Evaluation of LSTM and Wavelet Methods for Wind Speed Forecasting in Bahia, Brazil

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The pursuit of sustainable development is intricately linked to the effective management of renewable energy resources, with wind energy emerging as a key player on the global stage. However, the inherent volatility and intermittency of wind patterns pose significant challenges to accurate wind speed forecasting, which is crucial for the stable operation of wind turbines. Our study presents a novel forecasting model that integrates cutting-edge data decomposition techniques with Long Short-Term Memory (LSTM) networks in this context. Our approach leverages advanced methodologies such as Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and Enhanced Empirical Mode Decomposition (EEMD) to segment time series data into distinct high and low-frequency components. These segmented signals are then individually forecasted using Bidirectional LSTM (BiLSTM) networks, with the amalgamation of these predictions providing the final forecast output. Our empirical findings demonstrate that the hybrid model, particularly utilizing EMD and EEMD, exhibits superior performance compared to existing forecasting models in terms of both accuracy and stability. By effectively combining sophisticated data decomposition techniques with state-of-the-art deep learning algorithms, our proposed model offers a robust solution for wind speed forecasting. This facilitates the efficient management of renewable energy resources and advances the cause of sustainable development initiatives worldwide.
Keywords: Wind Energy. Wind Speed Forecasting. Data Decomposition. Long Short-Term Memory. Wavelet Transform.

Introduction

In the quest for sustainable energy solutions, wind energy has emerged as a viable alternative for large-scale power plants and wind farms. It has proven its efficacy in smaller-scale applications [1,2]. The energy generation by wind turbines hinges on wind speed consistently ranging between 4m/s and 5m/s [3], implying that fluctuations in speed can significantly impact generation [4].

Wind speed forecasting models are categorized into three main types: physical, statistical, and hybrid [5]. Recent advancements in machine learning and deep learning have showcased their superior predictive capabilities over traditional models [6]. Techniques such as support vector regression (SVR) and artificial neural networks (ANN) have set the standard in wind speed forecasting [7].

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Hybrid models, amalgamating machine learning and deep learning techniques stand out as the most robust and dependable means of predicting wind speed, promising enhanced accuracy and reliability. Effective wind speed forecasting emerges as a pivotal element in wind farm management, ensuring optimal turbine operation and maximal energy production. However, wind's inherently volatile and intermittent nature poses formidable challenges in modeling and accurately forecasting its speed. This study delves into an advanced approach that integrates deep learning techniques and wavelet-based time-series analysis to tackle this issue and present a dependable forecasting system. In this context, a promising method embraced in the literature involves hybrid models marrying the Wavelet Transform (WT) and Long Short-Term Memory (LSTM)[8]. WT is often leveraged to disaggregate wind speed signals, eliminating noise and irregularities from the data. The precision of this wavelet-based decomposition process crucially hinges on the selection of decomposition levels and the choice of the mother wavelet [9].

Conversely, owing to the intermittent and nonlinear nature of wind speed data, Ensemble Empirical Mode Decomposition (EEMD) has emerged as a potent data decomposition technique that eliminates noise and analyzes intricate time series [10]. LSTM networks, particularly bidirectional ones, exploit available information to the fullest extent, considering both past and future observations of wind speed data [11]. Fusing WT and LSTM facilitates robust and optimized data analysis, ensuring more accurate and reliable forecasts.

Related Works

Several studies have focused on LSTM-based models and eliminating noise from wavelet decomposition-based data. In the work of Kovoor and colleagues [12], a hybrid WT-LSTM-SVR model was proposed, combining Wavelet Transform (WT), Short and Long Term Memory Network (LSTM), and Support Vector Regression (SVR) to improve wind speed forecasting. The model achieved an RMSE of 0.218 m/s, MAE of 0.203 m/s, and MAPE of 2.014%, highlighting its superiority compared to traditional approaches. The study by Ziggah and colleagues [13] proposes a new hybrid model, DWT-PSR-AOA-BPNN, to predict wind speed, combining the Discrete Wavelet Transform (DWT), Phase Space Reconstruction (PSR), Aquila Optimization Algorithm (AOA), and Backpropagation Neural Network (BPNN).

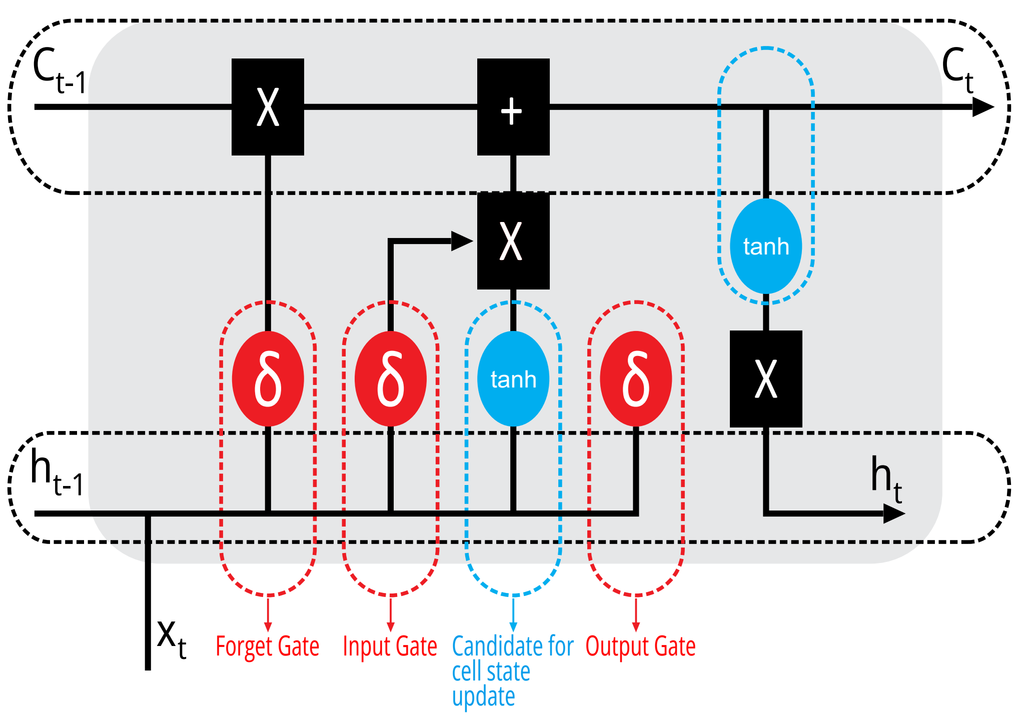
Materials and Methods

An LSTM (Long Short-Term Memory) is a recurrent neural network (RNN) designed to handle data sequences, such as time series, more efficiently than traditional RNNs (Figure 1).

In Figure 1, we observe the intricate architecture of the LSTM cell, characterized by three distinct ports: the forgetting, input, and output ports. Central to LSTM networks is the memory cell, acting as a repository for state information, which sets them apart from conventional neural networks. Activation of the input gate initiates the absorption of new information into the cell, while the forget gate, when triggered, expunges previous data.

Within the feedback loop, the sigmoid function determines the retention or dismissal of information within the memory cell, while the hyperbolic

Figure 1. Structure of the internal LSTM cell.



tangent function regulates its input and output. Through the seamless integration of these functions, LSTM networks can selectively encode or discard information, enabling them to manage time series data and generate accurate forecasts adeptly.

Study area - City of Alagoinhas - BA

In this study, we used a data set from a station named Alagoinhas, Station Code: 83249, Latitude: -12◦14'86", Longitude: -38◦50'57", Altitude: 47.56, Start Date: 2000-05-12, End Date: 2023-07-14 (Table 1).

Table 1. Characteristics of the study area.

Characteristics	Data
Location	North Coast
Latitude	-12° 14' 86"
Longitude	38° 42' 52"
Average temp	24.7°
Precipitation	1400 mm

The Data Set

The National Institute of Meteorology of the Government of Brazil provides the wind speed time series with daily measurements. Table 2 presents the details of the data sets.

Table 2. Statistical analysis of dataset with daily average from 01/2000 to 2023-07-14 .

Metric	Average Daily Speed (m/s)
mean	1.563804
std	0.157013
min	1.184804
25%	1.444741
50%	1.548888
75%	1.684539
max	1.993306

Data Decomposition Technique

The various data decomposition techniques investigated in this study include wavelet transforms, empirical mode decomposition, ensemble empirical mode decomposition, and empirical wavelet transforms. Here, we highlight the theoretical basis of Empirical Mode decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD).

Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition - EMD. This method divides the original signal into many IMFs (Intrinsic Mode Functions) and a residual component.

Ensemble Empirical Mode Decomposition (EEMD)

EEMD is an extension of EMD. It was proposed to solve the problem of mixed modes often observed in EMD. The main feature of EEMD is repeatedly adding white noise to the original signal and then applying EMD to each of these noisy versions. Daubechies (db1) is applied to wind speed data and decomposed into three levels, resulting in three detail components and one approximation component (Figure 2).

The Proposed Hybrid Method

During the data cleaning phase for Alagoinhas, missing values, inconsistent data, and other anomalies that could compromise the integrity of the data were identified and corrected. Next came the integration stage, and since the data could come from different sources or sensors, it must be consolidated cohesively. Finally, the transformation phase involved activities such as normalizing values, converting units, and, in some cases, creating new derived variables. Figure 3 shows the structure of the proposed method.

Figure 2. Decomposition of wind speed data time series using WT in data sets from Alagoinhas/BA.

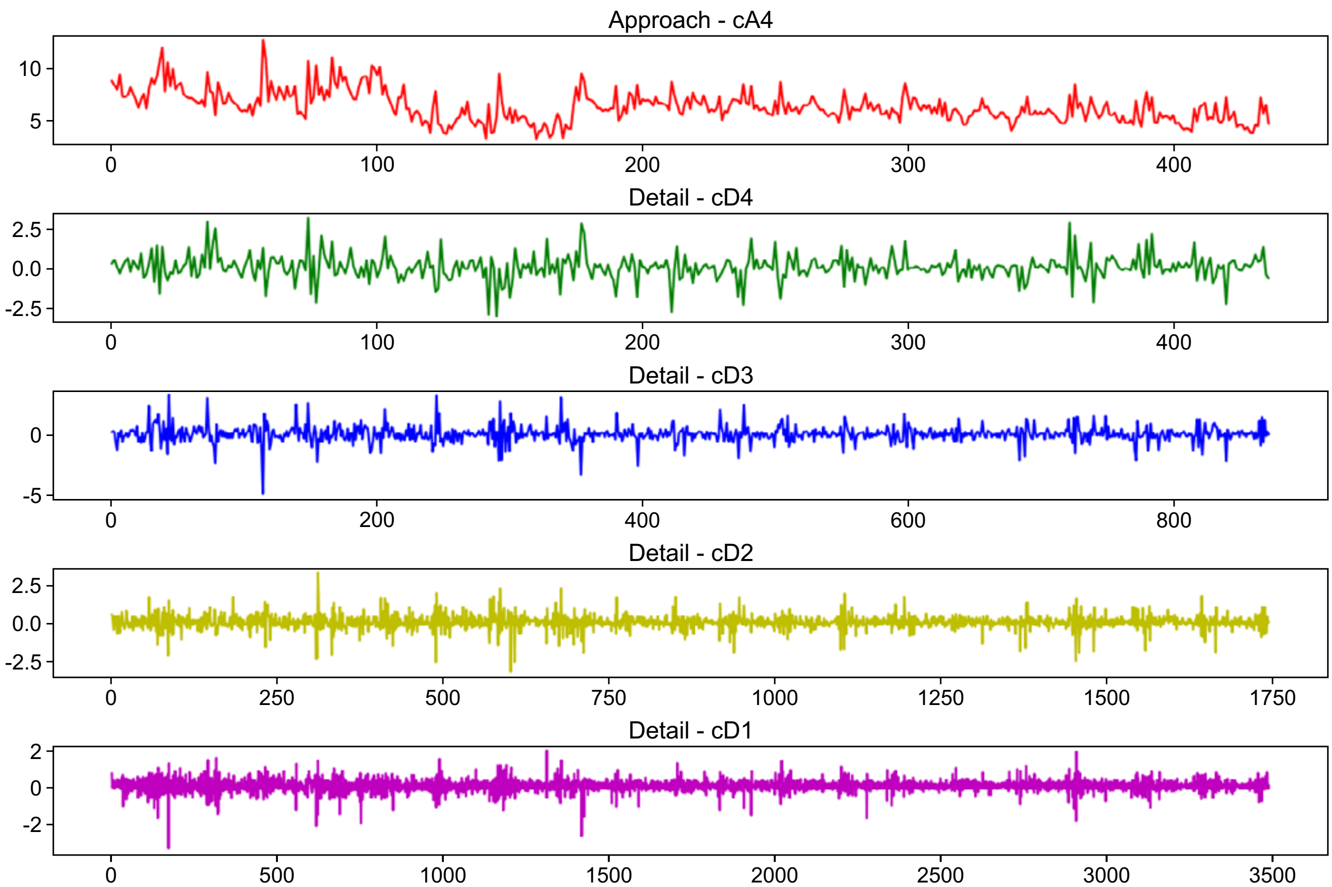
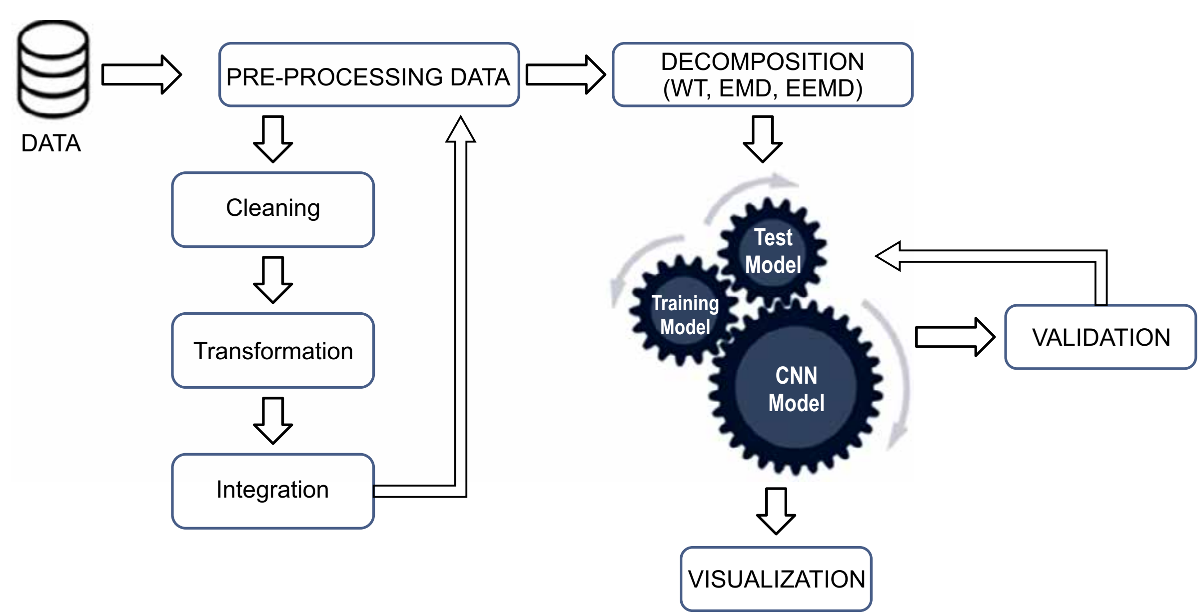


Figure 3. The structure of the hybrid model.



About Validation

The efficiency of the proposed hybrid EEMD-based model is evaluated by comparing its performance with benchmark models, namely decomposition-based LSTM models, decomposition-based SVR models, and individual models such as LSTM, SVR, and ANN. Extensive evaluation of the proposed hybrid decomposition-based models uses statistical error indicators such as the MAE index, RMSE, and R^2.

The MAE (mean absolute error) is the difference between actual and observed values. A thorough evaluation of the proposed hybrid decomposition-based models ensures a robust assessment of their performance and efficiency against established benchmarks and individual models.

Results and Discussion

The combination of these techniques (LSTM and WT) aimed to exploit the ability of LSTMs to learn and memorize long-term dependencies in time series and the ability of the Wavelet Transform to filter out noise and highlight key features in the data (Table 3).

Table 3. LSTM and WT Model metrics.

Metric	Value
MSE	0.0028
MAE	0.0357
RMSE	0.0528
ASM	17.34%
MBE	0.0016
rMBE	0.79%
rRMSE	25.86%
R^2	0.4722

The Mean Square Error (MSE) recorded is 0.0028, close to zero, suggesting that the model performed well, with predictions relatively close to the actual values. Additionally, the Mean Absolute Error (MAE) is 0.0357, indicating that, on average, the model's predictions deviate by 0.0357 units from the actual value. The Root Mean Square Error (RMSE) of 0.0528 suggests that the model is sensitive to outliers but offers reasonable accuracy.

The Mean Absolute Percentage Error (MAPE) of 17.34% suggests that the model may not be suitable for high-precision applications. The Gross Mean Error (MBE) and Relative Gross Mean Error (rMBE) are 0.0016 and 0.79%, respectively. Values close to zero indicate no systematic bias in the forecasts, which is a good sign. The Relative Root Mean Square Error (rRMSE) is 25.86%, suggesting that the model has an average percentage deviation of approximately 25.86% from the real values. Finally, the coefficient of determination (R^2) was 0.4722. This metric indicates how well the model's predictions correspond to the actual values. It suggests that the model explains around 47.22% of the variance in the observed data.

Using LSTM + EMD

Table 4 shows the hybrid model evaluation metrics for each Intrinsic Mode Function (IMF).

Upon examining the values presented in Table 4, a discernible trend emerges, showcasing an enhanced accuracy of estimates as we progress from the initial MFIs to the latter ones. Notably, the MSE initially stands at 0.003 for MFI1, steadily declining to a remarkable 0.0001 for MFIs 11 and 12. This pattern is mirrored in metrics like MAE and RMSE, which attain their lowest points in the final MFIs.

The R^2 value, serving as the coefficient of determination, offers insights into the predictability of variance in dependent data based on independent variables.

Furthermore, attention is drawn to the MAPE, whose high values, particularly in cases where actual values approach zero, can be attributed to the disproportionate impact of minor absolute errors on percentage errors.

The MBE and rMBE shed light on whether the models overestimate or underestimate actual values on average. Data analysis suggests that the models demonstrate improved performance in the later MFIs compared to their earlier counterparts.

Using LSTM + EEMD

Looking at the values in Table 5, the MSE starts at 0.0021 for MFI1 and decreases consistently, reaching shallow values in the later MFIs. Similarly, the MAE and RMSE follow the same trend, indicating that the later MFIs have less variation and are more predictable. The MAPE for MFI10 is remarkably low, just 0.05%, suggesting excellent percentage accuracy, while the initial MFIs have higher values.

The MBE and rMBE indicate, on average, whether the models overestimate or underestimate the real values. As seen in most MFIs, values close to zero indicate no clear systematic bias in the forecasts.

Table 4. Evaluation for each Intrinsic Mode Function (IMF) after the EMD application.

Metric	MSE	MAE	RMSE	MAPE	MBE	rMBE	rMSE	R^2
IMF1	0.003	0.038	0.054	775.27%	0.600	-117.29%	1062.32%	0.238
IMF2	0.001	0.019	0.027	469.28%	0.620	-126.54%	554.59%	0.853
IMF3	0.001	0.010	0.012	191.89%	0.700	34.45%	236.76%	0.981
IMF4	0.001	0.002	0.003	52.20%	0.180	35.50%	63.99%	0.999
IMF5	0.001	0.002	0.002	41.43%	0.200	39.29%	42.91%	0.999
IMF6	0.001	0.001	0.001	21.8%	0.060	12.09%	25.16%	1.000
IMF7	0.001	0.001	0.001	18.82%	-0.070	-14.87%	21.10%	1.000
IMF8	0.001	0.001	0.001	15.71%	-0.080	-16.08%	17.62%	1.000
IMF9	0.001	0.002	0.002	37.37%	-0.160	-33.26%	34.78%	0.999
IMF10	0.001	0.001	0.001	16.41%	-0.090	14.85%	18.53%	0.999
IMF11	0.0001	0.000	0.000	9.72%	-0.010	-8.81%	11.20%	1.000
IMF12	0.0001	0.000	0.000	17.48%	-0.030	-12.20%	19.51%	1.000

Table 5. Evaluation for each Intrinsic Mode Function (IMF) after application of EEMD.

Metric	MSE	MAE	RMSE	MAPE	MBE	rMBE	rMSE	R^2
IMF1	0.0021	-0.0309	0.0459	6.59%	-0.0002	-0.05%	9.35%	0.3958
IMF2	0.0003	0.0126	0.0180	2.67%	0.0022	0.45%	3.71%	0.8878
IMF3	0.000	0.0038	0.0053	0.78%	0.0008	0.15%	1.02%	0.9952
IMF4	0.000	0.0013	0.0016	0.29%	0.0009	0.20%	0.34%	0.9997
IMF5	0.000	0.0013	0.0017	0.31%	-0.0004	0.20%	0.38%	0.9997
IMF6	0.000	0.0008	0.0010	0.19%	-0.0006	-0.13%	0.21%	0.9999
IMF7	0.0000	0.0007	0.0008	0.15%	0.0007	0.14%	0.15%	10000
IMF8	0.000	0.0008	0.0009	0.19%	-0.0008	0.16%	0.18%	10000
IMF9	0.000	0.0018	0.0019	0.42%	0.0018	0.16%	0.44%	0.9993
IMF10	0.000	0.0002	0.0002	0.05%	0.0002	0.05%	0.05%	10000
IMF11	0.0000	0.0011	0.0012	inf	-0.0010	-2.43%	0.05%	0.9989

For MFIs 7 to 10, the R^2 values are equal to or close to 1, indicating an almost perfect fit. On the other hand, IMF1 has a lower value, 0.3985, indicating a less precise fit.

Therefore, the models perform significantly better in the later MFIs than the initial ones, with the error metrics reaching minimum values and the R^2 approaching 1 in the later MFIs—significant potential for making accurate predictions.

Comparative Study

The performance of the proposed model is evaluated against other EWT-based models proposed by various researchers. Table 6 compares the MAE and RMSE values of some published models.

A comparison of the proposed model in terms of MAE and RMSE reveals that the model outperforms other models in predicting wind speed. As the table shows, the error values increase as the prediction horizon increases, which decreases the model's accuracy.

Conclusion

The proposed hybrid model adopted data decomposition methods such as WT, EMD, and EEMD to partition the wind speed data into high and low-frequency signals. LSTM networks were applied to train and predict these different signals. Specifically, the model proved superior to those presented, and its effectiveness was further optimized by incorporating jump connections.

Despite the achievements, we recognize some limitations in the proposed model, which also indicate valuable directions for future research. The current model focuses on predictions based on univariate LSTM networks without incorporating correlated characteristics. Thus, a logical expansion would be to develop multivariate BiDLSTM models, including temperature and wind direction. In addition, adopting hybrid data decomposition techniques can be explored to improve model performance further.

Finally, considering computational efficiency, using lighter networks, such as echo networks, represents a promising path.

Table 6. Comparison of the best results from related studies.

Reference	MAE(m/s)	RMSE(m/s)	MAPE%
Our Study (IMF10)	0.0002	0.0002	0.0475
U and Koover [12]	0.203	0.218	2.014
Jnr et al [13]	1.1490	1.4190	0.2743

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