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RESEARCH ARTICLE

Enhancing Short-Term Solar Photovoltaic Power Forecasting Using a Hybrid Deep Learning Approach

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ABSTRACT Solar photovoltaic (PV) power generation is gradually increasing, but its intermittent nature poses challenges to grid stability. To address this, advanced forecasting methods, such as deep learning (DL) algorithms, can be employed to ensure a more stable and reliable energy supply. Accurate short-term forecasts are essential for electricity grids to effectively mitigate the impact of solar intermittency and enhance grid performance. This research contributes by developing a hybrid DL model that combines a 1-dimensional convolutional neural network (1D CNN) with a gated recurrent unit (GRU), referred to as "1D CNN-GRU". The 1D CNN module extracts essential features from time series data, such as solar PV power generation, while the GRU component provides high-precision short-term forecasts. Additionally, data preparation techniques, including feature selection using SHapley Additive exPlanations (SHAP), data smoothing with an exponential moving average (EMA), and data augmentation with Gaussian noise, are employed to enhance the performance of the proposed 1D CNN-GRU model. To evaluate the effectiveness of the proposed model, it was compared with other DL models, including CNN, GRU, long short-term memory (LSTM), and CNN-GRU. The forecasting was performed using the Hydro-Floating Solar Plant dataset, obtained from the 45 MW hydro-floating solar installation located at Sirindhorn Dam in Ubon Ratchathani province, Thailand. The proposed 1D CNN-GRU model was tested using data from three different seasons: winter, summer, and the rainy season. The model achieved the lowest root mean square error (*RMSE*) across all seasons, with values of 0.025 (winter), 0.050 (summer), and 0.094 (rainy), and demonstrated the shortest training time. The forecasting results indicated that the proposed model outperformed all other models in terms of both accuracy and training time.

INDEX TERMS Deep learning, energy forecasting, hydro-floating solar plant, solar photovoltaic.

I. INTRODUCTION

A significant transition towards renewable energy sources, i.e., wind energy, biomass, hydroelectricity, and solar energy, in the electricity sector has been observed globally [1]. From 2011 to 2023, the installed capacity for solar energy generation has seen an exponential increase, exceeding 1,400 GW. This remarkable growth can be primarily attributed to the advancements and cost reductions in solar photovoltaic (PV) technology [2]. The increasing deployment of solar energy aligns with global efforts to reduce carbon emissions and combat climate change. As countries strive

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to meet their commitments under international climate agreements, such as the Paris Agreement, the transition towards solar power becomes even more critical [3].

In the context of Thailand, the move towards renewable energy sources is a significant part of the country's energy strategy, particularly in solar PV power generation. The aim is to reduce dependence on fossil fuels and promote environmental preservation. The Thai government has laid out a comprehensive plan to increase renewable energy sources in the electricity sector, specifically focusing on solar PV power generation. The goal is to reach a 10 GW capacity by 2037. The plan includes a variety of approaches, such as expanding large-scale solar farms with battery energy storage systems, promoting smaller-scale installations like solar rooftops on residential and commercial buildings, and investing in hydro-floating solar systems at large-scale dams. This multi-faceted strategy positions Thailand as an active participant in global renewable energy and climate change mitigation efforts [4]. Solar PV power generation is growing rapidly, but it presents a challenge to the stability of electricity grids due to the intermittent nature of solar energy. The National Control Center (NCC), responsible for the efficient management of power plant dispatch, electricity generation, and nationwide transmission [5], will face this challenge because solar PV power generation heavily depends on environmental conditions like weather, sunlight availability, and cloud coverage. Many solar PV installations connected to the grid make managing power distribution difficult [6]. To address these challenges, advanced forecasting methods, such as deep learning (DL) algorithms, a subset of artificial intelligence (AI), can enhance the forecasting capability for solar PV power generation. DL can analyze data using neural networks, consider various factors like weather patterns, and more efficiently forecast the supply and demand balance in the electricity grid. This approach mitigates the impact of solar intermittency, ensuring a more stable and reliable energy supply [7], [8], [9].

Over the years, a variety of research studies have utilized DL models, such as long short-term memory (LSTM) [10], [11], [12] and gated recurrent unit (GRU) [13], [14], to forecast solar PV power generation. LSTM models excel in capturing complex temporal patterns in solar PV power generation data, enabling accurate predictions. On the other hand, GRU models have a more straightforward structure that enables faster training, making them highly desirable in applications where training time is a crucial factor. To enhance the accuracy of short-term forecasting, various convolutional neural network (CNN) architectures have been investigated [15]. Moreover, CNNs also contribute to fault diagnosis in solar panels with thermal images, thereby enhancing overall solar PV forecasting performance [16]. Furthermore, a hybrid CNN-GRU model is commonly used to enhance forecasting performance [17], [18], [19], [20]. Recently, a novel hybrid 1D CNN-GRU model has been introduced for solar PV power generation forecasting. With this model, it is possible to predict solar PV power output up to four days in advance with a high resolution of 5 minutes, which outperforms other state-of-the-art models [21]. The existing research often lacks a focus on diverse geographic and climatic conditions. There is a significant gap in the literature regarding the application of DL models to specific regions like Thailand, which presents unique environmental challenges for solar PV forecasting due to its tropical climate and variable weather patterns.

This paper introduces a novel approach tailored to the specific requirements of short-term solar PV power generation forecasting in Thailand with the requirements of the NCC to address the research gaps. Firstly, unlike previous studies that target longer forecasting horizons, this research emphasizes very short-term forecasting (three hours). This precision is vital for the NCC's operations, allowing for more responsive and accurate adjustments to energy distribution in the face of fluctuating solar output. Secondly, a hybrid DL model combining 1D CNN with GRU architectures is developed. This approach leverages the spatial feature extraction capabilities of CNN and the temporal sequence processing strengths of GRU, resulting in a robust model that excels in capturing complex patterns in solar PV generation data. To enhance the model's performance, advanced data preparation techniques, including feature selection with SHapley Additive exPlanations (SHAP), data smoothing with an exponential moving average (EMA), and data augmentation are employed. SHAP ensures that the most relevant features are included in the model, improving its predictive power, while EMA helps reduce noise in the data, leading to more stable and reliable forecasts. Data augmentation techniques expand the dataset, providing the model with more diverse examples to learn from, which improves its generalization ability. The proposed model is validated using real-world data from the Hydro-Floating Solar Plant dataset, derived from a 45 MW installation at Sirindhorn Dam in Thailand. This real-world application demonstrates the model's practical utility and relevance to the specific climatic and operational conditions of the region. Finally, a comparative analysis of the proposed hybrid model against other established DL models (CNN, GRU, LSTM, and a hybrid CNN-GRU) is conducted. The evaluation uses performance metrics such as root mean square error ($RMSE$), mean absolute error (MAE), and the coefficient of determination (R^2) score to assess the precision and reliability of the forecasts.

The structure for the remaining sections of the paper is as follows: Section II outlines the methodology used in this research. Section III includes the presentation of experiments, results, and discussion. Finally, Section IV concludes the paper and suggests possible future work.

II. METHODOLOGY

The methodology section of this research is structured into three primary components of significance: (i) data preparation, (ii) system model approach for DL forecasting, and (iii) evaluation matrices.

A. DATA PREPARATION

Data preparation is a critical stage in research, where raw data is transformed into a format conducive to accurate modeling. In this study, min-max normalization was employed to scale the data within a predefined range. This normalization technique is essential to ensure that all input variables are given equal consideration during analysis. By rescaling the data to a typical range, typically between 0 and 1, the risk of features with larger scales dominating the modeling process is mitigated. This prevents potential biases and ensures that the underlying patterns in the data are effectively captured by the model.

Additionally, SHAP-based feature selection using a random forest (RF) or RF-SHAP was utilized to identify the most relevant features within the dataset. By calculating the importance scores of features, it was determined which features had the most significant impact on solar PV power generation. This step refines the model by focusing on the most influential factors, thereby enhancing its resilience and interpretability. Subsequently, data smoothing with EMA was applied to capture the underlying trends by filtering out noise and stabilizing the data. Furthermore, data augmentation with Gaussian noise was used to increase the dataset's diversity and help prevent overfitting by introducing slight variations. Overall, these data preparation techniques contribute to developing a more precise and dependable forecasting model, which is essential for accurate predictions in solar PV power generation scenarios.

1) MIN-MAX NORMALIZATION

Min-max normalization ensures that all the data points are adjusted or converted to fit into a particular range, typically between 0 and 1. It helps maintain consistency across datasets, which is particularly useful when comparing measurements with different units or scales [22]. In the context of this study, min-max normalization was applied to standardize the dataset, ensuring that all values are proportionately scaled down to a range between 0 and 1. The normalized value (x') is computed as

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{1}$$

where x is actual value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values, respectively.

2) RF-SHAP

A robust method integrates the strengths of RF and SHAP values to identify the most essential features in a dataset. RF is an ensemble learning method that constructs multiple decision trees (DT) and combines their outputs to make more accurate predictions. This approach makes RF more robust to noise and less sensitive to outliers. Additionally, the aggregation process inherent in RF, known as bootstrap aggregating (Bagging), helps prevent overfitting, a common issue in machine learning (ML) models. Furthermore, the bagging method leads to faster computation compared to boosting methods because it allows for parallelization [23]. Derived from game theory, SHAP values provide a way to elucidate the contribution of each feature to the model's predictions [24]. The process of feature selection follows these steps:

1) Train an RF Model: An RF model is constructed and trained using the dataset. This model consists of numerous DTs, each providing predictions based on subsets of the data.
2) Calculate SHAP Values: SHAP values for each feature i are computed using the trained RF model. These values quantify the contribution of each feature to a specific prediction. The SHAP value ϕ_i for a feature is calculated by

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)], \tag{2}$$

where N is the set of all features, S is a subset of features not including i, $|\cdot|$ denotes the cardinality, $\cup$ represents the union operation, and $f(S)$ is the prediction of the model using the features in subset S.
3) Aggregate SHAP Values: The SHAP values for each feature are summed across all data points to obtain an overall importance score. This score indicates how much each feature contributes to the model's predictions on average.
4) Rank Features: The features are meticulously ranked based on their aggregated SHAP values. Features with higher SHAP values, indicating more significant influence on the model's predictions, are considered more important.
5) Select Features: The top 10 ranked features were selected as input for model training in this research by focusing on the most important score of features.

3) DATA SMOOTHING WITH EMA

An EMA is a method used to smooth out data fluctuations on a chart to reveal trends better. In comparison to a basic moving average, which equally considers all data points within a set window, EMA assigns greater importance to recent data, resulting in increased responsiveness to new information. The EMA is calculated using a smoothing factor, also known as the smoothing constant, which influences the rate at which older data points are discounted [25]. The formula for EMA at any given time t is:

$$EMA_t = \alpha X_t + (1 - \alpha) EMA_{t-1}, \tag{3}$$

where X_t is the current data point at time t, EMA_{t-1} is the EMA of the previous period, and α is smoothing factor calculated by

$$\alpha = \frac{2}{N + 1}, \tag{4}$$

with N being the number of periods. The smoothing factor is pivotal in determining the weight assigned to the most recent data point. A higher value drives the EMA to react more rapidly to changes, while a lower value yields a smoother line, causing the EMA to react more slowly.

4) DATA AUGMENTATION WITH GAUSSIAN NOISE

Data augmentation using Gaussian noise is a method employed to expand the scope and diversity of a dataset, ultimately enhancing the effectiveness and resilience of ML models. This approach entails introducing random Gaussian noise to the initial data points, thereby generating slightly modified versions that maintain the fundamental characteristics of the original data [26]. The process of adding Gaussian noise can be described as

$$X' = X + \mathcal{N}(\mu, \sigma^2), \tag{5}$$

where X' is the new augmented data point, X is the original data point, and $\mathcal{N}(\mu, \sigma^2)$ is the Gaussian noise with mean μ and variance σ^2.

B. SYSTEM MODEL APPROACH FOR DL FORECASTING

This paper investigates the performance of various DL models such as CNN, LSTM, GRU, CNN-GRU, and the proposed 1D CNN-GRU model. This comparison aims to identify the limitations of conventional models in predicting solar PV power generation and showcase the strengths and efficiencies of tailored 1D CNN-GRU architecture.

1) CONVOLUTIONAL NEURAL NETWORK (CNN)

The CNN is a powerful DL model that takes inspiration from the complex visual systems found in living organisms. The structure of CNN is shown in Fig. 1. This advanced model replicates how biological vision processes and interprets visual data, enabling machines to accurately perform tasks like object identification, recognition, and classification. CNNs use a structured hierarchy of layers to extract features and patterns to understand complicated visual scenes [27]. There are the four following types of layers in a CNN:

- **Convolution Layer:** This layer forms the foundation of CNNs and applies various filters to the input data to extract essential features such as edges and textures.
- **Pooling Layer:** The pooling layer reduces the spatial dimensions of the input volume for the following convolution layer, resulting in a decreased number of parameters and computations in the network.
- **Activation Function:** This function introduces non-linearity to the network, which allows it to learn complex patterns.
- **Fully Connected Layer:** This layer is connected to every neuron in the previous layer and produces the CNN's final output.

2) LONG SHORT-TERM MEMORY (LSTM)

The LSTM network, a subtype of the recurrent neural network (RNN), specifically addresses the challenges of vanishing and exploding gradients that occur during the training of traditional RNNs [28]. The LSTM is designed to regulate the flow of information, allowing it to discard or retain data in its memory over long sequences, thereby facilitating the learning of long-term dependencies. LSTMs achieve the ability to learn long-term dependencies through a sophisticated architecture consisting of three main gates [29]: the forget gate (f_t), the input gate (i_t), and the output gate (o_t), along with the cell state (c_t) maintained in its memory over long sequences. The corresponding equations for these components are given by

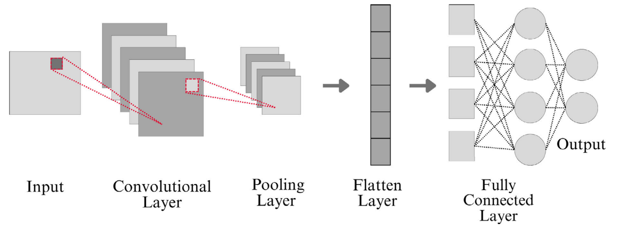


FIGURE 1. CNN structure.

$$f_t = \sigma(W_f x_t + W_f h_{t-1} + b_f), \tag{6}$$
$$i_t = \sigma(W_i x_t + W_i h_{t-1} + b_i), \tag{7}$$
$$o_t = \sigma(W_o x_t + W_o h_{t-1} + b_o), \tag{8}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + W_c h_{t-1} + b_c), \tag{9}$$

where x_t is input data, c_{t-1} is the previous cell state, $\sigma(\cdot)$ is a sigmoid activation function, $\tanh(\cdot)$ is a hyperbolic tangent activation function, $\odot$ is an element-wise multiplication, W is weight, b is bias, and h_{t-1} is the previous hidden state h_t, which is expressed as

$$h_t = o_t \odot \tanh(c_t), \tag{10}$$

3) GATED RECURRENT UNIT (GRU)

The GRU is a variant of the RNN, like LSTM, but simplifies the architecture [30]. GRU has two gates: the update gate (r_t) and the reset gate (z_t), as demonstrated in Fig. 2. These gates enable the GRU to manage information flow for relatively short sequences efficiently. The update gate decides the extent to which the unit retains old information, while the reset gate determines how much past information to forget. The equations for these gates illustrate the mathematical foundation behind their functionality, showcasing the GRU's ability to learn dependencies in data over shorter periods. The corresponding equations are given by

$$r_t = \sigma(W_r x_t + W_r h_{t-1} + b_r), \tag{11}$$
$$z_t = \sigma(W_z x_t + W_z h_{t-1} + b_z), \tag{12}$$
$$\begin{aligned} h_t &= z_t \odot h_{t-1} + (1 - z_t) \\ &\quad \odot \tanh(W_h x_t + W_h(r_t \odot h_{t-1}) + b_h), \end{aligned} \tag{13}$$

where x_t is input data, and h_{t-1} is the previous hidden state h_t.

4) CNN-GRU

The CNN-GRU is a hybrid DL model that combines 2-dimensional CNN (2D CNN) with GRU, as demonstrated

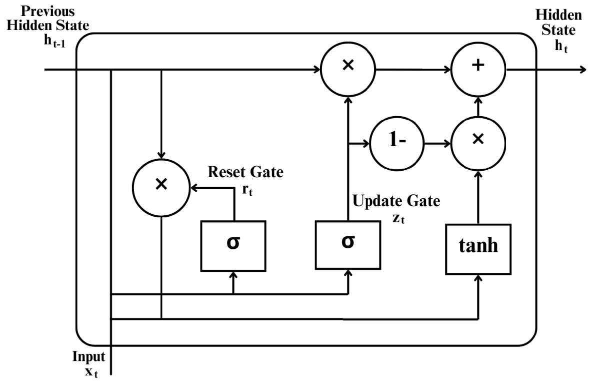


FIGURE 2. Block diagram of GRU unit.

in Fig. 3. The 2D CNN part of the model processes input data in two dimensions (such as images or spatially distributed data), utilizing convolutional layers to identify and extract spatial patterns and relationships within the data. This is particularly effective for tasks that involve complex visual contexts or spatially distributed datasets. After the 2D CNN layers extract spatial features, the GRU component processes the temporal or sequential aspects of the data. This hybrid model is particularly beneficial for applications that require understanding spatial and temporal dynamics [17], [18], [19], [20].

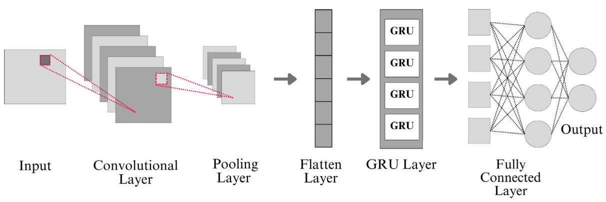


FIGURE 3. CNN-GRU structure.

5) PROPOSED MODEL (1D CNN-GRU)

The proposed model, 1D CNN-GRU, stands out with its unique hybrid approach that combines 1D CNN and GRU. Unlike the traditional CNNs that are mainly designed for processing 2D data like images, the introduction of 1D CNN addresses the need to handle 1D data such as time series or sequential data. In 1D CNNs, the architecture includes convolutional layers, pooling layers, activation functions, and fully connected layers are employed, similar to the layers found in traditional 2D CNNs. These layers work together to process the input data. The convolutional layers apply filters to the input data to detect local patterns, while pooling layers reduce the dimensionality of the data, retaining the most important information. Activation functions introduce non-linearity into the model, enabling it to learn complex patterns, and fully connected layers consolidate the features extracted by the convolutional layers [31]. According to the proposed model, the 1D CNN in this architecture meticulously analyzes the input data, identifying and extracting essential features that encapsulate the underlying patterns over time [32]. These features are then fed into the GRU network, which is known for its efficient handling of sequential data. GRU utilizes these features to understand the temporal dynamics and dependencies within the data, making it particularly adept at forecasting future outputs based on past and present data, even over shorter periods. This adaptability of the 1D CNN-GRU hybrid approach ensures its effectiveness across a wide range of data types and scenarios. The proposed model structure shown in Fig. 4.

C. EVALUATION METRICS

This research employs three key metrics to evaluate the accuracy of the forecasting models: root mean square error ($RMSE$), mean absolute error (MAE), and coefficient of determination (R^2) score. $RMSE$ measures the magnitude of forecasting error, providing insight into the accuracy of predictions as

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}}, \tag{14}$$

MAE offers a straightforward measure of forecasting accuracy as

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|, \tag{15}$$

R^2 score assesses the model's suitability for the observed data, indicating how well the model fits the data as

$$R^2 = 1 - \frac{\sum(y_t - \hat{y}_t)^2}{\sum(y_t - \bar{y})^2}, \tag{16}$$

where y_t is the actual value at a time t, $\hat{y}_t$ is the predicted value at a time t, $\bar{y}$ is the mean of the actual value, and n is the number of samples. Lower $RMSE$ and MAE values are better for prediction, while a higher R^2 score indicates better model fit.

III. EXPERIMENTAL RESULTS, DISCUSSION, AND COMPARISON

A. DATASET AND SYSTEM FLOW

This paper introduced a DL approach combining 1D CNN with GRU to forecast solar PV power generation three hours in advance. The research utilized an extensive dataset from the hydro-floating solar installation at Sirindhorn Dam, in Ubon Ratchathani province, Thailand. This hydro-floating solar boasts a capacity of 45 MW and comprises seven distinct solar array islands, with 144,420 solar PV panels floating on the water's surface. These floating islands harness solar energy by converting sunlight into electricity through the photovoltaic effect, where solar cells absorb photons and generate an electric current. The buoyant platforms on which these panels are mounted are specially designed to be both environmentally friendly and resilient against the aquatic conditions of the reservoir, ensuring stability and efficiency [33].

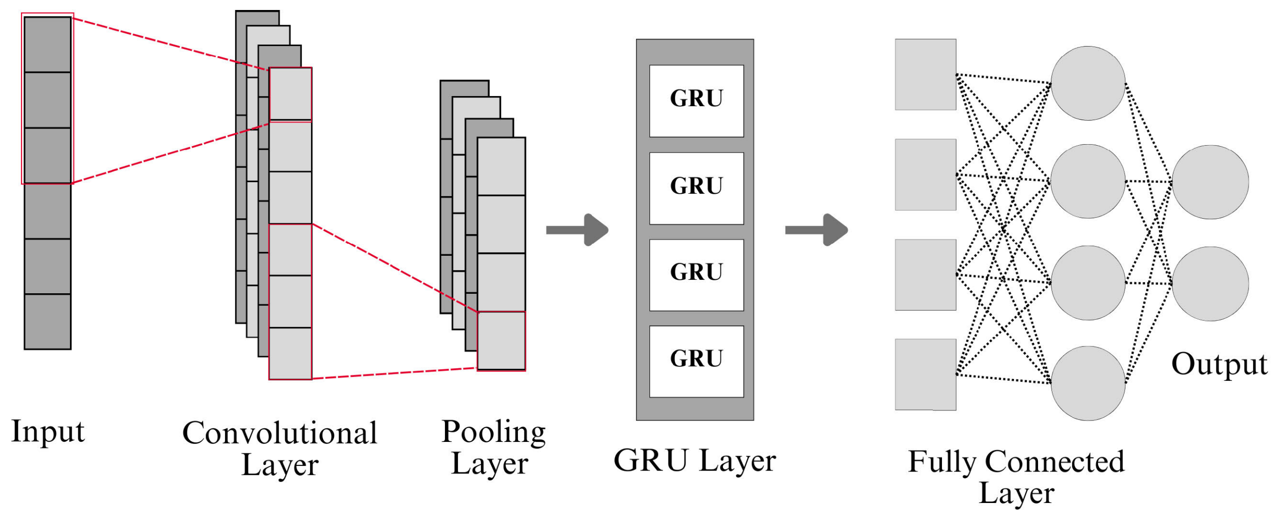


FIGURE 4. Proposed model 1D CNN-GRU structure.

The data collection spanned from October 1, 2022, to April 31, 2024, with the dataset recorded at minute intervals. The dataset utilized encompasses a comprehensive collection of 101 features meticulously gathered from sensors deployed across all seven PV islands. These features are methodically grouped for each island, covering a wide array of data points, including timestamps, solar PV power generation, direct radiation, obliquity radiation, ambient temperature, panel temperature, humidity, wind speed, wind direction, and plant outage events. This dataset offers the impacting factors of solar PV power generation, including environmental and operational conditions. Group of input features in dataset for DL models are summarized in Table 1.

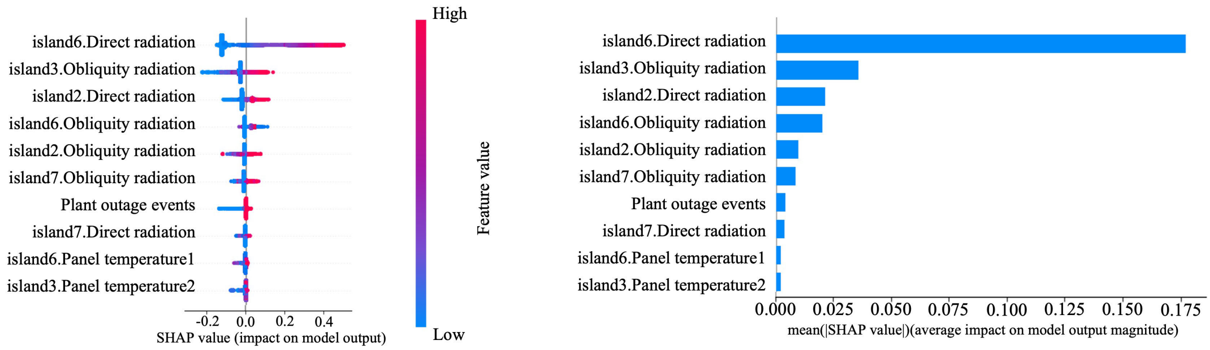
Upon collecting the dataset, the data was normalized to a range between 0 and 1, and the missing values were addressed by replacing them with those found immediately below the missing record. To identify features with a strong correlation to solar PV power generation, RF-SHAP was utilized to select the top 10 features with the highest SHAP values, including island6.Direct radiation, island3.Obliquity radiation, island2.Direct radiation, island6.Obliquity radiation, island2.Obliquity radiation, island7.Obliquity radiation, Outage plant event, island7.Direct radiation, island6.Panel temperature1, and island3.Panel temperature2 features. The description of the top 10 features is shown in Table 2. This method utilizes the robustness of RF and the interpretability of SHAP values to provide a clear and effective approach for feature selection, helping to improve model accuracy and understanding. Fig. 5 presents the SHAP analysis of the top 10 features. Fig. 5(a) shows the SHAP importance plot for the top 10 features, highlighting their respective contributions to the RF model's predictions. Fig. 5(b) shows the SHAP summary plot, illustrating the distribution and impact of each feature.

Subsequently, these 10 chosen features and the label were selected, reducing the fluctuations of the data was required. Since the data was collected every minute, the graph patterns were very erratic, making it difficult for the model to identify underlying patterns. This could lead to model overfitting, low accuracy, and long training times. To address this, data smoothing with EMA was applied to mitigate fluctuations before training the model. EMA smoothing helps capture underlying trends by filtering out high-frequency noise from the data. Additionally, it enhances the model's ability to generalize by making patterns more discernible and stable. Following data smoothing, Gaussian augmentation was employed due to the limited data available when segmented by Thai seasons: summer, rainy, and winter. Data augmentation was essential to increase the dataset size, providing sufficient training data for the model by generating synthetic data for the three Thai seasons. Gaussian augmentation increases the diversity of the dataset, helping the model to better generalize to unseen data. It also mitigates the risk of overfitting by providing a more varied training set. This research augmented data for 3 months, corresponding to Thai seasons (1 month for the summer season, 1 month for the rainy season, and 1 month for the winter season). The training set included data from October 1, 2022, to September 30, 2023, along with the augmented data, while the testing set used data from three different seasons: the rainy season from October 1, 2023, to October 31, 2023, the winter season from January 1, 2024, to January 31, 2024, and the summer season from April 1, 2024, to April 30, 2024.

Once the dataset is split into a train set and a test set, it will be prepared for input before being utilized by DL models. The sliding window technique will be used, where the input data consists of 3 days (4,320 minutes) and the output data consists of 3 hours (180 minutes). The forecasting model will then be evaluated using various metrics, including $RMSE$, MAE, and R^2 score, all of which will be calculated on the train set and test set. The research's flowchart is illustrated in Fig. 6. In Fig. 6, the performance of the proposed "1D CNN-GRU" model is examined alongside CNN, LSTM,

TABLE 1. Summarized group of features in the dataset of hydro-floating solar installation at Sirindhorn Dam.

Group of features	Unit	Description
Timestamps	-	The specific date and time at which the data was recorded.
Solar PV power generation	MW	The amount of electrical power generated by solar PV panels at a given time.
Direct radiation	W/m^2	The amount of solar radiation received per square meter directly from the sun without being scattered or reflected.
Obliquity radiation	W/m^2	The solar radiation received per square meter that has been scattered or diffused in the atmosphere before reaching the surface.
Ambient temperature	°C	The air temperature surrounding the solar PV installation.
Panel temperature	°C	The surface temperature of solar PV panels.
Humidity	%	The percentage of water vapor in the air around the solar PV panels.
Wind speed	m/s	The velocity of wind at the location of the solar PV installation.
Wind direction	°	The direction in which the wind blows.
Plant outage events	-	The report of any solar PV plant issues that affect power generation.



(a) (b)

FIGURE 5. The top 10 features with the highest SHAP values (a) SHAP importance plot for the top 10 features, (b) SHAP summary plot for the top 10 features.

TABLE 2. Description of the top 10 features with the highest SHAP values.

Selected features	Sensor points	Description
island6.Direct radiation	island 6	The amount of solar radiation received per square meter directly from the sun without being scattered or reflected, collected from island 6.
island3.Obliquity radiation	island 3	The solar radiation received per square meter that has been scattered or diffused in the atmosphere before reaching the surface, collected from island 3.
island2.Direct radiation	island 2	The amount of solar radiation received per square meter directly from the sun without being scattered or reflected, collected from island 2.
island6.Obliquity radiation	island 6	The solar radiation received per square meter that has been scattered or diffused in the atmosphere before reaching the surface, collected from island 6.
island2.Obliquity radiation	island 2	The solar radiation received per square meter that has been scattered or diffused in the atmosphere before reaching the surface, collected from island 2.
island7.Obliquity radiation	island 7	The solar radiation received per square meter that has been scattered or diffused in the atmosphere before reaching the surface, collected from island 7.
Plant outage events	-	The report of any solar PV plant issues that affect power generation.
island7.Direct radiation	island 7	The amount of solar radiation received per square meter directly from the sun without being scattered or reflected, collected from island 7.
island6.Panel temperature1	island 6	The surface temperature of solar PV panels, collected from island 6.
island3.Panel temperature2	island 3	The surface temperature of solar PV panels, collected from island 3.

GRU, and CNN-GRU models in forecasting solar PV power generation.

B. EXPERIMENTAL SETUP

To achieve precise solar PV power generation forecasting, the architecture of the proposed model combines four layers of 1D CNN and three layers of GRU. Positioned at the forefront of this proposed model are the 1D CNN layers, designed explicitly with four convolution layers followed by four max-pooling layers, all activated by the rectified linear unit (ReLU) function [34]. ReLU activation is favored for its ability to introduce nonlinearity, enabling the model to learn complex patterns by setting negative values to zero and maintaining positive values [35]. ReLU is suited for

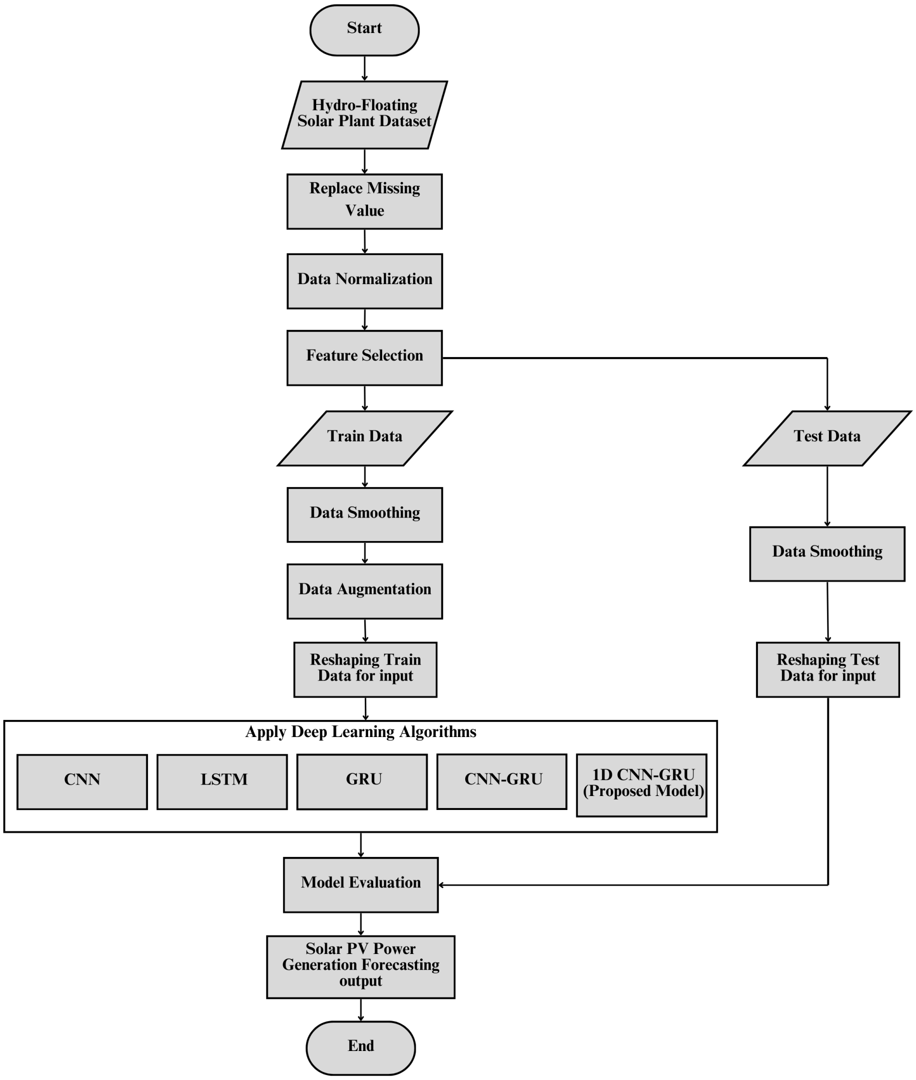


FIGURE 6. The flowchart of this research.

1D CNN layers since it accelerates the training process while preserving the ability to capture nonlinearities in time series data, resulting in more efficient and effective feature extraction. This setup is essential for efficiently extracting pivotal features from the dataset. Subsequently, the model incorporates three GRU layers, each activated by the tanh function [36] responsible for forecasting solar PV power generation. The tanh activation function, chosen for its ability to map input values to a range between -1 and 1, is instrumental in processing the extracted features from the 1D CNN, facilitating accurate generation forecasts [35]. This layered approach, combining feature extraction and sequential data processing, forms the core of the proposed model for forecasting solar PV power with high precision. The architecture of the proposed model is illustrated in Fig. 7.

The model training and testing were conducted on a MacBook Pro M2 with 10 CPU cores and a 3.4 GHz processor (6 performance and 4 efficiency cores), alongside a GPU of 16 cores, using Keras based on the TensorFlow framework in Python 3.8. The model's hyperparameters underwent fine-tuning. Expressly, the number of epochs was set to 30. The root mean square propagation (RMSprop) optimizer was employed to optimize the neural network training. This algorithm adapts the learning rate during training to resolve the vanishing or exploding gradient problems. The RMSprop optimizer achieves this by maintaining a moving average of the squares of gradients for optimization purposes [37]. The details of the parameter setting are available in Table 3. The array of filters in CNN, CNN-GRU, and 1D CNN-GRU models, as well as the array of filter or hidden nodes in LSTM, GRU, CNN-GRU, and 1D CNN-GRU, represent the filters or nodes from the first to the last layers, arranged from left to right.

C. RESULTS AND PERFORMANCE COMPARISON

As mentioned above, this research proposes the 1D CNN-GRU model against other established DL models, including CNN, GRU, LSTM, and a hybrid CNN-GRU.

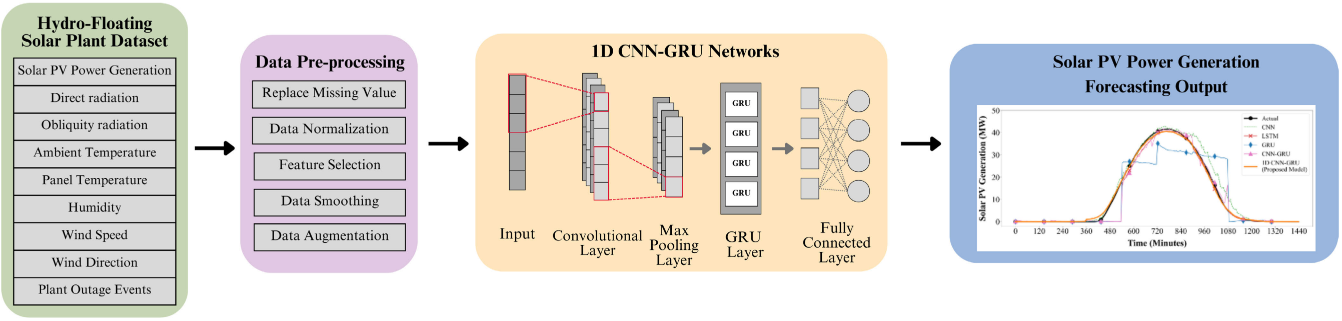


FIGURE 7. Architecture of the proposed 1D CNN-GRU model.

TABLE 3. The model parameters.

Model	Parameter	Value
CNN	Conv-2D Layer	4 layers
	Filter	[1024,512,256,128]
	Kernel Size	(3,3)
	Max Pooling Layer	4 layers
	Pool Size	(2,2)
	Activation	ReLU
	Dropout	0.1
LSTM	LSTM Layer	3 layers
	Hidden Node	[200,100,50]
	Activation	tanh
	Dropout	0.1
GRU	GRU Layer	3 layers
	Hidden Node	[200,100,50]
	Activation	tanh
	Dropout	0.1
CNN-GRU	Conv-2D Layer	4 layers
	Filter	[1024,512,256,128]
	Kernel Size	(3,3)
	Max Pooling Layer	4 layers
	Pool Size	(2,2)
	Conv-2D Activation	ReLU
	GRU Layer	3 layers
	Hidden Node	[200,100,50]
	GRU Activation	tanh
	Dropout	0.1
1D CNN-GRU (Proposed Model)	Conv-1D Layer	4 layers
	Filter	[1024,512,256,128]
	Kernel Size	(1,1)
	Max Pooling Layer	4 layers
	Pool Size	(2,1)
	Conv-1D Activation	ReLU
	GRU Layer	3 layers
	Hidden Node	[200,100,50]
	GRU Activation	tanh
	Dropout	0.1

Fig. 8 shows the three-hour-ahead forecasting results, presenting a 1-day horizon of solar PV power generation forecasted, spanning 1,440 minutes. The results show the proposed model's outstanding performance over its counterparts. Especially in the winter season, Fig. 8(a) shows the result of solar PV generation forecasted in the winter season closely aligning with actual data points.

Moreover, the summer season, shown in Fig. 8(b), and the rainy season, shown in Fig. 8(c), present the forecasted results of the proposed model closely aligning with actual data, even when the actual data has fluctuations and irregular patterns. This demonstrates that the proposed model effectively captures the patterns of fluctuations in actual data and follows these patterns. This not only highlights the proposed model's outstanding performance but also underscores the unique benefits of integrating 1D CNN with GRU. The 1D CNN component excels in extracting spatial features from the solar PV power generation data, while the GRU layers are adept at understanding the temporal sequences. This strategic combination enables the model to produce forecasts that closely align with actual data points.

The proposed model has significantly outperformed other models in terms of accuracy, as evidenced by its remarkably low *RMSE* and *MAE* across all seasons (winter, summer, and rainy), with these results illustrated in Table 4, particularly in the winter season. The *RMSE* of the proposed model for all seasons is 0.025, 0.050, and 0.094, respectively. Similarly, the *MAE* of the proposed model for all seasons is 0.014, 0.031, and 0.048, respectively. When compared to other models such as CNN, LSTM, GRU, and CNN-GRU, the proposed 1D CNN-GRU model demonstrates excellent performance. Specifically, the proposed model achieves lower *RMSE* and *MAE* values across all seasons. These comparative metrics highlight the proposed model's exceptional capability to forecast solar PV power generation three hours ahead with greater precision and reliability.

The outstanding accuracy of the proposed model is further highlighted by its R^2 score across all seasons of 0.994, 0.956, and 0.891, as illustrated in Table 4. The proposed model's R^2 score is higher than those of the other models. This R^2 score signifies the model's exceptional precision in forecasting, closely mirroring actual data. The closeness of the model's forecasts to actual observations underscores its effectiveness, showcasing its ability to provide almost perfect predictions in the context of solar PV power generation forecasting.

The proposed model not only showcased exceptional forecasting accuracy but also demonstrated remarkable computational efficiency, as highlighted in Fig. 9. It significantly outperformed other models in terms of training time, completing its tasks in 1,038.6 seconds. In contrast, the training times for the CNN, LSTM, GRU, and CNN-GRU models performed at 8,354.1 seconds, 3,622.9 seconds,

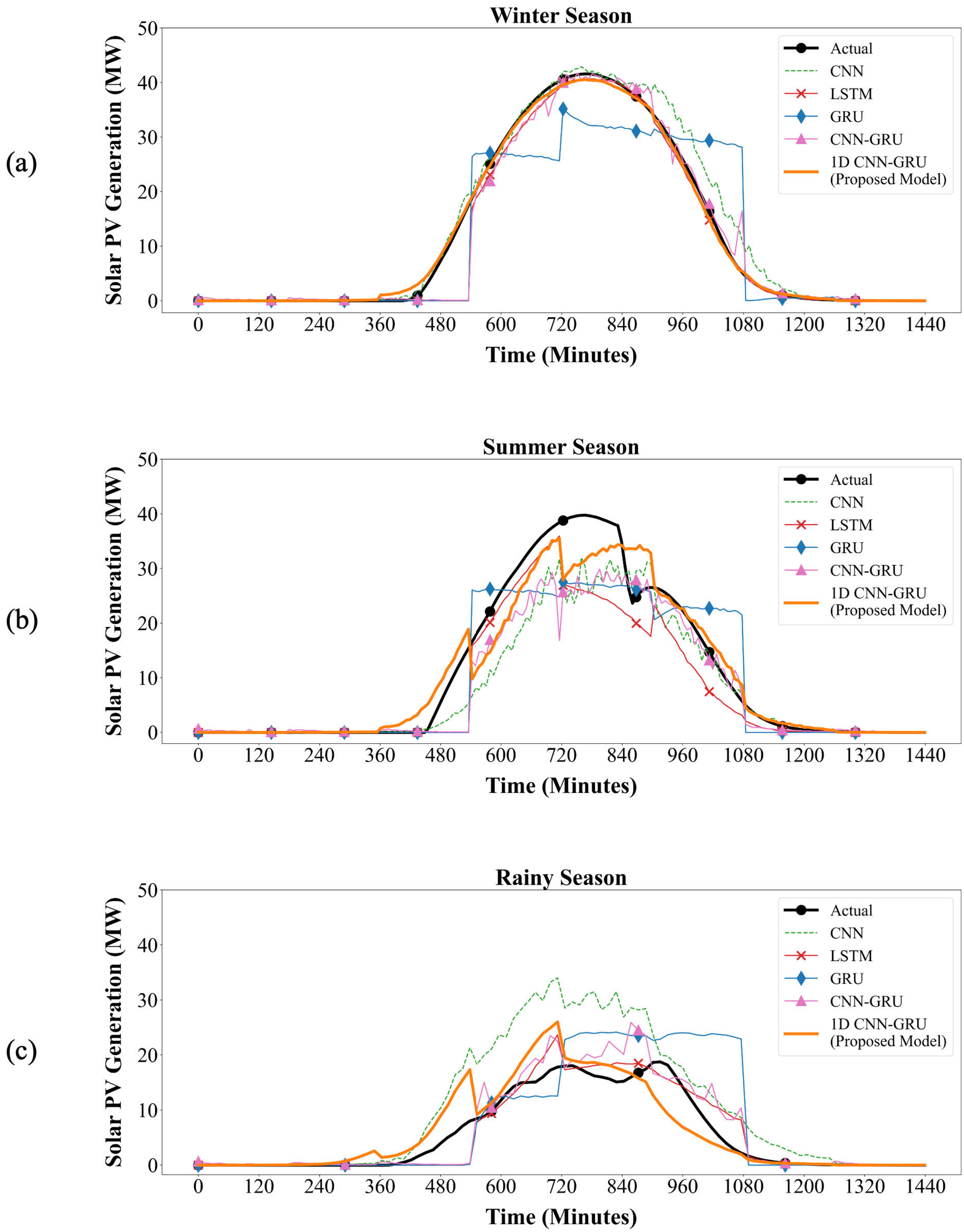


FIGURE 8. 1-day horizon of solar PV power generation forecasted at minute intervals. (a) The result of solar PV generation forecasted in the winter season, (b) The result of solar PV generation forecasted in the summer season, (c) The result of solar PV generation forecasted in the rainy season.

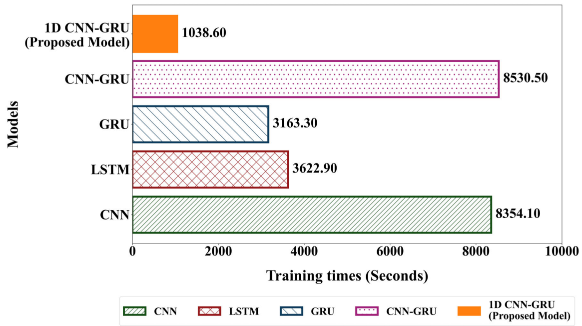


FIGURE 9. Training times comparison of the proposed model with another model.

TABLE 4. Performance comparison of the proposed model with another model across all seasons.

Seasonal	Model	*RMSE*	*MAE*	R^2 Score
Winter	CNN	0.055	0.033	0.97
	LSTM	0.062	0.025	0.963
	GRU	0.139	0.081	0.813
	CNN-GRU	0.059	0.027	0.966
	1D CNN-GRU (Proposed model)	**0.025**	**0.014**	**0.994**
Summer	CNN	0.073	0.065	0.877
	LSTM	0.096	0.069	0.851
	GRU	0.101	0.083	0.78
	CNN-GRU	0.094	0.07	0.85
	1D CNN-GRU (Proposed model)	**0.05**	**0.031**	**0.956**
Rainy	CNN	0.121	0.067	0.812
	LSTM	0.122	0.06	0.817
	GRU	0.15	0.086	0.721
	CNN-GRU	0.108	0.058	0.849
	1D CNN-GRU (Proposed model)	**0.094**	**0.048**	**0.891**

3,163.3 seconds, and 8,530.5 seconds, respectively. The proposed model's training time was significantly shorter, with reductions of 87.57%, 71.33%, 67.17%, and 87.82% compared to the CNN, LSTM, GRU, and CNN-GRU models, respectively. The proposed model demonstrates outstanding operational efficiency compared to other models due to its structure, which combines feature extraction and sequence modelling with exceptional effectiveness. The utilization of ReLU and tanh activation functions during training hastens the convergence process, enabling the model to achieve an optimal solution expeditiously while consuming less training time. This efficiency in processing underscores the model's capability to deliver not only accurate but also swift forecasts, essential for practical implementation of solar PV power generation forecasting, where timely and precise forecasting plays a vital role.

As summarized, the proposed model performs better and faster than all other models based on a comprehensive evaluation of various metrics and training times. The proposed model excels because it integrates the spatial feature extraction capabilities of 1D CNN with the sequence forecast strengths of GRUs, enabling it to capture both temporal and spatial dependencies in the data effectively. This synergy allows for a more nuanced understanding of complex patterns, which is essential for accurate short-term forecasting in solar PV power generation. Furthermore, the proposed model is optimized to reduce computational load, allowing for faster training times without sacrificing the quality of the analysis, making it highly efficient for operational use.

This combination positions the proposed model as a powerful model for energy management and strategic planning in the renewable energy sector. Its efficiency and reliability enable swift, informed decision-making, which is essential for optimizing solar PV systems. This capability is precious in dynamic environments requiring rapid adjustments to energy production strategies, enhancing operational efficiency and reliability.

D. COMPARISON WITH EXISTING RELATED WORKS

In this subsection, the performance of the proposed 1D CNN-GRU model is compared with existing related works in the field of short-term solar PV power generation forecasting. The comparison is focused on *RMSE* metrics to provide insights into the advancements achieved by the model. The comparison models include LSTM [11], GRU [13], CNN and CNN-LSTM [15], CNN-GRU [20], and 1D CNN-GRU [21]. Table 5 summarizes the *RMSE* metrics of the proposed model compared with existing works.

According to the results in Table 5, the proposed 1D CNN-GRU model performs exceptionally well, achieving an *RMSE* of 0.025 for the winter season, which outperforms other models referenced in previous studies. Moreover, when comparing the *RMSE* for the summer season with that reported by Suresh et al. [15], the proposed model demonstrates a lower *RMSE* than their model for the summer period.

However, it should be noted that the GRU model discussed in the study by Wang et al. [13] exhibits exceptional accuracy with an average *RMSE* of 0.036, making it the most accurate model among those compared, with a lower average *RMSE* than the proposed model for the summer and rainy seasons. Wang et al. [13] emphasize a clustering algorithm to group the dataset, resulting in increased complexity and training time compared to the proposed model, which simplifies the process and provides seasonal accuracy.

Furthermore, Wang et al. [13] rely on a 1-hour data frequency, potentially overlooking temporary fluctuations and rapid shifts in conditions that proposed model, utilizing data collected at 1-minute intervals, can capture. This limitation could impact its practicality in scenarios requiring prompt decision-making. In contrast, the proposed 1D CNN-GRU model integrates four Conv-1D layers with varying filter sizes and three GRU layers, tailored to handle high-frequency data. This design is particularly suitable for large-scale commercial solar projects.

The study by Sabri and El Hassouni [20] introduced a CNN-GRU model for solar PV power generation forecasting with a focus on 5-minute intervals, reporting an *RMSE* of 0.103. Although their model demonstrates robust performance, The proposed 1D CNN-GRU model achieves lower *RMSE* across all seasons, showcasing its superior accuracy.

TABLE 5. Summarized *RMSE* metrics of the proposed model and existing works.

Reference	Model	Forecasting Output	Forecasting Horizon	Data Frequency	*RMSE* Metric
Konstantinou et al. [11]	LSTM	Solar PV power generation	1.5 hour	15 minutes	0.0939
Wang et al. [13]	GRU	Solar PV power generation	1 hour	1 hour	0.036
Suresh et al. [15]	CNN and CNN-LSTM	Solar PV power generation	1 hour in summer and winter	15 minutes	Summer period CNN: *RMSE* = 0.068 CNN-LSTM: *RMSE* = 0.053 Winter period CNN: *RMSE* = 0.466 CNN-LSTM: *RMSE* = 0.297
Sabri and El Hassouni [20]	CNN-GRU	Solar PV power generation	5 minutes	5 minutes	0.103
Babalhavaeji et al. [21]	1D CNN-GRU	Solar PV power generation	4 days	5 minutes	0.230
Proposed Model	**1D CNN-GRU**	**Solar PV power generation**	**3 hour**	**1 minutes**	**Winter season** ***RMSE* = 0.025** **Summer season** ***RMSE* = 0.050** **Rainy season** ***RMSE* = 0.094**

Similarly, Babalhavaeji et al. [21] proposed a 1D CNN-GRU model for solar PV power generation forecasting with a longer forecasting horizon of 4 days and 5-minute intervals, achieving an *RMSE* of 0.230. Compared to the proposed model, their approach aims at longer-term forecasting but with a higher *RMSE*. The proposed proposed model, with its focus on high-frequency data and shorter forecasting horizons, provides more accurate predictions suitable for operational decision-making.

Overall, the superior performance of the proposed 1D CNN-GRU model across different seasons underscores its effectiveness in forecasting solar PV power generation. By leveraging DL techniques and high-frequency data, the model surpasses existing approaches, providing more accurate and timely predictions essential for operational decision-making.

IV. CONCLUSION AND POSSIBLE FUTURE WORKS

In this paper, a hybrid DL model named ''1D CNN-GRU'' is proposed, combining 1D CNN and GRU models to improve computation time and reduce resource usage in short-term solar PV power generation forecasting, specifically for three hours in advance. The aim is to enhance short-term forecasting for the efficient operation of NCC, refine energy distribution, enhance grid stability, and effectively integrate renewable sources. The proposed model employs various data preparation techniques consisting of SHAP-based feature selection, data smoothing with EMA, and data augmentation with Gaussian noise to enhance its performance, mitigate fluctuations in the data and increase the dataset size. Essential features are extracted from time series data, like solar PV power generation, by the 1D CNN module, while the GRU component delivers high-precision short-term forecasts using the Hydro-Floating Solar Plant dataset from the hydro-floating solar installation at Sirindhorn Dam in Ubon Ratchathani province, Thailand. The accuracy of the forecasting models was evaluated using metrics, i.e., *RMSE*, *MAE*, and R^2 score, and the training time was also evaluated with all seasons in Thailand. According to the results, all other models were outperformed by the proposed model in both accuracy and training time. The proposed model achieved the lowest *RMSE* of 0.025 (winter), 0.050 (summer), and 0.094 (rainy), and the lowest *MAE* of 0.025 (winter), 0.050 (summer), and 0.094 (rainy), with a training time of 1,038.60 seconds. The proposed model excels by integrating feature extraction and sequence modeling, leading to superior operational efficiency. This efficiency highlights the model's capability for precise, swift forecasts. It is an essential tool for energy management and strategic planning in the renewable energy sector, where rapid adjustments are crucial.

The potential direction is to extend the forecasting horizon beyond three hours to include day-ahead predictions. Enhancing the model with granular weather data (e.g., cloud cover, atmospheric pressure) and advanced ML techniques (e.g., ensemble learning, reinforcement learning) could further improve accuracy and capture complex interactions between weather and solar PV power generation. Furthermore, investigating the model's scalability to larger datasets and its adaptability to various geographical and climatic conditions is crucial. This includes evaluating performance under extreme weather conditions and assessing sensitivity to data quality and quantity, particularly in areas with limited data infrastructure, to ensure real-world applicability.

In summary, by extending the forecasting horizon, incorporating more granular weather data, assessing scalability and adaptability, and integrating emerging ML techniques, future research can build upon the foundation laid by this study and further advance the field of solar PV power generation forecasting.

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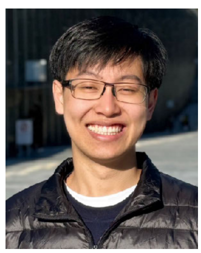

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