

Data-Driven Short Term Solar Irradiation Forecasting Using Quadratic Mode Decomposition with Hybrid Bi-Directional GRU Model

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Abstract

Accurate short-term prediction of solar radiation is very important for a more effective integration of solar energy in the grids. To overcome these limitations, the authors propose a new approach based on quadratic mode decomposition (QMD) and a hybrid bi-directional gated recurrent unit (BiGRU) in this paper. The process begins with tackling the noise in the Global Horizontal Irradiance (GHI) data, which is done using Sample entropy (S entropy), and variational mode decomposition (VMD), and combination of complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to obtain a set of stationary intrinsic mode functions (IMFs). For each IMF, an HBiGRU setup captures ties to major influences on solar output like weather and time yielding separate predictions. The short-term GHI estimate is the sum of all the above. Real-life experiments using data from a site in India demonstrate the enhanced reliability of forecasts using this hybrid system, as it reduced the normalized root mean square error (RMSE) by 5.04% and mean absolute error (MSE) by 3.21% compared with the other systems, while increasing the coefficient of determination by 22.7%.

Keywords: short-term solar irradiance forecasting; hybrid bi-directional GRU; CEEMDAN; VMD; quadratic mode decomposition

1. Introduction

In recent years, due to the rapid decline of fossil fuel stocks along with the rapidly increasing pollution caused by human activities around the world, there is a consensus about promoting alternative energy solutions to replace the traditional fossil fuels. Among the growing renewables, solar energy generation is one of the fastest growing energy resources with its renewability, safety and cleanliness. However, the forecasting of solar irradiance is plagued by various weather factors, such as intensity of sunlight, temperature and cloudiness, and shows significant randomness and variability. Connecting large PV arrays to the grid makes grid management difficult and increases the risk to reliable and cost-effective operations. Short-term solar irradiance forecasting provides valuable information to develop and optimize dispatch plans and significantly reduce grid operating costs. Hence, the challenge of improving the accuracy of short-term solar irradiance forecasts very much remains as an urgent task to be addressed.

Two main methods for short-term weather forecasting of solar irradiance are physical and statistical methods [5-6]. The modelling process is complicated and the precision needs for the input data are high, so researchers often use statistical approaches for solar irradiation forecasts

with short time horizons [9].

some of the statistical methods include aid support vector machine device (SVM) [10], echo kingdom community [11] and neural networks community (NN) [12], however the above statistical methods are constrained in their capacities to address complex non-linear problems and absolutely-characterizing courting between the solar irradiation records and the elements that require its influence is a challenge so that it will pose an impediment to the development of forecast accuracy.

Because of their robust nonlinear fitting ability, the usage of these deep mastering techniques in strength gadget failure identification [13], distribution community reconfiguration [14], country estimation [15], forecasting [16], renewable electricity strength predication [17] and more has been extensively adopted in the past few years. The prediction of the sun irradiation in [18] is carried out by the use of convolutional neural networks (CNN). The BPNN and CNN fashions, however, don't remember the time of the past facts, which leads to low predictability of PV electricity. This is an upscale model of recurrent neural network (RNN) that tackles the issue of gradient explosion in RNN and can capture the time behavior of the statistics to make extra correct predictions. In [19] the ameliorated major problem evaluation is trained on paintings over the information regarding the solar irradiation and a GRU model is employed to forecast the solar irradiation. In [20] a brief term solar irradiation forecast model mainly based on CNN and GRU is proposed and the obtained result shows that CNN and GRU version is more accurate than the GRU version in forecasting solar irradiation. Furthermore, unlike standalone forecasting models, mixed forecasting approaches are able to fully leverage the advantages of the exceptional models in capturing the characteristics of the dataset in a more comprehensive manner and thereby generate more unique forecasting results [21]. Even now there are forms of blended forecasting strategies. The next one is to partition the GHI data to reduce the complexity of the data series, and then to model the data series one by one; the well-known methods of data decomposition are EMD [26] WT [25] and EEMD [27] etc.; however, EMD approach has a high adaptive capacity, but it is usually prone to mode blending phenomenon, which affects the PV's accuracy strength prediction; and the other is to adopt a deep learning version with a clever optimization algorithm and guide the optimization process to search for the optimal parameters of deep learning version to obtain higher forecast performance [22] but such an approach does not eliminate the influence of non-smoothness of the original GHI data on the forecast performance, that is, it does not remove the non-smoothness effect. In [28] the effects are also better than the EMD and EEMD methods of decomposition, even though there are still a few differences between the data that are recovered using the VMD approach and the real data. However, VMD approach was employed to decompose the solar irradiation information, and the average of the mode mixing difficulty of EMD is achieved by adding white noise to the original data, which leads to a certain amount of noise being present in the high-frequency components that VMD decomposes and affecting the accuracy of the solar irradiation prediction. Although a hybrid solar forecast method mainly using EMDAN and stepped forward SVM is recommended in [29] to resolve the mode mixing challenge of the EMD and the issue of high amount of ultimate noise from low frequency components of EEMD, the high frequency noise additive decomposed from CEEMDAN is not removed.

To tackle the above challenges, the short-term prediction of solar irradiation based on quadratic mode decomposition (QMD) and hybrid BiGRU is proposed in this work. There are these main contributions:

- 1) The HBiGRU prediction model is established by help of CNN, bi-directional gated recurrent unit (BiGRU) and attention mechanism (AM) and in the HBiGRU input layer, CNN digs deep into links between solar irradiance subseries and linked weather data; at the output layer, temporal attention sharpens focus on key time-based factors affecting predictions, markedly boosting BiGRU accuracy.
- 2) A QMD approach leveraging complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), S entropy (SE), and VMD gets proposed. CEEMDAN tackles EMD's mode mixing flaws and EEMD's surplus low frequency terms, followed by subseries reconstruction guided by SE values. Then VMD curbs noise interference in decomposition results to the greatest degree, delivering sharper forecasts than standalone decomposition techniques.

2. Solar Irradiation Data Decomposition Based on QMD

The QMD approach is used for breakdown of original Global Horizontal Irradiance sequence into multiple components with different modes, which helps simplify the complexity of the initial GHI data. The QMD process is illustrated in Fig. 1.

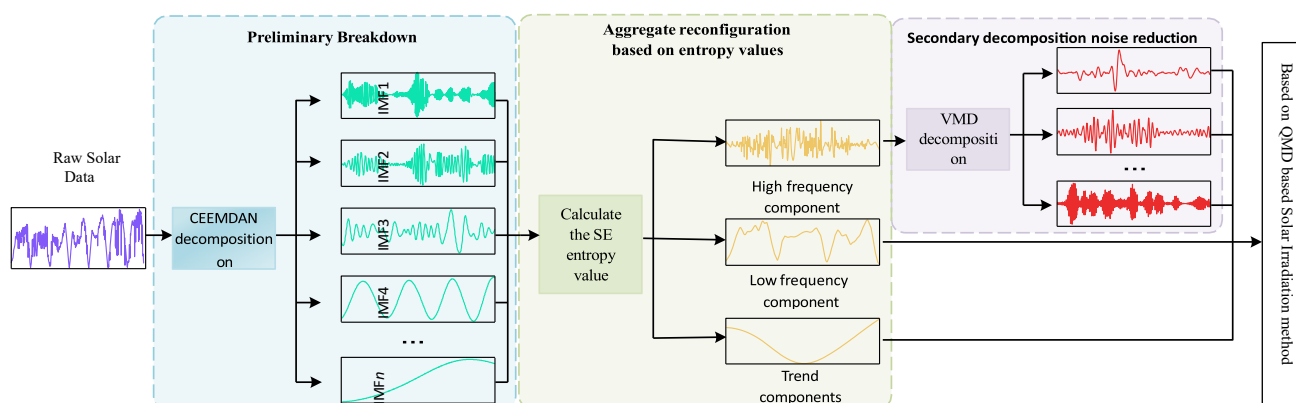


Figure 1 Flow chart of Quadratic Mode Decomposition

Firstly, CEEMDAN decomposes solar irradiation data to lower the complexity of its time series; secondly, SE quantifies complexity in each CEEMDAN-obtained component and reconstructs components sharing similar intricacy levels to additionally diminish model complexity; lastly, VMD re-decomposes those reconstructed high-frequency components, which suppresses leftover noise within high frequency parts, thus it boosts the decomposition results.

2.1 CEEMDAN

CEEMDAN that breaks data in a finite number of intrinsic mode function (IMF) featuring varied time scales through incorporating noise of opposing signs during decomposition, successfully addressing modal aliasing and surplus leftover noise issues in EMD and EEMD. The CEEMDAN steps listed below:

- 1) Add n pairs of Gaussian white noise to the signal $x(t)$ awaiting decomposition to generate a collection

of signals $x_i(t)$, where i ranges from 1 to n .

$$x_i(t) = x(t) + \alpha v_i(t) \quad (1)$$

Here α is Gaussian noise coefficient; $v_i(t)$ represents the i -th Gaussian noise.

2) Perform EMD decomposition on $x_i(t)$ to obtain the first IMF component and the mean of the n resulting components. This average serves as the first IMF component produced by CEEMDAN.

$$\bar{C}_1(t) = \frac{1}{x} \sum_{i=1}^x C_1^i(t) \quad (2)$$

The residual is calculated as:

$$\bar{r}_1(t) = x(t) - \bar{C}_1(t) \quad (3)$$

1. Add Gaussian noise to the residual $r_1(t)$ to form a fresh data set and repeat step 2 to extract the second IMF component and the updated residual.
2. Repeat steps 2 and 3 until no more can be broken down.

2.2 S entropy (SE)

CEEMDAN substantially boosts the forecasting model's precision by preprocessing the raw solar irradiation sequence, yet as IMF components grow, the model's complexity rises sharply, causing extended training durations. Grouping components by similar complexity effectively cuts computation time. Thus, SE measures intricacy for each IMF component and rebuilds those sharing identical intricacy levels.

SE quantifies time series complexity via approximate entropy. Its outcomes remain unaffected by data volume and show strong consistency. Greater SE signals elevated intricacy in the sequence data. SE computation proceeds in detail as follows:

- 1) Let us suppose that we have a sequence of times s of length N . Let i denote the index of the m dimensional formed vector, and form the vector s into an m dimensional vector, denoted as

$$S(x) = [s(x), s(x+1), \dots, s(x+m-1)] \quad (4)$$

- 2) Determine the maximum difference $d_{\max}(S(x), S(k))$ between $S(x)$, $S(k)$ between $S(l)$ and the corresponding elements of $S(k)$ ($k = 1, 2, \dots, N-m+1$, and $k \neq 1$).

$$d_{\max}(S(x), S(k)) = \max_{\varphi \in [0, m-1]} s(l+\varphi) - s(k+\varphi) \quad (5)$$

- 3) Let the threshold is r ($r > 0$), determine the number of $d_{\max}(S(x), S(k))$ less than r and calculate their proportion, denoted as $D^m(r)$:

$$D_l^m(r) = \frac{1}{N-M} \text{num}\{d_{\max}(S(x), S(k)) < r\} \quad (6)$$

- 4) Calculate the S entropy for the time series s based on $D^m(r)$ and $D^{m+1}(r)$:

$$\text{SampEn}(m, r) = \lim_{N \rightarrow \infty} \left\{ -\ln \frac{D^{m+1}(r)}{D^m(r)} \right\} \quad (7)$$

2.3 Variational Mode Decomposition (VMD)

Following IMF component reconstruction based on their entropy values, high-frequency components retain residual noise. This study applies VMD method to re-decompose these high-frequency components, further reducing forecast model complexity.

VMD constitutes a non-recursive decomposition approach that transforms sequences into variational problems, adaptively adjusting central frequencies and bandwidths of each mode via iterative optimization toward the variational model's optimal solution, thereby achieving effective IMF separation [32], demonstrating superior adaptability and robustness versus alternative decomposition techniques.

VMD is carried out in a step-by-step fashion, as follows:

The signal γ is broken up into z finite bandwidth modal functions $\{u_j(t)\}$ which are truncated by Hilbert Transform of their one-sided spectra.

The frequency of the spectrum of $u_j(t)$ which is central to the frequency of the mode of $u_j(t)$ is shifted to base band to produce the respective modal function..

The constrained variational problem is estimated by estimating $u_j(t)$ signal bandwidth, which is done by calculating the L2 norm of the demodulated gradient of $u_j(t)$:

$$\left\{ \min_{\{u_j\}, \{\varepsilon_j\}} \sum_{j=1}^z \partial_t \left\| \left[\delta(t) + j \left(\frac{1}{\pi t} \right)^* u_j(t) \right] e^{-j\omega_j t} \right\| \right\} \quad (8)$$

$$\{s.t. \sum_{j=1}^z u_j = \gamma\}$$

In which, the set of modal functions is: u_j ; the set of derivative frequencies of the spectrum with respect to the modal functions is: ∂_j ; ∂_t represents the partial derivative operator; and $\delta(t)$ represents a function of Dirac distribution.

- 1) To For efficiency of calculation the introduction of the following new variables: the Lagrangian multiplier $\lambda(t)$ and the quadratic penalty factor β transform the above variational and can be solved by alternating direction multiple method.

$$L(\{u_j\}, \{\varepsilon_j\}, \lambda) = \sum_{j=1}^z \left\| \partial_t \left[\delta(t) + j \left(\frac{1}{\pi t} \right)^* u_j(t) \right] e^{-j\omega_j t} \right\|_2^2 + \left\| \lambda(t) - \sum_{j=1}^z u_j(t) \right\|_2^2 + \langle \lambda(t), \gamma(t) - \sum_{j=1}^z u_j(t) \rangle \quad (9)$$

3. Hybrid Bi-Directional Gated Recurrent Unit Prediction Model

3.1 Convolutional Neural Network (CNN)

The CNN model efficiently extracts salient capabilities of the statistics with the aid of mapping the information [33]. The CNN version shape is proven in Fig 2 in which the convolutional layer separates the functions of the enter statistics by applying a convolutional kernel whose weights are shared and applies a activation feature to make a non-linear mapping of the neurons.

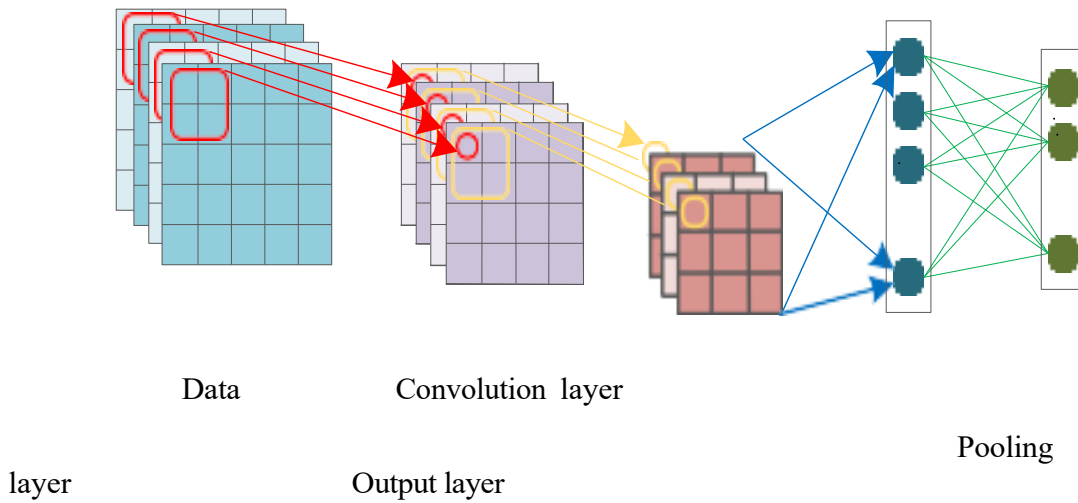


Figure 2 CNN Structure

3.2 Bidirectional Gating Recurrent Unit (BiGRU)

BiGRU is a structured GRU that consists of two layers of GRU, the information flow directions of which are anti-correlated, and the information output is the same. Unlike most existing models, BiGRU model does not forget the past and future information, so it can fully reflect the temporal characteristics of input data

power, thereby improving forecast accuracy [34]. In Figure 3, illustrate the design of a GRU.

The parameter of the GRU model represented as:

$$\begin{bmatrix} c_t = \delta(y_c[h_{t-1}, k_t]) \\ p_t = \delta(y_g[h_{t-1}, k_t]) \\ h_t = \tanh(W \cdot [C_t h_{t-1}, X_n]) \\ h_t = (1 - p_t)h_{t-1} + g_t h_t \end{bmatrix} \quad (10)$$

Figure 4 depicts BiGRU as comprised of a forward propagation GRU and a backward propagation GRU where $h_{i f}$ is the forward GRU output at time t and $h_{t b}$ is the backward propagation GRU output at time t .

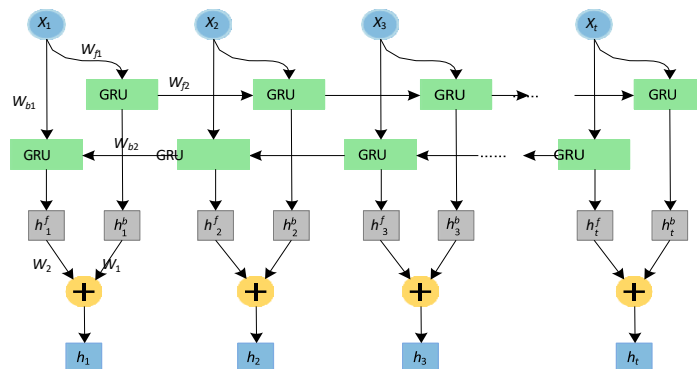


Figure 3 Diagram of BiGRU

The model of BiGRU can be given as:

$$h_t^f = \delta(W_{f1}X_t + W_{f2}h_{t-1}^f) \quad (11)$$

$$h_t^b = \delta(W_{b1}X_t + W_{b2}h_{t+1}^b) \quad (12)$$

$$h_t = \delta(W_1h_t^f + W_2h_t^b) \quad (13)$$

where, W_{f1} and W_{f2} are the forward GRU's input weight matrix and the output weight matrix at time $t-1$, correspondingly; W_{b1} and W_{b2} are the input weight matrix of the backward GRU and the output weight matrix at time $t+1$, correspondingly; W_1 and W_2 are the output weight matrices of forward GRU and backward GRU correspondingly.

3.3 Attention Mechanisms (AM)

AM represents a weighting approach designed to mimic how the human brain distributes attention resources, rapidly pinpointing key data elements by adaptively prioritizing various input features[35]. Figure 5 illustrates the structure of the attention mechanism unit.

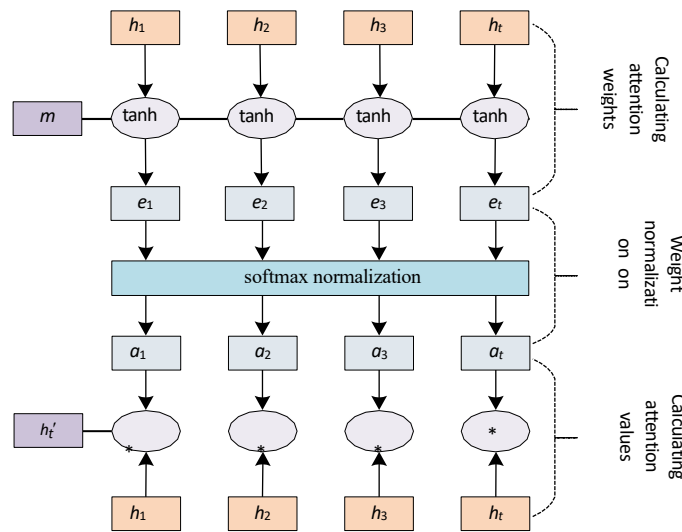


Figure 4 Diagram of AM

- 1) Evaluate the input value of feature attention e_i .

$$e_t = \mu \tanh(w h_t + b) \quad (14)$$

Where, the weight factor is μ and w ; b represents the bias factor.

- 2) Normalize the attention weight by the softmax function:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1} \exp(e_j)} \quad (15)$$

- 3) Perform a weighted sum of the input information to obtain the attention value h'_t

$$h_t = \sum_{j=1}^t \alpha_j \times h_j \quad (16)$$

3.4 Hybrid Bidirectional Gated Recurrent Unit (HBiGRU)

Figure 5 presents architecture of our proposed HBiGRU prediction model, which combines CNN's robust feature extraction abilities with AM's dynamic weight assignment to significantly improve BiGRU's forecasting accuracy.

The HBiGRU model consists of these five key layers:

- 1) Input data sequences and meteorological data of length T undergo preprocessing before entering the prediction model.
- 2) CNN layer. This comprises a 1-Dimensional convolutional layer, 1-Dimensional pooling layer, and fully connected layer designed to capture essential input features. The convolutional layer applies tanh activation, while maximum pooling handles dimensionality reduction.
- 3) BiGRU layer. ReLU activation helps uncover inherent relationships and temporal patterns within the localized features produced by CNN.
- 4) Attention layer. Equations (17)–(19) compute weighting coefficients for diverse hidden vectors, revealing temporal dependencies among features.
- 5) Output layer. Sigmoid activation processes the attention layer's output to generate the ultimate prediction

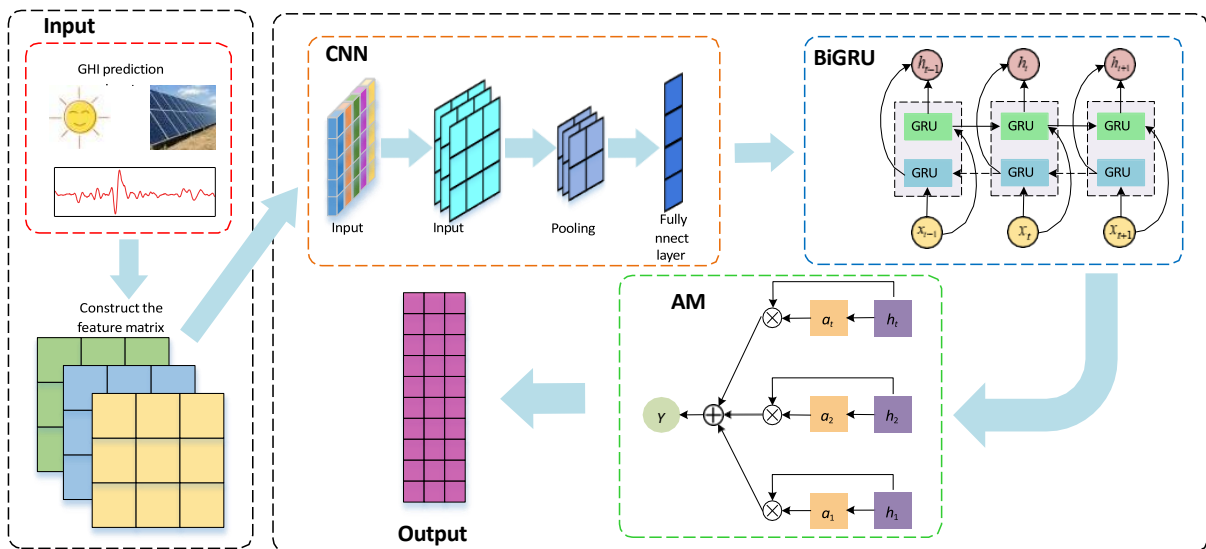


Figure 5 Structure of HBiGRU

4. Forecasting Model based on QMD-HBiGRU.

In order to improve solar irradiation forecast accuracy, this paper proposes a hybrid short term solar irradiation forecasting model, as shown in Figure 6 and the overall process of the proposed model is as follows:

GHI information processing: The original Solar irradiation data is broken down into N intrinsic mode functions (IMFs) by the QMD method that can be represented as

[D1MF1, D1MF2,.....D1MFN}

Normalization of Data: Each component is made normalized as:

$$z'=(z-z_{\max})/(z_{\max}-z_{\min}) \quad (17)$$

z and $z^{\wedge}$ are data, before as well as after normalization they became $f_{\min}$, $f_{\max}$ as the lowest and highest values of the data set.

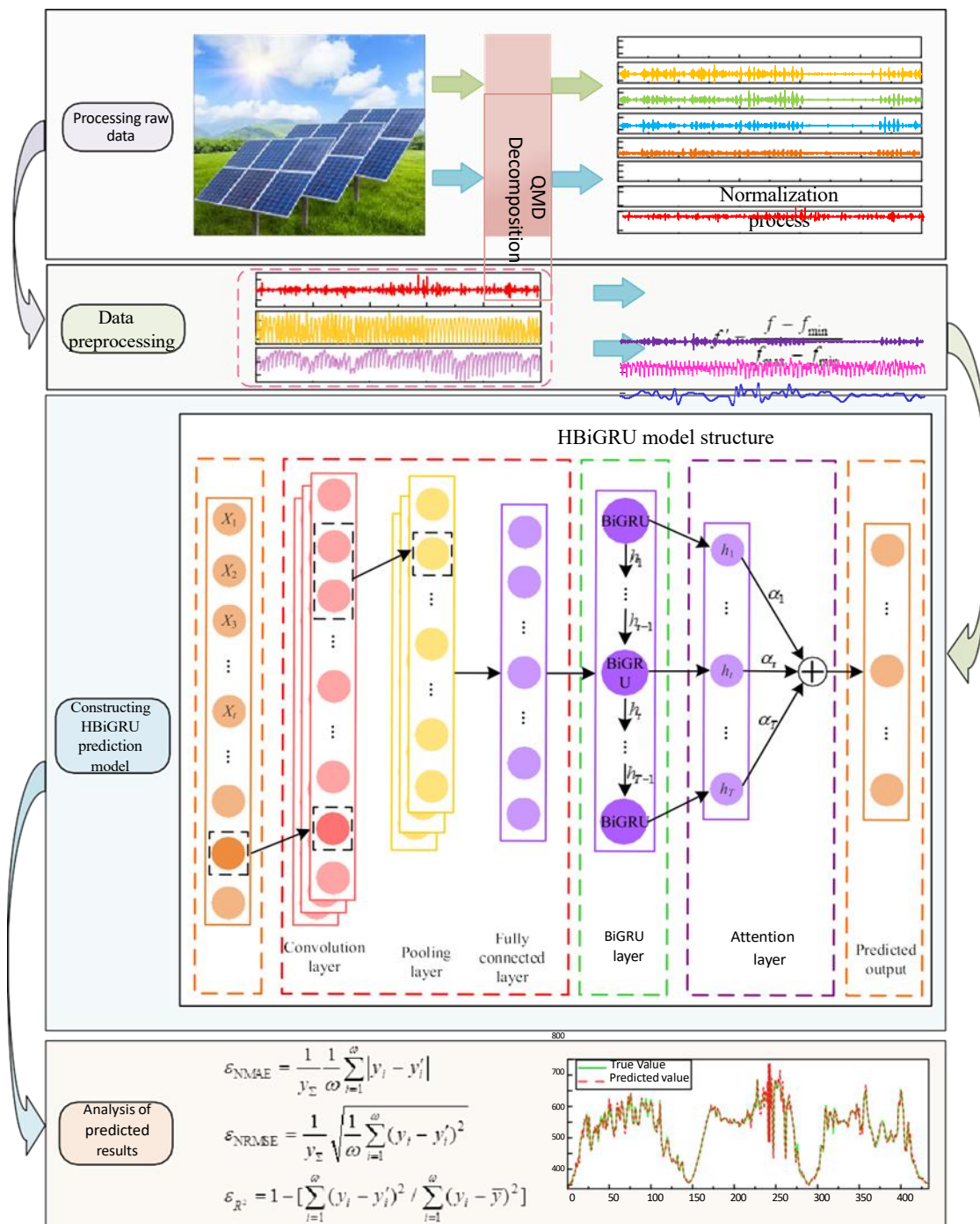


Figure 6 Forecasting model

5. Case Studies

5.1 Data Source

The short-term solar irradiance prediction model runs on the TensorFlow framework within Jupyter IDE. We validate it through simulations using real NSRDB data from a specific site,

covering GHI and weather details from January 1 to March 10, 2017. Given solar irradiance's daily cycle with minimal GHI at night we select daytime data (7:00–19:00) at 5-minute intervals, plotted in Figure 8. The first 66 days provide 9504 points for training, the last 3 days yield 432 points for testing, and runs occurred on an Intel i7-10875H (2.30 GHz), Nvidia RTX2060 GPU, 16 GB RAM setup

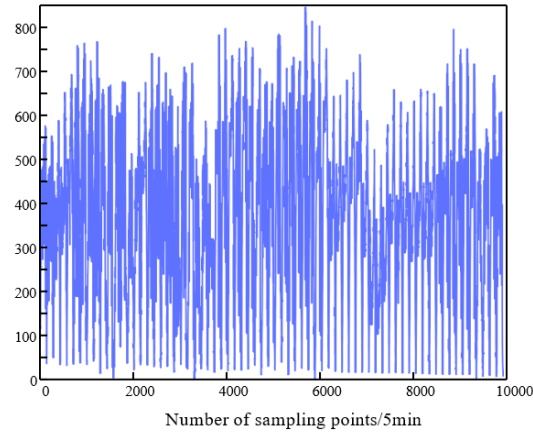


Figure 7 Global Horizontal Irradiance Data

5.2 Error Metrics

The error metrics used to measure the model's forecasting performance.

$$\varepsilon_{NMAE} = \frac{1}{y_{\infty}} \frac{1}{w} \sum_{i=1}^w |y_i - y'_i| \quad (18)$$

$$\varepsilon_{NRMSE} = \frac{1}{y_{\infty}} \sqrt{\frac{1}{w} \sum_{i=1}^w (y_i - y')^2} \quad (21)$$

$$\varepsilon_{R^2} = 1 - \left[\frac{\sum_{i=1}^w (y_i - y'_i)^2}{\sum_{i=1}^w (y_i - \bar{y})^2} \right] \quad (22)$$

where, ω is the anticipated time duration; y_{∞} is the Irradiation measurable rated capacity; y_i and y'_i are the solar irradiation real and anticipated levels at the time stamp i , respectively; and $\bar{x}$ denotes the mean solar irradiation value.

5.3 Results of QMD

1) CEEMDAN-SE decomposition results

To boost solar irradiance prediction reliability, CEEMDAN first breaks down the irradiance time series into 13 IMF components. Using S entropy (SE) principles, we compute entropy values and thresholds for each IMF, as depicted in Figure 8.

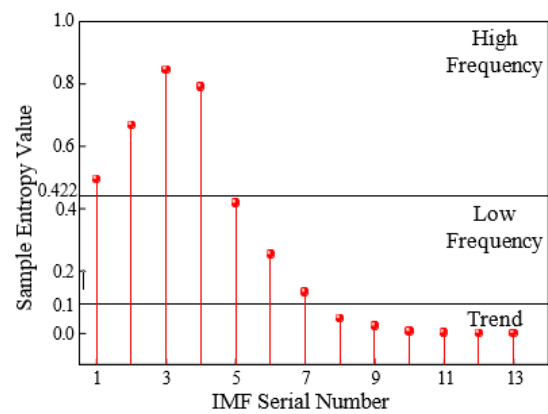


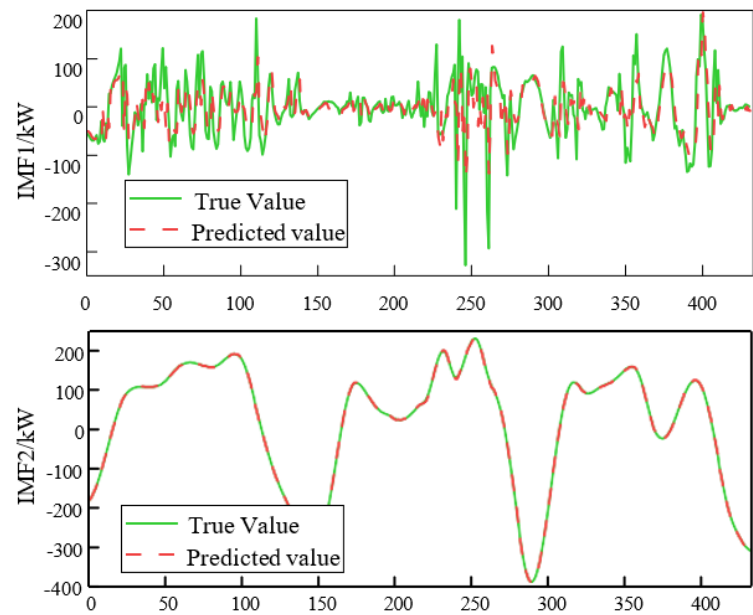
Figure 8: S entropy levels across each IMF component

Figure 8 indicates that the first four IMF components exceed the S entropy threshold, marking them as high-frequency. Thus, these four are combined for forecasting. The remaining IMFs undergo similar grouping, with superposition results detailed in Table 1.

Table 1 Outcomes of superposition of IMF components

Serial Number	Original IMF component
A	One, two three, four
B	Five, six, seven
C	Eight, nine, ten, eleven, twelve, thirteen

We build the HBiGRU model for each combined IMF component, with prediction outcomes shown in Figure 9



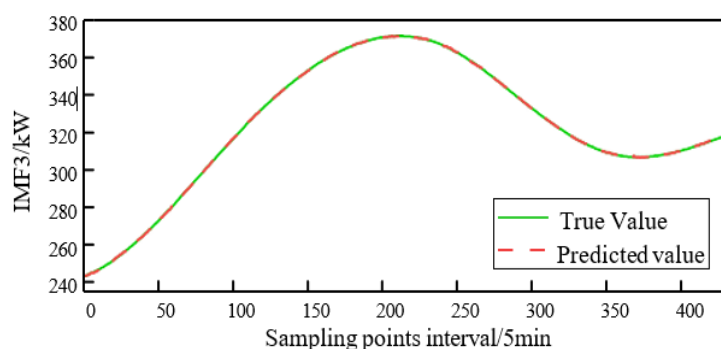


Figure 9: Forecasting outcomes for reconstructed IMF1–3 components.

Figure 9 reveals that, post-superposition and reconstruction, IMF2 and IMF3 exhibit smoother trends with strong alignment between predicted and actual values. In contrast, IMF1 remains erratic, showing poorer prediction fidelity than IMF2 and IMF3. This highlights persistent noise in the high-frequency component from CEEMDAN-SE processing, undermining overall forecast precision.

2) RESULT OF QMD

To confirm the proposed QMD approach's effectiveness, we use VMD to refine the IMF1 component from CEEMDAN-SE, stripping out extraneous noise and thereby improving high-frequency component prediction reliability.

For VMD, the number of decompositions K needs to be predetermined. Too high a K causes over-decomposition and extra noise, whereas too low a K results in under-decomposed modes—both harming prediction performance. Over-decomposition is flagged by closely spaced central frequencies across modes. Yet, no consistent benchmark exists for "close" frequencies. Here, we compute reconstruction errors for various K values showing tight central frequencies, then choose the best K by error comparison. Table 2 lists central frequencies for various K settings.

Table 2 Different mode decomposition number

F_1	F_2	F_3	F_4	F_5	F_6	F_7
0.031	0.096	0.196	-	-	-	-
0.030	0.107	0.277	0.475	-	-	-
0.050	0.124	0.222	0.355	0.413	-	-
0.028	0.077	0.137	0.207	0.329	0.395	-
0.030	0.066	0.110	0.161	0.161	0.476	0.315

Table 2 shows that central frequency gaps between components narrow progressively with rising K values. For K values of 5, 6, and 7, Table 3 presents IMF1 component's reconstruction errors.

Table 3 Comparison of IMF1 reconstructions errors when $K=5,6,7$

K	$\epsilon_{NMAE}/\%$	$\epsilon_{NRMSE}/\%$	ϵ_R
5	2.08	3.03	0.83
6	1.48	2.10	0.91
7	1.91	2.65	0.87

Table 3 reveals that IMF1 reconstruction error hits its minimum when $K=6$. Here, NMAE drops by 0.6% versus $K=5$ and 0.43% versus $K=7$; NRMSE falls by 0.93% and 0.55% respectively, while R^2 climbs to 0.91. Thus, we pick $K=6$ for VMD decomposition of IMF1.

Table 4 and Figure 10 illustrate the IMF1 component's prediction results across QMD and CEEMDAN-SE decomposition techniques.

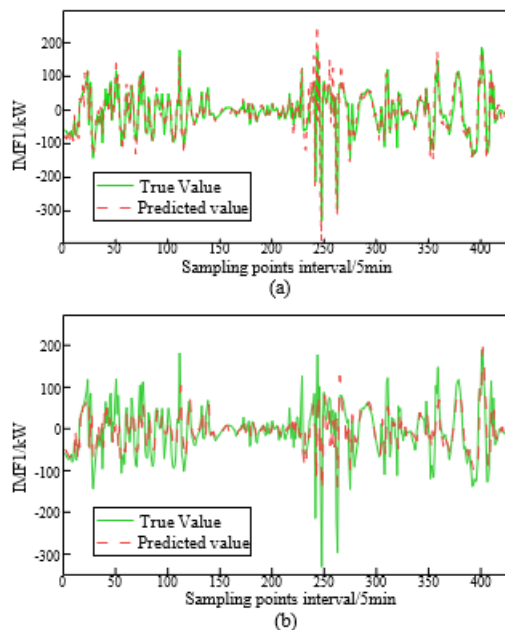


Figure 10: IMF1 prediction outcomes contrasted—(a) results from QMD decomposition, (b) results from CEEMDAN-SE decomposition.

Table 4: IMF1 Prediction Error Comparison Across Decomposition Methods

Methods	$\epsilon_{NMAE}/\%$	$\epsilon_{NRMSE}/\%$	ϵ_{R^2}
CEEMDAN-SE	3.19	5.23	0.37
QMD	1.73	2.25	0.78

As seen in Figure 10 and Table 4, after processing the IMF1 component with VMD and then using the HBiGRU model for prediction, NMAE and NRMSE are reduced by 1.58% and 2.78% respectively compared with the method of direct prediction after decomposition by CEEMDAN-SE and R^2 is increase from 0.47 to 0.88. This indicates that the QMD technique suggested in this work can significantly diminish the decomposition noise and successfully raise the accuracy of the forecast of the HBiGRU model.

6. Conclusion

This article proposes a short-term solar irradiation forecasting methodology and the final points are listed below:

- 1) The proposed QMD algorithm demonstrates superior performance in mitigating extraneous noise in the high- frequency components, thus enhancing the precision of the forecast. Compared to conventional single-mode decomposition techniques, the NMAE and NRMSE are overcome by 1.58% and 2.78% respectively, and R^2 rose from 0.47 to 0.88.
- 2) The HBiGRU model we created smartly taps into CNN's strengths for pulling out key data features., and the attention mechanism can dynamically allocate weights, comprehensively capture the connection between solar irradiation series and meteorological data, and improve prediction and boosts overall precision.
- 3) Test outcomes demonstrate that the typical NMAE, NRMSE, and R^2 values of the suggested QMD-HBiGRU model are superior to the other five models, and exhibit significant potential for practical implementation in short-term solar irradiation forecasting

applications.

The majority of extant Solar irradiance forecasting research only focus on a single solar irradiation site, and fewer studies have been conducted on irradiation cluster forecasting. Future research directions include extending the proposed QMD-HBiGRU model to multi-site irradiation cluster forecasting scenarios.

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