

A GRID SEARCH OPTIMIZED HYBRID MODEL FOR SOLAR IRRADIANCE FORECAST USING EMPIRICAL MODE DECOMPOSITION AND BIDIRECTIONAL GATED RECURRENT UNIT

Rajnish Mitter¹, Manish Kumar Saini¹, Sumit Saroha^{2,*}

Received: October 24, 2024; Revised: January 04, 2025; Accepted: January 29, 2025

Abstract

To ensure the reliable operation of the power grid, an accurate forecasting of solar irradiance (SI) is highly essential. Classical forecasting methods struggle to capture the fundamental nonlinearity of SI, resulting in low forecasting accuracy. A hybrid model based on deep learning (DL) technique called EMD-GS-BiGRU, which is the combination of empirical mode decomposition (EMD) with Bidirectional gated recurrent unit (BiGRU) predictor and grid search algorithm is proposed in this paper. The suggested EMD-GS-BiGRU model constructed and tested in two different Indian locations: Chennai and Jammu, for different popular models: artificial neural network (ANN), long short-term memory (LSTM), gated recurrent unit (GRU), and their EMD-based hybrid version i.e. EMD-GS-LSTM and EMD-GS-GRU. The evaluation of the performance of the proposed model is performed by statistical and graphical analysis of one hour ahead seasonal SI forecasts. According to the findings, the lower average root means square error (RMSE) of 64.39 W/m²-83.46 W/m² is obtained by proposed model compared to contrast models. The proposed model also obtained higher yearly R² value, 0.9366-0.955 compared to other models. Furthermore, the study found that the EMD with grid search optimized BiGRU enhanced the RMSE (39.23%-47.31%) and mean absolute percentage error (MAPE) (41.82%-52.31%) compared to other standalone contrast models.

Keywords: Bidirectional Gated Recurrent Unit; Empirical Mode Decomposition; Grid Search; Long Short-Term Memory; Solar Forecasting

¹ Department of Electrical Engineering, DCRUST, Murthal, India. E-mail: rajnishmitter@gmail.com; manishkumar.ee@dcrustm.org

² Department of Electrical and Electronics Engineering, Guru Jambheshwar University of Science & Technology, Hisar, India. E-mail: ssumitsaroha8@gmail.com*

* Corresponding author

DOI: <https://doi.org/10.55766/sujst6471>

Suranaree J. Sci. Technol. 32(1):010353(1-13)

Introduction

The reliance on conventional energy of each country is increasing day by day as the population expands (Singla *et al.*, 2022c). Even, India is also an emerging country towards each sector. India's large central power plants predominantly rely on fossil fuels, releasing approximately one billion tons of CO₂ into the atmosphere annually (Badoni *et al.*, 2023). As per the figures presented by Ministry of Statistics and Program Implementation 2019, energy generation climbed by 5.71% in 2017-2018, while consumption increased by 7.39% (Makade *et al.*, 2021). As a result, the adoption of the renewable resources by all over the world is increased to meet their electricity demands. Solar energy represents a key renewable resource, contributing for 68.33% of total renewable energy resource (Singla *et al.*, 2021a). However, the integration of renewable energy resources with power systems puts a burden on grid planning, scheduling, and balance. As an operator, you must balance predictions and power usage, which is a difficult undertaking in and of itself. Because solar photovoltaic (PV) output is strongly dependent on meteorological factors, climatic circumstances, and location peculiarities, accurate SI forecasting is the difficult aspect to generation of power. In this context, various academics are researching the best technique for accurately predicting SI (Gupta *et al.*, 2020).

The literature proposes multiple approaches for predicting SI for different time horizons. Furthermore, the selection of the forecasting model and mechanism are completely reliant on the type of data and prediction window. As a result, researchers are investigating alternative approaches for forecasting SI that can be generalized to any data set and horizon. Many models have been created using time series to predict SI, and machine learning (ML) based method appear to be becoming increasingly popular for precise forecasting of SI. Several machine ML models are reported in the past studies, including artificial neural networks (ANN) (Amer *et al.*, 2023), support vector machines (SVM) (Saxena *et al.*, 2024) linear regression (LR) (Singla *et al.*, 2023b), and decision trees. P. Singla *et al.* forecasted the SI using the ANN, SVM, and LR with the help of different normalization methods. The study focused on the behavior of different models on the data normalization technique. From the study, it is observed that the clear sky index (CSI) method improved the learning ability of all the models (Singla *et al.*, 2022d).

Furthermore, several researchers have used a range of DL models, such as long short-term

memory (LSTM) and gated recurrent unit (GRU), to predict SI and have successfully proved that they outperform standard ML techniques. D.K. Dhakad *et al.* estimated the solar PV output using the LSTM and backpropagation neural network. The developed model evaluated using the mean absolute error (MAE), MAPE, R². From the evaluation, the study observed that the LSTM model outperforms the backpropagation neural network (Dhakad *et al.*, 2023). Likewise, the solar energy has been predicted by N.L.M. Jailani *et al.* using the LSTM based models. The standalone model LSTM and convolution neural network (CNN), gated recurrent unit (GRU), hybrid models: CNN-LSTM is developed in this study. From the observation, it is found that the LSTM based hybrid model obtained the better outcomes than standalone models (Jailani *et al.*, 2023). J. Wojtkiewicz *et al.* predicted the SI in hour ahead time horizon using multivariate GRU. The study trains the models using the time series data along with exogenous hybrid data. To evaluate the performance of the developed model, the study compared the proposed model with LSTM. From the study, it is observed that the LSTM and GRU significantly improved the forecasting accuracy of the model (Wojtkiewicz *et al.*, 2019). Moreover, P. Singla *et al.* observed the performance of LSTM using different training algorithms. The study employed the ADAM, SGDM and RMSprop training algorithms to observe the forecasting accuracy of the LSTM model. from the study, it is observed that the ADAM algorithm significantly improved the performance of the LSTM model (Singla *et al.*, 2022g).

Aside from that, the solo model struggles to predict a complicated SI time series with distinct patterns, periods, and erratic changes. Therefore, such models have poor forecasting accuracy and substantial forecasting errors. As a result, the usage of composite models is strongly encouraged in order to achieve high accuracy. Many of the past studies employed an integration of a preprocessing approach and a predictor (Singla *et al.*, 2021a). These preprocessing techniques use decomposition algorithms to demodulate the original SI into sub-bands with hidden data attributes. Discrete wavelet transforms (WT) (Singla *et al.*, 2021b), variational mode decomposition (VMD) (Singla *et al.*, 2022a), principal component analysis (PCA), complete ensemble empirical mode decomposition with adaptive noise is some of the renowned named of signal processing techniques used in latest research. According to current research, the most often used preprocessing techniques are DWT and its variant:

wavelet packet decomposition (WPD) (Singla *et al.*, 2022b) (Saroja *et al.*, 2021). To achieve optimal results, the levels of Discrete Wavelet Transform (DWT) and Wavelet Packet Decomposition (WPD) are varied from one to seven, using different wavelets. For instance, C.S. Lai *et al.* utilized the same wavelet transform (WT) with the DB4 wavelet and a support vector machine (SVM), finding the lowest RMSE values ranging from 32.10 W/m² to 46.13 W/m² (Lai *et al.*, 2021). Likewise, P. Singla *et al.* employed WT for prediction of SI with DB7 wavelet for an Indian site. The developed model obtained reduced RMSE (45.61W/m²) and MAPE (6.48%) (Singla *et al.*, 2021b). Additionally, solar-related literature has explored various nature-inspired algorithms. R. Kumar *et al.* employed PSO-particle swarm optimization, BFOA-bacterial foraging optimization algorithm, and a hybrid of the two reduce and regulate power fluctuations in a two-area, connected with a large-scale PV farm (Kumar *et al.*, 2022a). Likewise, the potential of swarm-based hybrid metaheuristic optimizer PSO-BFOA tuned by PI controller is also assessed by R. Kumar *et al.* for wind, PV and their hybridization (Kumar *et al.*, 2022b). Furthermore, R. Kumar *et al.* showcased improved oscillation damping and power flow control in a two-area model integrated with a large-scale PV farm by utilizing the PSO-BFOA approach (Kumar *et al.*, 2021).

Motivation

Based on the preceding investigations, the following findings are recorded: (a) A solo model cannot extract hidden characteristics from a time series accurately. (b) Preprocessing is necessary to improve predictor performance. (c) The fine tuning of hyperparameters of DL models improves the forecasting accuracy. (d) Adaptive preprocessing algorithms simplify systems. Therefore, to solve non-stationary time series SI forecasting challenges, an ensemble of EMD and Bidirectional GRU model with grid search algorithm is used in the paper due to their benefits in time series modelling. As per the knowledge this is the first time, the combination of EMD-GS-BiGRU is used for SI forecasting problem. The following are the main contributions to the work:

1. Use of EMD algorithm to extract the inherent features of the historical input time series.
2. Employment of the grid search (GS) algorithm to fine tune the DL models.
3. Development of the different models utilizing above two steps with LSTM, GRU and BiGRU.
4. A case study is conducted for two distinct sites in India to assess the performance of the

proposed approach. The effectiveness is evaluated using metrics such as RMSE, mean absolute percentage error (MAPE), and R². The proposed model is then compared to several benchmark standalone models and their corresponding EMD-GS-based hybrid variants.

The remaining part of the paper is designed as follows that Section 2 discuss the details of the datasets used for training and testing of the models. The theoretical details of the methodology and the framework of proposed model discussed in Section 3. Sections 4 elaborated the results obtained by the developed models. Finally, section 5 dedicated to the conclusions.

Dataset Description

This study uses hourly SI data from the National Solar Radiation Database (NSRDB). Data was collected for Chennai (Lat./Long: 13.09/80.26) and Jammu (Lat./Long: 32.73/74.86) for time horizon of 1-hour period on year 2018 and 2019. Both the location of the India selected for evaluation of the model have diverse climatic characteristics. Moreover, according to the Köppen climate classification, Jammu experiences a humid subtropical climate (Cwa), while Chennai features a tropical savanna climate with a dry summer (As), closely bordering the dry-winter variant (Aw). Furthermore, according to Indian meteorological department, the yearly dataset is divided into four sub-datasets based on SI season: winter, summer, monsoon, and autumn. The winter dataset covers the three months: December, January, and February, the summer dataset covers the March, April and May month. Likewise, the monsoon season covers the four months: June, July, August and September, the Autumn dataset covers the September and October month (Singla *et al.*, 2022f). Table 1 summarizes key features of the four seasonal datasets of both the locations. Solar irradiation sub-datasets are separated into training and test subsets based on temporal factors between surrounding locations. The initial 80% of the data is used for training the models, while the last 20% is employed to evaluate their performance. Moreover, the input data undergoes normalization because of its different dimensions and value ranges. To make the uniformity in the variables within the same range, the clear sky index approach is used Eq. 1.

$$CSI = \frac{SI_e}{SI_{ext}} \quad (1)$$

Table 1. Basic Information of datasets

Location	Season	Data Frame	Mean	Standard Deviation
Chennai	Winter	01 Sept. 2018 - 31 Jan 2019	435.94 W/m ²	229.74
	Summer	19 Dec. 2018 - 31 May 2019	535.12 W/m ²	257.28
	Monsoon	25 Feb. 2019 - 31 Jul 2019	516.60 W/m ²	274.76
	Autumn	16 Jul 2019 - 30 Nov. 2019	403.29 W/m ²	248.07
Jammu	Winter	09 Sept. 2019 - 31 Jan 2019	391.39 W/m ²	218.51
	Summer	22 Nov. 2019 - 31 May 2019	421.37 W/m ²	274.25
	Monsoon	18 Feb. 2019 - 31 Jul 2019	488.23 W/m ²	299.19
	Autumn	Jul 2019 - 30 Nov. 2019	405.28 W/m ²	252.76

where CSI is the clear sky index, SI_e and SI_{ext} are the solar irradiation at earth and extraterrestrial solar irradiation.

From the Table 1, it is clear that the season monsoon has highest standard deviations in both the datasets. The highest standard deviation shows the higher uncertainty in the dataset. Moreover, the Jammu dataset has higher standard dataset among both the dataset, represents maximum uncertainty in the dataset of Jammu.

Methodology

This section covers the proposed prediction algorithm architecture and its key components, such as the EMD method and GRU structure for SI forecasting model.

Grid Search

Optimizing the hyperparameters of a predictor is a vital and significant task. Failing the tuning of hyperparameters results in the wrong or poor forecasted results. This article uses the grid search algorithm to optimize the hyperparameter of the deep learning network. Following are the steps followed for the grid search mechanism:

- Step 1: Initialize the following parameters: learning rate, batch size, drop rate, epoch, hidden layer.
- Step 2: create grid for selected parameters.
- Step 3: Select the base model.
- Step 4: Start Grid search mechanism using learning rate, batch size, drop rate, epoch, hidden layer.
- Step 5: Grid search with train_features and train_labels.
- Step 6: : obtain optimal grid

Empirical Mode Decomposition

A signal decomposition approach breaks down the SI into higher and lower frequency bands, retaining the original characteristics of the signal with reducing nonlinear aspects. In recent years, empirical mode decomposition (EMD) has become

a popular signal decomposition approach in time series prediction. It divides the original SI input sequence into finite intrinsic mode functions (IMF) and residue. There are two conditions of the EMD: (i) the maxima and minima should be equal or differ by one of the datasets. (ii) the average of the envelope of local maxima and minima must be zero (Jamei *et al.*, 2023). The algorithm for EMD is mention below (Singla *et al.*, 2023a):

To produce the average of envelope curve $a_1(t)$, first determine the maxima and minima points of the input time series $s(t)$ using spline interpolation. The upper and lower envelope curves, $r_{max}(t)$ and $r_{min}(t)$ respectively are then combined.

$$a_1(t) = \frac{r_{min}(t) + r_{max}(t)}{2} \quad (2)$$

Subtract $a_1(t)$ from $s(t)$ to generate a new sequence $p_1(t)$.

$$p_1(t) = s(t) - a_1(t) \quad (3)$$

Despite having negative and positive local maxima, $p_1(t)$ does not belong to the IMF component. To acquire the first IMF component, $p_1(t)$ should be treated as the original signal and repeat Step 1 until the IMF requirements are fulfilled.

To generate a residual sequence $res_k(t)$ eliminate high-frequency components as follows: $res_k(t) = s(t) - h_k(t)$.

Repeat the above methods to acquire the remaining IMF components. Currently, the original time series data $s(t)$ may be represented as:

$$s(t) = \sum_{m=1}^n IMF_m(t) + res_n(t) \quad (4)$$

where $IMF_m(t)$ and $res_n(t)$ represents the m-th IMF and residual obtained after decomposition, and n represents the number of IMFs.

Gated Recurrent Unit

The GRU network is a DL network, which is a modified version of the LSTM network, that can shorten training time while maintaining predicting

accuracy. Compared to the conventional LSTM network, GRU contains fewer parameters and control gate, with only two (update and reset). The update gate decides whether previous state information persists in the current state. The update gate checks if earlier state information remains in the current state (Singla *et al.*, 2022e). The reset gate controls how much status information from the previous state is disregarded. The single cell of the GRU network is shown S_t in Figure 1.

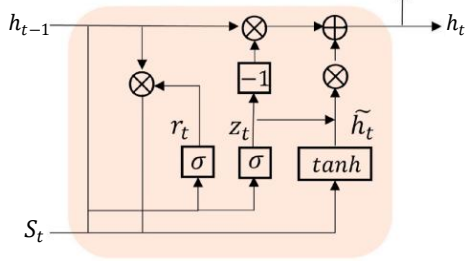


Figure 1. Gate Recurrent Unit Network Cell

The propagation mechanism through the GRU network can be explained by following equations:

$$r_t = \partial(\omega_r S_t + \vartheta_r h_{t-1}) \quad (5)$$

$$z_t = \partial(\omega_z S_t + \vartheta_z h_{t-1}) \quad (6)$$

$$\tilde{h}_t = \tanh(r_t \times \vartheta h_{t-1} + \omega S_t) \quad (7)$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \quad (8)$$

where the reset gate and update gate are represented by r_t and z_t respectively.

The input of the cell is expressed as S_t at time t . h_t and h_{t-1} are the present and previous hidden state. The calculation of the input and output is represented by $\tilde{h}_t$. ∂ and $\tanh$ are the activation functions. The weight matrix for each gate is denoted by $\omega_r, \omega_z, \vartheta_r, \vartheta_z$.

Bidirectional GRU

The BiGRU is an updated version of GRU that can learn from previous and subsequent information.

The schematic diagram of BiGRU is shown in Figure 2. This unit has two separate units, one for forward movement and the other for backward movement. This permits knowledge from both the future and the past to influence present events.

The bi-GRU is described as follows:

$$\begin{aligned} \vec{h}_t &= GRU_{fd}[\vec{h}_{t-1}, S_t] \\ \overleftarrow{h}_t &= GRU_{bd}[\overleftarrow{h}_{t-1}, S_t] \end{aligned}$$

where, the forward and backward hidden layer are represented as: $\vec{h}_t$ and $\overleftarrow{h}_t$

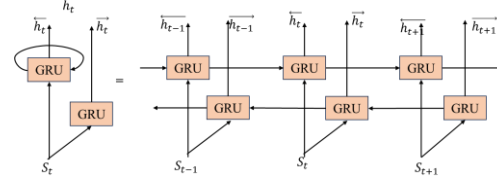


Figure 2. Bidirectional Gate Recurrent Unit Network Cell

Framework of proposed model

Figure 3 depicts the proposed hybrid EMD-GS-GRU model for hour ahead SI prediction. The proposed prediction approach involves following key steps: preprocessing, data decomposition, hyperparameter tuning, prediction, performance evaluation and visualizing the results.

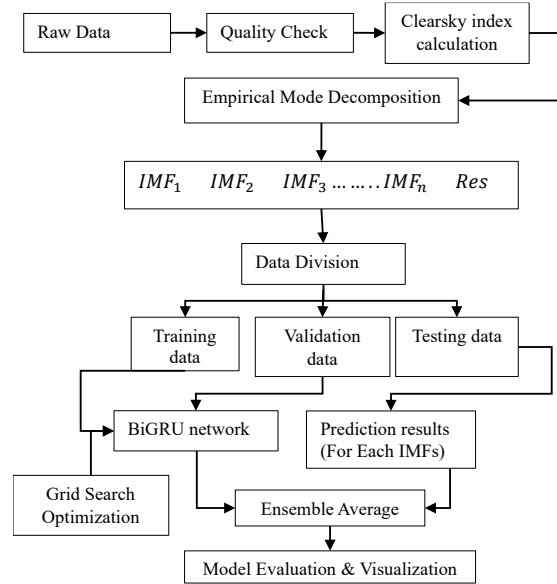


Figure 3. Framework of proposed model

Preprocessing: The case study utilized time series data of solar irradiance. Before feeding to the decomposition algorithm, the raw data is processed for quality check where missing values, false reading are corrected (Singla *et al.*, 2024). The data received from any agency for the training and testing of the model are likely to have some missing and false values. Therefore, the data used in the study is first check for missing and falsification. The entries act as outliers and the missing irradiance values are straightaway deleted. Moreover, the night data is also deleted from the dataset as zero SI is received on earth during these hours (Singh *et al.*, 2023). Apart from this, the dataset corresponds to

the solar zenith angle greater than 80° are also deleted due to the instrumentation imaging error. The leftover data is then used for further processing.

Data decomposition: The quality checked and corrected data is then breakdown using the EMD algorithm to extract the hidden features of the data. The EMD decomposes the dataset in several IMFs. These IMFs have different characteristics and the frequency. The process of decomposition of series is explained in previous section and detail of sample IMFs is presented in experiment section. These IMFs helps to reduce the prediction error of the predictor.

Hyperparameters Tuning: Before prediction using the DL models, the model's hyperparameters are tuned to get the optimal results. For the finding of optimal parameters, the dataset is divided into three different parts: training, validation and testing. The optimal parameters are obtained through training and validation dataset. In this step, the 60% of the total data is used as the training phase while 20% utilized as validation dataset. The study uses grid search method for tuning the different hyperparameters: learning rate, drop rate, epoch, hidden units etc. of the GRU for the autumn season of the location Chennai. After employment of the grid search mechanism, the study obtained learning rate equal to 0.0001, drop rate equal to 0.2, epoch equal to 400 and hidden units equal to 100. Furthermore, the last 20 hours reading of the dataset is used as an input feature of the model (Singla *et al.*, 2021b).

Prediction: The grid search mechanism-optimized GRU network (GS-GRU) is then used to forecast SI. In this step, the GS-GRU model is allocated to each decomposed IMF to forecast the future values of each IMF. These weighted sums of each IMF constitute to the original series that was aimed to forecast. Therefore, the study uses the average ensemble method to reconstruct the original series. Each forecasted IMF series is allocated the same weight and summed up to generate the final forecasted series.

Performance evaluation: Once the EMD-GS-BiGRU model is developed, the suggested model is assessed against contrast model using the RMSE, MAPE and R² with following formula (Singla *et al.*, 2021c):

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{m} \sum_{j=1}^m (S_j - S_{p,j})^2} \quad (9)$$

Mean absolute percentage error

$$MAPE = \frac{1}{m} \sum_{j=1}^m \left| \frac{S_j - S_{p,j}}{S_j} \right| \quad (10)$$

Coefficient of determination (R²):

$$R^2 = 1 - \frac{\sum_{j=1}^m (S_j - S_{p,j})^2}{\sum_{j=1}^m (S_j - \text{mean}(S_j))^2} \quad (11)$$

where, S_p is predicted SI at 'mth' level; whereas, S is the actual SI.

Visualizing results: To see how well forecasted and actual results match, utilize the prediction result curves. Moreover, the different charts are used for RMSE, MAPE and R² are used to visualize the performance of hybrid models.

Experimental Results

This section provides a complete evaluation of the hybrid EMD-GS-BiGRU model's prediction performance. Benchmarking and performance comparison are conducted using different contrast models (ANN, LSTM, GRU, EMD-GS-LSTM and EMD-GS-GRU).

This paper conducted a case study on dataset of two different location for predicting SI, for one-hour steps ahead. The prediction is performed for seasonal datasets to examine the impact of seasonal variations on models. The EMD technique divided the denoised SI data into several IMF and a residue. For the case of autumn dataset of Chennai location, the SI time series is divided into eight sub series and a residue as shown in Figure 4. The initial higher frequency IMF components primarily include random noise from time series. On the other hand, the low-frequency components mostly convey trend information, whereas the residuals indicate inaccuracies following EMD decomposition. For the analysis of EMD-GS algorithm, the said method is applied on LSTM as well as GRU. Furthermore, to compare the performance of these models, the standalone models: ANN, LSTM and GRU are also developed for the same datasets. Tables 2 and 3 provides the RMSE, MAPE and R² results of all models for Chennai and Jammu dataset respectively. From the statistical observations, it is found that the proposed model (EMD-GS-BiGRU) obtained the better forecasting accuracy over contrast models for both of the location. To evaluate the performance in better way, the study obtained the performance for different seasons with different characteristics. In case of standalone models, it is observed that the GRU and LSTM attained similar kind of results in terms of RMSE, MAPE and R². For a case of Chennai, season winter; LSTM has RMSE: 76.24 W/m², MAPE: 15.24% and R²: 0.932; whereas, GRU achieved RMSE: 77.82 W/m²,

MAPE: 15.41% and R^2 : 0.932. However, LSTM and GRU achieved the better and stable results than ANN (for a case of monsoon of Jammu, Lower RMSE (LSTM: 175W/m²; GRU: 168.82 W/m²) is obtained compared to ANN (RMSE: 178.86W/m²). In some cases, ANN achieved better results than LSTM and GRU (winter season of Jammu) but this

is due to data instability and cannot be inferred as stable results. Furthermore, compared to LSTM and GRU, GRU achieved better results than LSTM. For example, for a case of winter season of Jammu, GRU achieved lower RMSE (126.84W/m²) and lower MAPE (130.20%) than LSTM (RMSE: 127.02W/m²; MAPE: 139.91%). Besides of these

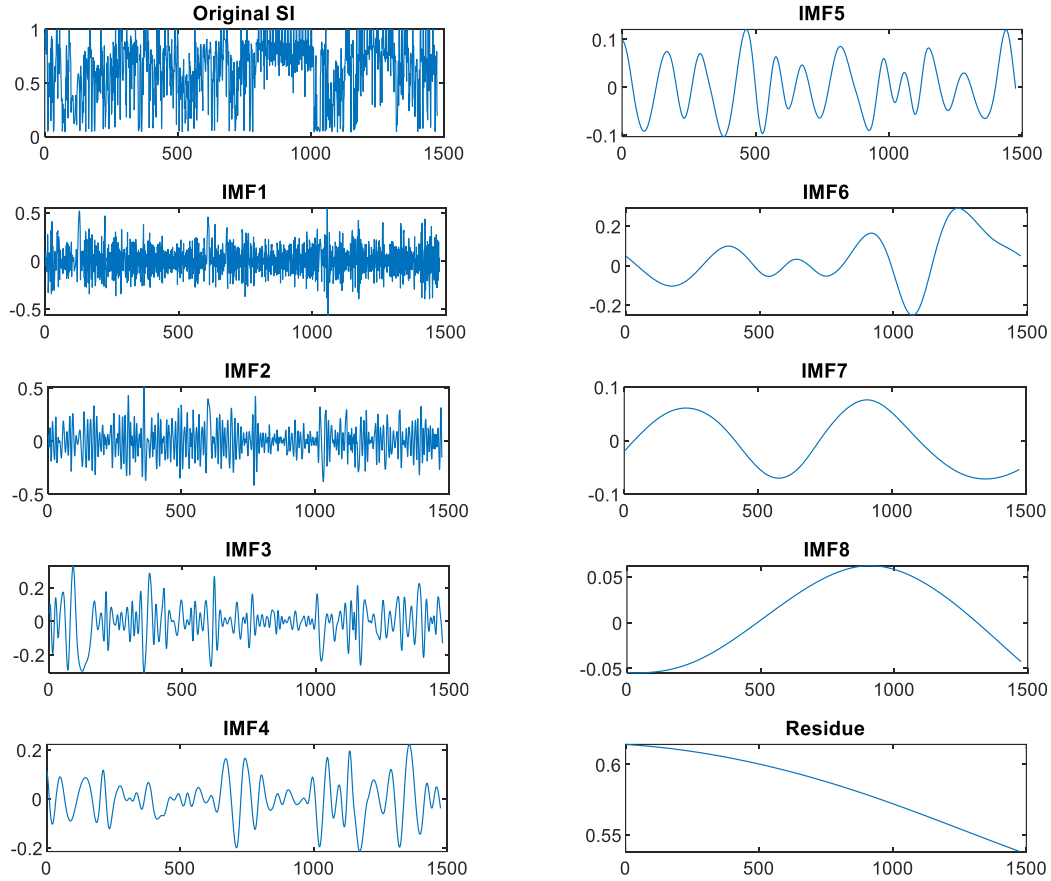


Figure 4. Decomposition of Chennai (autumn) data by EMD

Table 2. one-h forecast results of different models for Chennai

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m ²)	79.72	76.24	77.82	68.81	66.09	30.47
	MAPE (%)	15.98	15.24	15.41	13.93	13.55	6.288
	R^2	0.926	0.932	0.932	0.947	0.949	0.988
Summer	RMSE (W/m ²)	85.36	78.63	76.35	69.65	68.14	53.35
	MAPE (%)	32.82	23.49	25.04	21.58	20.38	16.82
	R^2	0.953	0.961	0.963	0.966	0.974	0.9806
Monsoon	RMSE (W/m ²)	195.2	140.16	141.06	113.24	112.06	91.86
	MAPE (%)	96.36	95.38	96.54	78.49	75.86	48.15
	R^2	0.692	0.825	0.811	0.890	0.892	0.929
Autumn	RMSE (W/m ²)	129.6	126.50	122.08	102.85	96.27	81.89
	MAPE (%)	59.66	57.72	57.07	35.04	35.41	29.92
	R^2	0.813	0.819	0.828	0.883	0.896	0.925
Average	RMSE (W/m ²)	122.4	105.38	104.32	88.63	85.64	64.39
	MAPE (%)	51.20	47.95	48.51	37.26	36.30	25.29
	R^2	0.846	0.884	0.883	0.921	0.927	0.955

results, the three hybrid models are developed in the study with the help of EMD-GS with LSTM, GRU and BiGRU. These hybrid models achieved better results than standalone models in all the cases. Nevertheless, the proposed model (EMD-GS-BiGRU) achieved better results among hybrid models. In case of hybridization of proposed technique with BiGRU obtained lower RMSE compared to LSTM and GRU. For example, for a case of monsoon of Jammu, proposed model achieved lower RMSE (104.05W/m^2) than EMD-GS-LSTM (153.50W/m^2) and EMD-GS-GRU (152.53W/m^2).

On the other side, the MAPE is also improved by proposed model proposed model for EMD-GS-GRU (3.02%) and EMD-GS-LSTM: (4.08%). Similarly, the proposed improved the MAPE of ANN, LASTM and GRU. From this result, it can be interpreted as the proposed model achieved the better forecasting accuracy than all other contrast models.

For the deep insight, the results the visualized through the graphical representation. Figure 5 shows the performance of LSTM, GRU, EMD-GS-LSTM, EMD-GS-GRU and proposed models for one consecutive day (ten hrs in day). From the

Table 3. one-h forecast results of different models for Jammu

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m^2)	122.63	127.02	126.84	119.07	114.92	75.39
	MAPE (%)	109.03	111.91	109.20	85.02	79.02	77.52
	R^2	0.792	0.792	0.779	0.812	0.828	0.9203
Summer	RMSE (W/m^2)	148.94	143.46	141.16	132.76	132.57	83.85
	MAPE (%)	53.52	54.61	55.11	34.72	34.47	25.61
	R^2	0.876	0.887	0.893	0.903	0.906	0.9612
Monsoon	RMSE (W/m^2)	178.86	175.17	168.82	153.50	152.53	104.05
	MAPE (%)	103.63	108.26	96.84	60.75	60.09	58.27
	R^2	0.793	0.799	0.815	0.843	0.848	0.932
Autumn	RMSE (W/m^2)	110.41	111.96	112.83	106.32	102.22	70.58
	MAPE (%)	92.79	94.88	97.00	64.34	61.90	53.37
	R^2	0.825	0.828	0.824	0.840	0.853	0.9332
Average	RMSE (W/m^2)	140.21	139.40	137.41	127.91	125.56	83.46
	MAPE (%)	89.74	92.41	89.53	61.20	58.87	53.69
	R^2	0.821	0.810	0.827	0.849	0.858	0.9366

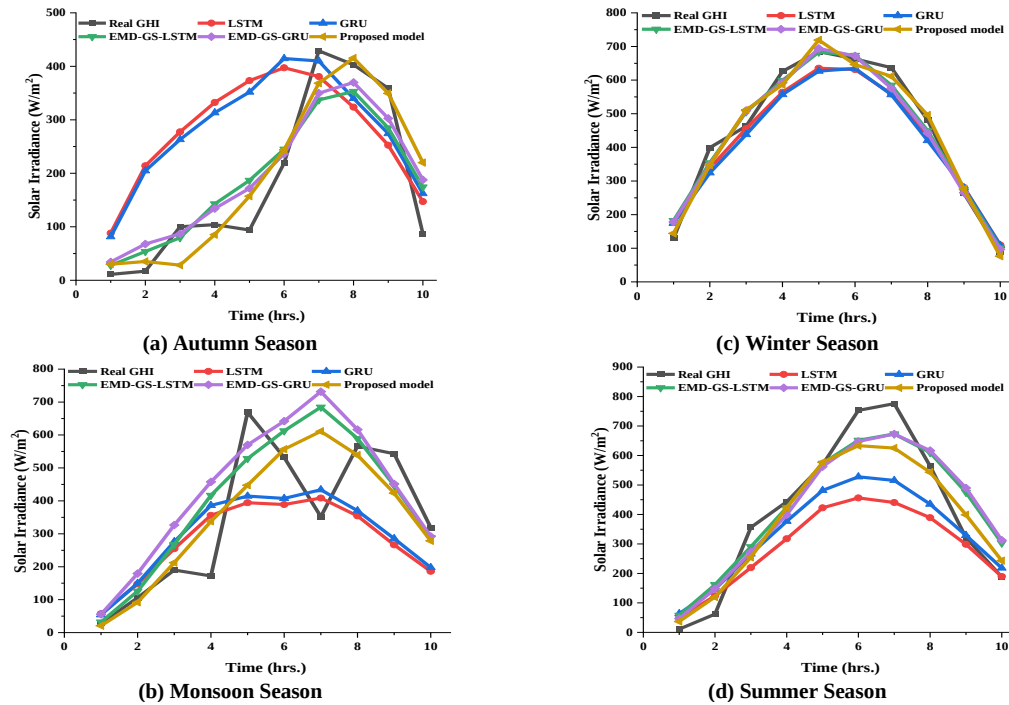


Figure 5. Forecasting performance of different models for one day data of Chennai

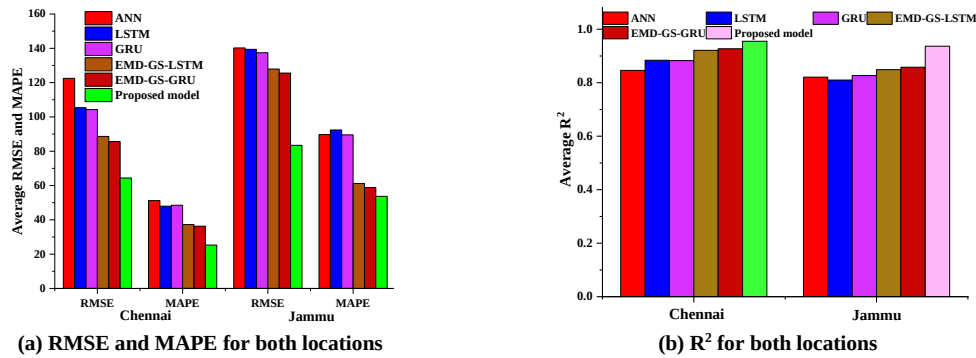


Figure 6. Results obtained by different models for both locations

Figure 5, it is evident that the EMD-GS-BiGRU model is able to trace the real SI compared to LSTM, GRU and EMD-GS-LSTM and EMD-GS-GRU model. However, for case of monsoon season, the proposed model unable to track the actual SI perfectly. This is due to highly uncertain data of the monsoon season due to rainy days. However, the performance of the proposed model is still better than contrast model in such case also. Moreover, Figure 6 shows the bar graph for RMSE (W/m^2) and MAPE (%), which represent the lower RMSE and MAPE of the proposed model. From this visualization, it is clear that the proposed models outperform all other standalone and hybrid models in terms of RMSE, MAPE and R^2 . The performance can be observed outstanding for both the dataset. In addition to this, the performance of every model is degraded for dataset of Jammu compared to Chennai. The reason behind such performance can be relate to the standard deviations in the dataset. As already discussed, the higher is the standard deviation, higher is the uncertainty in the data. Therefore, Jammu region has higher uncertainty results in the degraded performance in the forecast.

Discussion

This section discusses the performance of the models based on the results obtained in previous section.

Percentage Improvement

The percentage improvement is the ratio of difference between reference model and proposed model to the reference model. This parameter provides the improvement by the proposed model in RMSE, MAPE and R^2 of the compared models. Tables 4 and 5 provide the percentage improvement in RMSE, MAPE and R^2 of the standalone and hybrid models.

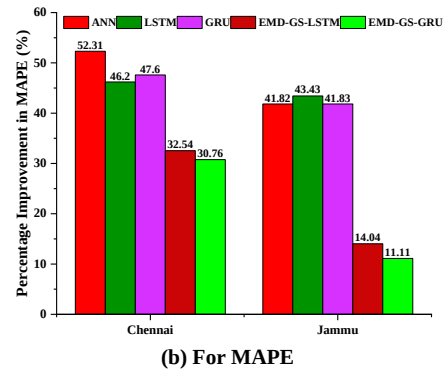
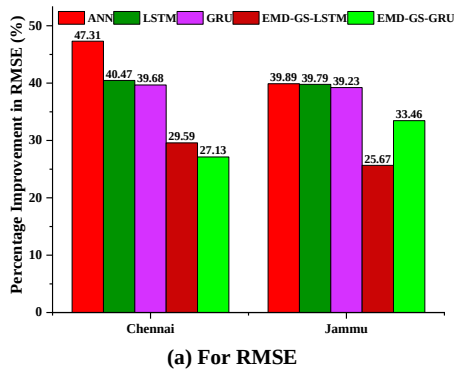
As can see the outcome of percentage improvements calculations, the proposed model significantly improves the forecasting efficacy of the model by lowering the RMSE and MAPE. For instance, for the case of Chennai results in autumn season, the proposed model improved RMSE (36.81% for ANN; 35.26 % for LSTM; 32.92% for GRU; 20.37% for EMD-GS-LSTM and 14.93% for EMD-GS-GRU), MAPE (49.84% for ANN; 48.16

Table 4. Percentage improvement by proposed model on other models for Chennai

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU
Winter	RMSE (W/m^2)	62.01	60.03	60.84	55.71	53.89
	MAPE (%)	60.65	58.74	59.91	54.86	53.59
	R^2	5.66	5.66	5.66	4.14	3.97
Summer	RMSE (W/m^2)	37.5	32.15	30.12	23.40	21.70
	MAPE (%)	48.75	28.39	32.82	22.05	17.46
	R^2	2.75	1.93	1.73	1.42	0.61
Monsoon	RMSE (W/m^2)	52.94	34.46	34.87	18.88	18.02
	MAPE (%)	50.03	49.51	50.12	38.65	36.52
	R^2	25.51	11.19	12.70	4.19	3.98
Autumn	RMSE (W/m^2)	36.81	35.26	32.92	20.37	14.93
	MAPE (%)	49.84	48.16	47.57	14.61	15.50
	R^2	12.10	11.45	10.48	4.54	3.13
Average	RMSE (W/m^2)	47.31	40.47	39.68	29.59	27.13
	MAPE (%)	52.31	46.2	47.60	32.54	30.76
	R^2	11.50	7.55	7.64	3.57	2.92

Table 5. Percentage improvement by proposed model on other models for Jammu

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU
Winter	RMSE (W/m ²)	38.00	40.06	40.56	36.68	34.39
	MAPE (%)	28.90	30.73	29.01	8.82	1.89
	R ²	16.16	13.91	15.32	11.73	10
Summer	RMSE (W/m ²)	43.70	41.55	40.59	36.84	36.75
	MAPE (%)	52.14	53.10	53.52	26.23	25.77
	R ²	8.86	7.71	7.09	6.05	5.74
Monsoon	RMSE (W/m ²)	41.82	40.60	38.36	32.21	31.78
	MAPE (%)	43.77	46.17	39.82	4.08	3.02
	R ²	14.91	14.27	12.55	9.54	9.01
Autumn	RMSE (W/m ²)	36.07	36.95	37.44	33.61	30.95
	MAPE (%)	42.48	43.75	44.97	17.05	13.78
	R ²	11.59	11.27	11.70	9.98	8.59
Average	RMSE (W/m ²)	39.89	39.79	39.23	25.67	33.46
	MAPE (%)	41.82	43.43	41.83	14.04	11.11
	R ²	12.88	23.58	11.66	9.325	16.67

**Figure 7. Percentage improvement by proposed model in RMSE and MAPE**

% for LSTM; 47.57% for GRU; 14.61% for EMD-GS-LSTM and 15.50% for EMD-GS-GRU) and R² (12.10% for ANN; 11.45 % for LSTM; 10.48% for GRU; 4.54% for EMD-GS-LSTM and 3.13% for EMD-GS-GRU).

Overall, the proposed improved the average RMSE (47.31% for ANN; 40.47% for LSTM; 39.68% for GRU; 29.59% for EMD-GS-LSTM and 27.13% for EMD-GS-GRU), average MAPE (52.31 for ANN; 46.2% for LSTM; 47.60% for GRU; 32.54% for EMD-GS-LSTM and 30.76% for EMD-GS-GRU) for the dataset Chennai. Likewise, the proposed improved the average RMSE (39.89% for ANN; 39.79% for LSTM; 39.23% for GRU; 25.67% for EMD-GS-LSTM and 33.46% for EMD-GS-GRU), average MAPE (41.82% for ANN; 43.43% for LSTM; 41.83% for GRU; 14.04% for EMD-GS-LSTM and 11.11% for EMD-GS-GRU) for the dataset Jammu. Moreover, the yearly average percentage improvement by proposed model over LSTM, GRU, EMD-GS-LSTM and EMD-GS-GRU is shown in Figure 7. It can be visualized that the proposed model performs better than other model in term of percentage improvement in RMSE, MAPE and R².

To validate the performance of the models, Table 6 - 9 provides the SI forecasting performance for longer duration (2 - 3 steps ahead) for both the datasets.

From the results of Table 6-9, it is clear that the proposed model is effectively forecast better compared to the other contrast models. The lower RMSE, MAPE and higher values of R² for two to three ahead forecasts validate the effectiveness of the proposed model. However, the performance of proposed model degraded compared with the one hour ahead forecast with marginal values. These trends and results can be inferred as the model performance decreases with the increase in the steps. Still the proposed model outperforms other models in terms of accuracy with the increase in the steps.

Benchmarking with Previous Work

Table 10 provide the results comparison of some potential studies: From the Table 10, it is clear that the proposed approach significantly improves the forecasting efficacy of the model.

Table 6. Two hr forecast results of different models for Jammu

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m ²)	156.2	139.82	138.46	130.46	127.75	77.52
	MAPE (%)	197.02	188.25	179.25	168.25	137.83	85.9
	R ²	0.660	0.739	0.714	0.77	0.778	0.916
Summer	RMSE (W/m ²)	170.21	157.98	155.36	143.69	142.36	90.85
	MAPE (%)	60.5	59.86	60.08	43.36	42.69	38.96
	R ²	0.868	0.864	0.871	0.880	0.887	0.932
Monsoon	RMSE (W/m ²)	208.2	187.52	179.92	159.01	158.2	111.29
	MAPE (%)	152.48	153.01	142.48	108.49	107.65	65.59
	R ²	0.705	0.763	0.787	0.837	0.834	0.922
Autumn	RMSE (W/m ²)	146.42	123.06	122.87	114.91	112.36	80.06
	MAPE (%)	160.53	126.3	128.02	94.67	87.78	57.28
	R ²	0.683	0.783	0.783	0.801	0.824	0.912
Average	RMSE (W/m ²)	170.25	152.09	149.15	137.01	135.16	89.93
	MAPE (%)	142.63	131.8	127.4	103.69	93.98	61.93
	R ²	0.7292	0.7876	0.789	0.823	0.831	0.921

Table 7. Three-hr forecast results of different models for Jammu

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m ²)	160.74	142.78	142.46	135.69	142.81	78.58
	MAPE (%)	214.02	190.68	199.64	133.61	117.54	90.58
	R ²	0.658	0.705	0.708	0.758	0.759	0.853
Summer	RMSE (W/m ²)	174.32	168.72	165.29	147.26	145.26	95.36
	MAPE (%)	130.35	62.81	63.24	51.362	50.36	42.46
	R ²	0.842	0.845	0.854	0.872	0.882	0.903
Monsoon	RMSE (W/m ²)	195.42	195.58	187.33	164.53	162.98	113.59
	MAPE (%)	154.66	156.55	146.64	115.21	114.05	70.23
	R ²	0.757	0.739	0.767	0.823	0.825	0.919
Autumn	RMSE (W/m ²)	137.56	132.5	132.25	142.48	131.99	74.64
	MAPE (%)	147.49	134.62	138.32	99.06	93.8	56.24
	R ²	0.729	0.738	0.740	0.707	0.749	0.924
Average	RMSE (W/m ²)	167.01	159.89	156.83	147.49	145.76	90.54
	MAPE (%)	161.63	136.16	136.96	99.81	93.93	64.87
	R ²	0.745	0.757	0.766	0.790	0.804	0.900

Table 8. Two hr forecast results of different models for Chennai

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m ²)	83.49	80.99	78.52	70.25	69.26	33.33
	MAPE (%)	15.58	15.21	15.18	17.04	13.48	6.53
	R ²	0.930	0.930	0.930	0.928	0.946	0.986
Summer	RMSE (W/m ²)	90.39	78.8	78.48	69.56	71.76	56.08
	MAPE (%)	28.17	26.16	26.6	21.36	21.32	17.83
	R ²	0.945	0.921	0.926	0.936	0.942	0.958
Monsoon	RMSE (W/m ²)	200.36	148.02	154.72	116.08	115.02	95.32
	MAPE (%)	103.35	101.22	103.03	83.89	81.37	51.06
	R ²	0.675	0.803	0.782	0.885	0.888	0.904
Autumn	RMSE (W/m ²)	134.75	135.49	128.63	109.18	100.35	86.59
	MAPE (%)	60.03	64.63	62.78	37.96	38.85	33.7
	R ²	0.799	0.792	0.810	0.869	0.887	0.917
Average	RMSE (W/m ²)	127.24	110.8	110.08	91.26	89.09	67.83
	MAPE (%)	51.78	51.80	51.89	40.06	38.7	27.28
	R ²	0.837	0.861	0.862	0.904	0.916	0.941

Table 9. Three hr forecast results of different models for Chennai

Season		ANN	LSTM	GRU	EMD-GS-LSTM	EMD-GS-GRU	EMD-GS-BiGRU
Winter	RMSE (W/m ²)	85.08	82.36	80.62	72.03	69.61	40.55
	MAPE (%)	15.89	15.54	14.88	17.17	13.97	7.45
	R ²	0.929	0.933	0.923	0.902	0.941	0.979
Summer	RMSE (W/m ²)	93.66	80.54	79.06	73.01	72.12	58.48
	MAPE (%)	29.66	29.39	27.76	23.36	23.32	18.84
	R ²	0.896	0.90	0.901	0.914	0.925	0.946
Monsoon	RMSE (W/m ²)	210.02	154.8	153.63	120.02	118.83	98.31
	MAPE (%)	107.13	105.32	108.63	88.56	85.88	53.51
	R ²	0.652	0.783	0.754	0.877	0.881	0.895
Autumn	RMSE (W/m ²)	158.6	142.74	133.37	112.23	102.32	90.97
	MAPE (%)	70.31	68.98	65.73	38.84	40.25	36.99
	R ²	0.776	0.770	0.798	0.864	0.883	0.909
Average	RMSE (W/m ²)	136.84	115.11	111.67	94.32	90.72	72.07
	MAPE (%)	55.7475	54.8075	54.25	41.9825	40.855	29.1975
	R ²	0.813	0.847	0.844	0.889	0.907	0.932

Table 10. Comparison of present study with previous studies

Ref.	YOP	Dataset	Model	Performance
(Gayathry <i>et al.</i> , 2024)	2024	Bangalore	SARIMAX	RMSE:65.1, R ² :0.96, MAE: 32.6
(Qing and Niu, 2018)	2018	Santiago	LSTM	RMSE: 76.24
(Foo and Goh, 2021)	2021	-	EVLNN	RMSE: 104.08
(Singla <i>et al.</i> , 2021b)	2022	Ahmadabad	WT-BiLSTM	RMSE:88.36
(Obiora <i>et al.</i> , 2023)	2023	Solcast's Limpopo weather repository	ConvLSTM	RMSE: 75.52
This Study	2024	Jammu, Chennai	EMD-GS-BiGRU	RMSE:64.39

Conclusion

Accurate solar irradiation forecast enables decision-makers to plan ahead and alter heating system operations accordingly. This work developed a hybrid model using EMD with grid search optimized BiGRU for single step ahead SI prediction. To evaluate the performance of the proposed EMD-GS-BiGRU model, two hybrid models (EMD-GS-LSTM, EMD-GS-GRU) and three standalone models (ANN, LSTM and GRU) are compared in four seasonal datasets for two different locations. The study's findings are (a) The proposed model outperforms other models in estimating solar irradiation over one hours, with minimal RMSE, MAPE, and higher R². From the statistical results, the proposed EMD-GS-BiGRU model has been validated as superior. (b) Data is processed initially and normalized using clear sky index, followed by EMD for decomposition. The 1535grid search mechanism is then implemented to fine tune the hyperparameters of the LSTM, GRU and BiGRU. (c) The decomposed IMFs is then applied to grid search optimized BiGRU which enhance the prediction accuracy of the model compared to standalone as well as contrast hybrid models. (d) The proposed EMD-GS-BiGRU model

outperforms previous models in accuracy and stability across seasonal datasets. Overall, the suggested model performs well in solar irradiation prediction tasks, despite seasonal changes.

References

- Amer, H.N., Dahlan, N.Y., Azmi, A.M., Latip, M.F.A., Onn, M.S., and Tumian, A. (2023). Solar power prediction based on artificial neural network guided by feature selection for large-scale solar photovoltaic plant. *Energy Reports*, 9(Supplement 12):262-266. <https://doi.org/10.1016/j.egyr.2023.09.141>
- Badoni, M., Singh, A., Singh, A.K., Saxena, H., and Kumar, R. (2023). Grid tied solar PV system with power quality enhancement using adaptive generalized maximum versoria criterion. *CSEE Journal of Power and Energy Systems*, 9(2):722-732.
- Dhaked, D.K., Dadhich, S., and Birla, D. (2023). Power output forecasting of solar photovoltaic plant using LSTM. *Green Energy and Intelligent Transportation*, 2(5):100113. <https://doi.org/10.1016/j.geits.2023.100113>
- Foo, Y.W., and Goh, C. (2021). Solar irradiance forecasting in tropical weather using an evolutionary lean neural network. In *2021 IEEE Congress on Evolutionary Computation, CEC 2021 - Proceedings* (pp. 490-497). <https://doi.org/10.1109/CEC45853.2021.9504875>
- Gayathry, V., Kaliyaperumal, D., and Salkuti, S.R. (2024). Seasonal solar irradiance forecasting using artificial intelligence techniques with uncertainty analysis.

- Scientific Reports, 14(1):1-19. <https://doi.org/10.1038/s41598-024-68531-3>
- Gupta, A., Gupta, K., and Saroha, S. (2020). Solar irradiation forecasting technologies: A review. *Strategic Planning for Energy and the Environment*, 39(3-4):319-354.
- Jailani, N.L.M., Dhanasegaran, J.K., Alkaws, G., Alkahtani, A.A., Phing, C.C., Baashar, Y., Capretz, L.F., Al-Shetwi, A.Q., and Tiong, S.K. (2023). Investigating the power of LSTM-based models in solar energy forecasting. *Processes*, 11(5):1382. <https://doi.org/10.3390/pr11051382>
- Jamei, M., Karbasi, M., Ali, M., Malik, A., Chu, X., and Yaseen, Z.M. (2023). A novel global solar exposure forecasting model based on air temperature: Designing a new multi-processing ensemble deep learning paradigm. *Expert Systems with Applications*, 222:119811. <https://doi.org/10.1016/j.eswa.2023.119811>
- Kumar, R., Diwania, S., Khetrapal, P., and Singh, S. (2022a). Performance assessment of the two metaheuristic techniques and their hybrid for power system stability enhancement with PV-STATCOM. *Neural Computing and Applications*, 34(5):3723-3744. <https://doi.org/10.1007/s00521-021-06637-9>
- Kumar, R., Diwania, S., Khetrapal, P., Singh, S., and Badoni, M. (2021). Multimachine stability enhancement with hybrid PSO-BFOA based PV-STATCOM. *Sustainable Computing: Informatics and Systems*, 32:100615. <https://doi.org/10.1016/j.suscom.2021.100615>
- Kumar, R., Diwania, S., Singh, R., Ashfaq, H., Khetrapal, P., and Singh, S. (2022b). An intelligent hybrid wind-PV farm as a static compensator for overall stability and control of multimachine power system. *ISA Transactions*, 123:286-302. <https://doi.org/10.1016/j.isatra.2021.05.014>
- Lai, C.S., Zhong, C., Pan, K., Ng, W.W.Y., and Lai, L.L. (2021). A deep learning-based hybrid method for hourly solar radiation forecasting. *Expert Systems with Applications*, 177:114941. <https://doi.org/10.1016/j.eswa.2021.114941>
- Makade, R.G., Chakrabarti, S., and Jamil, B. (2021). Development of global solar radiation models: A comprehensive review and statistical analysis for Indian regions. *Journal of Cleaner Production*, 293:126208. <https://doi.org/10.1016/j.jclepro.2021.126208>
- Obiora, C.N., Hasan, A.N., and Ali, A. (2023). Predicting solar irradiance at several time horizons using machine learning algorithms. *Sustainability*, 15(11):8927. <https://doi.org/10.3390/su15118927>
- Qing, X., and Niu, Y. (2018). Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. *Energy*, 148:461-468. <https://doi.org/10.1016/j.energy.2018.01.177>
- Saroha, S., Zurek-Mortka, M., Szymanski, J.R., Shekher, V., and Singla, P. (2021). Forecasting of market clearing volume using wavelet packet-based neural networks with tracking signals. *Energies*, 14(19):6065. <https://doi.org/10.3390/en14196065>
- Saxena, N., Kumar, R., Rao, Y.K.S.S., Mondloi, D.S., Dhapekar, N.K., Sharma, A., and Yadav, A.S. (2024). Hybrid KNN-SVM machine learning approach for solar power forecasting. *Environmental Challenges*, 14:100838. <https://doi.org/10.1016/j.envc.2024.100838>
- Singh, S., Saini, S., Gupta, S.K., and Kumar, R. (2023). Solar-PV inverter for the overall stability of power systems with intelligent MPPT control of DC-link capacitor voltage. *Protection and Control of Modern Power Systems*, 8(1):15. <https://doi.org/10.1186/s41601-023-00285-y>
- Singla, P., Duhan, M., and Saroha, S. (2021a). A comprehensive review and analysis of solar forecasting techniques. *Frontiers in Energy*, p. 1-37.
- Singla, P., Duhan, M., and Saroha, S. (2021b). An ensemble method to forecast 24-h ahead solar irradiance using wavelet decomposition and BiLSTM deep learning network. *Earth Science Informatics*, 15(1):291-306. <https://doi.org/10.1007/s12145-021-00723-1>
- Singla, P., Duhan, M., and Saroha, S. (2021c). Review of different error metrics: A case of solar forecasting. *AIUB Journal of Science and Engineering (AJSE)*, 20(4):158-165. <https://doi.org/10.53799/ajse.v20i4.212>
- Singla, P., Duhan, M., and Saroha, S. (2022a). A dual decomposition with error correction strategy based improved hybrid deep learning model to forecast solar irradiance. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 44(1):1583-1607. <https://doi.org/10.1080/15567036.2022.2056267>
- Singla, P., Duhan, M., and Saroha, S. (2022b). A hybrid solar irradiance forecasting using full wavelet packet decomposition and Bi-Directional Long Short-Term Memory (BiLSTM). *Arabian Journal for Science and Engineering*, 47(11):14211-14185. <https://doi.org/10.1007/s13369-022-06655-2>
- Singla, P., Duhan, M., and Saroha, S. (2022c). An integrated framework of robust local mean decomposition and bidirectional long short-term memory to forecast solar irradiance. *International Journal of Green Energy*, 20(10):1073-1085. <https://doi.org/10.1080/15435075.2022.2143272>
- Singla, P., Duhan, M., and Saroha, S. (2022d). Different normalization techniques as data preprocessing for one step ahead forecasting of solar global horizontal irradiance. *Artificial Intelligence for Renewable Energy Systems*, p. 209-230. <https://doi.org/10.1016/B978-0-323-90396-7.00004-3>
- Singla, P., Duhan, M., and Saroha, S. (2022e). Different optimizers-based gated recurrent unit network to forecast one step ahead solar irradiance. *Lecture Notes in Electrical Engineering*, 812:105-114. https://doi.org/10.1007/978-981-16-6970-5_9
- Singla, P., Duhan, M., and Saroha, S. (2022f). One hour ahead solar irradiance forecast by deep learning network using meteorological variables. *Lecture Notes in Electrical Engineering*, 822:103-113. https://doi.org/10.1007/978-981-16-7664-2_9
- Singla, P., Duhan, M., and Saroha, S. (2022g). Solar Irradiance Forecasting by Long-Short Term Memory Using Different Training Algorithms. In: Khosla, A., Aggarwal, M. (eds) *Renewable Energy Optimization, Planning and Control. Studies in Infrastructure and Control*. Springer, Singapore. https://doi.org/10.1007/978-981-16-4663-8_7
- Singla, P., Duhan, M., and Saroha, S. (2023a). A point and interval forecasting of solar irradiance using different decomposition based hybrid models. *Earth Science Informatics*, 16(3):2223-2240. <https://doi.org/10.1007/s12145-023-01020-9>
- Singla, P., Duhan, M., and Saroha, S. (2023b). Performance evaluation of various solar forecasting models for structural & endogenous datasets. *Distributed Generation & Alternative Energy Journal*, 38(2):467-490. <https://doi.org/10.13052/dgaej2156-3306.3825>
- Singla, P., Saroha, S., Duhan, M., Shekher, V., and Singh, K. (2024). A solar irradiance forecasting model using iterative filtering and bidirectional long short-term memory. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 46(1):8202-8222. <https://doi.org/10.1080/15567036.2024.2370335>
- Wojtkiewicz, J., Hosseini, M., Gottumukkala, R., and Chambers, T.L. (2019). Hour-ahead solar irradiance forecasting using multivariate gated recurrent units. *Energies*, 12(21):4055. <https://doi.org/10.3390/en12214055>