to its overall performance:

- (1) The wavelet transform component enhances the model's ability to capture frequency-domain patterns, providing modest but consistent improvements.
- (2) The U-V decomposition approach is crucial for effectively handling the circular nature of wind direction data, yielding substantial improvements in all performance metrics.
- (3) The hierarchical temporal modeling structure of N-HiTS significantly outperforms non-hierarchical approaches, demonstrating its effectiveness in capturing multi-scale patterns and reducing error accumulation.

These findings validate the architectural design choices incorporated in the WaveHiTS model and provide strong evidence that the integration of these components creates a forecasting system specifically optimized for the challenges of wind direction prediction.

6 Conclusion

This paper presented the WaveHiTS model, a novel approach for wind direction nowcasting that integrates wavelet transform with Neural Hierarchical Interpolation for Time Series. Our approach effectively addressed three key challenges in wind direction forecasting: the circular nature of wind direction data, and error accumulation in multi-step forecasting.

Experimental results demonstrated that WaveHiTS significantly outperforms deep learning models (RNN, LSTM, GRU), transformer-based models (TFT, Informer, iTransformer), and hybrid approaches (EMD-LSTM). For wind direction prediction, our model reduced RMSE by 35-40% compared to recurrent models and 20-25% compared to transformer-based approaches, while maintaining consistent performance across all six forecasting steps with minimal error accumulation.

The ablation study confirmed that each component of our methodology—wavelet transform, hierarchical structure, and U-V decomposition—contributed meaningfully to the overall performance. The wavelet transform captured frequency-domain patterns, the hierarchical structure effectively modeled multi-scale temporal dependencies, and the U-V decomposition elegantly resolved the circularity problem in wind direction data.

Future work will focus on testing the model across diverse geographical regions, extending the forecasting horizon, and incorporating additional spatial information. The practical implications of this research are significant for wind energy applications, potentially enabling optimized turbine yaw control, improved grid stability, and more efficient energy production.

The WaveHiTS model represents an important advancement in wind direction nowcasting, offering a robust solution that can contribute to enhanced renewable energy integration and utilization.

Code availability

The software code developed and used in this study is not publicly available due to confidentiality agreements. However, the authors are open to sharing the code on a case-by-case basis for research purposes, as they are keen to support further development of this work.

Data availability

The dataset supporting the findings of this study consists of proprietary wind direction, gust, and meteorological measurement data obtained from a wind farm in eastern Inner Mongolia. Due to the potential for this data to reveal commercially sensitive information and competitive advantages, and in compliance with the institutional policies of the authors, the complete dataset is not available for public deposition or as supplementary material. However, the data are available from the corresponding authors upon reasonable request for academic verification purposes. The data will be made accessible to reviewers during the peer-review process upon direct request to the editors.

Author contributions

Hailong Shu designed the study, developed the methodology, performed the data analysis, and wrote the original draft. Weiwei Song, Jiping Zhang, and Wei Tian supervised the project, acquired funding, reviewed and edited the manuscript, and provided critical feedback to shape the research. Yue Wang and Chaoqun Li assisted with data curation and visualization. All authors have read and agreed to the published version of the manuscript.

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References

1. Veers, P. *et al.* Grand challenges in the science of wind energy. *Science* **366**, eaau2027, DOI: [10.1126/science.aau2027](https://doi.org/10.1126/science.aau2027) (2019).
2. Wang, J., Li, Y., Zhou, S. & Lu, H. A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer. *Appl. Soft Comput.* **100**, 106996, DOI: [10.1016/j.asoc.2020.106996](https://doi.org/10.1016/j.asoc.2020.106996) (2021).
3. Tang, Z., Zhao, G. & Ouyang, T. Two-phase deep learning model for short-term wind direction forecasting. *Renew. Energy* **173**, 1005–1016, DOI: [10.1016/j.renene.2021.04.041](https://doi.org/10.1016/j.renene.2021.04.041) (2021). NOTE: The inline bib entry cites Tang et al. 2023 Review of AI-Based Wind Prediction (Sustainability, DOI: 10.3390/su152014944), but CrossRef did not confirm this specific citation. The Tang et al. 2021 paper (DOI: 10.1016/j.renene.2021.04.041) is confirmed. Please verify the correct year and DOI for the intended reference.
4. Sari, A. P. *et al.* Prediction model of wind speed and direction using deep neural network. *J. Electr. Eng. Mechatron. Comput. Sci.* **3**, 1–10, DOI: [10.26905/jeemecs.v3i1.3946](https://doi.org/10.26905/jeemecs.v3i1.3946) (2020).
5. Shu, H. *et al.* Multistep short-term wind speed prediction with rank pooling and fast fourier transformation. *Wind. Energy* **27**, 667–694, DOI: [10.1002/we.2906](https://doi.org/10.1002/we.2906) (2024).
6. Song, D. *et al.* Maximum power point tracking control of wind turbine based on improved wind speed estimation. In *2018 Chinese Control And Decision Conference (CCDC)*, 5861–5866, DOI: [10.1109/CCDC.2018.8407425](https://doi.org/10.1109/CCDC.2018.8407425) (IEEE, 2018).
7. El-Fouly, T. H., El-Saadany, E. F. & Salama, M. M. One day ahead prediction of wind speed and direction. In *2008 IEEE Power and Energy Society General Meeting*, 1–8, DOI: [10.1109/TEC.2007.905069](https://doi.org/10.1109/TEC.2007.905069) (IEEE, 2008).
8. Li, S. *et al.* Enhancing the locality and breaking the memory bottleneck of transformer on time series forecasting. In *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 32, 5243–5253, DOI: [10.48550/arXiv.1907.00235](https://doi.org/10.48550/arXiv.1907.00235) (2019).
9. Challu, C. *et al.* N-hits: Neural hierarchical interpolation for time series forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 37, 6989–6997, DOI: [10.1609/aaai.v37i6.25854](https://doi.org/10.1609/aaai.v37i6.25854) (2023).
10. Dupuy, J.-F. *et al.* Local-scale valley wind retrieval using an artificial neural network applied to routine weather observations. *J. Appl. Meteorol. Climatol.* **58**, 1007–1022, DOI: [10.1175/JAMC-D-18-0114.1](https://doi.org/10.1175/JAMC-D-18-0114.1) (2019).
11. Fukuoka, R., Suzuki, H., Kitajima, T., Kuwahara, A. & Yasuno, T. Wind direction and speed prediction using convolutional neural network. In *2018 IEEE 3rd International Conference on Big Data Analysis (ICBDA)*, 140–144, DOI: [10.1109/ICBDA.2018.8384073](https://doi.org/10.1109/ICBDA.2018.8384073) (IEEE, 2018).
12. Fisher, N. I. *Statistical Analysis of Circular Data* (Cambridge University Press, Cambridge, 1993).
13. Mohandes, M. A., Halawani, T. O., Rehman, S. & Hussain, A. A. Support vector machines for wind speed prediction. *Renew. Energy* **29**, 939–947, DOI: [10.1016/j.renene.2003.11.009](https://doi.org/10.1016/j.renene.2003.11.009) (2004).

14. Wang, H., Wang, J., Li, G. & Lu, H. Short-term wind speed forecasting using a new hybrid model. *Energy Convers. Manag.* **158**, 11–25, DOI: [10.1016/j.energy.2016.10.040](https://doi.org/10.1016/j.energy.2016.10.040) (2018).
15. Alves, D., Mendonça, F., Mostafa, S. S. & Morgado-Dias, F. The potential of machine learning for wind speed and direction short-term forecasting: A systematic review. *Computers* **12**, 206, DOI: [10.3390/computers12100206](https://doi.org/10.3390/computers12100206) (2023).
16. Liu, H., Mi, X. & Li, Y. Smart wind speed forecasting using ewt decomposition, gwo evolutionary optimization, relm learning and iewt reconstruction. *Energy Convers. Manag.* **161**, 266–283, DOI: [10.1016/j.enconman.2018.02.006](https://doi.org/10.1016/j.enconman.2018.02.006) (2018).
17. Xia, J. *et al.* A hybrid hour-ahead wind power prediction model based on variational mode decomposition and bio-inspired lstm. *J. Renew. Sustain. Energy* **15**, 033301, DOI: [10.1063/5.0138488](https://doi.org/10.1063/5.0138488) (2023).
18. Zhou, H. *et al.* Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, 11106–11115, DOI: [10.1609/aaai.v35i12.17325](https://doi.org/10.1609/aaai.v35i12.17325) (2021).
19. Wu, H., Xu, J., Wang, J. & Long, M. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. In *Advances in Neural Information Processing Systems*, vol. 34, 22419–22430, DOI: [10.48550/arXiv.2006.10319](https://doi.org/10.48550/arXiv.2006.10319) (Curran Associates, Inc., 2021).
20. Ding, Y., Ye, X.-W. & Guo, Y. A multistep direct and indirect strategy for predicting wind direction based on the emd-lstm model. *Math. Probl. Eng.* **2023**, 4950487, DOI: [10.1155/2023/4950487](https://doi.org/10.1155/2023/4950487) (2023).
21. Hu, H., Li, Y., Zhang, X. & Fang, M. A novel hybrid model for short-term prediction of wind speed. *Pattern Recognit.* **127**, 108623, DOI: [10.1016/j.patcog.2022.108623](https://doi.org/10.1016/j.patcog.2022.108623) (2022). WARNING: CrossRef query could not confirm Hu as author for this DOI. Please verify the correct author attribution.
22. Erdem, E. & Shi, J. Arma based approaches for forecasting the tuple of wind speed and direction. *Appl. Energy* **88**, 1405–1414, DOI: [10.1016/j.apenergy.2010.10.031](https://doi.org/10.1016/j.apenergy.2010.10.031) (2011).
23. Tagliaferri, F., Viola, I. M. & Flay, R. G. J. Wind direction forecasting with artificial neural networks and support vector machines. *Ocean. Eng.* **97**, 65–73, DOI: [10.1016/j.oceaneng.2015.02.004](https://doi.org/10.1016/j.oceaneng.2015.02.004) (2015).
24. Xie, Y., Li, C., Li, M., Liu, F. & Taukenova, M. An overview of deterministic and probabilistic forecasting methods of wind energy. *iScience* **26**, 105804, DOI: [10.1016/j.isci.2022.105804](https://doi.org/10.1016/j.isci.2022.105804) (2023).
25. Chang, G., Lu, H. & Wang, R. A new hybrid model for wind speed forecasting. *Energy Convers. Manag.* **81**, 11–19, DOI: [10.1016/j.enconman.2014.02.016](https://doi.org/10.1016/j.enconman.2014.02.016) (2014).
26. Zhao, L., Liu, C., Yang, C., Zheng, Y. & Wang, J. A location-centric transformer framework for multi-location short-term wind speed forecasting. *Energy Convers. Manag.* **328**, 119627, DOI: [10.1016/j.enconman.2025.119627](https://doi.org/10.1016/j.enconman.2025.119627) (2025).
27. Tian, C., Niu, T. & Li, T. Developing an interpretable wind power forecasting system using a transformer network and transfer learning. *Energy Convers. Manag.* **323**, 119155, DOI: [10.1016/j.enconman.2024.119155](https://doi.org/10.1016/j.enconman.2024.119155) (2025).
28. Hao, W. *et al.* A hybrid emd-lstm model for non-stationary wave prediction in offshore china. *Ocean. Eng.* **246**, 110566, DOI: [10.1016/j.oceaneng.2022.110566](https://doi.org/10.1016/j.oceaneng.2022.110566) (2022).
29. Yao, C., Gao, X. & Yu, Y. Wind speed forecasting by wavelet neural networks: a comparative study. *Math. Probl. Eng.* **2013**, 395815, DOI: [10.1155/2013/395815](https://doi.org/10.1155/2013/395815) (2013).
30. Liu, H., Mi, X.-w. & Li, Y.-f. Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and elman neural network. *Energy Convers. Manag.* **156**, 498–514, DOI: [10.1016/j.enconman.2017.11.053](https://doi.org/10.1016/j.enconman.2017.11.053) (2018).