An ensemble method to forecast 24-h ahead solar irradiance using wavelet decomposition and BiLSTM deep learning network

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Received: 5 February 2021 / Accepted: 28 October 2021 / Published online: 17 November 2021
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Abstract

In recent years, the penetration of solar power at residential and utility levels has progressed exponentially. However, due to its stochastic nature, the prediction of solar global horizontal irradiance (GHI) with higher accuracy is a challenging task; but, vital for grid management: planning, scheduling & balancing. Therefore, this paper proposes an ensemble model using the extended scope of wavelet transform (WT) and bidirectional long short term memory (BiLSTM) deep learning network to forecast 24-h ahead solar GHI. The WT decomposes the input time series data into different finite intrinsic model functions (IMF) to extract the statistical features of input time series. Further, the study reduces the number of IMF series by combining the wavelet decomposed components (D1-D6) series on the basis of comprehensive experimental analysis with an aim to improve the forecasting accuracy. Next, the trained standalone BiLSTM networks are allocated to each IMF sub-series to execute the forecasting. Finally, the forecasted values of each sub-series from BiLSTM networks are reconstructed to deliver the final solar GHI forecast. The study performed monthly solar GHI forecasting for one year dataset using one month moving window mechanism for the location of Ahmedabad, Gujarat, India. For the performance comparison, the naïve predictor as a benchmark model, standalone long short term memory (LSTM), gated recurrent unit (GRU), BiLSTM and two other wavelet-based BiLSTM models are also simulated. From the results, it is observed that the proposed model outperforms other models in terms of root mean square error (RMSE) & mean absolute percentage error (MAPE), coefficient of determination (R^2) and forecast skill (FS). The proposed model reduces the monthly average RMSE by range from 26.04–58.89%, 5.17–31.35%, 23.26–56.06% & 21.08–57% in comparison with benchmark, standalone BiLSTM, GRU & LSTM networks respectively. On the other hand, the monthly average MAPE is reduced by range from 9 to 51.18%, 12.59–28.14%, 30.43–59.19% & 26.54–58.92% in comparison to benchmark, standalone BiLSTM, GRU & LSTM respectively. Further, the proposed model obtained the value of R^2 equal to 0.94 and forecast skill (%) of 47% with reference to the benchmark model.

Keywords Solar irradiance forecasting · Deep learning · Long short term memory · Gated recurrent unit · Bidirectional long short term memory · Wavelet transform · Hyperparameters

Article Highlights

- A state of the art literature review of deep learning networks.
- Development of conventional LSTM, GRU and BiLSTM along with naïve predictor.
- Implementation of wavelet transforms to the input data series.
- Selection of best wavelet IMF combinations to improve the accuracy of model.
- Ensemble of selected wavelet IMF combinations with BiLSTM deep learning network.
- Performance comparisons of proposed model with naïve, LSTM, BiLSTM, GRU, WT-BiLSTM (T) & WT-BiLSTM (Mod).

Communicated by: H. Babaie

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Introduction

Solar energy is one of the leading renewable energy resources (RER) to generate electricity with zero carbon emission (Wang et al. 2019) and its market is increasing rapidly from the last decade due to its sustainable & supported characteristics (Chen et al. 2020). According to the international energy agency (IEA), by the end of 2030, the total capacity of the PV installation will hit the 1700GW level (Labouret and Villos 2010). However, this power capacity was 8GW in 2007 and now reported 402 GW in 2017, as per the global energy states report (REN 21) (Hales and Renewables 2018). Moreover, as per numerous investigations, the power grid will be 100% fully operational on

the RER by the end of the year 2050 (Jacobson et al. 2017). But, due to the direct dependency of solar PV output over climatic & geographical conditions, the stability of solar irradiance is always a subject of discussion in regard to grid management (Lan et al. 2019). Its inherent variable characteristics & uncertainties must be accommodated by the resource planners to make a reliable grid- interconnected power system (Dong et al. 2020). Therefore, the precise and accurate forecasting of solar components is one of the prime requirements for two basic reasons. (a) to make the reliable grid-interconnected system which accommodates volatile, intermittent & random characteristics of solar generation, (b) to increase the utilization ratio of solar PV output along with maximum returns on the capital investment on solar park development (Zang et al. 2020a). However, reliable solar irradiance forecasting is not an easy task as it is very susceptible to seasonal and climatic effects. A minor fluctuation in the meteorological variables directly affects the stability & reliability of the dependent systems (AlSkaif et al. 2020). In such situations, an appropriate forecasting model is highly requested. Several examinations have already been conducted on the development of methods to forecast the PV power or the solar irradiance components (Yu et al. 2019). In general, the forecasting methods can be divided into five different sections: based on process type, based on prediction method, based on spatial scale forecasting process, time horizon-based forecasting, prediction form-based forecasting, and method / approach-based forecasting (Lai et al. 2019). The different categories are shown in Fig. 1.

An approach-based forecasting is commonly used over various time horizons, systems, shapes and sizes (Lai et al. 2019). The persistence approach assumes the past similar day/h value of the target vector as the value of the present-day/h. If ' t ' is the present time, then the value of target vector at ' t ' time is considered as the value of ' $t + k$ ' where ' k ' is the time horizon for which forecasting is being performed (Kumler et al. 2019). On the other hand, the physical approach generates the mathematical relationship between the target GHI to the meteorological & geographical parameters. These models performed the forecasting of solar GHI

by the use of meteorological and geographical variables instead of historical time series data. However, these models are not popular due to its high computational cost and worst precision (Alonso-Montesinos and Batlles 2015). European Centre for Medium-Range Weather Forecasts (ECMWF) & Weather Research and Forecasting (WRF) models are the two popular models used for forecasting the atmospheric & operational services (Richardson et al. 2020; Perez et al. 2012; Yang and Kleissl 2016).

Conversely, the statistical approach improves the accuracy and minimizes the error of the model by managing the correlation mapping between input and output parameters (Ruhang 2016). Grey theory (Li and Zhang 2019), Regression Analysis (Doorga et al. 2019), Fuzzy method (Reza Parsaei et al. 2020), time-series method (Bigdeli et al. 2017) and machine learning (ML) (Lai et al. 2020) are the different categories of statistical approach. The regression Auto Regressive Integrated Moving Average (ARIMA) techniques (Shadab et al. 2020), support vector regression (SVR) (Mohammadi and Aghashariatmadari 2020), Gaussian Progress Regression (GPR) (Sheng et al. 2018) and ML approach based models proved to be best in the recent years in terms of forecasting (Gao et al. 2020). ML approach such as artificial neural network (ANN) (Jahani and Mohammadi 2019), support vector machine (SVM) (Zeng and Qiao 2013), and Elman neural network (ENN) (Dumitru et al. 2016) were used historical data to learn the pattern which improves the accuracy of the model. Along with, a standalone model sometimes relies on the limited characteristics of the data and failed to learn hidden characteristics of data. This limited learning of the model leads to the poor performance of the model. To overcome this problem, hybrid models has been developed such as: PLA-k-means-HGWO-RF (Liu and Sun 2019), ANFIS-ANN (Kumar and Kalavathi 2018), ECMWF-ANN (Aguilar et al. 2016), SVM-RBF-WT (Shamshirband et al. 2016), WT-NNMFOA-GMDHMFOA (Heydari et al. 2019), WMIM-ELM (Cornejo-Bueno et al. 2019), LASSO-ANN (Huang et al. 2019) etc.

In addition, the deep learning approach emerges with great advantages with better accuracy for the forecasting of

Fig. 1 different categories of solar irradiance forecasting methods

solar GHI. Due to its highest accuracy and great power of data processing abilities, this approach is dominating the ML approach (Bedi and Toshniwal 2019). Qing X. et al. forecasted the solar GHI on hourly basis using LSTM network in which weather data was used as an input feature of the LSTM network. The paper compared the performance of proposed network with the persistence, linear regression and back propagation neural network. The designed network outperformed the other model with RMSE of 122.71 W/m^2 and proved that the LSTM is better than ANN and other regression based models (Qing and Niu 2018). An ensemble method of deep learning and extreme gradient boosting was developed to avoid the problem of over fitting and compared with the persistence and SVR. The proposed model achieved the RMSE of 51.35 W/m^2 which was lesser in comparison to other models (Kumari and Toshniwal 2021). Likewise, the LSTM and convolution neural network (CNN) were combined by Zang H. et al. to forecast the global solar irradiance. In this study, LSTM network used to acquire temporal features of the input dataset and CNN was used to fetch the spatiotemporal features (Zang et al. 2020b). A very short-term solar forecast using sky images was performed by Cong Feng et al. where, 20 layers, 13 convolution layers and five-max pooling layers with two fully connected layers based CNN model was developed to forecast the solar GHI. The model achieved 116.82 W/m^2 of RMSE, -4.56 W/m^2 of MBE and 25.14% of forecast skill score for 1-h ahead prediction (Feng and Zhang 2020). Further, the combination of a residual network (ResNet) & dense convolution network (DenseNet) was used by Hanxia et al. to forecast the 1-h ahead PV power. The variational mode decomposition was used as a preprocessing tool, to decompose the input dataset into trends, seasonal and random components (Zang et al. 2020a). The WT along with LSTM was utilized by Wang F et al. and the results proved that the models accuracy can be improved by WT (Wang et al. 2018). The WT and LSTM network was also used by M. Mishra et al. The study predicted the solar power for 1-h to 1-day ahead of time horizon in which WT was used to decompose the input raw data series into different frequency components and LSTM was used to forecast solar power (Mishra et al. 2020). In the same line, the GRU network was proposed by B. Gao et al. to forecast the day ahead solar irradiance. The model predicted the day ahead solar GHI with the combination of time series and meteorological data as an input. The GRU network provided the minimum RMSE of 122.45 W/m^2 with 42.01% of forecast skill (Gao et al. 2019).

Several other studies on deep learning are also available in the literature and most of them used LSTM, CNN for PV power forecasting & wind forecasting (Ding et al. 2019; Kumar et al. 2020; Hu and Chen 2018). But, a few studies are available with the BiLSTM network to forecast the solar irradiance. However, BiLSTM network

have already been used in electric load (Wu et al. 2020) & price forecasting (Cheng et al. 2019), tourism demand forecasting (Kulshrestha et al. 2020), user's next location forecasting (Bao et al. 2020), stock & demand forecasting (Kim and Moon 2019), wind speed forecasting (Ding et al. 2019; Hu and Chen 2018) as well as covid-19 (Zeroual et al. 2020) predictions. With respect to BiLSTM, Li C. et al. predicted the solar irradiance using the standalone BiLSTM network. The BiLSTM network utilized the meteorological data to predict the hourly solar radiation. The results of the study clearly showed that the BiLSTM network is superior to the LSTM, SVR and LR models with RMSE of 98.44 W/m^2 , MAE of 71.49 W/m^2 (Li et al. 2021). Rai A. et al. predicted the solar radiations for the time horizon of two months using the CNN and BiLSTM. The CNN was used to extract the features of the input data time series; whereas, BiLSTM exploited the dependencies of the time series. This study proved that the CNN-BiLSTM model performed better than LSTM, GRU, CNN-LSTM and GRU-LSTM (Rai et al. 2021). Therefore, inspired from the above work, this paper proposes an ensemble model to forecast 24-h ahead solar GHI using wavelet transform (WT) and BiLSTM with an objective to improve forecasting accuracy. For the justification of superiority of proposed model, the performance is compared with the reproduced naïve predictor and other proven deep learning networks such as: unidirectional LSTM, unidirectional GRU, BiLSTM, traditional wavelet-based BiLSTM (WT-BiLSTM(T)) and modified wavelet-based BiLSTM (WT-BiLSTM(Mod)).

In brief, the major contributions are as follows:

- A brief literature of solar forecasting based on deep learning network by considering almost all important factors related to forecasting.
- Reproduction of naïve predictor (benchmark), three different standalone deep learning models: unidirectional LSTM, unidirectional GRU and BiLSTM network.
- With the aim to fill the space of WT-BiLSTM process, the various scenarios of WT based BiLSTM models are analyzed. For this, the traditional WT is combined with BiLSTM (WT-BiLSTM (T)) network to forecast the solar GHI. In the other scenario, the scope of WT is extended by combining the different wavelet decomposed sub-series (IMF) and fed to BiLSTM network (WT-BiLSTM (mod)) to forecast solar GHI.
- Implementation of proposed model based on forecasting of wavelet decomposed component using BiLSTM (WT-BiLSTM(CF)). The proposed model is developed to improve the forecasting using the best use of WT with BiLSTM. The model allocates an individual BiLSTM network to the best combination of wavelet decomposed subseries. The forecasted value obtained from BiLSTM

for each subseries are reconstructed to generate the final forecast.

- Performance analysis of proposed model in comparison with other reproduced models along with benchmark model. The proposed model observed as a best performer among all models with lesser annual RMSE of 45.61 W/m², MAPE of 6.48% and R² of 0.94. The forecast skill of the proposed model against naïve predictor is also observed and found 47%.

Therefore, the paper is structured in such a way that the theoretical context of the wavelet transformation, LSTM and BiLSTM deep learning network is defined in Section 2. Section-3 deals with the framework of the suggested model while Section-4 addresses various experimental scenarios. All experiments are analyzed as a discussion in section-5. Finally, the conclusion is drawn in section-6.

Theoretical background

This section provides a brief overview of the pre-processing i.e. WT and deep learning networks related to the proposed forecasting model.

Wavelet transform (WT)

It is a tool to process the highly random & time-varying data signals by which time domain signal can be directly transformed into the time-scaled frequency domain (Zhang et al. 2020). In other words, WT decomposes nonlinear and the non-stationary data in to set of different frequency profiles. These frequency profiles extract the appropriate statistical characteristics of the input data series. The high frequency components provide the short term variations in the data and can be used to improve the forecasting accuracy for short term prediction. The WT can be categorized into two types according to the input signal: Continuous wavelet transform (CWT) and Discrete wavelet transform (DWT) (El-Hendawi and Wang 2020). This CWT can be expressed mathematically as:

$$W_{CWT}(a, b) = a^{-1/2} \int_{-\infty}^{\infty} GHI(t) \psi\left(\frac{t-b}{a}\right) dt \quad (1)$$

where, ' W_{CWT} ' is CWT, ' $GHI(t)$ ' is global horizontal irradiance time series, ' $\psi(t)$ ' is mother wavelet which is scaled & time shifted by ' a ' & ' b ' respectively.

Whereas, the DWT for a time series $GHI(t)$; $t = 1, 2, 3$, can be expressed as a mother wavelet ' $\psi_{m,k}$ ' & father wavelet ' $\varphi_{m,k}$ ' and expressed mathematically as (El-Hendawi and Wang 2020):

$$\psi_{m,k}(t) = (2^m)^{1/2} \psi(2^m - t) \quad (2)$$

$$\varphi_{M,k}(t) = (2^M)^{1/2} \varphi(2^M - t) \quad (3)$$

In DWT, the convolution of father wavelet ' φ ' with original series ' $GHI(t)$ ' gives the approximation components ' $A_{m,k}$ '. Whereas, the convolution of mother wavelet ' ψ ' with original series ' $GHI(t)$ ' gives the detail components ' $D_{m,k}$ '.

$$\text{So, } A_{M,k} = \int_{-\infty}^{\infty} GHI(t) \varphi_{M,k} dt \quad (4)$$

$$D_{m,k} = \int_{-\infty}^{\infty} GHI(t) \psi_{m,k} dt \quad (5)$$

$$\text{However, } GHI(t) = \sum_{k \in \mathbb{Z}} A_{M,k} \varphi_{M,k}(t) + \sum_{m=1}^M D_{m,k} \psi_{m,k}(t) \quad (6)$$

Or in simple terms, for a finite length of series with finite decomposition is (Sarooha and Aggarwal 2018):

$$GHI(t) = D1 + D2 + D3 + \dots + Dn + A1 + A2 + A3 + \dots + An$$

Where " $D1, D2, D3, \dots, Dn$ " are the detailed components of input time series and " $A1, A2, A3, \dots, An$ " are the approximation components of input time series.

Long short-term memory network (LSTM)

For processing the sequence data, J. J. Hopfield proposed a structure in 1982, called Recurrent Neural Network (RNN). Unlike conventional ANN, the output of RNN is connected back to the input through feedback which acts as dynamic memory (Zang et al. 2020b). This network performed best for the short term forecasting but becomes unstable for long term forecasting. This instability is due to exploding of gradient i.e. sudden large variations in training weights (Hochreiter and Schmidhuber 1997). The solution of gradient exploding was provided by LSTM network by allowing memory cells in the hidden layer(s). These memory cells are used to appropriately store the information or discard the relevant information of the data. The basic architecture of the LSTM is shown in Fig. 2.

Each cell of the LSTM consists of forget gate (f_t), input gate (i_t) and output gate (O_t) to accept or discard of any information (Kulshrestha et al. 2020). For a forward movement function, the previous cell state ' C_{t-1} ' has been discarded by the network. At present time ' t ', the LSTM

Fig. 2 LSTM architecture

network have three inputs ‘ $GHI(t)$ ’, previous memory cell output ‘ h_{t-1} ’ and bias ‘ b_f ’ of forget gate (Fischer and Krauss 2018). Therefore, the activation values can be expressed as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, GHI_i(t)] + b_f) \quad (7)$$

The following equations are used by the network to decide whether the information about data has to be discarded or retained.

$$i_t = \sigma(W_i \cdot [h_{t-1}, GHI_i(t)] + b_i) \quad (8)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, GHI_i(t)] + b_c) \quad (9)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (10)$$

Now, the final output of the memory cell becomes:

$$O_t = \sigma(W_o \cdot [h_{t-1}, GHI_i(t)] + b_o) \quad (11)$$

$$h_t = O_t * \tanh(C_t) \quad (12)$$

where ‘ b_i ’, ‘ b_f ’, ‘ b_c ’ & ‘ b_o ’ are bias vectors of LSTM network; ‘ W_i ’, ‘ W_f ’, ‘ W_c ’ & ‘ W_o ’ are weight vectors of LSTM network and σ is sigmoid function ranges from ‘0’ to ‘1’.

Bidirectional long short-term memories (BiLSTM)

The BiLSTM network is composed of forward and backward LSTM in which data can be processed in forward as well as in backward direction. The backward direction processing captures the hidden characteristics and pattern of the data which was generally ignored by LSTM (Yildirim 2018). The

Fig. 3 BiLSTM architecture

basic architecture of BiLSTM network is shown in Fig. 3 (Li et al. 2021).

The forward hidden layer ‘ L_f ’, the backward hidden layer ‘ L_b ’ and output sequence ‘ $GHI_o(t)$ ’ used to update the network. The network updates iteratively in backward i.e. from ‘ T ’ to ‘ 1 ’ and forward direction i.e. ‘ 1 ’ to ‘ T ’. The updated parameters of the network can be expressed mathematically as:

$$L_f = \sigma(W_1 GHI_i(t) + W_2 L_{f-1} + b_{L_f}) \quad (13)$$

$$L_b = \sigma(W_3 GHI_i(t) + W_5 L_{b-1} + b_{L_b}) \quad (14)$$

$$GHI_o = W_4 L_f + W_6 L_b + b_{GHI_o} \quad (15)$$

Where, ‘ L_f ’, ‘ L_b ’ & ‘ $GHI_o(t)$ ’ are forward pass, backward pass and final output layers respectively. ‘ W ’ is the weights coefficient and ‘ b_{L_f} ’, ‘ b_{L_b} ’ & ‘ b_{GHI_o} ’ are the biases (Cheng et al. 2019).

Structure of proposed WT based BiLSTM model

The basic idea of this work is to improve the forecasting accuracy of Solar GHI using WT based BiLSTM network in which different scenarios of WT pre-processing are being applied. The Fig. 4 shows the pictorial representation of proposed model and description of each step is given below:

A) Quality control of data: Initially, the collected data from any site is available in the raw form and has a great influence on the model’s performance. There might be possibilities of presence of negative or incomplete data records due to weak pyranometer response. So, these

Fig. 4 Structure of proposed forecasting model

entries must be removed or corrected before the application to the forecasting model (Yousif et al. 2013). In addition to this, the night hours data are also removed from the dataset due to absence of solar irradiances in night time. The data just before the sunset and just after the sunrise is also a culprit factor in the model's performance due to cosine error of instruments and must be removed. In a single statement, this process can also be understood as the removal of data having solar zenith angle greater than 80° (Lauret et al. 2015).

- B) Data Stationarity: The majority of the solar data collected from the site is often random and nonlinear in nature which consists of periodicity and seasonality (Singh et al. 2018). Therefore, to enhance the model's efficiency, the data has to be rendered stationary before providing to the forecasting model. This paper considers the clear-sky index (CSI) calculation to render the data

stationary or to turn in the "0–1" range. The CSI can be calculated as (Benali et al. 2019):

$$GHI_{CSI}(tk) = \frac{GHI_i(t)}{CS_i(t)} \quad (16)$$

where, $CS_i(t) = I_o \exp \left(-\frac{\tau}{\sin^{b(h(t))}} \right) \sin(h(t))$
 where $h(t)$ is height of solar (degree).
 I_o = Extra-terrestrial irradiation.
 b = parameter of fitting.

Most research, however, have already shown that the clear sky GHI is nearly identical to the CS and can be replaced with each other, so

$$k = \frac{GHI_i(t)}{GHI_{cs}}$$

where, GHI_{cs} = clear-sky GHI.

III) Data decomposition: Using data quality control, once the time series has been cleaned & converted into CSI. The WT is applied on the input data series to decompose into approximation and detail components. This work observed the Daubechies (db7) wavelet provides the required smoothness of considered data. However, the wavelet decomposition up to level 1–10 was observed experimentally where level-7 with db7 found best for the dataset used in the study. The pictorial representation of level-7 decomposition is shown in Fig. 5; whereas, Fig. 6 represents the wavelet decomposition results for the original solar GHI time series.

Fig. 5 Level-7 decomposition using discrete wavelet transform

Here, $GHI(t) = D1 + D2 + D3 + D4 + D5 + D6 + D7 + A7$

IV) Selection of hyperparameters: One of the significant tasks in case of a deep learning algorithm is the tuning of hyperparameters. However, no such thumb-rule is present in the literature to set these hyperparameters at optimal range. But, the study obtained the optimal hyperparameters using the grid search algorithm by varying each parameter's value within a specific bound. The specific process of searching the best hyperparameter is shown in Fig. 7 using a flow graph whereas, Table 1 provides the best values along with their corresponding bounds. This study kept these fine-tuned hyperparameters constant throughout the work to maintain the fairness in the comparison of different models. The specific rules to select best hyperparameters are mentioned below:

- 1) Set the initial hyperparameter at a default value.
- 2) Set the optimum learning rate.
- 3) Choose the perfect epoch with batch size.
- 4) Choose the relevant optimizer.
- 5) Select the appropriate activation function.
- 6) Choose suitable numbers of the hidden layer.

E) Forecasting Process: Input data is decomposed at level 7 using db7 wavelet in which eight components: A7 and D7-D1 are obtained. So, as input features, the eight components D1 to D7 and A7 with sufficient time lags are configured. This study performed a comprehensive experiment to obtain best solar GHI forecast for different combinations of decomposed components as input to the predictor for different level's decomposition (refer Table 5). For the same, the input dataset have been divided into two phases: the training phase and forecasting phase. With the aid of one year training data, forecasting is performed on monthly basis up-to next 12 months with moving window mechanism. The proposed model forecasts 24-h ahead of hourly data for each month. The output sequence is reconstructed to have the actual CSI at this stage. Although, using the following equation, this sequence is further transformed into real solar GHI from CSI.

$$GHI(t) = CS(t) \times CSI$$

Where, " $CS(t)$ " & " CSI " are Clear sky GHI & clear sky index respectively.

Fig. 6 Level-7 wavelet decomposition results

F) Performance Calculations:

Mean absolute percentage error (Sobri et al. 2018):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{GHI_i - \tilde{GHI}_i}{GHI_i} \right| \quad (17)$$

where “ $\tilde{GHI}$ ” is forecasted value of GHI at “ i^{th} ” level whereas, GHI is observed value of GHI.

Root Mean Square Error (Sobri et al. 2018):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(GHI_i - \tilde{GHI}_i \right)^2} \quad (18)$$

Coefficient of determination (R^2):

It used to represent the goodness of fit of a model and it is square of correlation coefficient ranges from 0 to 1.

$$R^2 = 1 - \frac{\sum_{i=1}^n \left(GHI_i - \tilde{GHI}_i \right)^2}{\sum_{i=1}^n \left(GHI_i - \text{mean}(GHI_i) \right)^2} \quad (19)$$

Forecast Score (FS):

The percentage improvement in the forecasting by a developed model w.r.t. reference model is demonstrated by FS.

$$FS = 1 - \frac{\text{Error Indicator}_{\text{proposed method}}}{\text{Error Indicator}_{\text{ref. method}}} \quad (20)$$

Simulation results

This work originated with the wavelet & BiLSTM network in order to enhance the accuracy of forecasts. The performance of proposed model has been compared with some other standard models such as: naïve predictor, standalone deep learning networks (LSTM, GRU & BiLSTM) and other WT based models. The simulation is performed in MATLAB 2020 environment where different scenarios of the models have been evaluated. To suggest an accurate model, the various simulations are performed as follows:

- 1) Naïve predictor, unidirectional LSTM, GRU and BiLSTM network.
- 2) Traditional wavelet decomposition technique with BiLSTM (WT-BiLSTM (T)).
- 3) Modified wavelet decomposition technique with BiLSTM (WT-BiLSTM (Mod)).
- 4) Proposed wavelet decomposition forecasted technique, which summed all forecasted decomposed components (WT-BiLSTM (CF)), where CF means for component forecasted.
- 5) Evaluation of forecasting performance of proposed model using RMSE, MAPE, R^2 & FS and compared with naïve, LSTM, GRU, BiLSTM, WT-BiLSTM(T) and WT-BiLSTM(mod) models.

Data description

Because of the large investments in the renewable sector and exponentially increasing scope in India, this work considers the Indian location data set for the forecasting. This work utilizes the hourly data gathered from NSRDB, for

Fig. 7 Flow graph for selecting hyperparameters

Ahmadabad city situated in northern Gujarat, India with latitude / longitude of 23°03 N/72°58E with an average elevation of 53 m. According to the Koppen climate classification, the studied location has mixed kind of climate with subtropical hot steppe ('bsh') and humid subtropical ('cwa').

The collected dataset are the hourly recordings of different meteorological parameters along with historical solar GHI. However, a dataset of year 2013 & 2014 have been used to train, validate and test the proposed model. The entire dataset was split into different datasets: training dataset (80%), validation dataset (10%) and test dataset (10%). The study used the dataset of year 2013 for the training purpose while the next year data have been carried out to evaluate the model using monthly forecasting.

Experimental setup

All the developed models including proposed model are evaluated in terms of error (RMSE, MAPE), coefficient of determination (R^2) and forecasting skill (FS). To implement the improved & accurate forecasting model, different scenarios of experiments have been conducted. The RMSE, MAPE & R^2 for all scenarios are recorded in Tables 2, 3, and 4 and are discussed below:

Scenario 1: Forecast using naïve, LSTM, GRU & BiLSTM

This experiment is all about the development of benchmark & standalone deep learning models such as: Naïve, standalone LSTM, GRU and BiLSTM. The experiment is conducted for the forecasting of different month-wise 24-h ahead solar GHI where input initialization and fine-tuning of the hyperparameters of deep learning networks is one of the important tasks to achieve the better accuracy. The 15 time lags of input data series are provided to these deep learning based standalone models as an input features; whereas, the solar GHI is used as an output feature. Finally, the value of MAPE obtained by naïve, standalone LSTM, GRU and BiLSTM ranges from 2.41%–30.03%, 3.31–32.97%, 3.66–33.18%, and 2.51–18.96% respectively; RMSE ranges from 32.02–185.44 W/m², 40.33–161.84 W/m², 32.73–164.01 W/m² and 30.94–113.06 W/m² respectively. Moreover, the correlation coefficient R^2 ranges from 0.33–0.95, 0.40–0.95 and 0.41–0.97 for naïve, standalone LSTM, GRU and BiLSTM respectively. Figure 8 shows the annual average RMSE & MAPE comparison of this scenario. From these observations, It is clear that the BiLSTM

Table 1 Hyperparameters values used in the study

Hyperparameter	Searched range	Value	Hyperparameter	Searched range	Value
Hidden Units	50–120	100	Epochs	100–600	500
Initial Learning Rate	0.0001–0.1	0.0007	Optimizer	adam, sgd, RMSprop	Adam
Learning Rate Drop Period	50–150	125	Learning Rate Drop Factor	Default	0.2

Table 2 RMSE (W/m²) comparison of developed models

Models	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec	Annual
Naïve	56.85	78.70	45.95	32.02	54.14	87.23	168.46	185.44	158.09	69.74	47.33	52.03	86.33
LSTM	40.33	57.60	45.16	43.61	58.63	82.95	161.72	161.84	141.35	68.40	59.58	49.40	80.88
GRU	42.81	56.36	39.70	32.73	48.87	71.55	164.01	163.64	149.35	60.60	54.93	39.79	77.03
BiLSTM	33.57	44.94	37.46	31.92	49.25	65.97	88.90	113.06	84.51	56.94	34.94	30.94	56.03
WT-BiLSTM (T)	32.52	40.69	32.67	29.86	44.72	61.21	84.10	107.17	79.80	50.64	32.40	25.53	51.77
WT-BiLSTM (Mod)	31.91	40.41	31.46	29.96	43.08	58.60	81.19	106.65	74.16	49.16	34.02	23.78	50.36
Proposed Model	31.83	35.69	26.85	23.26	36.46	52.84	85.61	96.38	65.78	46.50	24.96	21.24	45.61

Table 3 MAPE (%) comparison of developed models

Models	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec	Annual
Naïve	6.43	7.68	3.02	2.41	4.92	10.97	28.55	30.03	28.07	7.35	6.72	4.83	11.74
LSTM	5.98	7.13	3.74	3.31	5.93	10.19	31.39	29.35	32.97	7.96	8.80	5.70	12.70
GRU	6.59	6.97	4.43	3.66	6.43	9.66	31.92	29.80	33.18	8.02	8.10	5.38	12.84
BiLSTM	3.77	4.99	2.93	2.51	5.57	8.72	16.23	18.96	16.29	6.38	5.88	4.07	8.02
WT-BiLSTM (T)	3.66	4.51	2.69	2.39	5.17	8.11	15.21	17.11	16.17	5.81	5.52	3.56	7.49
WT-BiLSTM (Mod)	3.43	4.40	2.62	2.39	5.03	7.76	14.23	17.46	15.28	5.84	5.59	3.34	7.28
Proposed Model	3.30	3.86	2.26	2.02	4.36	6.72	14.18	14.66	13.54	5.54	4.22	3.11	6.48

Table 4 R² comparison of developed models

Models	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec	Average
Naïve	0.91	0.86	0.95	0.93	0.92	0.78	0.46	0.33	0.56	0.88	0.93	0.92	0.78
LSTM	0.95	0.92	0.95	0.95	0.90	0.80	0.43	0.40	0.58	0.88	0.90	0.92	0.80
GRU	0.96	0.93	0.97	0.97	0.94	0.84	0.43	0.41	0.57	0.90	0.94	0.95	0.82
BiLSTM	0.97	0.95	0.97	0.96	0.94	0.87	0.82	0.69	0.86	0.92	0.96	0.97	0.91
WT-BiLSTM (T)	0.97	0.96	0.97	0.97	0.94	0.88	0.84	0.72	0.87	0.93	0.96	0.98	0.91
WT-BiLSTM (Mod)	0.97	0.96	0.98	0.97	0.95	0.89	0.85	0.73	0.89	0.94	0.96	0.98	0.92
Proposed Model	0.97	0.97	0.98	0.98	0.96	0.92	0.86	0.78	0.92	0.95	0.98	0.98	0.94

Fig. 8 Annual average RMSE (W/m²) & MAPE (%) of different models

network outperforms over LSTM & GRU as is also claimed in various previous studies (Li et al. 2021; Rai et al. 2021).

Scenario 2: Forecast using traditional WT and BiLSTM (WT-BiLSTM (T))

The traditional WT is used in this experiment to decompose the input data time series. This experiment utilizes all the decomposed components of WT along with the fifteen time lags of input data as input features of the BiLSTM model. The results in the Tables 2, 3 and 4 shows that the WT-BiLSTM(T) achieved lesser RMSE, MAPE and improved R^2 in comparison to standalone LSTM, GRU and BiLSTM networks. This model achieved MAPE ranges from 2.39–17.77%, RMSE ranges from 25.53–107.17 W/m² and R^2 ranges from 0.72–0.98. Moreover, the average annual RMSE, MAPE and R^2 obtained from the same is 51.77 (W/m²), 7.49% and 0.91 respectively.

Scenario 3: Forecast using Modified wavelet decomposition and BiLSTM (WT-BiLSTM (Mod))

Unlike, the traditional wavelet where all decomposed components were used as input features to the BiLSTM network. This experiment employs the different combinations of decomposed components as an input feature with the time lag input data. A thorough analysis has been done to observe the effect of these combinations of decomposed components as an input feature to the performance of model. Table 5 shows the observations recorded for different combinations of decomposed components as input features. Here, the observations from these combinations are shown only for the month of January. It is evident that the BiLSTM network provides lesser RMSE of 31.91 W/m² and MAPE of 3.43% with the combinations A7, D7 and sum (D1–D6). In this combination, the detail components D1–D6 are added and resultant subseries is considered as a single input feature to the model instead of six subseries (D1 to D6).

Finally, A7, D7, sum (D1–D6) with time lag input series are used as an input features to the BiLSTM network to forecast the solar GHI. It is evident from Tables 2, 3, 4,

this model obtained MAPE ranges from 2.39–17.46%, RMSE ranges from 23.78–106.65 W/m² and R^2 ranges from 0.73–0.98. Moreover, the average annual RMSE obtained from the same is 50.36 (W/m²), MAPE is 7.28% and R^2 is 0.92. From the results, it can be seen that this model improves the forecasting accuracy in comparison to naïve, LSTM, GRU, BiLSTM, and WT-BiLSTM (T).

Scenario 4: Forecast using proposed WT BiLSTM Model (WT-BiLSTM (CF))

The proposed model is implemented in this scenario with an aim to achieve credible improvements in the forecasting accuracy. Unlike, all above experiments, this experiment allocated the separate BiLSTM network to each of the resultant decomposed series i.e. A7, D7 and Sum (D1 to D6) to forecast the future subseries's values. The fifteen-time lags of every decomposed component series are considered as the input features to their respective networks. The final prediction is obtained by the wavelet reconstruction process where outputs of each BiLSTM networks are further added to each other. From Tables 2 and 3, the MAPE obtained by the proposed model ranges from 2.02–14.66% whereas RMSE is from 21.24–96.38 W/m². Table 4 shows the value obtained for R^2 which is ranges from 0.78–0.98. Moreover, this model achieved the lowest annual average RMSE (45.61(W/m²)), MAPE (6.48%) and R^2 (0.94).

Discussion

The research has been conducted to forecast the 24-h ahead solar GHI for the location of Ahmadabad, Gujarat, India in which various experiments are carried out to obtain the precise forecast model with improved forecasts. In order to show the superiority of proposed model, the forecasting performance has been compared with naïve predictor, unidirectional LSTM, unidirectional GRU, BiLSTM and wavelet-based BiLSTM models.

From the prospective of overall results,

Table 5 Analysis of WT components combinations as an input features

Combination	RMSE (W/m ²)	MAPE (%)	Combination	RMSE (W/m ²)	MAPE (%)
A7, D7, D6, D5, D4, D3, D2, D1	32.52	3.66	A7, D7, D6, D5, D4, D3, Sum(D1–D2)	32.49	3.82
A7, D7, D6, D5, D4, D3, D2	34.75	3.86	A7, D7, D6, D5, D4, Sum (D1–D3)	34.37	3.72
A7, D7, D6, D5, D4, D3	34.90	3.80	A7, D7, D6, D5, Sum (D1–D4)	33.92	3.80
A7, D7, D6, D5, D4	34.95	3.99	A7, D7, D6, Sum (D1–D5)	32.35	3.69
A7, D7, D6, D5	33.02	3.82	A7, D7, Sum (D1–D6)	31.91	3.43
A7, D7, D6	35.22	3.99	A7, Sum (D1–D7)	32.07	3.54
A7, D7	32.72	3.75			

- a) Naïve predictor provides the largest annual average RMSE of 86.33 W/m^2 and MAPE of 11.74% due to poorest RMSE in months of February, June–September. The R^2 is also lesser in case of naïve predictor which represents the worst forecasting accuracy among all models.
- b) As far as, the standalone models are concerned, BiLSTM is the best performer among the naïve, LSTM & GRU. The annual average RMSE, MAPE & R^2 obtained by BiLSTM is 56.03 W/m^2 , 8.02% & 0.91% respectively. Whereas, among naïve, GRU and LSTM; GRU performed well than the LSTM & benchmark model with annual average RMSE, MAPE & R^2 of 77.03 W/m^2 , 12.84% and 0.82 respectively.
- c) The traditional WT based BiLSTM model (WT-BiLSTM (T)) performed better than the standalone deep learning based & naïve models. It obtained 51.77 W/m^2 of annual average RMSE, 7.49% annual average MAPE and $0.91 R^2$. However, the WT-BiLSTM (mod) model achieved the next level lowest annual average RMSE (50.36 W/m^2) and annual average MAPE (7.28%). This model obtained the R^2 equals to the 0.92 .
- d) Finally, the proposed model performed the best with lowest annual average RMSE (45.61 W/m^2), annual average MAPE (6.48%). The credible improvement can also be seen in the coefficient of determination R^2 (0.94). From the Fig. 9, it is evident that the maximum percentage improvement is provided by the proposed model in RMSE & MAPE is 57% & 58.92% respectively concerning to standalone LSTM model. However, this improvement is 56.06% & 59.19% respectively against standalone GRU and 31.35% & 28.14% respectively against standalone BiLSTM model. Even, the proposed model also shows a great percentage improvement in RMSE against the naïve predictor ranges from 26.04% – 58.89% . It provides the great improvements of above 40% in the eight months i.e. Jan, Feb, March, July, Aug, Sep, Nov and December.

From the month wise prospective,

- a) From the literature, no doubt naïve predictor provides the good accuracy for the shorter time horizon with lesser variations in the dataset. However, it is not suitable for the larger time horizon as well as the dataset having larger variations. From the results, it is obvious that the naïve predictor performed better than the LSTM in the month of April, May & November while better than GRU in month of April and November with a minor difference in RMSE. The MAPE obtained by naïve predictor in month of January, March April, May, July, September, October, November and December are better than LSTM & GRU. These lowest results are however, uncertain but due to the variations in the datasets.
- b) On the other hand, in comparison to the traditional standalone LSTM, GRU & BiLSTM models, the performance of standalone BiLSTM model is better than the LSTM & GRU for all months. The standalone BiLSTM model obtained minimum RMSE of 30.94 W/m^2 for the month of December & MAPE of 2.51% for the month of April. Moreover, the R^2 for BiLSTM model is also better for each month. Even, the naïve predictor, LSTM & GRU model obtained the worst R^2 for the month of July, August & September i.e. $0.46, 0.33, 0.56$ for naïve, $0.43, 0.40, 0.58$ for LSTM and $0.43, 0.41, 0.47$ for GRU. The results demonstrated that the R^2 for these three months are drastically improved by BiLSTM model i.e. $0.81, 0.69$, and 0.86 . So, the standalone BiLSTM model improves the forecasting accuracy as compared to standalone unidirectional LSTM, GRU and naïve predictor due to its learning capabilities in both directions.
- c) By contrast, the wavelet-based models produced high accuracy with lesser error than the standalone models. The traditional wavelet based BiLSTM model performed better than all standalone models including naïve predictor for all months due to extraction of statistical features of input series. It obtained lowest RMSE & MAPE of $29.86 \text{ (W/m}^2\text{)}$ and 2.39% respectively in month of

Fig. 9 Percentage improvement by proposed model over different models

April. The maximum RMSE & MAPE obtained by WT-BiLSTM (T) is 107.17 (W/m²) and 17.11% in month of August. The maximum R² (0.98) is achieved by the WT-BiLSTM (T) for the month of December.

- d) It is also evident from the results that the modified approach of WT with the summation of decomposed components D1-D6 improved the forecasting accuracy than a traditional WT. The lowest RMSE is 23.78 W/m² for the month of December & maximum RMSE is 106.65 W/m² for the month of august for the modified WT i.e. WT-BiLSTM (mod). Whereas, it is 25.53 W/m² & 107.17 W/m² for a traditional WT respectively for the same months. However, the R² value for the month December for WT-BiLSTM (mod) is same as WT-BiLSTM(T) i.e. 0.98 but the improvement was obtained in month of august i.e. 0.73 for WT-BiLSTM(mod) and 0.72 for WT-BiLSTM(T).
- e) Finally, the proposed model where each component of WT was separately forecasted using BiLSTM, performed better than all other models. The proposed model obtained lowest RMSE (21.24 W/m²) for month of December and maximum RMSE (96.38 W/m²) for the month of August. Whereas, the MAPE obtained by the proposed model is also lesser than others i.e. minimum MAPE of 2.02% and maximum MAPE of 14.66%. Moreover, the R² value is also improved in month of august i.e. 0.78 which was initially 0.33 for naïve predictor. The maximum R² (0.98) is achieved by the proposed Model for the months of March, April, November and December.

For a deep look into the results, the Fig. 10 provides the graphical analysis of real and forecasted GHI for three consecutive days (2nd to 4th day) of two months (March & August). These two months are to visualize the results of month with lesser RMSE (March) and larger RMSE (August). Nevertheless, for a clear presentation, only real GHI and forecasted GHI curves of proposed model is presented for selected months. It is clear from the Fig. 10; the large variations in the real GHI curve provided the larger

error in the results. For instance, the month of March has a smooth curve due to clear sky conditions and easily traceable by the model. Unlike this month, the real GHI is frequently varying in the month of August due to presence of cloudy or rainy days, and is hard to trace by the model results in maximum errors. From these curve traces, it can be concluded that higher is the variations in real GHI, lower is the similarity in real and forecasted GHI. Similarly, lower are the variations in the real GHI; higher is the degree of similarity between real and forecasted GHI. But, the proposed model also follows uncertainties associated with real GHI with in tolerance band of error. Therefore, these observations yield that the proposed model is a suitable forecasting model not only for stable type of seasons but also for unstable seasons.

For further explanation of forecasting performance, Table 6 shows the FS% results of proposed model and WT-BiLSTM (mod) for annual RMSE & MAPE with reference to benchmark model.

Lastly, to validate the performance of the proposed model against previously reported models is presented in Table 7. The superiority of the proposed model is shown in terms of RMSE, MAPE and FS.

According to the Table 7, the proposed model appears to be the best and excellent model to forecast solar GHI over latest developed models. The model performed shows its superiority in terms of lower RMSE & MAPE and higher forecasting skills over LSTM, GRU, CNN-LSTM, DFT-PCA-Elman and standalone BiLSTM. Therefore, the overall results suggested that the proposed model can be a good choice to forecast solar GHI for practical solar power systems also.

Table 6 Annual %FS of proposed model

Model	FS _{RMSE}	FS _{MAPE}
WT-BiLSTM(mod)	42%	38%
Proposed Model	47%	45%

Fig. 10 a, b Performance of proposed model for month March & August respectively

Table 7 Comparison of proposed Model to the previously developed models

Ref.	YOP	Location	Time horizon	Model	RMSE (W/m ²)	MAPE (%)	FS%
(Qing and Niu 2018)	2018	Santiago, Cape Verde	1-h	LSTM	126.31	–	–
(Lan et al. 2019)	2019	Qingdao, China	24-h	DFT + PCA + Elman/BPNN	127.3	–	6.3
(Gao et al. 2019)	2019	Denver, USA	24-h	GRU	122.45	–	42.01
(Zang et al. 2020b)	2020	Texas, USA	1-h	CNN-LSTM	69.26	–	–
(Kumari and Toshniwal 2021)	2020	New Delhi, India	1-h	XGBF-DNN	51.35	–	40.2
(Li et al. 2021)	2021	US	1-h	BiLSTM	98.44	–	–
<i>This Work</i>		<i>Ahmadabad, India</i>	<i>24-h</i>	<i>WT-LSTM(CF)</i>	<i>45.61</i>	<i>6.48</i>	<i>47</i>

Conclusion

In the renewable energy markets, solar energy has its own space & significance. The stability and efficiency of solar forecasting are therefore crucial for the regular operation of interconnected grid systems. Most of the time, the standalone models are unable to capture the fluctuating inherent solar time series characteristics. So, an ensemble model to forecast the 24-h ahead hourly solar GHI is proposed using the WT and BiLSTM network. The performance of the proposed model is rigorously evaluated by the GHI forecast on monthly basis for a year 2014 using moving window. The WT is used to extract the statistical features of the input time series using low and high frequency time series (IMF) while BiLSTM network is employed to the forecast. Meanwhile, the forecasting performance of the proposed model is compared with the naïve predictor, standalone LSTM, GRU, BiLSTM and two different WT based BiLSTM model. The results show that the proposed model outperforms the other models with minimum annual average RMSE (45.61 W/m²) and MAPE (6.48%). The forecast skill and the R² for the proposed model are 47% and 0.94 respectively. Finally, the maximum percentile improvement in RMSE by proposed model is 58.38%, 58.11%, 56.06% & 31.35% over benchmark model, standalone LSTM, GRU and BiLSTM respectively; whereas, maximum percentile improvement in MAPE is 51.76%, 58.92%, 59.19% & 28.14% over benchmark model, standalone LSTM, GRU and BiLSTM respectively. Therefore, proposed model is proved to be the best forecasting model for 24-h ahead solar forecasts with consideration of all seasonal as well as monthly aspects. However, the study observed some challenges while designing the models such as: selection of precise hyperparameters and simulation time. So, in future by considering these challenges, more accurate and efficient results can be obtained within quick simulation time.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability The codes of this study are available from the corresponding author upon reasonable request.

Declarations

Not Applicable.

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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