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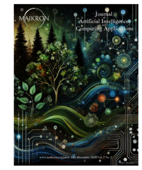

*Exploration Paper*

# An Exploratory Application of Empirical Mode Decomposition and Recurrent Neural Networks for Meteorological Time Series Prediction

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**ABSTRACT**

Accurate short-term weather forecasting remains a critical yet complex task, particularly in tropical regions where high variability and abrupt climatic shifts can have immediate impacts on agriculture, infrastructure, and public safety. Traditional statistical methods often struggle to capture the non-linear and multi-scale nature of meteorological time series, limiting their effectiveness in localized forecasting scenarios. To address this challenge, this paper presents an exploratory prototype that combines Empirical Mode Decomposition with Recurrent Neural Networks, specifically Long Short-Term Memory (LSTM) architectures. Daily data on temperature, humidity, and atmospheric pressure from Mérida, Yucatán (2000–2018) were decomposed into Intrinsic Mode Functions, which served as input features for training separate LSTM models. The hybrid system achieved promising results, particularly for temperature and humidity, capturing key short-term patterns while highlighting limitations in pressure forecasting. These findings suggest that EMD-based preprocessing can enhance neural sequence models in dynamic forecasting contexts, offering a pathway toward more adaptive, data-driven approaches in weather-sensitive applications.

**Keywords:** empirical mode decomposition, recurrent neural networks, weather forecasting

## 1. Introduction

Weather forecasting remains one of the most challenging tasks in data science due to the inherently dynamic and complex nature of atmospheric systems [1, 2]. In regions with tropical climates, such as Mérida in southeastern Mexico, the difficulty is compounded by high variability, localized phenomena, and abrupt transitions in key meteorological variables [3, 4]. Accurately predicting conditions like temperature, humidity, and pressure is crucial not only for day-to-day planning but also for sectors such as agriculture, infrastructure management, and public safety [5]. However, traditional forecasting models often struggle to cope with the nonlinear and non-stationary behavior exhibited by real-world weather data [6, 7]. In this context, the development of novel methods capable of identifying patterns in chaotic time series has become increasingly relevant, particularly in light of growing interest in localized climate-sensitive decision-making [8].

Despite advances in statistical modeling, traditional forecasting methods often fall short when dealing with the intricacies of real-world meteorological data [9, 10].

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These methods typically rely on assumptions of linearity and stationarity that rarely hold in practice [11], especially when variables exhibit abrupt shifts, irregular cycles, or long-term dependencies. As a result, they tend to oversimplify the underlying dynamics, leading to suboptimal predictions [12]. Furthermore, standard time series techniques often fail to account for the hierarchical nature of temporal patterns—some of which unfold over hours, while others emerge over weeks or months [13]. This limitation becomes particularly evident in tropical regions, where weather systems are influenced by both seasonal cycles and transient atmospheric disturbances [14]. Capturing such multi-scale dependencies requires more flexible, adaptive approaches capable of learning directly from the data [15].

To address these challenges, this project explores a hybrid approach that combines Empirical Mode Decomposition (EMD) [16] with Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) architectures [17, 18]. EMD is an adaptive signal processing technique that decomposes complex, non-linear time series into a finite set of oscillatory components known as Intrinsic Mode Functions (IMFs). These IMFs capture meaningful temporal structures at different scales, effectively isolating patterns while reducing noise and irregularities present in the original data. Once the meteorological variables are decomposed into IMFs, they can be used as input features for training an LSTM model. This type of RNN is particularly well-suited for sequential data, as it retains information over long periods and is capable of modeling temporal dependencies [19]. By combining the noise-filtering capabilities of EMD with the sequence learning strength of LSTM networks, the proposed method aims to improve short-term forecasting accuracy in a data-driven and adaptive manner.

This work presents the design and implementation of a prototype system that integrates EMD and RNNs for the short-term forecasting of key meteorological variables in Mérida, Yucatán. Specifically, the project focuses on predicting daily values of temperature, humidity, and atmospheric pressure using historical data provided by the Comisión Nacional del Agua (CONAGUA). The goal is not to develop a production-grade forecasting tool, but rather to explore the feasibility and performance of the proposed hybrid approach in a real-world context. As such, the system operates as an early-stage proof of concept, emphasizing methodological exploration, performance evaluation, and identification of practical challenges in data preprocessing, model training, and result interpretation.

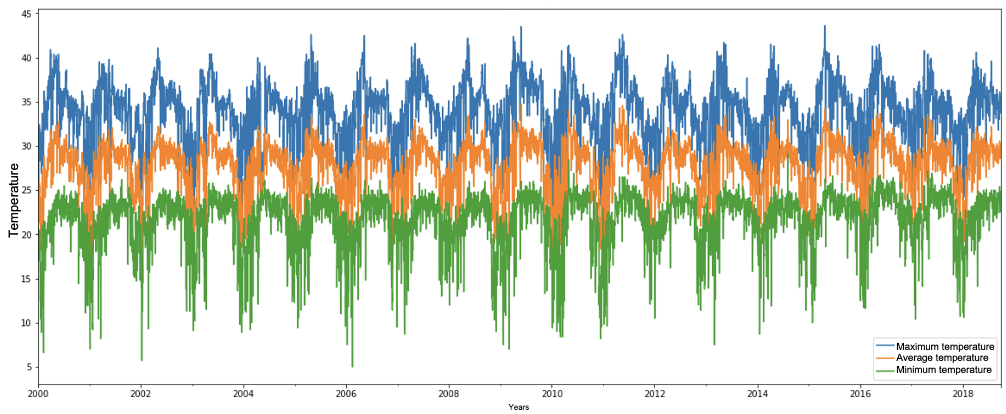
This project represents an exploratory effort to prototype an AI-based solution for a real-world forecasting challenge. Rather than offering a finalized or production-ready system, it emphasizes the early stages of implementation, highlighting both the potential and limitations of applying advanced learning techniques to meteorological data. By experimenting with the integration of EMD and recurrent neural architectures, the work contributes practical insights into how data-driven models can be developed and adapted for complex time series tasks. Although focused on a localized use case, the approach offers a foundation for future applications in fields such as agriculture, disaster preparedness, and environmental monitoring, where improved short-term weather prediction can lead to more informed and timely decisions.

## 2. Project Description

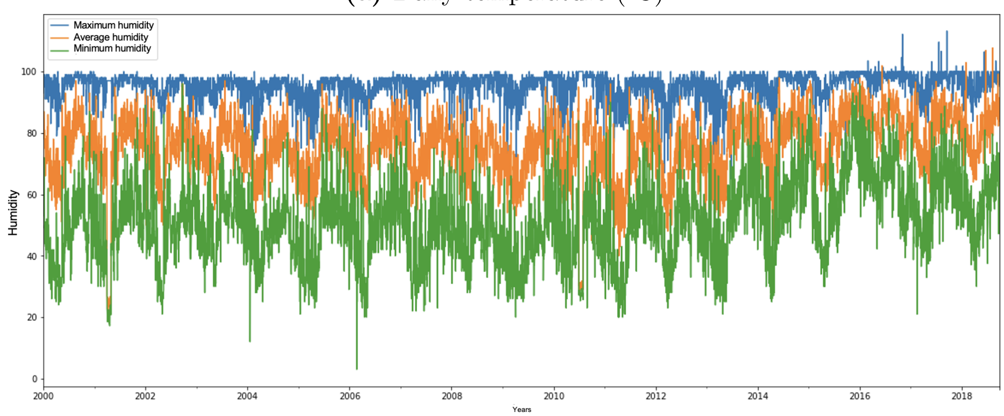
The proposed system follows a modular architecture designed to process raw meteorological time series and generate short-term forecasts through a hybrid machine learning pipeline. At its core, the system integrates EMD as a preprocessing step with a RNN based on LSTM units for prediction. The pipeline begins by taking daily meteorological variables as input—specifically temperature, humidity, and atmospheric pressure—collected over a multi-year period. These raw time series are then subjected to EMD to extract IMFs that isolate oscillatory patterns and reduce noise. The resulting IMFs serve as enhanced input features for the LSTM model, which is trained to learn sequential dependencies and generate forecasts for the following day. This sequential flow—from raw data to decomposition to sequence modeling—defines a structured yet flexible prototype aimed at improving prediction accuracy in complex, real-world weather scenarios.

The dataset used in this project consists of daily meteorological records for the city of Mérida, Yucatán, spanning from the year 2000 to 2018. The data was obtained from the CONAGUA, the national authority responsible for weather monitoring in Mexico. Three primary variables were selected for analysis: temperature (in degrees Celsius), relative humidity (percentage), and atmospheric pressure (in hPa). Each variable was recorded at consistent daily intervals, resulting in a structured time series with over 6,500 data points per variable. Prior to modeling, the raw data underwent a preprocessing stage that included the removal of missing or anomalous values, normalization of scales, and conversion into CSV format for compatibility with machine learning tools. The dataset was then divided into training and validation subsets, maintaining chronological order to preserve the integrity of the temporal structure essential for time series forecasting. The seasonal patterns and short-term variability of the three variables are illustrated in Figure 1.

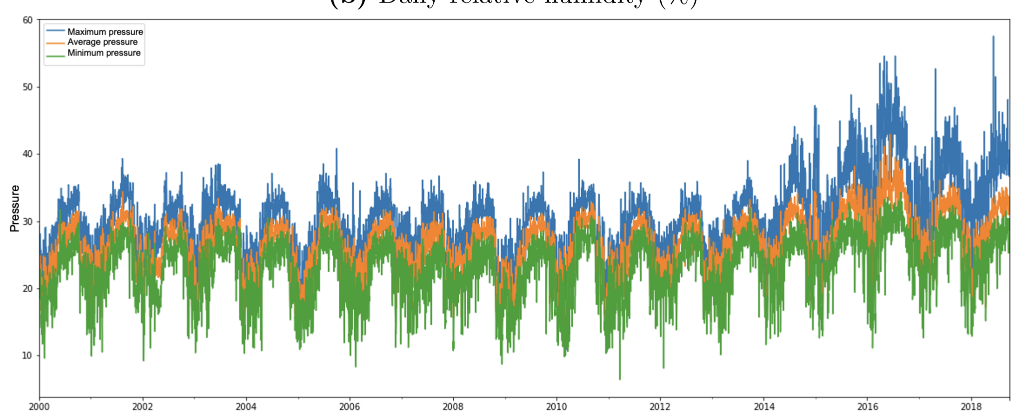
EMD was applied individually to each meteorological variable to extract its underlying oscillatory modes in the form of IMFs. This adaptive, data-driven technique decomposes a non-linear and non-stationary time series into a set of components that represent localized fluctuations at different temporal scales. The decomposition was performed using the PyEMD library, a Python implementation that automates the sifting process without requiring predefined basis functions. For each variable, the EMD process yielded a series of IMFs ranked from high-frequency (short-term variations) to low-frequency (long-term trends). To balance model




**(a)** Daily temperature (°C)




**(b)** Daily relative humidity (%)




**(c)** Daily atmospheric pressure (hPa)

**Figure 1.** Meteorological Time Series for Mérida (2000–2018). Daily values of the three meteorological variables used in this study: (a) temperature, (b) relative humidity, and (c) atmospheric pressure, as recorded by CONAGUA. These raw time series illustrate seasonal variability and short-term fluctuations that make forecasting a challenging task.

complexity and performance, the five most informative IMFs were selected for each variable and used as input features for the forecasting model. This step allowed the neural network to learn from a cleaner, multi-scale representation of the data, reducing the impact of noise and enhancing its ability to capture relevant temporal patterns. An example of the decomposition applied to the temperature variable is shown in Figure 2.

The forecasting component of the prototype was built using a RNN with LSTM units, designed to model the temporal dynamics of the decomposed meteorological data. Each input sequence to the LSTM consisted of five IMFs per variable, spanning a historical window of five consecutive days. The model was trained to predict the value of the corresponding meteorological variable for the next day, establishing a one-day forecasting horizon. Separate LSTM models were trained for temperature, humidity, and pressure, allowing each network to specialize in the dynamics of its respective variable. The architecture included a single LSTM layer followed by a dense output layer, using the Adam optimizer and mean squared error as the loss function. The use of IMFs as input features represents a distinctive departure from conventional raw-sequence modeling, providing the network with richer, frequency-aware representations that enhance its ability to learn from complex time series data.

The design of the prototype was guided by the need to address the limitations of traditional models in capturing the complexity of meteorological time series. EMD was selected as a preprocessing step due to its capacity to handle non-linear, non-stationary signals without requiring a priori assumptions about the data's structure. This made it particularly well-suited for tropical weather patterns, which often display irregular and multiscale behavior. LSTM networks were chosen over other machine learning models because of their proven effectiveness in modeling long-term dependencies in sequential data. One of the innovative aspects of the prototype lies in the use of selected IMFs—especially those representing higher-frequency components—as input features, allowing the network to focus on short-term fluctuations that are critical for daily forecasting. Although the system remains in an exploratory stage, the modularity of the design and the coupling of signal decomposition with deep learning present a promising direction for future refinement and application.

## 3. Implementation and Results

The implementation of the prototype was carried out using Python as the primary development environment, leveraging a combination of specialized libraries for signal processing and deep learning. The PyEMD library was used to perform EMD on each meteorological variable, producing a set of IMFs that were stored and managed using NumPy and Pandas for efficient manipulation. For model development and training, the Keras API within TensorFlow was employed to build and compile the LSTM architectures. Each variable—temperature, humidity, and pressure—was processed separately through the EMD step, generating five IMFs per variable, which were then fed into independent LSTM models. The training pipeline included data normalization, reshaping of input sequences, and batching for efficient training. The experiments were conducted on a standard consumer-grade laptop with 16 GB of RAM and no dedicated GPU, with each model requiring approximately 10 to 20 minutes to train, depending on sequence length and hyperparameter settings.

Each LSTM model was trained independently for the three target variables—temperature, humidity, and atmospheric pressure—using a consistent training procedure tailored to the temporal structure of the data. Input sequences were generated using a sliding window of five previous days' IMFs to predict the value for the next day. The models were trained over 100 epochs with a batch size of 32, using an 80/20 split between training and validation data. Dropout layers with a rate of 0.2 were incorporated to mitigate overfitting, and the Adam optimizer was used with a default learning rate. Mean squared error (MSE) served as the loss function and primary performance metric. Training progress was monitored via loss curves, and although no early stopping mechanism was applied, performance was assessed visually through plots of training and validation loss to detect signs of underfitting or overfitting. This manual tuning process provided insight into the model's learning behavior across variables and informed minor adjustments in model architecture and input formatting.

The models achieved promising results in short-term forecasting, with performance varying slightly across the three meteorological variables. For temperature prediction, the LSTM model trained on EMD-derived IMFs yielded the best accuracy, reaching a mean squared error (MSE) of 0.75 on the validation set. Humidity forecasts followed closely with an MSE of 1.08, while pressure predictions proved more challenging, resulting in a slightly higher error of 1.32. Qualitative assessments using line plots of predicted versus actual values revealed that the models were particularly effective at capturing short-term fluctuations and general trends in temperature and humidity. In contrast, pressure exhibited more irregular patterns that the model struggled to anticipate consistently, likely due to its lower variability and subtler temporal shifts. An example of the forecast performance for temperature is shown in Figure 3, where the EMD-LSTM model's predictions closely track the actual values. Despite some limitations, the results demonstrate that the hybrid approach is capable of learning meaningful representations from decomposed time series and producing forecasts that align well with observed data, especially for highly dynamic variables.

During implementation, several practical challenges emerged that shaped the development process and highlighted areas for future refinement. One of the most notable difficulties was the occasional instability of the EMD algorithm when applied to noisy or irregular segments of the time series, which sometimes produced

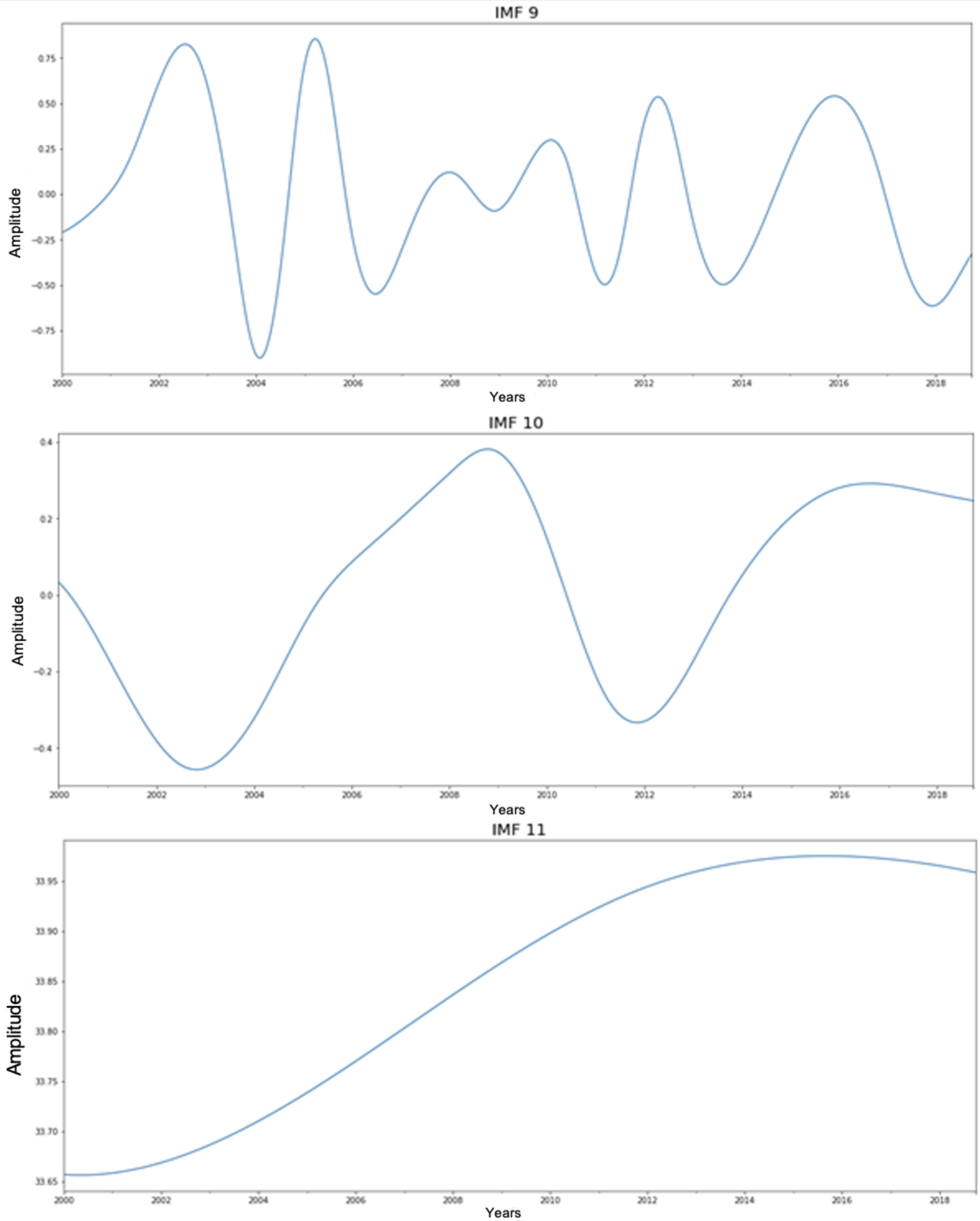



**Figure 2.** Intrinsic Mode Functions (IMFs) Extracted from Temperature Time Series via EMD. Decomposition of the temperature time series into IMFs using Empirical Mode Decomposition. The IMFs represent distinct oscillatory components at different frequency scales and serve as input features for the LSTM model, enabling the network to learn from multi-scale temporal patterns.

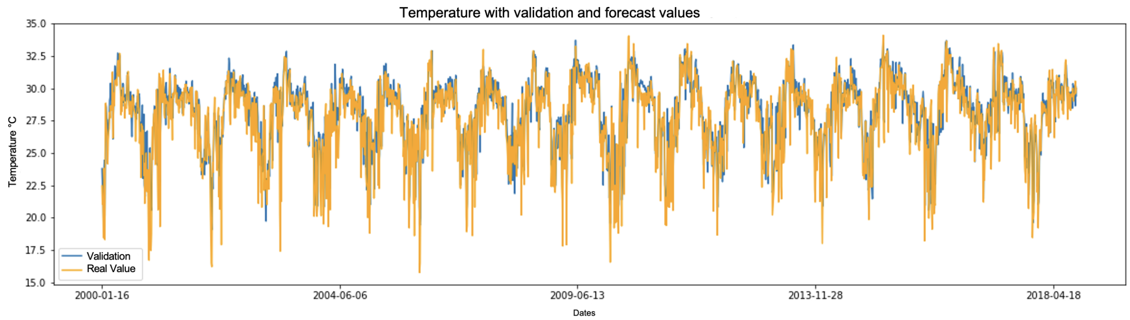



**Figure 3.** Forecast Results Using the EMD-LSTM Model for Temperature. Comparison between actual and predicted temperature values on the validation set using the EMD-LSTM model. The hybrid approach effectively captures short-term trends and daily fluctuations, demonstrating the potential of IMF-based neural forecasting for dynamic meteorological variables.

overlapping or distorted IMFs. This required manual inspection and, in some cases, adjustments to the preprocessing pipeline to ensure the decomposition yielded consistent and meaningful components. On the modeling side, tuning LSTM networks with a relatively small dataset proved to be delicate; minor changes in window size, batch configuration, or dropout rate significantly impacted validation performance. Additionally, while temperature and humidity exhibited clear temporal dependencies, pressure showed less predictable behavior, making it harder for the model to generalize. These limitations suggest the need for more robust IMF selection criteria, possible data augmentation strategies, and exploration of ensemble or multi-variate architectures in future iterations to enhance stability and performance across all variables.

## 4. Discussion and Potential Impact

The results obtained from this prototype suggest that the combination of EMD and LSTM networks offers a viable strategy for short-term weather forecasting, particularly in environments characterized by high temporal variability. By isolating frequency components through EMD and feeding them into a memory-based neural architecture, the system was able to effectively capture and reproduce short-term fluctuations in temperature and humidity. This indicates that decomposing time series into simpler, interpretable components can significantly enhance the learning capacity of sequence models, especially when working with relatively small datasets. The consistency in trend alignment between predicted and actual values further supports the notion that hybrid architectures can offer meaningful improvements over traditional end-to-end learning on raw sequences. These observations point toward the potential of refining and scaling this approach for broader forecasting scenarios, where data complexity and noise often limit the effectiveness of standard methods.

By leveraging EMD to preprocess complex time series, the system reduces noise and exposes latent temporal structures that are more readily learnable by recurrent networks like LSTMs. This layered approach demonstrates that coupling domain-agnostic signal processing methods with deep learning can improve forecasting outcomes without requiring specialized features or handcrafted inputs. Moreover, the architecture's modularity and adaptability suggest that it could be extended to a wide range of applications involving time-dependent data—such as energy demand forecasting, financial market analysis, or patient monitoring in healthcare. The ability to distill relevant patterns from noisy signals using this hybrid strategy opens up promising avenues for AI systems designed to operate under real-world constraints and data imperfections.

Accurate short-term weather forecasts hold substantial value across multiple sectors, particularly in regions where sudden climatic variations can have immediate consequences [20]. In agriculture, timely predictions of temperature and humidity can inform irrigation schedules, pest control measures, and crop protection strategies, ultimately improving yields and resource efficiency [21]. Urban planning and infrastructure management also benefit from short-range forecasts, which can aid in traffic regulation, drainage planning, and energy distribution during periods of extreme weather [22]. In the realm of public safety, early warnings based on localized forecasts can enhance emergency preparedness and response to heatwaves, storms, or unexpected weather shifts [23]. Even at a prototype stage, the system developed in this project illustrates the feasibility of building lightweight, adaptable tools that translate raw meteorological data into actionable insights, laying the groundwork for more robust decision-support systems tailored to the needs of specific communities or institutions.

While the current prototype demonstrates the potential of the EMD-LSTM approach, several avenues remain open for future improvement and exploration. Expanding the dataset to include more recent years or data from additional meteorological stations could enhance the model's generalizability and robustness. Further research is also needed to refine the IMF selection process, potentially incorporating automated criteria or relevance-based filtering to improve signal quality and model input. Exploring multivariate models that can jointly predict multiple variables, or ensemble approaches that combine different architectures, may yield more comprehensive forecasts. Additionally, comparing the LSTM performance with alternative architectures such as Gated Recurrent Units (GRUs) [24] or Transformer-based models [25] could offer insight into trade-offs between complexity and accuracy. Finally, integrating external data sources—such as satellite imagery, radar data, or environmental indices—could enrich the feature space and support more context-aware predictions, bringing the system closer to real-world operational deployment.

This project set out to explore the feasibility of using a hybrid approach that combines EMD with LSTM networks for short-term weather forecasting in a tropical urban setting. Motivated by the challenges posed by non-linear and non-stationary meteorological data, particularly in regions like Mérida, the goal was to develop a prototype capable of learning meaningful temporal patterns from raw climate observations. The core methodology involved decomposing daily time series data into IMFs to isolate key oscillatory components, and then using these components as input features for LSTM models trained to predict temperature, humidity, and atmospheric pressure. The project remained exploratory in nature, focusing on the practical steps and limitations involved in building a working AI-based forecasting system from real-world data.

The results of the prototype highlight the potential of the EMD-LSTM combination to improve forecasting accuracy, particularly for highly dynamic variables such as temperature and humidity. The use of intrinsic mode functions as input features allowed the models to learn from cleaner, frequency-resolved representations of the data, leading to lower prediction errors and better alignment with observed short-term patterns. While the model encountered some limitations in predicting pressure, overall performance metrics demonstrated that the hybrid approach outperformed what might be expected from standard modeling on raw time series alone. These findings underscore the practical value of integrating signal processing and neural modeling in applied AI contexts, especially when working with complex, real-world datasets. By addressing a concrete forecasting problem in a localized environment, the project contributes to the broader effort of translating AI research into functional solutions with societal relevance.

As an exploratory effort, this project demonstrates the early-stage viability of combining empirical decomposition and deep learning for meteorological forecasting, while also revealing important directions for continued development. The prototype serves as a foundation for further experimentation with larger and more diverse datasets, more sophisticated decomposition strategies, and expanded model architectures capable of handling multivariate interactions. Future research could aim to operationalize the system as part of decision-support platforms, particularly in climate-sensitive sectors such as agriculture, disaster risk management, or urban planning. Additionally, integrating external data sources and comparing performance across alternative neural models would help refine the system's predictive capabilities and adaptability. By advancing from concept to implementation, this work opens a pathway toward scalable, AI-driven forecasting solutions tailored to the unique demands of specific regions and applications.

## CRediT authorship contribution statement

**Jesús H. Sarabia-Osorio:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT in order to improve readability. After using this tool, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

## Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## References

[1] U. Huiningsumbam, A. Jain, and N. Verma, "Artificial neural network for weather forecasting: A review," in *2020 IEEE International Conference on Technology, Engineering, Management for Societal impact using Marketing, Entrepreneurship and Talent (TEMSMET)*. IEEE, 2020, pp. 1–7.

[2] M. Hasan, K. Islam, M. S. Rahman, and S. Li, "Weather forecasting using artificial neural network," in *Recent Findings in Intelligent Computing Techniques*, 2019, pp. 171–180.

[3] R. I. Rasel, N. Sultana, and P. Meesad, "An application of data mining and machine learning for weather forecasting," in *Proceedings of the International Conference on Engineering Research and Applications*, 2017, pp. 169–178.

[4] S. Navarro-Tec, M. G. Orozco-del Castillo, J. C. Valdiviezo-Navarro, D. R. Ordaz-Bencomo, M. R. Moreno-Sabido, and C. Bermejo-Sabbagh, "Análisis del crecimiento urbano y su relación con el incremento de temperaturas en la ciudad de mérida utilizando imágenes satelitales." *Res. Comput. Sci.*, vol. 147, no. 7, pp. 285–294, 2018.

[5] A. P. Rodrigues, R. Fernandes, and P. Vijaya, "A study on the evaluation of different regressors in weather prediction," in *2022 International Conference on Artificial Intelligence and Data Engineering (AIDE)*. IEEE, 2022, pp. 13–18.

[6] P. Mahajan, C. Nawale, S. Kini, and K. Shinde, "Weather forecasting using neural network," *International journal of engineering research and technology*, vol. 5, 2018.

[7] M. Sharma, L. Mathew, and S. Chatterji, "Weather forecasting using soft computing and statistical techniques," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Energy*, vol. 3, pp. 11 285–11 290, 2014.

[8] S. B. Nuthalapati and A. Nuthalapati, "Accurate weather forecasting with dominant gradient boosting using machine learning," *International Journal of Science and Research Archive*, 2024.

[9] M. Raghuwanshi, Y. Katre, A. Sahu, D. Sharma, A. Udapure, and C. Lonarkar, "Weather prediction with machine learning," *International Journal of Innovative Science and Research Technology (IJISRT)*, 2024.

[10] E. A. Suárez-Gallareta, J. J. Hernández-Gómez, G. Cetzal-Balam, M. G. Orozco-del Castillo, M. R. Moreno-Sabido, and R. A. Silva-Aguilera, "Sistema hıbrido basado en redes neuronales artificiales y descomposición modal empırica para la evaluación de la interrelación entre la irradiancia solar total y el calentamiento global," *Res. Comput. Sci*, vol. 147, no. 5, pp. 319–332, 2018.

[11] S. Bhatia, B. B. Naib, N. Goel, B. Agarwal, B. Mallikarjun, and M. Arvindhan, "A new era in weather forecasting: Harnessing the potential of machine learning," in *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, 2024, pp. 1355–1361.

[12] P. Das, P. Parmar, S. Sahoo, A. Saluja, and S. Pande, "An intelligent regression approach for weather forecasting system using machine learning," in *2024 1st International Conference on Cognitive, Green and Ubiquitous Computing (IC-CGU)*, 2024, pp. 1–6.

[13] P. R. P. G. Hewage, M. Trovati, E. Pereira, and A. Behera, "Deep learning-based effective fine-grained weather forecasting model," *Pattern Analysis and Applications*, vol. 24, pp. 343–366, 2020.

[14] N. Ng, H. Gopalan, V. Raghavan, and C. Ooi, "Day-ahead forecasting for the tropics with numerical weather prediction and machine learning," in *2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, 2022, pp. 125–130.

[15] P. Nazareth, A. K. Konnur, A. M. Chavan, and K. M. D. Shetty, "Weather forecasting using machine learning approach," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2024, pp. 1–7.

[16] G. Chen, S. Liu, and F. Jiang, "Daily weather forecasting based on deep learning model: A case study of shenzhen city, china," *Atmosphere*, 2022.

[17] M. Ndiaye and M. Mboup, "Empirical mode decomposition with envelope extraction and lstm for univariate time series forecasting," in *2023 International Conference on Machine Learning and Applications (ICMLA)*, 2023, pp. 459–464.

[18] M. G. Orozco-del Castillo, E. C. Orozco-del Castillo, E. Brito-Borges, C. Bermejo-Sabbagh, and N. Cuevas-Cuevas, "An artificial neural network for depression screening and questionnaire refinement in undergraduate students," in *International Congress of Telematics and Computing*. Springer, 2021, pp. 1–13.

[19] S. Zhou, B. J. Bethel, W. Sun, Y. Zhao, W. Xie, and C. Dong, "Improving significant wave height forecasts using a joint empirical mode decomposition–long short-term memory network," *Journal of Marine Science and Engineering*, 2021.

[20] V. Kumar, Shaktibala, and S. Khan, "Importance of weather prediction for sustainable agriculture in bihar, india," *Archives of Agriculture and Environmental Science*, vol. 2, no. 2, pp. 105–108, 2017. [Online]. Available: https://journals.aesacademy.org/index.php/aaes/article/view/02-02-08

[21] P. Stana and M. Vladu, "The importance of the accuracy of public weather forecasts for farmers in the context of climate change in the management of agro-technical decisions," *Annals of the University of Craiova - Agriculture Montanology Cadastre Series*, 2020.

[22] Y. Gong, Y. Zhang, F. Wang, and C.-H. Lee, "Deep learning for weather forecasting: A cnn-lstm hybrid model for predicting historical temperature data," in *Proceedings of the 5th International Conference on Signal Processing and Machine Learning*, 2024. [Online]. Available: https://www.ewadirect.com/proceedings/ace/article/view/17393

[23] J. Xu, Z. Wang, X. Li, Z. Li, and Z. Li, "Prediction of daily climate using long short-term memory (lstm) model," *International Journal of Innovative Science and Research Technology (IJISRT)*, 2024.

[24] W. A. Respaty, C. Hong, N. K. Putra, F. Kurniadi, and Riccosan, "Weather prediction in jakarta: An analysis of climate data and regional influences using lstm and gru," in *2023 International Conference on Data Science and Its Applications (ICoDSA)*, 2023, pp. 408–413.

[25] Y. Arifin, I. Sonata, Maryani, and E. P. Gunawan, "Weather prediction in agriculture yields with transformer model," *Procedia Computer Science*, 2024.