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Empirical mode decomposition-based OS-ELM for short-term solar irradiance forecasting: A case study in Hanoi

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Abstract

Solar irradiation forecasting is vital for the growth of renewable energy sources. In this paper, we propose a hybrid model that integrates Empirical Mode Decomposition (EMD) and an online sequential extreme learning machine (OS-ELM) for multiple steps ahead forecasting of solar irradiation. Initially, the solar irradiation dataset is processed and cleaned. Then, using the EMD model combined with the autocorrelation function, the cleaned dataset is decomposed into several Intrinsic Mode Functions (IMFs) and white noise, which is removed. Each IMF is subsequently predicted using OS-ELM. The final solar irradiation forecast is derived by aggregating the predictions from all Intrinsic Mode Functions (IMFs). The model's performance was assessed through forecasting solar irradiation in Hanoi, using weather data from 2018. The data was collected at 1-hour intervals and utilized for single-step, 12-step, and 24-step ahead forecasts. The forecasting accuracy of the proposed model was compared with four other models, including both single and hybrid approaches: Bidirectional Long Short-Term Memory network, ELM, OS-ELM, and EMD-ELM. Two evaluation metrics of RMSE and MAE were used to assess the forecasting performance of the models. The computational results show that when the multi-step ahead increases, accuracy decreases. In any case, the proposed method outperforms the others, achieving the lowest error rates at 18,01 W/m^2 for RMSE and 8,51 W/m^2 for MAE at 24-step.

***Keywords**: solar irradiation, empirical mode decomposition (EMD), online sequential extreme learning machine (OS-ELM), short-term forecasting, hybrid model, multiple step*

Abbreviations

EMD	Empirical Mode Decomposition
OS-ELM	Online Sequential Extreme Learning Machine
ELM	Extreme Learning Machine
GRU	Gated Recurrent Units
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
IMFs	Intrinsic Mode Functions
ARMA	Autoregressive And Moving Average
ARIMA	Autoregressive Integrated Moving Average
ML	Machine Learning
DL	Deep Learning
SPG	Solar Power Generation
HHT	Hilbert-Huang Transform

1. Introduction

With climate change advancing at an alarming rate, many countries are actively pursuing alternative energy sources to reduce greenhouse gas emissions. In the electricity sector globally, the share of renewable energy is projected to rise from 30% in 2023 to 46% by 2030, with solar and wind accounting for the majority of this growth [1]. Despite the numerous advantages for solving climate change, several challenges still need to be addressed. Most renewable power sources are heavily dependent on weather conditions, leading to instability and fluctuations that pose significant challenges for grid integration. Consequently, forecasting systems play a crucial role in optimizing the integration of renewable energy into power grids. Such systems enhance grid stability by predicting solar power variability, enabling operators to balance supply and demand effectively while reducing reliance on costly backup reserves. Accurate forecasts facilitate improved energy planning, lower operational costs, and minimize risks in energy trading. Moreover, by supporting higher penetration of renewable energy, forecasting systems help reduce dependency on fossil fuels, cut greenhouse gas emissions, and contribute to environmental goals. Additionally, they enhance the efficiency of renewable systems, improve microgrid reliability, and ensure a smoother transition to sustainable energy solutions [2]. As a result, renewable energy forecasting — especially for wind and solar power — has become increasingly popular, with various statistical and machine learning methods being applied.

Over the past two decades, statistical methods, along with Machine Learning (ML) and Deep Learning (DL) techniques, have been successfully applied to forecast solar radiation and photovoltaic (PV) power. Common statistical methods for solar irradiation forecasting include autoregressive integrated moving average (ARIMA) models [3], autoregressive and moving average (ARMA) models [4], and regression method [5]. These statistical models often yield more accurate short-term solar irradiation forecasts since they incorporate historical irradiation data and continuously optimize model parameters. However, they have notable limitations. For instance, the time-series data used in AR, ARMA, and ARIMA models must be stationary, and developing a regression-based forecasting model is challenging due to the need for explanatory variables.

Machine learning, considered as the simplest layer of AI, has facilitated the resolution of many complex problems. In the

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field of forecasting, various machine learning models have been proposed, including the extreme learning machine (ELM) [6], fuzzy models [7], and support vector machines [8]. These models' effectiveness is strongly influenced by the proper handling of input data and the accurate extraction of data order. However, due to the minimal assumptions that machine learning methods make about data characteristics, their performance is highly contingent on the availability of sufficient, high-quality data. This dependency becomes particularly pronounced when dealing with non-stationary series that exhibit seasonality and trends [9].

To address the limitations of traditional machine learning approaches, several deep learning models—such as Convolutional Neural Networks (CNN) [10] or Recurrent Neural Networks (RNN) [11] — have demonstrated promising results in solar forecasting. These advanced models typically achieve greater accuracy than their machine learning counterparts due to their superior data extraction and representation capabilities. Nonetheless, a significant challenge associated with deep learning lies in the preprocessing and transformation of data into formats suitable for these models. This step is especially critical as deep learning architectures are designed to process multidimensional data, which often requires substantial adaptation to align with the sequential nature of time series data.

An optimized ELM model developed by Sahu et al. [12] is utilized to forecast real-time Solar Power Generation (SPG) in the state of Chhattisgarh, India, while accounting for weather conditions. The performance of the ELM model is improved by fine-tuning key parameters, including weights, biases, and the number of hidden layers. This approach necessitates advanced computational techniques capable of effectively handling high-dimensional and complex problems. The Online Sequential Extreme Learning Machine (OS-ELM) represents a significant advancement over the traditional ELM model, offering enhanced capabilities for real-time learning and adaptability. In their study, Parida et al. conducted a comparative analysis between a hybrid model combining Empirical Mode Decomposition (EMD) with ELM (EMD-ELM) and the OS-ELM model for the purpose of photovoltaic (PV) power forecasting [13]. The performance of these models was evaluated using standard error metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings demonstrated that the OS-ELM model consistently outperformed the EMD-ELM hybrid model across these metrics, providing superior overall forecasting accuracy.

Additionally, in order to enhance forecasting accuracy, hybrid models are often utilized [14], [15]. A popular approach is to combine an effective decomposition method with a strong forecasting model, which generally achieves better results than using single models alone. Among the decomposition methods, common method is EMD, an enhancement of the Hilbert-Huang Transform (HHT) is a widely used decomposition technique. EMD decomposes a time series into a set of intrinsic mode functions (IMFs) that represent the inherent oscillatory modes embedded in the data. Unlike wavelet transform, which operates in the time-frequency domain, EMD processes the data entirely in the time domain. This makes EMD particularly well-suited for handling non-linear and non-stationary time series, as it allows for adaptive decomposition without the need for a predefined basis function. By isolating different frequency components in the time series, EMD provides a clearer understanding of the underlying dynamics and facilitates more accurate forecasting [16].

In one study, Redekar et al. [17] proposed hybrid models for predicting soiling levels and uncertainties affecting photovoltaic (PV) arrays, utilizing wavelet transform-based support vector regression (WT-SVR) and empirical mode decomposition-based support vector regression (EMD-SVR). Their study showed that wavelet transform twin support vector regression (WT-TSVR) and EMD-TSVR significantly improved performance, with EMD-based models excelling in computational efficiency and handling random events in soiling-prone environments. Another model, proposed by Reski et al. [18], combines a time-varying filter-empirical mode decomposition (TVF-EMD) technique with an ELM model for PV forecasting. By decomposing power data into stable subseries, the TVF-EMD-ELM model demonstrated high accuracy, achieving a normalized Root Mean Square Error (n-RMSE) below 4% across diverse Algerian climates.

With most ongoing solar forecasting research focusing on deep learning models with much higher requirements for data preprocessing and model training, OS-ELM can be a faster and better model with less complexity, offering a simpler and more practical solution to forecasting. This research proposes a combination of OS-ELM and the EMD decomposition method for short-term predictions of solar irradiance. The EMD algorithm is first applied to decompose the original dataset into 16 smaller IMFs, each exhibiting reduced non-linearity compared to the original data. Each IMF is then individually used as input for the OS-ELM model in the forecasting process. Finally, the results from these predictions are combined to generate the complete forecasting output.

The contribution of this paper is as follows:

- A hybrid model based on machine learning and signal decomposition is proposed. This method utilizes the signal decomposition ability of EMD with the powerful prediction performance of OS-ELM for solar irradiation forecasting.
- The EMD was used for decomposition, effectively decomposed the data into smaller IMF with less nonlinearity, allowing the model to capture the intricacy and trend from the data. OS-ELM possessed the ability to learn data chunk-by-chunk, resulting in extremely fast convergence with great generalization ability.
- To evaluate performance, four additional models — ELM, EMD-ELM, Bi-LSTM, and OS-ELM — are used for comparison. The models are assessed for both 1-step and 24-step forecasting using MAE and RMSE as evaluation metrics.

The next section outlines the foundational methodologies, including the EMD decomposition process, the forecasting approaches using OS-ELM, and the framework for the proposed hybrid model. Section 3 presents the prediction results and corresponding discussion. The original dataset was divided into training and testing subsets with an 80:20 ratio, and the accuracy of the proposed model was evaluated using 1-step, 12-step, and 24-step forecasting. Lastly, Section 4 summarizes the conclusions of this study.

2. Methodology

2.1. Empirical Mode Decomposition (EMD)

The empirical mode decomposition (EMD) [19] is a time-frequency analysis method that adaptively decomposes complex signals, including nonlinear and non-stationary signals. The EMD method breaks down a given signal X(t) into Intrinsic Mode Functions (IMFs), each possessing more stationary characteristics than the original data. The mathematical formulation of this decomposition is as follows:

$$X(t) = \sum_{j=1}^{n} C_j(n) + R_n \quad (1)$$

where, $C_j(n)$ represents the j[th] IMF component and R_n denotes the residual portion of the original dataset after extracting n IMFs. Each IMF exhibits distinct amplitude and frequency characteristics but retains fundamental properties. The resulting IMFs contain an equal count of extrema and zero-crossings, which may differ from those in the initial dataset. At any given data point, the mean of the envelope is determined by local maxima, while the envelope based on local minima is considered zero.

Figure 1 illustrates the step-by-step process of this method. In this figure, the process begins with an input signal $x(t)$, where local extrema are identified to construct upper and lower spline envelopes. The mean of these envelopes, $m_k(t)$, is subtracted from the signal to obtain a candidate function $d_k(t)$. If $d_k(t)$ satisfies the conditions of an IMF — having nearly equal zero crossings and extrema, with a local mean of zero — it is extracted as $c_n(t)$. Otherwise, the process iterates until an IMF is obtained. The residual signal, $r_n(t)$, is then computed by subtracting the sum of extracted IMFs from the original signal. If the residual remains oscillatory, the decomposition continues; otherwise, if it is monotonic, the process stops, and the signal is reconstructed as the sum of IMFs and the residual.

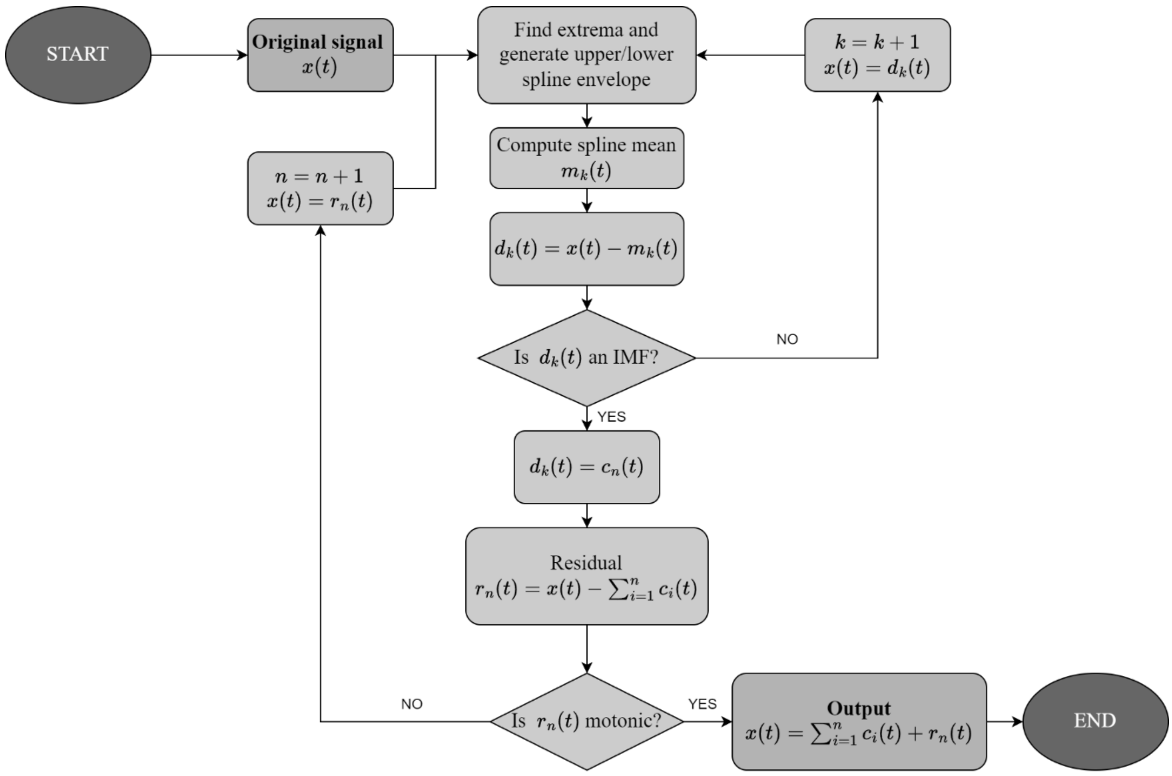

Figure 1: The flowchart of EMD method

2.2. Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) is a novel model for training single-hidden layer feedforward neural networks (SLFNs) [20]. It works by randomly selecting hidden nodes and then determining the output weights analytically. Introduced by Huang et al. [21]., ELM is recognized for its simplicity and efficiency. Unlike traditional neural networks that iteratively adjust hidden layer parameters, ELM initializes the hidden layer weights and biases randomly, while the output weights are computed using a least-squares solution. This method significantly reduces both computational complexity and training time. ELM excels in handling large datasets with high-dimensional features while maintaining strong generalization capabilities, making it a popular choice for tasks such as classification, regression, and function approximation.

For generalized SLFNs the output function of ELM is written as the following equation (2):

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \quad (2)$$

where $\beta_i = (\beta_1,\ \beta_2, \ldots, \beta_L)$ is the output weights vector between the output neurons $(m \geq 1)$ and L hidden layer neurons, $h(x) = [(h_1(x), h_2(x), \ldots, h_L(x))]$ is the hidden layer output function with respect to x.

2.3. Online Sequential Extreme Learning Machine (OS-ELM)

While ELM provides rapid learning capabilities, it has certain limitations. Specifically, an excessively large number of hidden neurons can lead to overfitting. Moreover, when dealing with complex data sequences, ELM may produce substantial prediction errors.

The Online Sequential Extreme Learning Machine (OS-ELM) [22] is an enhanced variation of ELM designed to address such challenges, particularly in scenarios where data arrives in a sequential or real-time fashion. Unlike the standard ELM, which requires the entire dataset to be available before training, OS-ELM has the ability to learn data chunk-by-chunk or one-by-one. This feature makes it particularly well-suited for real-time forecasting.

OS-ELM preserves the key advantages of ELM, including rapid training and high accuracy, while adding the ability to process continuously evolving data streams. It utilizes online learning algorithms to update the model with minimal computational complexity, enabling adaptive and efficient learning in dynamic environments. Due to its scalability and ability to handle large, time-sensitive datasets, OS-ELM is a valuable tool for applications such as forecasting, classification, and pattern recognition [23]. Figure 2 presents an illustration over the framework of OS-ELM.

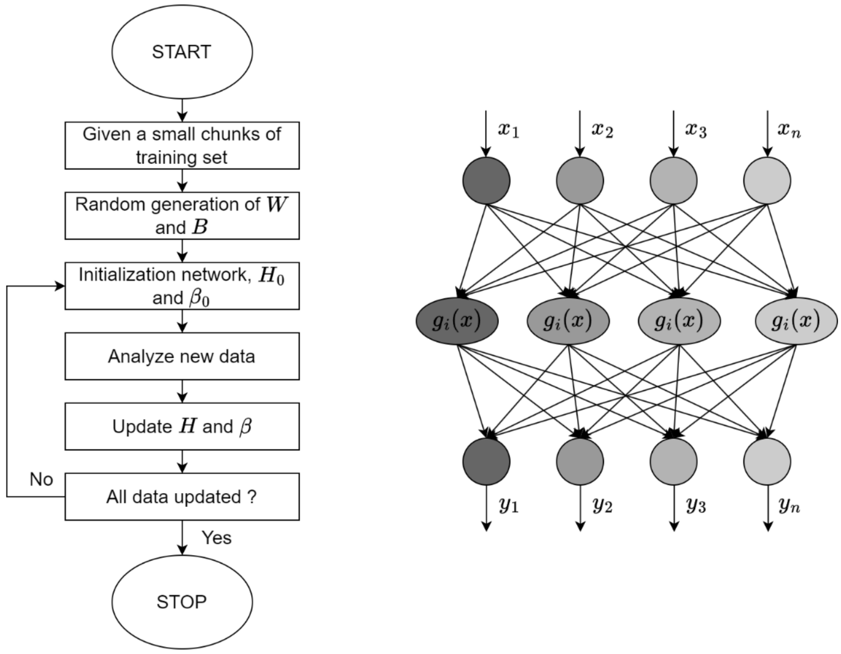

Figure 2: Illustration of OS-ELM structure

The structure of OS-ELM can be described as follows:

Initially, a small batch of training data, denoted as $\aleph_0 = \{(\boldsymbol{x_i}, \boldsymbol{t_i})\}_{i=1}^{N_0}$ is selected for model initialization. This batch must satisfy the condition $\boldsymbol{N_0} \geq \boldsymbol{L}$, where $\boldsymbol{L}$ represents the rank of $\boldsymbol{H_0}$. The initialization process consists of the following steps:

Step 1: Randomly assign parameter values.

Step 2: Compute the initial hidden layer output matrix H_0.

Step 3: Estimate the initial output weight $\beta_{(0)}$ using the equation:

$$\beta_{(0)} = \mathbf{P_0 H_0^T T_0} \tag{3}$$

where P_0 is derived from $\left(\mathbf{H_0^T H_0}\right)^{-1}$ and $\mathbf{T_0}$ is represented as $\left[\mathbf{t_1}, \dots \mathbf{t_{N_0}}\right]^{\mathbf{T}}$.

Step 4: The initial chunk index is set to zero (k=0). During the sequential learning phase, the model processes new batches of data incrementally, where each new chunk at step $\boldsymbol{k+1}$ is given by:

$$\aleph_{\mathbf{k+1}} = \{(\mathbf{x_i}, \mathbf{t_i})\}_{\mathbf{i}=\sum_{j=0}^{k} N_j+1}^{\sum_{j=0}^{k+1} N_j} \tag{4}$$

2.4. The proposed model

The proposed model utilized data pre-processing, decomposition, and forecasting techniques to significantly enhance the accuracy of predictions in complex time-series data. The proposed model structure is illustrated using Figure 3. The process begins with data pre-processing, where the raw time-series data undergoes EMD. EMD is a powerful technique that breaks down non-linear and non-stationary data into simpler components called IMFs along with a residual component R_n. This decomposition isolates the various oscillatory modes within the data, effectively simplifying the complex time-series and enabling more focused analysis. By breaking the data into IMFs, the model can separately analyze distinct patterns and frequencies, improving the accuracy of subsequent forecasts.

Following this, each IMF is forecasted independently using OS-ELM, a highly efficient machine learning algorithm optimized for real-time data processing. OS-ELM is particularly well-suited for sequential learning, as it can update model predictions as new data becomes available without significantly increasing computational costs. At this stage, the residual component R_n is excluded from the forecasting process, allowing the model to focus on the patterns within the IMFs without being distracted by long-term trends or noise. This separate forecasting of each IMF ensures that the model accurately captures the behavior of distinct data components, thus maximizing prediction accuracy. After the forecasting results from each IMF are obtained, they are recombined to produce the final prediction.

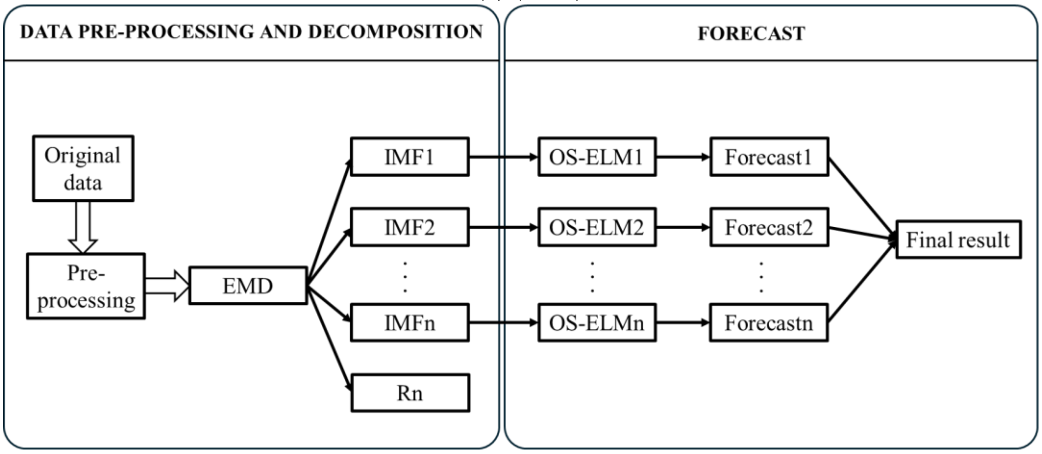

Figure 3: Construction of the proposed model

By combining EMD for data decomposition and OS-ELM for efficient forecasting, this hybrid model produces robust and reliable results for complex time-series data. As illustrated in Figure 3, the approach is particularly effective for handling non-linear, non-stationary datasets, which often pose challenges for traditional forecasting methods.

2.5. Evaluation metrics

In this study, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and are used to accurately assess the performance of the proposed model compared to other comparison models. The equations below illustrate the formula for the metrics:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} |A_i - F_i|}{N} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (A_i - F_i)^2}{N}} \tag{6}$$

Where N is the number of sample data, A_i is the actual value, $\overline{A}$ is the mean of the actual value and F_i is the estimated value

3. Results and Discussion

3.1. Data acquisition

The dataset utilize for this research is the weather data of Hanoi in 2018, acquired from Hanoi Meteorological Company. The GHI variable is picked among the variables presented in the dataset for solar irradiance forecasting. The interval between each data point is 1-hour, which results in 8000 data points in a span of 1 year. To better illustrate the dataset Figure 4 was drawn using the original weather dataset.

3.2. Data analysis

3.2.1. *Data pre-processing*

Before being decomposed using EMD, the dataset must be preprocessed. In this paper, two formulas (5) and (6) are utilized for handling missing values and outliers of the dataset. The formulas are presented as follows:

$$F(x_{i,t}) = \begin{cases} \frac{x_{i,t-1} + x_{i,t+1}}{2}, x_{i,t} \in \mathrm{NaN} \\ x_{i,t}, \ \text{else} \end{cases} \tag{8}$$

$$F(x_{i,t}) = \begin{cases} \mathrm{avg}(x_{i,t}) + 2\sigma(x_{i,t}), \text{if } x_{i,t} > x_{i,t}^{*} \\ x_{i,t}, \qquad \text{else} \end{cases} \tag{9}$$

where $x_{i,t}$ is the solar irradiation value at hour i, $x_{i,t}^{*}$ is computed by the mean avg $(\cdot)$ and the standard deviation $\sigma(.)$ for each time interval.

3.2.2. *Data decomposition*

As mentioned in the methodology section, the EMD technique was used to decompose the preprocessed historical data into multiple components. The decomposition process resulted in 16 IMFs along with a residual component, as demonstrated in Figure 5. The residual is considered noise and excluded from the training process to increase efficiency.

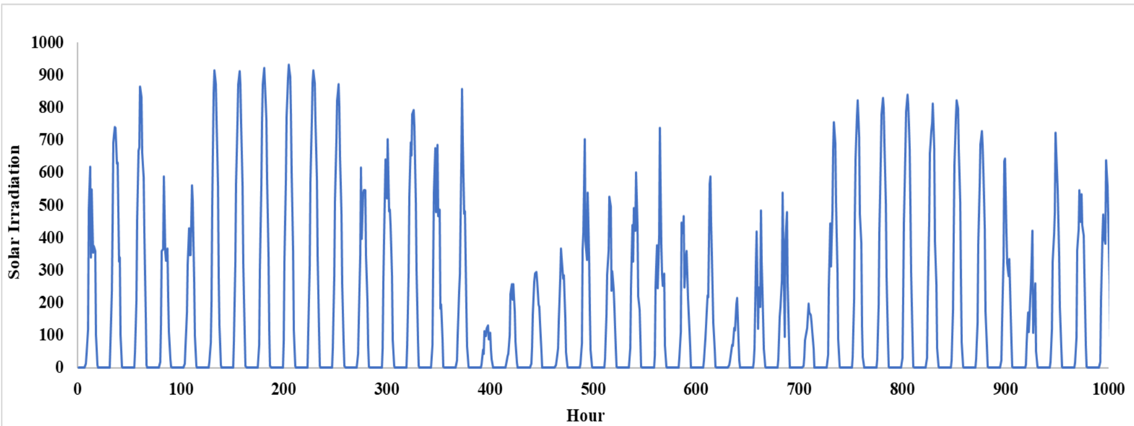

Figure 4: Visualization of the original dataset

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3.3. Forecasting results and evaluations

3.3.1. *Forecasting model parameters*

The parameters for the EMD-based comparative models (ELM, OS-ELM and EMD-ELM) with the proposed model (EMD-OS-ELM) can be listed as follows:

Table 1: Proposed model parameters

Models	Parameters				
	nDim Input	nDim Output	Num Neu-rons	lamb	output-WeightFF
ELM-based models	numLags	1	50	0,0001	0,99

In these models, nDimInput represents the parameter indicating the number of input dimensions or features in the dataset. The variable numLags denotes the number of time lags or historical observations used as input features for the model. This approach, commonly used in time-series analysis, utilizes lagged values to capture temporal dependencies in the data.

The parameter nDimOutput defines the number of output dimensions, which is set to 1 in this case. This indicates that the model is designed for univariate output, predicting a single value at each time step.

The variable numNeurons specifies the number of neurons in the hidden layer of the neural network. With a value of 50, the model employs 50 nodes in its hidden layer, which are responsible for learning and extracting patterns from the input data.

Finally, the parameter lamb (lambda), the regularization factor, is set to 0,0001 to reduce the risk of overfitting by controlling the model's complexity and ensuring better generalization. Lastly, outputWeightFF is assigned a value of 0,99, representing the forgetting factor of the model.

The parameters of the three ELM-based models were chosen the same as the proposed model, while the BiLSTM's was set as default with 2 LSTM layers with 128 and 64 units.

a. Single and hybrid models:

The comparison between individual models (ELM, Bi-LSTM, OSELM) and hybrid decomposition-based models (EMD-ELM, Proposed) reveals the following insights: Decomposition-based models consistently outperform individual models due to their ability to simplify the data by breaking it into more manageable components. The proposed model significantly outperforms EMD-ELM across all prediction steps, demonstrating the added value of the optimized structure (EMD-OS-ELM). For instance, in 1-step prediction, the RMSE reduction between EMD-ELM and the Proposed model is approximately 19,57 W/m², and in 24-step prediction, it increases to 30,15 W/m². This highlights the proposed model's greater capacity to handle complex datasets and maintain accuracy over longer horizons.

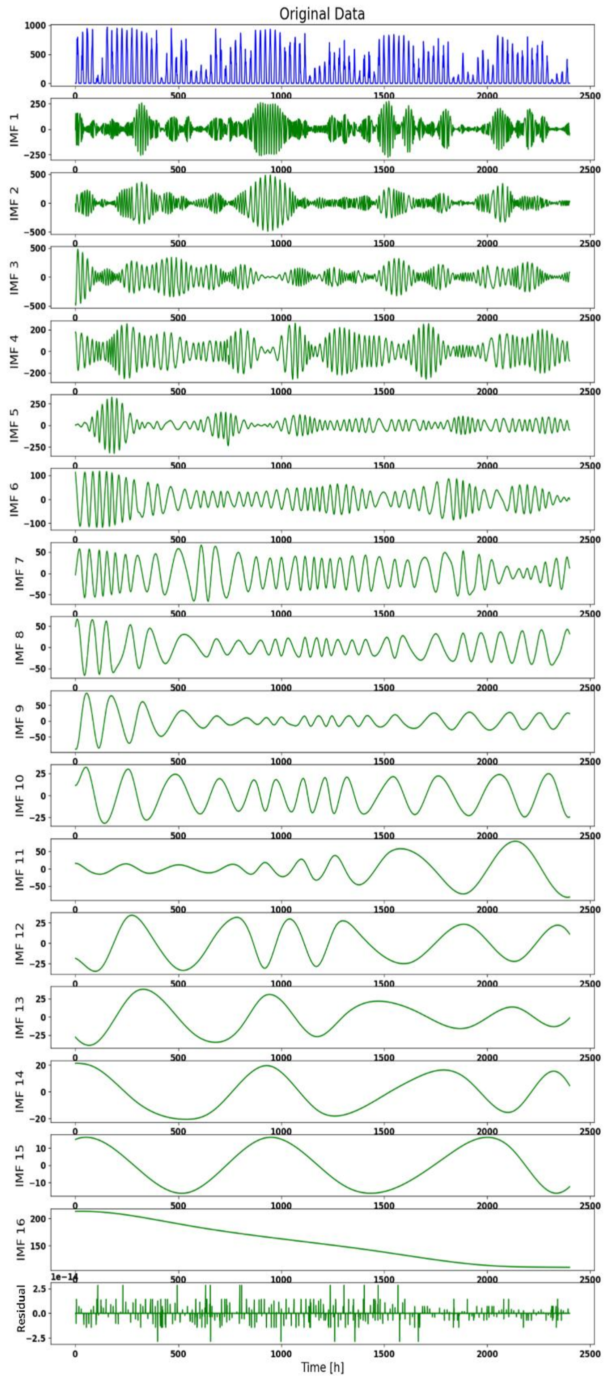

Figure 5: 16 IMFs produced using EMD on the dataset

b. Forecasting steps: The accuracy of all models varies significantly with the number of forecasting steps (1-step, 12-step, and 24-step).

All models perform the best at 1-step predictions due to the reduced complexity and lower uncertainty associated with short-term forecasting. The Proposed model achieves remarkable accuracy (RMSE = 8,98 W/m² and MAE = 4,88 W/m²), which is significantly better than the second-best model, EMD-ELM (RMSE = 28,55 W/m², MAE = 24,87 W/m²). Errors are relatively low for all models, but the advantage of hybrid models (EMD-ELM and Proposed) becomes evident.

As the forecasting horizon extends, all models experience an increase in errors due to the accumulation of uncertainties over time. The proposed model continues to deliver the lowest errors (RMSE = 12,75 W/m², MAE = 6,49 W/m²),

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maintaining its superiority over EMD-ELM (RMSE = 32,79 W/m², MAE = 30,60 W/m²). The RMSE difference between the Proposed and EMD-ELM models increases to 20,04 W/m², indicating the proposed model's resilience in medium-term forecasting.

24-step forecasting results introduce the greatest challenges due to compounding uncertainties. Errors increase for all models, but the Proposed model remains the most accurate, with RMSE = 18,01 W/m² and MAE = 8,51 W/m². The difference in RMSE between the Proposed and EMD-ELM models grows further (30,15 W/m²), showing the Proposed model's robustness in handling long-term predictions. Errors for non-hybrid models (ELM, Bi-LSTM, OSELM) rise sharply, demonstrating their limitations in capturing the complexity of long-term time-series data.

In conclusion, hybrid decomposition-based models (EMD-ELM and Proposed) consistently outperform individual models, with the Proposed model being the most effective overall. The Proposed model demonstrates superior accuracy and robustness, with smaller errors across all forecasting steps, particularly excelling in long-term forecasting where other models struggle. This underscores the importance of integrating decomposition techniques to enhance forecasting performance.

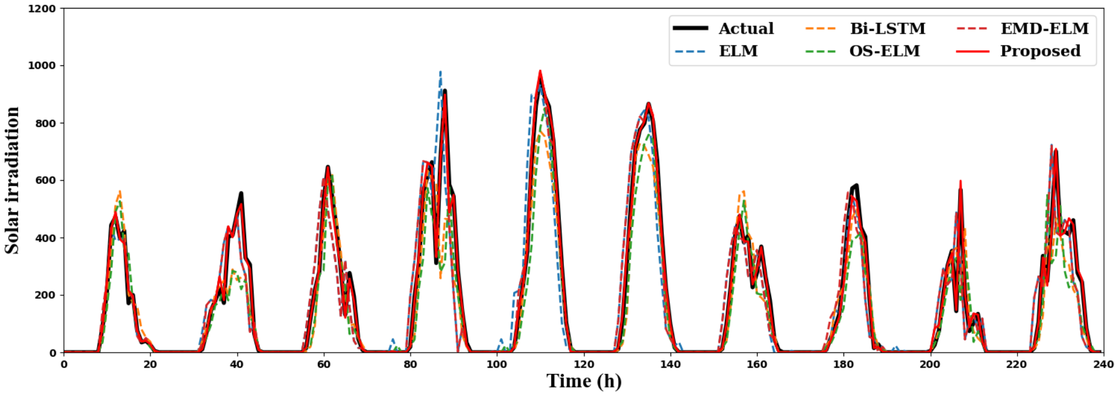

Figure 6: Time-series forecasting results comparison (24-step forecasting)

Table 2: Accuracy evaluation of the forecasting models on the seasonal datasets

Forecasting Step	Evaluation Criteria	ELM	Bi-LSTM	OSELM	EMD-ELM	Proposed
1-Step	RMSE (W/m²)	56,88	42,99	51,87	28,55	8,98
	MAE (W/m²)	49,50	34,50	37,55	24,87	4,88
12-Step	RMSE (W/m²)	76,23	57,79	73,98	32,79	12,75
	MAE (W/m²)	56,90	42,46	46,17	30,60	6,49
24-Step	RMSE (W/m²)	86,63	63,71	80,50	48,16	18,01
	MAE (W/m²)	63,98	50,94	53,52	42,39	8,51

4. Conclusion

In this study, a decomposition-based solar irradiation forecasting model utilizing Online Sequential Extreme Learning Machine (OS-ELM) networks was developed. The model aims to enhance the accuracy and reliability of solar irradiation forecasts by integrating data decomposition and machine learning techniques. The original solar irradiation data was first preprocessed and decomposed into multiple Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD). This decomposition helps isolate various oscillatory components within the data, allowing the model to capture different underlying patterns. During this step, any white noise present in the original data was identified and removed, further improving the quality of the input data for forecasting. Subsequently, the OS-ELM network was employed to train and forecast each IMF independently. OS-ELM's ability to handle data in a sequential manner made it particularly well-suited for this task, enabling efficient real-time forecasting. The forecasting performance was evaluated using two criteria: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These metrics provided a comprehensive assessment of the model's accuracy and error minimization across different data patterns.

The results demonstrated that the hybrid decomposition method significantly outperformed other single forecasting models. At the 1-step forecasting horizon, the proposed model achieved an RMSE of 8,98 W/m² and an MAE of 4,88 W/m², surpassing all other models. Similarly, for 24-step forecasting, the proposed model attained an RMSE of just 18,01 W/m², outperforming the second-best model (EMD-ELM) by a margin of 30,15 W/m². By combining EMD for data preprocessing and decomposition with the OS-ELM for forecasting, the proposed model achieved the best performance with minimal errors across all evaluation criteria. This indicates that the model is highly effective at capturing complex, non-linear patterns inherent in solar irradiation data, leading to more accurate and reliable forecasts compared to traditional methods. It should be noted that applying this method to other case studies or datasets would require modifications to account for differences in climate and geographical properties. Future work can involve testing this model in a variety of case study to test its effectiveness under more conditions or combining this technique with other better decomposition algorithms to improve its effectiveness.

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