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TOPICAL REVIEW

Recent Advances and Future Challenges of Solar Power Generation Forecasting

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ABSTRACT The unprecedented growth of Renewable Energy Sources (RES) positions solar power as a leading contender in the global energy mix. Solar energy offers a sustainable alternative to fossil fuels, mitigating carbon emissions and promoting environmental sustainability. This study explores the crucial role of forecasting algorithms within photovoltaic (PV) systems. We aim to provide a comprehensive understanding of methodologies, datasets, and recent advancements for enhancing predictive accuracy in solar power generation forecasting. While machine learning has dominated previous research, recent studies highlight challenges in achieving optimal efficiency and accuracy. A significant obstacle lies in the deficiency of real-world application for large-scale specifically for solar power generation forecasting. To address this gap, this study defines prevalent forecasting methodologies and illuminates datasets with diverse characteristics and their relevance. This study meticulously provides and explore recent advanced methods and datasets, emphasizing their impact on forecasting performance. This study not only deepens our understanding of existing methodologies but also provides valuable insights for future advancements in solar power generation forecasting.

INDEX TERMS Solar power, machine learning, PV, solar energy.

I. INTRODUCTION

Electricity demand is increasing rapidly year by year. All sectors, such as industrial, residential, and others, need the power to provide their activities and business steadily. For the past few years, we have needed more fuel, diesel, and gas in electricity production. It has a significant impact on climate change and global warming. Hence, renewable energy is widely used to substitute common sources for various purposes. There are solar energy, wind energy and ocean, geothermal energy, hydropower, and bioenergy [1]. One of the popular is Solar energy. Everyone has moved and implemented this Renewable Energy Source. Solar Photovoltaic (PV) capacity additions increased yearly from 2010 to 2023 [2].

There are several challenges to solar power generation implementation in the real world. Weather conditions and parameters play the main role in producing the power. It depends on the climate conditions and intensity of sunlight in a specific place. Due to this challenge, accurate forecasting of solar power generation algorithms is essential. Hence, It can reduce the impact of PV power uncertainty on the grid, improve system reliability, maintain power quality, and increase the penetration level of PV systems [3].

Previous studies have used several statistical, Machine Learning (ML), and hybrid methods. Mathematical techniques have disadvantages in terms of accuracy caused by the increasing forecasting horizon [4]. Other studies showed ML has often been used to achieve better performance. Long Short-Term Memory (LSTM) is repeatedly used as a base algorithm to be analyzed in these studies [5], [6], [7], [8], [80]. Recently, hybrid methods have outperformed traditional

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and basic ML algorithms regarding performance. However, previous studies proved that using the combined method affects the complexity of training [4], [30], [40].

The critical role of accurate solar power generation forecasting is well-established for integrating renewable energy into the smart grid. Numerous review papers have explored various forecasting methodologies, showcasing the dominance of Machine Learning approaches and delving into their strengths and limitations [4], [9], [10], [11], [12], [13], [14]. However, a gap exists in comprehensively addressing the performance and datasets that underpin these forecasting methods. This research field still faces challenges with real-world applications. This study aims to bridge this gap by systematically reviewing solar power generation forecasting. We will not only examine the limitations of existing methodologies but also strongly emphasize the various recent advanced methods and datasets available and their suitability for different forecasting tasks.

This study provides a comprehensive review of solar power generation forecasting methodologies. Recent algorithms described include architecture and workflow. This study's contributions can be summarized as follows:

1) **Classification of forecasting methods**: Provided an overview of different forecasting methods and categorized them according to different algorithms in building a prediction model for solar power generation forecasting.
2) **Datasets available for research**: Identified and explained relevant datasets that researchers can utilize to train and test various forecasting techniques.
3) **Recent advancements**: Explored the latest developments and frequently utilized in forecasting methodologies
4) **Comparative review**: Conducted a comprehensive review of recent studies (2019-2024) on solar power generation forecasting. Our analysis focused on the datasets used, forecasting horizons, methods employed, results achieved, and evaluation metrics. This comparative overview empowers researchers to make informed decisions when selecting the most suitable forecasting technique for their specific research objectives.

This study is organized as follows: Section II describes the foundation of PV systems and highlights solar power integration to the grid. Section III delves into solar power forecasting classifications. Section IV analyzes diverse datasets available for solar power forecasting. Building on this data foundation, Section V explores recent advances in solar power generation forecasting methods, examining prominent algorithms and their strengths and limitations in this context. Section VI acts as a critical juncture, presenting a comparative review of the forecasting methods and datasets explored earlier, identifying optimal combinations for achieving the most accurate and reliable solar power generation forecasts. Finally, Section VII acknowledges the ongoing challenges and proposes avenues for future research to refine forecasting methodologies further. Section VIII concludes this review paper by summarizing the key findings and reiterating the significance of accurate solar power generation forecasting for a sustainable and reliable energy future.

II. METHODOLOGY

A comprehensive review of recent advancements and future solar power generation forecasting challenges was conducted. To investigate and execute our contributions, we utilized the following processes:

- *Research question*: we initiated several questions to be searched in the next step, which include:
    1) What forecasting algorithms are commonly used for solar power generation prediction?
    2) What types of datasets are commonly utilized for solar power forecasting tasks?
    3) What recent innovations and developments have shaped the solar power forecasting methodologies field in the past few years?
    4) How do various forecasting algorithms compare accuracy, computational efficiency, and robustness?
- *Comprehensive Search*: We extensively explored these leading databases, IEEE Xplore, ScienceDirect, Elsevier, MDPI, Springer, Hindawi, and Google Scholar, to gather relevant research. The keywords used to collect all the references were: "PV power generation," "solar power forecasting," "machine learning," "deep learning," and "time series forecasting,"
- *Screening*: We conducted a comprehensive literature search, identifying 278 relevant references. To narrow our focus, we filtered these references to include only those specifically related to solar or PV power generation forecasting. This process yielded 139 relevant sources, encompassing journal articles, conference papers, and dataset sources. When selecting all references, we prioritized highly cited articles.

III. PHOTOVOLTAIC SYSTEMS

Photovoltaic (PV) systems have been beneficial in providing electricity and could decrease carbon emissions. Today, researchers still find methods for obtaining power from renewable sources to achieve zero-emission and avoid climate change. However, there are some challenges regarding efficiency and cost for saving the excess power from PV systems. Buying batteries to store the overabundance of electricity will be a high cost. Hence, PV systems connected to the grid can be a solution to reduce tariffs and maintenance [15]. Grid-connected PV systems can be shown in Figure 1.

The conventional grid we use today has many issues, such as undependable, low efficiency, losses and interruptions, and so on [16]. Researchers found the solution for these limitations is creating a smart grid. A smart grid is a sophisticated network with an automated control and monitoring system. It can communicate, store information, make decisions based on the situation, and integrate and deliver the benefits of an electricity network to all parties involved [17].

Smart grid parts include an integrated communication system, modernized hardware, intelligent control and instrumentation, and smart software [18]. Artificial intelligence (AI) is part of intelligent control that predicts energy production and monitors the system. Nevertheless, there are limitations to the unpredictable weather that could cause the performance of forecast power generation from the PV system. Therefore, researchers are still studying and developing accurate forecasting algorithms for PV power generation to achieve a potential and reliable smart grid.

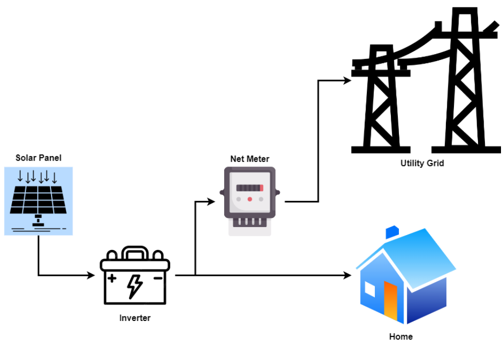

FIGURE 1. Grid-connected PV systems.

IV. CLASSIFICATION OF PV POWER GENERATION FORECAST METHOD

Researchers could consider several approaches to achieving the study's objectives. In this study, the classification of PV power generation forecasting is divided into four categories: physical, statistical, hybrid, and AI-based methods. The diagram of classification based on our review is shown in Figure 2.

A. STATISTICAL METHOD

In this section, the classification of statistical methods is divided as follows: based on forecast horizon, area scale, time step, direct and indirect, and deterministic and probabilistic [9], [14]. The perspectives mentioned earlier should be considered before starting the experiment and choosing the model or algorithm. Statistical models that have been used in previous studies, such as ARMA [19], ARIMA [20], and SARIMA [21] should be considered. Moreover, performance metrics would be affected by non-suitable methods and approaches.

1) FORECAST BASED ON HORIZON

Forecast Horizon can be categorized into four types: very short-term (1 second to less than 1 hour), short-term forecast (1 to 24 hours), medium-term forecast (1 week to 1 month), and long-term forecast (1 month to 1 year) [6]. Very short-term is applicable for optimal reserves, power smoothing, and electricity dispatch, while short-term is functional to raise the grid's security. Medium-term helps sustain the power system planning and maintenance schedule by forecasting the obtainable electric power in the future. Lastly, Long-term is helpful for electricity generation planning, transmission, distribution authorities, energy bidding, and security operations [4]. The summary of the forecast horizon is shown in Table 1.

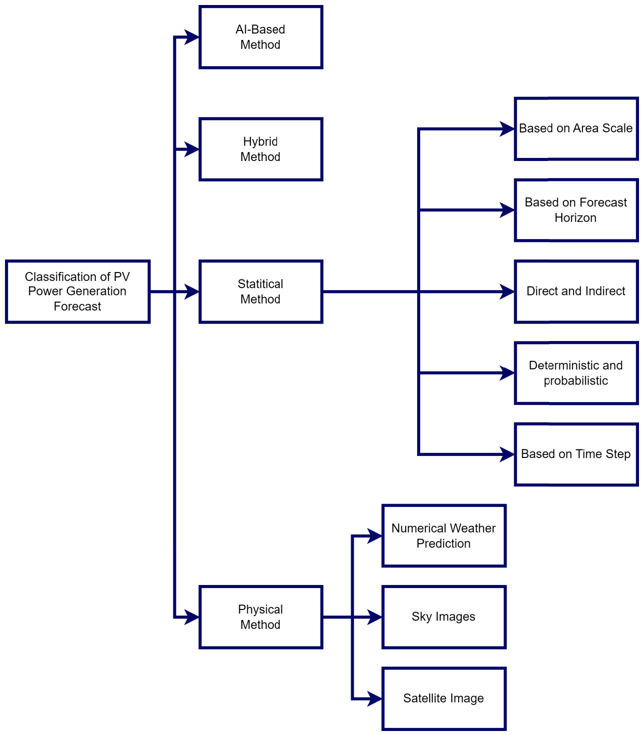

FIGURE 2. Classification of PV power generation forecast method.

TABLE 1. Classification based on forecast horizon.

Horizon	Time	Advantage
Very Short-Term	1 second<1 hour	Power smoothing, Electricity dispatch, and optimal reserves.
Short Term	1 - 24 hour	Security improvement of the grid.
Medium Term	1 week - 1 month	Power system planning suistanable.
Long Term	1 month - 1 year	Electricity generation planning, transmission, and distribution authorities.

2) FORECAST BASED ON AREAL SCALE

Models for predicting the power output of PV systems can be classified into two categories based on the scope of their application: single-field and regional forecasts. The single-field category focuses on forecasting for a single PV plant [9]. In contrast, regional forecasts consider a broader area, encompassing multiple PV plants distributed across a larger region [14]. Classification of the areal scale forecast can be shown in Figure 3.

Previous studies related to regional forecasting [75], [80], [129], [130] have been researched and investigated. Regional

Forecast approaches can be split into Bottom-up and Up-scaling [14]. For the bottom-up approach, the output of each plant in the regional area will be predicted first. Subsequently, these individual results are statistically combined to produce the overall regional forecast. The upscaling approach involves either substituting individual PV sites with a hypothetical power plant at the regional level or selecting representative PV sites to predict regional power output, adjusting for differences in capacity.

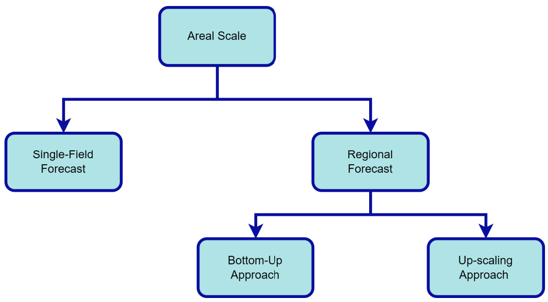

FIGURE 3. **Types of areal scale forecast.**

3) FORECAST BASED ON DIRECT AND INDIRECT

Direct and indirect forecast methods have been used in previous studies. Direct forecasting models analyze historical data to determine the relationship between the input variables and PV output power [9]. Some studies have implemented direct forecasts [22], [23]. Indirect forecasting is divided into two steps: the weather factors that affect solar PV output power, such as solar irradiation, are modeled, while the second step transforms the result of the first step into predicted PV output power.

The procedure to forecast PV power by indirect method is as follows: First, collect solar irradiance and meteorological data, PV plant location information, PV panel, and inverter characteristics. Second, data-driven models can forecast solar irradiance on a horizontal plane. Third, use combination models to calculate the plane of array solar irradiance. Fourth, POA irradiance is applied as an input in PV performance models to forecast solar power [10]. However, the indirect method has limitations due to overlay error hindering the improvement of PV prediction accuracy [24].

4) FORECAST BASED ON DETERMINISTIC AND PROBABILISTIC

A forecast based on deterministic makes a forecast of the PV output power into the future without considering the forecast uncertainties [9]. Probability forecasts can provide prediction intervals in addition to precise values with which the forecast is expected to fall with some predefined confidence level or probability [14]. In [25] implemented, deterministic and probabilistic based on wavelet transform and deep convolutional neural network.

5) FORECAST BASED ON TIME STEP

A forecast model that predicts only the next immediate time step, such as a minute, 5 minutes, 15 minutes, or an hour, is known as a single-time step forecast. Contrarily, a forecast model that predicts more than one future time step is called a multiple-time-step forecast [14]. One of the previous studies forecast based on multiple-time-step from 15-min to 24 hours [26].

B. PHYSICAL METHOD

The physical method employs a physics-based model to simulate solar energy conversion into electricity. By using weather parameters like cloud cover, temperature, and solar irradiance as inputs, the model predicts power output through physical equations [9]. The physical Method can be divided as follows: Based on Numerical Weather Prediction (NWP), sky images, and satellite images [27]. This approach is critical as part of a feasibility study to determine the amount of PV generation before it is constructed [14].

C. HYBRID METHOD

Hybrid methods combine two or more techniques, often incorporating an optimization theorem. This combination enhances the overall accuracy of the hybrid by leveraging the advantages of each method [4]. In [28], a hybrid GCN-BiLSTM model was used to predict solar power generation from seven PV sites, and the proposed method proved to outperform time-series forecasting methods. GRU-CMM model was used in [29] and achieved the lowest error rates using this hybrid method. Also, other studies implemented a hybrid method recently [30], [31], [32], [33], [34]. It proved that it enhances the performance better than other methods.

D. AI-BASED METHOD

The AI-based method uses machine learning or Deep Learning (DL) algorithms to solve a specific task. Today, ML or DL is frequently used to predict PV power generation. Figure 4 provides an overview of AI, ML, and DL algorithms commonly used for solar power generation forecasting tasks.

Machine learning is a subset of AI. Machine learning algorithms can be broadly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning. Unsupervised learning encompasses dimensionality reduction and clustering techniques. Principal Component Analysis (PCA) is a widely used dimensionality reduction algorithm that can benefit the preprocessing of complex solar power generation data [89]. Clustering algorithms, such as K-means, are widely employed [37]. Supervised learning is frequently used in solar power generation forecasting due to its ability to learn from labeled data. Common supervised learning algorithms include regression models [97], decision trees [29], and support vector machines [106]. Reinforcement learning is less commonly used in solar power generation forecasting due to the poor fit between the workflow and the needs of this task.

Deep learning, a subset of machine learning, utilizes neural networks to learn complex patterns within data. Deep learning models have the advantage of directly learning features from datasets, enabling them to capture more complicated patterns and potentially improve training efficiency [51]. Several deep learning models have been studied previously, are ANN [124], CNN [56], RNN [84], ELM [85], and so on.

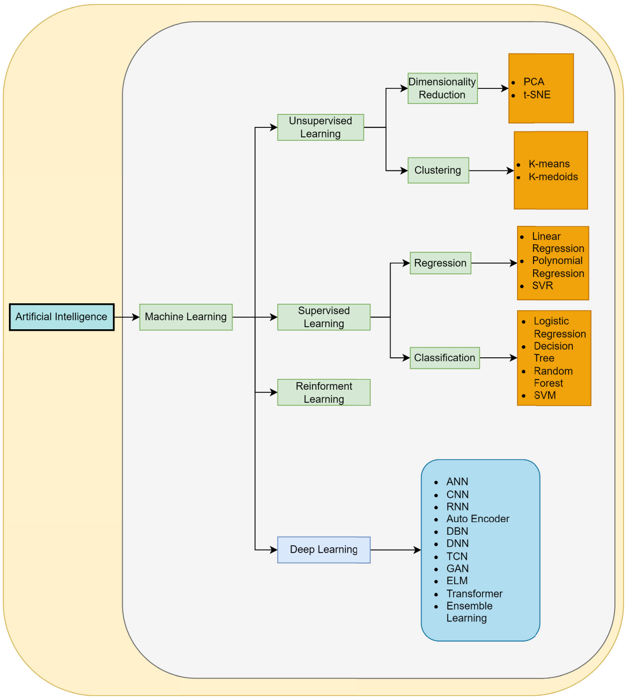

FIGURE 4. AI-Based algorithms and types for PV power generation forecasting tasks.

V. DATASET

The availability of high-quality datasets is crucial for training and evaluating ML algorithms in solar power generation forecasting. However, the field has historically been Hindered by a lack of openly accessible data, with prior studies relying on private datasets [54]. This has limited the reproducibility and generalizability of research findings.

Fortunately, a recent trend toward open data sharing has emerged in the solar power generation forecasting. Several academic journals now publish detailed datasets explicitly designed for this purpose [46], [47], [49], [24]. This section presents a selection of these datasets, many of which are publicly accessible and freely downloadable. We prioritized datasets that include photovoltaic (PV) power generation records. This allows researchers to choose the most suitable data for their research needs. These datasets are summarized in Table 2.

A. POWER GENERATION DATA

a comprehensive dataset was collected from a 20 kW rooftop PV power station in Shaoxing City, Zhejiang Province, China [44]. This dataset covers a four-year timeframe, spanning October 2014 to September 2018. The data acquisition frequency is prominently high, with measurements captured every 7.5 minutes. This granular resolution provides valuable insights into the dynamic behavior of the PV system under real-world operating conditions. The dataset specifically includes two key variables: PV power output and PV module temperature. This dataset has been used as referred to in its article [121]. The specification details of the dataset can be shown in Table 3.

B. SOLETE

SYSLAB, a renowned laboratory for distributed energy resources situated in Denmark, has documented the performance of SOLETE [45], a comprehensive energy system. This system comprises a meteorological station alongside an 11 kW wind turbine and a 10 kW PV array, meticulously capturing various parameters. These measurements, involving a timeframe from June 1, 2018, to September 1, 2019, have been diligently transferred to a centralized server for analysis. The dataset embraces critical variables such as timestamp, air temperature, relative humidity, pressure, wind speed, wind direction, global horizontal irradiance, plane of array irradiance, and active power derived from both the wind turbine and the PV inverter. Recorded at a sampling rate of 1 Hz, the data has been aggregated into 5-minute and hourly intervals, with timestamps adhering to the UTC format "yyyy-mm-dd hh:MM:ss". The dataset specifications are detailed in Table 4.

C. PVOD

The PV power output dataset (PVOD) includes a wealth of information crucial for understanding PV system performance, drawing from a diverse array of sources including metadata, numerical weather prediction data, and localized measurements [46]. Spanning ten PV systems situated in China, this dataset offers a comprehensive overview of the complexities involved in PV power generation within varying geographical and environmental contexts. By incorporating metadata alongside both regional and site-specific weather data, researchers gain valuable insights into the factors influencing PV system output, facilitating more accurate modeling and analysis. One of the previous studies that used PVOD dataset is Yao et al. The dataset specifications are outlined in Table 5.

D. SKIPP'D

a SKy Images and PV Power Generation Dataset (SKIPP'D) Originating from Stanford University's Environmental Assessment and Optimization (EAO) Group [47]. These images are extracted at 1-minute intervals from daytime video recordings (6:00 AM - 8:00 PM) captured by a commercially available 6-megapixel fish-eye camera mounted on Stanford University's Green Earth Sciences Building (37.427°, −122.174°). The PV power generation data are from a PV panel approximately 125 meters away from the camera on the roof of the Jen-Hsun Huang Engineering Center at Stanford University, which are logged by Stanford Utility and shared with us. The SKIPP'D dataset provided two types of data as follows:

TABLE 2. Solar power generation datasets.

Dataset	Type	Detail	Reference
Power generation data	Time series data	Eastern China (2017-18): 20kW PV	[44]
SOLETE	Time series data	15-month dataset (06/2018-09/2019): Wind & amp;amp; Solar (11kW/10kW), Meteorological data	[45]
PVOD	Time series data	PVOD (China): 10 PV Systems (Metadata, Weather, Local Measurements)	[46]
SKIPP'D	Images and PV power output	Sky images & PV Power (China): 3-year (2017-2019) Sky Images & PV Power	[47]
NIST campus PV arrays and weather station data sets	Time series data	NIST (USA): 3 Grid-Connected PV Arrays (2015-2018, 1-min & 1-sec data) - Irradiance, Temp, Wind, Electrical	[48]
UNISOLAR	Time series data	UNISOLAR (Australia): 42 PV Sites (2 years, 15-min data) - PV Power, Irradiance, Weather	[49]
PV power and weather parameters	Time series data	SolarTech Lab (Italy): 1-minute PV Power, Temp., Irradiance, Wind (Original Measurements	[81]

TABLE 3. Specification details of power generation dataset.

Component	Details
Dataset Name	Short-term Photovoltaic Power Forecasting based on Long Short Term Memory Neural Network and Attention Mechanism
Type of data	Power generation data, PV module temperature data
Data Format	Excel
Time period	October 2014 to September 2018
Temporal resolution	7.5 minutes
Data Source Location	Shaoxing city, Zhejiang Province, China (120°23'0"E, 29°7'2"N).
Data Availability	https://dx.doi.org/10.21227/9hje-dz22
Data Accessibility	Private (restricted to IEEE members or require a specific subscription)

TABLE 4. Specification details of SOLETE dataset.

Component	Details
Dataset name	SOLETE
Data type	Meteorological and PV and wind power generation data
File format	Table (.hdf5), Script (.py), Figure (.png)
Data source location	• Institution: Risø DTU National Laboratory for Sustainable Energy • City: Roskilde • Country: Denmark • Latitude and longitude: 55.6867, 12.0985
Temporal resolution	5 minutes and hourly
Time period	1st June 2018 - 1st September 2019
Data Availability	https://data.dtu.dk/articles/dataset/The_SOLETE_dataset/17040767
Data Accessibility	Public
Github repository	https://github.com/DVPombo/SOLETE

1) Processed (benchmark) data contains 1-min 64 × 64 sky images (.npy) and PV power generation (.npy) pairs, partitioned into model development set (training+validation) and test set, and further structured and stored as.hdf5 format.
2) Raw data: 2048 × 2048 sky videos recorded at 20 frames per second (.mp4), 1-min 2048 × 2048 sky images (.jpg) and PV power generation (.csv).

TABLE 5. Specification details of PVOD.

Component	Details
Dataset Name	A photovoltaic power output dataset
Data Type	Meteorological and PV power data
File Format	Comma-Separated Values (CSV)
Number of Sites	10
Location	Hebei Province, China (Lat: 36.64403–39.5155 N, Lon: 113.6419–117.4572 E)
Time Period	July 1, 2018 - June 13, 2019
Temporal Resolution	15 minutes
Number of Records	271,968
Features	NWP Variables (7): Global horizontal irradiance (GHI), Direct normal irradiance (DNI), 10-meter temperature, 10-meter humidity, 10-meter wind speed, Wind direction, Pressure
	Local Measurement Data (7): Global horizontal irradiance (GHI), Diffuse horizontal irradiance (DHI), Temperature, Pressure, Wind direction, Wind speed, PV output
Data Availability	http://www.doi.org/10.11922/sciencedb.01094
Data Accessibility	Public
Github repository	https://github.com/yaotc/PVODataset

To ensure consistent image quality, the camera maintains constant settings for aperture, white balance, and dynamic range. The high-resolution video (2048 × 2048 pixels at 20 fps) is then converted into individual JPEG images and down-sampled to a more manageable size of 64 × 64 pixels for further analysis. This approach provides a cost-effective and efficient method for capturing sky conditions relevant to solar power generation forecasting. Recent studies used this dataset for research purposes [50], [82], [83], [84]. The details of SKIPP'D dataset can be shown in Table 6.

E. NIST

The dataset comprises one-minute averaged values and one-second instantaneous values spanning 2015 to 2018, extracted from three grid-connected PV arrays on the NIST campus in Gaithersburg, Maryland, USA [7]. These arrays are

TABLE 6. Specification details of SKIPP'D dataset.

Component	Details
Dataset Name	SKIPP'D
Data Type	Sky images and PV power generation
File format	sky images (.npy), PV power generation (.npy; .csv), sky videos (.mp4), sky images (.jpg)
Specific subject area	PV power generation prediction; Sun tracking; Cloud detection; Cloud movement prediction
Data collection period	March 2017 - December 2019
Data Availability	https://purl.stanford.edu/sm043zf7254
Data Accessibility	Public
GitHub repository	https://github.com/yuhao-nie/Stanford-solar-forecasting-dataset

TABLE 7. Specification details of NIST dataset.

Component	Details
Dataset Name	NIST
Format	Text (Comma Separated Values, XML), Images (JPEG)
Data type	meteorological, solar, electrical, temperature, images
Data collection period	2015 - 2018
Temporal resolution	1 second most measurements
Data Dictionary	https://www.nist.gov/file/391591 [pdf]
Data Availability	[73]
Data Accessibility	Public

equipped with sensors to capture essential parameters such as irradiance, temperature, wind, and electrical measurements, providing a detailed insight into the operational dynamics of the PV systems across varying temporal scales. A historical PV power dataset collected from a parking lot canopy array monitored by NIST has been used for short-term PV power generation forecasting [70]. The specification of the NIST dataset is summarized in Table 7.

F. UNISOLAR

The UNISOLAR dataset represents a comprehensive repository of high-resolution data on PV solar energy generation, solar irradiance, and weather conditions, derived from 42 PV sites distributed across five campuses within La Trobe University, Victoria, Australia [49]. This dataset briefs an extensive collection of PV solar energy generation data spanning approximately two years, precisely recorded at 15-minute intervals. By encompassing such a diverse range of locations, researchers are afforded a unique opportunity to examine the complexity of solar energy production in a real-world context. The dataset specifications are detailed in Table 8.

G. PV POWER AND WEATHER PARAMETERS

The dataset provided covers PV power production data collected at the SolarTech Lab, situated at Politecnico di Milano, Italy. This dataset is made freely available for scientific research purposes and can be accessed through IEEE Dataport [65], [81]. The dataset consists of several key variables recorded at a temporal resolution of 1 minute, offering detailed insights into the performance of the PV system. These variables include timestamp information in the format "dd-MM-yyyy hh:mm:ss" (stated in Central European Time), PV module power output (Pm) at a fixed tilt of 30°, ambient temperature (Tair) obtained from the lab's weather station, Global Horizontal Irradiance (GHI), Global irradiance on the plane of array (GPOA) also at a tilt of 30°, measured Wind speed (Ws), and Wind direction (Wd) concerning cardinal directions. Dataset specifications are outlined in Table 9.

TABLE 8. Specification details of UNISOLAR dataset.

Component	Details
Dataset Name	UNISOLAR
Data Type	PV energy generation and weather data
File Format	CSV, JSON
Number of Sites	42
Github repository	https://github.com/CDAC-lab/UNISOLAR
Data Availability	https://www.kaggle.com/datasets/cdaclab/unisolar
Data Accessibility	Public
Location	La Trobe University campuses, Victoria, Australia.
Time Period	January 2020 - April 2022
Temporal Resolution	15 minutes

TABLE 9. Specification details of PV and weather parameters dataset.

Component	Details
Dataset Name	Photovoltaic Power and Weather Parameters
Type of Data	PV measurements and meteorological data
Data Source Location	SolarTech LAB facility located at Politecnico di Milano, Milan, Italy.
File Format	.CSV
Temporal resolution	One minute
Time period	1st January 2017 - 1st January 2018
Data Accessibility	Required to have an IEEE account
Data Availability	https://dx.doi.org/10.21227/42v0-jz14

VI. RECENT ADVANCES METHODS AND PERFORMANCE METRICS

A. AI-BASED METHOD

Artificial Intelligence-basedd method is one of the popular methods utilized in recent years. In the solar power forecasting field, supervised and unsupervised are mostly used [51]. As shown in Figure 4, many ML and DL algorithms have been used for the task. The diversity of ML algorithms from the previous studies is stated in Table 10.

In this section, the widely used and selected AI-based algorithm will be explained. The methodology for each method will be described.

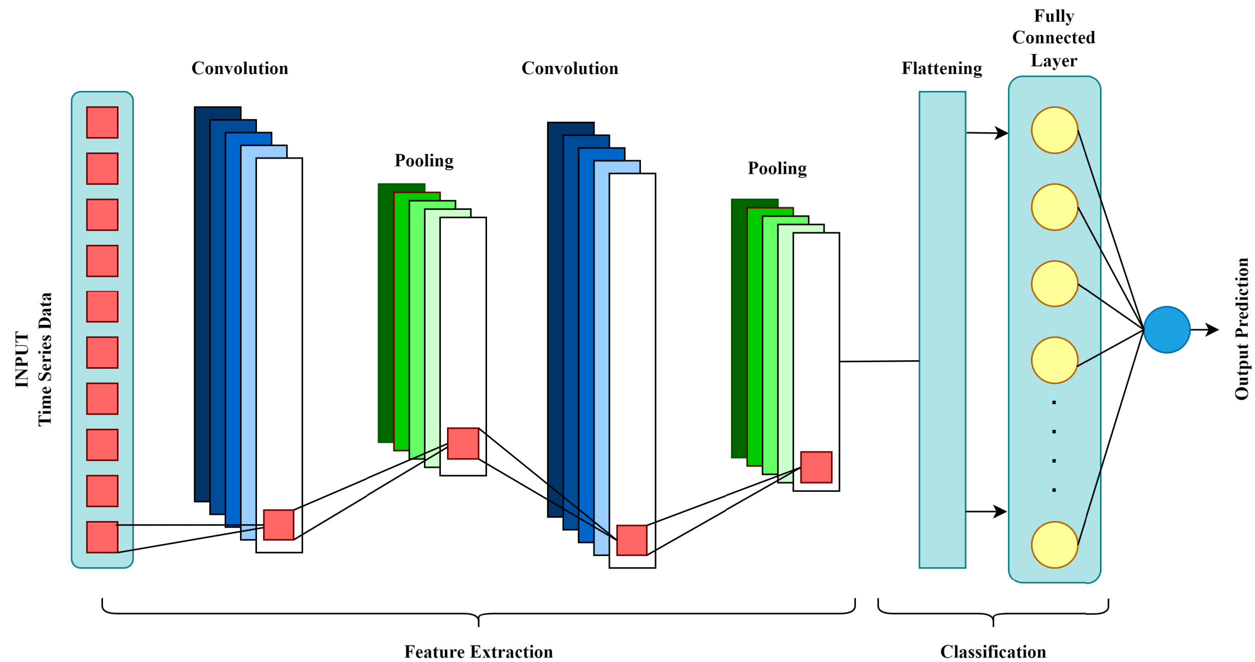

FIGURE 5. **Architecture of CNN for time series forecasting.**

1) LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a Recurrent Neural Network (RNN) type designed to handle the vanishing gradient problem in traditional RNNs. It does this by introducing memory cells and gates that can regulate the flow of information. This allows the network to remember important information for longer periods and forget irrelevant information. Matrices and Vectors are described below [128]:

1) W_i, W_f, W_g, W_o: These are weight matrices with dimensions $n_N \text{x} n_f$.
2) R_i, R_f, R_g, R_o: These are recurrent weight matrices with dimensions $n_N \text{x} n_N$.
3) b_i, b_f, b_g, b_o: These are bias vectors with dimensions $n_N \text{x}1$.

In the network's LSTM layer, the following computations are carried out:

$$i(k) = \sigma(W_i x(k) + R_i h(k-1) + b_i), \tag{1}$$

$$f(k) = \sigma(W_f x(k) + R_f h(k-1) + b_f), \tag{2}$$

$$g(k) = tanh(W_g x(k) + R_g h(k-1) + b_g), \tag{3}$$

$$o(k) = tanh(W_o x(k) + R_o h(k-1) + b_o), \tag{4}$$

$$c(k) = f(k) \circ c(k-1) + i_k \circ g(k), \tag{5}$$

$$h(k) = o(k) \circ tanh(c(k)). \tag{6}$$

LSTM models can also have a multi-sequence input configuration where various lags of the same or different time series can be presented as model inputs [72]. The algorithm flow can be shown in Figure 6.

2) CONVOLUTIONAL NEURAL NETWORK (CNN)

One kind of deep algorithm learning used to analyze data with pattern-like visuals is the Convolutional Neural Network (CNN) [73]. Convolution layers, pooling layers, and fully linked layers make up CNN's architecture. The scientific mechanisms by which the structure of the animal visual cortex generates patterns of neuronal connection are the source of inspiration for CNN. It performs a neuron-like function by multiplying an input by certain weights and returning the result. Figure 5 details the step-by-step process of the CNN algorithm for time series forecasting.

One Dimensional Convolutional Neural Network is utilized for solar power generation forecasting tasks. In a convolutional layer, the output (y_j^k) is calculated by multiplying the previous layer's input (x_i^k) with a set of filters (w_{ij}^k) and adding a bias term (b_j^k) for adjustment [30]. The convolution process can be calculated using Eq. (7).

$$y_j^k = \sum_i (x_i^k * w_{ij}^k) + b_j^k \tag{7}$$

3) MULTI-LAYER PERCEPTRON (MLP)

The Multi-layer Perceptron (MLP) is a specific artificial neural network architecture commonly used for regression and classification tasks [5]. It consists of an input layer receiving raw data, hidden layers with interconnected artificial neurons, and an output layer generating predictions [76]. Each hidden neuron applies an activation function (e.g., ReLU) to a weighted sum of its inputs from the previous layer, introducing non-linearity and enabling the network to learn complex patterns. Information flows forward through the network,

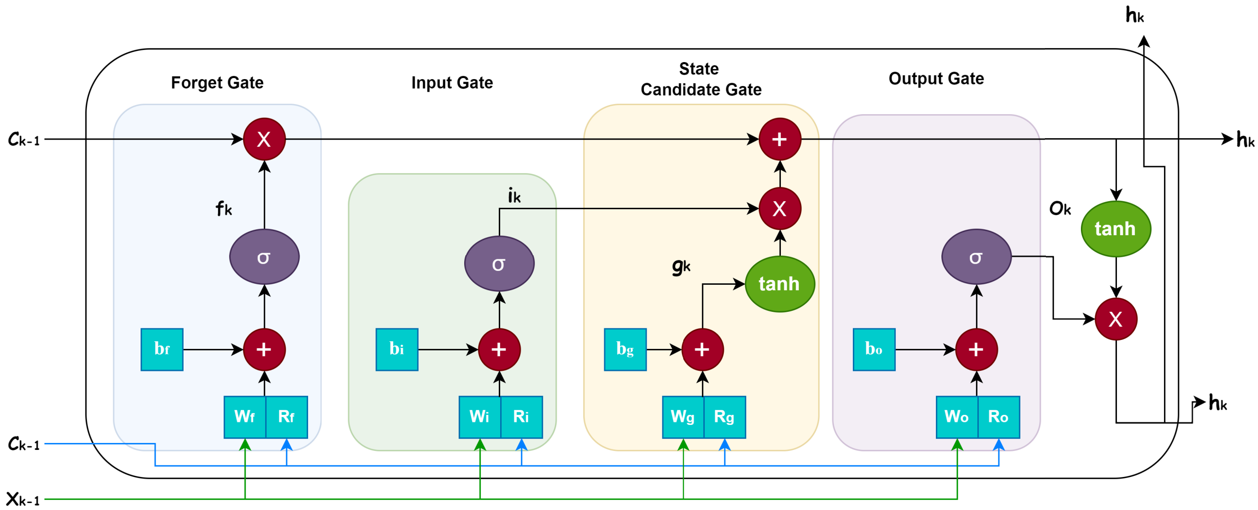

FIGURE 6. The architecture of LSTM.

with neurons in each layer receiving weighted inputs, applying activation functions, and passing their activations onward. During training, the MLP employs backpropagation to adjust connection weights, minimizing the difference between predicted and actual outputs. This iterative process allows the MLP to learn complex relationships within the data, making it a valuable tool for solar power generation forecasting. The sequence of operations within the algorithm is illustrated in Figure 7.

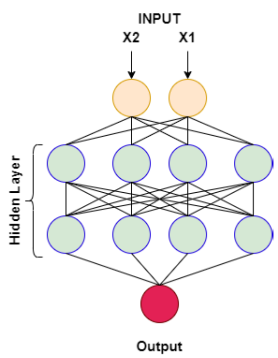

FIGURE 7. Architecture of multi-layer perceptron.

4) GATED RECURRENT UNIT (GRU)

Gated recurrent unit (GRU) is a kind of Recurrent Neural Network RNN and looks like LSTM, but is easier to calculate and use [77]. LSTM and GRU are very similar to each other, but they have some key differences: LSTM contains three gates (input, output, and forget), compared to two for GRU (reset and update). In a GRU, an update gate determines how much of the prior state must be retained, while a reset gate controls how new inputs are integrated with old memory. The input and forget gates in an LSTM perform the same function as the update gate. The ct memory is not present in every GRU gate unit [78]. The workflow of GRU method can be shown in Figure 8.

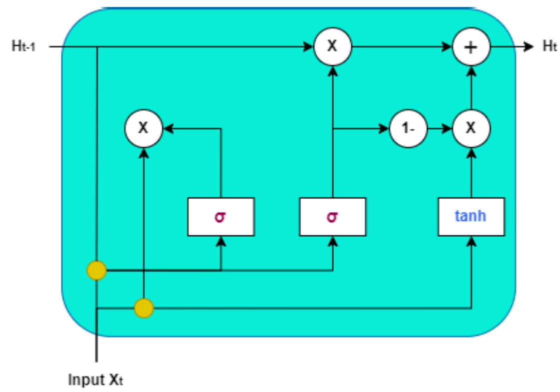

FIGURE 8. Architecture of GRU.

5) TRANSFORMER

The Transformer, introduced in 2017, represents a novel neural network architecture with significant potential for solar power generation forecasting [79]. Unlike traditional architectures that rely solely on recurrent connections, the Transformer leverages a powerful mechanism called "self-attention." This mechanism allows the model to dynamically assess the relative importance of different parts of the input sequence (e.g., historical power data and weather forecasts) during the prediction process. By attending to the most relevant segments of the input, the Transformer can capture complex long-term dependencies within the data, which is crucial for accurate solar power forecasting, especially for tasks requiring consideration of historical trends or seasonal patterns. This self-attention mechanism empowers the Transformer to learn involved relationships within the input sequence, potentially leading to superior forecasting performance compared to previous architectures. The Transformer's workflow is visually represented in Figure 9.

B. STATISTICAL ALGORITHM

The statistical technique uses regression analysis to develop the model. In the solar power generation field, ARIMA and other regression techniques have been used to achieve better performance in solar generation prediction tasks [92]. However, the techniques have limitations in solving non-linear data. This section explains two traditional algorithms, including ARMA and ARIMA.

1) AUTOREGRESSIVE MOVING AVERAGE (ARMA)

Autoregressive Moving Average (ARMA) is a kind of time-series model used in statistical analysis. It can be applied to answer problems involving a lot of historical observed data in the domains of mathematics, finance, and engineering [68]. The Auto-Regressive (AR) and Moving Average (MA) components comprise its two halves. Whereas the MA process smoothes oscillations around a time series' mean, the AR process fits a time series using a linear function of its historical values [69].

2) AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

Autoregressive Integrated Moving Average (ARIMA), an extension of ARMA models, accommodates non-stationary cases. In ARIMA, the non-stationary nature of a time series is addressed by applying finite differencing to the data points, transforming them into a stationary form [66]. ARIMA models come in two variations: non-seasonal and seasonal. A seasonal ARIMA model is employed when the time series data exhibits seasonality. Otherwise, for general cases without seasonality, the non-seasonal ARIMA model is applied [67].

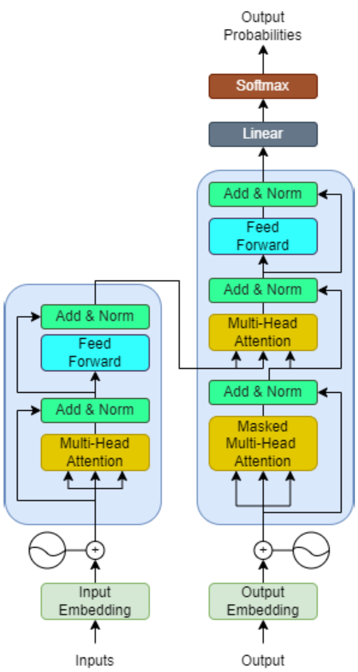

FIGURE 9. **Architecture of transformer network.**

C. PERFORMANCE METRICS

To analyze the accuracy of the forecast model, some metrics are mainly used and calculated such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Normalized Root Mean Squared Error (NRMSE), and Coefficient of Determination (R^2).

RMSE can be calculated given by Equation 8. It provides a global error measure during the entire forecasting period, where p_i represents the actual solar power generation at the i^{th} time step, p is the corresponding solar power generation estimated by a forecasting model, and N is the number of points estimated in the forecasting period [63].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - p_i)^2} \tag{8}$$

The MAE has been widely used in regression problems and by the renewable energy industry to evaluate forecast performance. It is also a global error measure metric, which, unlike the RMSE metric, does not excessively account for extreme forecast events [63]. It can be calculated as shown in Equation 9.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{p}_i - p_i| \tag{9}$$

MAPE measures prediction accuracy as a percentage of the error [64]. It can be calculated as shown in Equation 10.

$$MAPE = \frac{1}{N}\sum_{i}|\frac{p_i - \hat{p}_i}{p_i}| \tag{10}$$

NRMSE measures the average error of higher importance to outliers [64]. It can be calculated given by Equation 11.

$$NRMSE = \frac{1}{p}\sqrt{\frac{\sum_i (p_i - \hat{p}_i)^2}{N}} \tag{11}$$

R^2 is the measure of variability that represents how the model fits the observed data [64]. It can be calculated given by Equation 12.

$$R^2 = 1 - \frac{\sum_i (\hat{p}_i - p_i)^2}{\sum_i (\hat{p}_i - p_i)^2} \tag{12}$$

VII. DISCUSSION

The previous sections defined the PV power generation forecast methods and the several datasets utilized in the previous studies. Solar power generation forecasting has witnessed significant advancements in recent years, with a wide range of methods and techniques being explored. As illustrated in table 10, a comprehensive overview of recent solar power generation forecasting advancements is stated. It includes studies conducted between 2019 and 2024, utilizing various datasets in specific locations and forecasting horizons with diverse methods for solar power forecasting tasks.

TABLE 10. Recent advances methods in solar power generation forecasting.

Author	Year	PV data location	Horizon	Method	Best method	Metric used	Ref
AlKandari M et al	2019	Shagaya, Kuwait; Cocoa, Florida, USA	Not stated	Theta, LSTM, GRU, Auto-LSTM, Auto-GRU, Auto-MLSHM, T-MLSHM, Auto-MLHM, T-MLHM	T-MLSHM	NMAE, NMSE	[120]
Zhou et al	2019	Shaoxing city, Zhejiang, China	Short term	ALSTM, LSTM, PM, ARIMAX, MLP	ALSTM	MAE, RMSE, MAPE	[121]
Chai et al	2019	Zhejiang, China	Ultra short term	Bi-LSTM, LSTM, Time-LSTM, ITER-LSTM, FAF-LSTM, MR-LSTM, MRWE-LSTM, LFA-LSTM, AHPA-LSTM	AHPA-LSTM	MAPE, QRER, RMSE	[39]
Raza et al	2019	University of Queensland (UQ), Australia	Short term	Persistance, BPNN, FNN+PSO, WT+BPNN, WT+FNN+PSO	NNE	MAPE, error variance	[122]
Pan et al	2019	Weather forecasts from European Center for Medium-range Weather Forecasts (ECMWF)	Short term	EM, GBRT, RF, Persistence	EM	NRMSE, NMAE, NMBE, Forecast skill	[123]
Lee et al	2019	Gumi city in South Korea	Short term	Proposed LSTM, LSTM 2, ANN, ARIMA, S-ARIMA, DNN, DNN 2	Proposed LSTM	RMSE, MAE	[126]
Huang et al	2019	Taiwan	Short term	PVPNet, SVM, RF, DT, MLP, LSTM	PVPNet	MAE, RMSE	[74]
Parvez	2020	NREL	Short term	MLP	MLP	RMSE, NRMSE, MAE, NMAE, Min Abs Error, Max Abs Error, r, Score	[5]
Pawar	2020	University of Queensland	Short term	SVR and SVR-GN	SVR-GN	MAPE, MAE, MRE, MBE, RMSE	[55]
Rana	2020	Solar power data from AEMO	Short term	NNs, SVR, RF, CNNs, LSTM	CNNs	MAE, MRE	[56]
Kim	2020	Testing data: PV system in Yeonseong-gun, Gyeonggi-do, South Korea; Historical data: the Korea Open Data Portal	Short term	ELA, EL, LSTM, CNN	ELA	RMSE, MAPE, R^2	[24]
Behera et al	2020	SOA university Bhubaneswar, Odisha, India	Short term	EMD-SCA-ELM, SCA-ELM, EMD-ELM, ELM	EMD-SCA-ELM	RMSE, MAPE, MAE	[124]

Photovoltaic (PV) data is crucial for developing models that predict solar power generation; however, access to specific online datasets is often limited or restricted, posing challenges for researchers who rely on internet sources without institutional support to collect or establish their own PV systems. As detailed in table 2, a selection of datasets is predominantly publicly accessible and available for free download, making it essential to examine data specifications thoroughly before developing a solar power forecasting model. Long-term forecasting requires careful consideration

TABLE 10. *(Continued.)* **Recent advances methods in solar power generation forecasting.**

Author	Year	PV data location	Horizon	Method	Best method	Metric used	Ref
Kharlova	2020	a net zero house in Edmonton provided by Landmark Homes	Short term	Persistence, FFNN-E, FFNN-pdf, LSTM-E, LSTM-pdf, S2S-pdf, S2S-E, S2S-Attn-E, S2S-Attn-pdf	S2S-Attn-pdf	NRMSE, Nme, CRPS, SNRMSE	[85]
Hossain	2020	Desoto solar farm (25 MW) and the city of Arcadia in Florida from NREL	Intra-day (different seasons)	LSTM NN, RNN, GRNN, ELM	LSTM NN	MAE, RMSE, MAPE, MRE	[6]
Zhou	2021	PV data: the University of Macau (UM); Meteorological data: Macau Meteorological and Geophysical Bureau	Short term	LM-ANN, BP-ANN	LM-ANN	R, RMSE, MRE	[59]
Nguyen	2021	Solaw data: California Distributed Generation Statistics website;Historical weather: Long Beach airport, CA	Short term	SVM	SVM	MSE	[60]
Dimitropoulos	2021	the Copernicus database	Short term	LSTM, SVR, MLR, and XGBoost	XGBoost	RMSE, R^2	[57]
Luo	2021	PV data: two PV plants in Australia; Weather forecasts: ECMWF	Short term	PC-LSTM, Standard LSTM	PC-LSTM	MSE, MAE, R^2	[8]
Massoudi	2021	Desert Knowledge Alice Springs Center (DKASC) in Central Australia	Short term	MF, ELM, ET, KNN, DBN, EDBN	EDBN	RMSE, MAE, MAPE, R^2	[86]
Mahmud	2021	Alice Springs from DKA Solar Centre	Short term, Medium term, Long term	LR, PR, DTR, LSTM, SVR, RFR, MLP	-	MAE, MSE, MedAE, EVS, R^2	[87]
Lv	2021	Dunhuang at Gansu Province, China	Short term, Medium term	LSTM, StackedLSTM, Bidirectional, ELM, AutoML	LSTM (Short term), AutoML (Medium term)	RMSE, MAE	[88]
Kim	2021	PV data of Texas, USA from NREL	Short term	Proposed Transformer, LSTM, 1D-CNN, L.R.	Proposed Transformer	MAE, RMSE, PCC, R^2	[89]
Junhuathon	2021	a 14 MW solar cell system located in Northeastern region of Thailand	Short term	LSTM, FNN, NARX	LSTM	RMSE, MAE, MAPE	[90]
Guo	2021	Gaotang County, Shandong Province	Short term	BP, PSO-BP, PCA+PSO-BP	PCA+PSO-BP	NMAPE, NRMSE	[91]

TABLE 10. *(Continued.)* Recent advances methods in solar power generation forecasting.

Author	Year	PV data location	Horizon	Method	Best method	Metric used	Ref
Ma	2021	PV data from The Supervisory Control and Data Acquisition (SCADA) system	Short term	Elman, FA-Elman, MFA-Elman	MFA-ELMAN	MAE, MSE, RMSE	[125]
Fara	2021	Polytechnic University of Bucharest, Romania	Short term	ARIMA, ANN	ARIMA	rRMSE	[92]
Anuradha	2021	India	Short term	SVMR, LR, RFR	RFR	RMSE, MAE, MSE, Accuracy	[93]
Alam	2021	University of Queensland campus	Short term, Medium term	CNN, Multi-headed CNN, CNN-LSTM, ARMA, MLR	CNN-LSTM	RMSE, MAE, MBE	[94]
Agga	2021	a 15kW PV plant registered over two years. Location is not stated	Short term	CNN, CNN MH, CNN MC	CNN MC	MAE, MAPE, RMSE	[95]
Akhter	2022	University of Malaya, Malaysia	Short term	RNN-LSTM, ANN, SVR, ELM, SVR (PCA)	RNN-LSTM	RMSE, R^2	[53]
Elsaraiti	2022	Nova Scotia Community College in Halifax, Canada	Short term	LSTM and MLP	LSTM	MAE, MAPE, RMSE, R^2	[62]
Yao	2024	PVODataset in Hebei, China	very short term	ARIMA, SVR, FC-LSTM, ST-GCN, GMAN, No-DF, GSTANN-S, GSTANN	GSTANN	MAE, RMSE, MAPE	[96]
Li	2022	Xinjiang, China	Multi-step Short term	GRU, CNNLSTM, CNNGRU, K-GASVM, KHCG, HTSCG	HTSCG	RMSE, MAE, R^2	[26]
Karamdel	2022	São Paulo, Brazil	Short term	19 regression models	Interations LR, Stepwise LR, Medium Gaussian SVM, ensemble of bagged trees	RMSE, R^2, MSE, MAE	[97]
Piotrowski	2022	NA	very short term	MLP, WAE, RF, IT2FLS, KNNR, LR, SVR, GBT, NAIVE	MLP	RMSE, NMAPE, nAPEmax, MBE	[98]
Xiao	2022	Gansu Province	Short term	LSTM, BiLSTM, Prophet-LSTM, Prophet-BiLSTM, NP-LSTM, NP-BiLSTM	NP-BiLSTM	RMSE, MAE, MAPE, SMAPE	[99]
Theocharides	2022	Outdoor Test Facility (OTF) of the University of Cyprus (UCY)	Short term	Hourly modelling methodology, BRNN	Hourly modelling Methodology	MAPE, RMSE, NRMSE	[100]
Xie	2022	Solar Radiation Monitoring Laboratory, University of Oregon, Ashland, Oregon, USA	Ultra short term	CNN, CNN-GRU, LSTM, GRU	CNN-GRU	NMAE, NMAPE, NRMSE	[101]

TABLE 10. *(Continued.)* **Recent advances methods in solar power generation forecasting.**

Author	Year	PV data location	Horizon	Method	Best method	Metric used	Ref
Tian	2022	First dataset: the household microgrid in Hebei; Second dataset: the public DC competition dataset	Ultra short term	Transformer, GRU, DNN	Transformer	MAE, MSE, MAPE	[102]
Zazoum	2022	Port Harcourt	Not stated	SVM, GPR	GPR	RMSE, MAE, R^2	[103]
Montoya	2022	Ashland, Oregon	Short term	ENN, ELM, LSTMNN	LSTMNN	MAPE, NMAE,, NRMSE	[104]
Abubakar Mas'ud	2022	the King Abdullah City for atomic and renewable energy (KACARE).	Short term	MLR, KNN, DTR	KNN	MAE, RMSE, NRMSE, R^2	[105]
Luo	2022	Australia	Short term	AD-LSTM, OL-LSTM	AD-LSTM	MAE, MSE, R^2	[127]
Li	2022	Jinzhai	Short term	SVM, LSTM, Optimized LSTM	Optimized LSTM	RMSE, MAE	[106]
Kuo	2022	Taoyuan City, Taiwan	Short term	LSTM, GRU, ANN	LSTM	MAPE, MAE, RMSE	[107]
Khan	2022	PV data: Netherlands; Weather data: Solargis	Short term	ANN, LSTM, Bagging, DSE-XGB	DSE-XGB	R^2, RMSE, MAE	[108]
Hussain	2022	DKASC-AS-1A, DKASC-AS-1B, DKASC-AS-2Eco, and DKASC-Yulara-SITE-3A gathered in DKASC, Alice Springs (AS), Australia	Short term	DT, SVR, LSTM, GRU, CNN-LSTM, CNN-GRU, LSTM-CNN, GRU-CNN	GRU-CNN	RMSE, MSE, MAE, MBE	[29]
Gupta	2022	PV data from kaggle repository	Medium term	FB Prophet, XG Boost	XG Boost	MSE, MAE, MAPE	[109]
Das	2022	PV data from Malaysia and online weather data	Short term	PSO Optimized, GA-SVR, SVR, ANN, GPR	PSO Optimized	NRMSE, mape, Error(Max), Error(Avg)	[110]
Chen	2022	China	Short term	LSTM, GRU, TCN	LSTM	MAE, RMSE, MAPE	[111]
Bensalem	2022	Djelfa state, Algeria	Short term	LSTM, ARMA	LSTM	RMSE	[42]
Alharkan	2023	DKASC Alice Spring	Short term	DSCLANet, CNN, LSTM, GRU, CNNLSTM, CNNGRU	DSCLANet	MSE, MAE, RMSE	[40]
M. Al-Ali	2023	The Fingrid open dataset (Finland)	Short term	Combined LSTM, CNN, and Transformer	Combined LSTM, CNN, and Transformer	MAPE, RMSE, MAE	[30]
Phan	2023	Data collected by Central Weather Bureau (CWB) of Taiwan	Short term	Transformer, ANN, LSTM, GRU, XGBoost	Transformer	NMAPE, NRMSE	[58]
Jeong	2023	Suncheon, South Korea	Short term	RNN, GRU, LSTM, and Transformer	Transformer	MSE, MAE	[61]
Rangelov	2023	Berlin, Germany	Short term	RF, DNN, and LSTM	DNN	MAE, MSE, RMSE	[52]
Ledmaoui	2023	Benguerir city of Morocco	Long term	SVR, ANN, DT, RF, GAM, XGBoost	ANN	RMSE, MAE, MASE, R^2	[112]

TABLE 10. ***(Continued.)*** **Recent advances methods in solar power generation forecasting.**

Author	Year	PV data location	Horizon	Method	Best method	Metric used	Ref
Scott	2023	University campus, central Manchester	Short term	RF, NN, LR, SVM	RF	RMSE	[113]
Sharkawy	2023	Egypt	Not stated	MLFFNN, RNN, NARXNN	MLFFNN	MSE, RMSE	[114]
Heydari	2023	Chalokwa, Zambia	Short term	LSTM-MOPSO, LSTM-NSGA-11	LSTM-NSGA-11	RMSE, MAE, TIC, R	[43]
Fungtammasan	2023	University of Queensland (UQ) dataset and Sanyo dataset in Australia	Short term	P, MLP, RNN, LSTM, CNN, LSTM-Conv	LSTM-Conv	MAE, RMSE	[37]
Dehghan	2023	Germany	Short term	Conv2D, Conv3D, LSTM, BiLSTM, Conv-LSTM, ConvLSTM	Conv3D-BiLSTM	NRMSE, MAPE	[115]
Yang	2024	Northern China	Short term	ARIMA, SVR, LSTM, ConvLSTM, STLAN, K-means+SVR, K-Means+TF, K-Means+C-LSTM	STLAN	MAE, RMSE	[116]
Lee	2024	Jeongseon County, Gangwon Province	Ultra-Short term	LSTM, Seq2seq, TF, CNN_LSTM, FF, SCINet, Dlinear, DC_LSTM, DC_TF	DC_TF	MSE, MAE, EMAPE	[117]
Sulaiman	2024	India	Short term	EMA-DNN, DE-DNN, MO-DNN, PSO-DNN, HAS-DNN, DNN(ADAM), NARX	EMA-DNN	RMSE, MAE, MAX	[118]
Marques	2024	Amazonas, Brazil	Short term	MLP, LSTM2, LSTM_GRU	LSTM_GRU	MAE, MAPE, RMSE	[119]

of the appropriate period for training data; for instance, the study referenced in [120] utilized both short-term and long-term datasets, sourced from their collection and public access through IEEE Dataport, covering data from 2014 to 2018, which provided a suitable basis for training a long-term forecasting algorithm. In another study, Yao et al. employed the PVODataset to investigate very short-term forecasting [46], with PVOD offering a temporal resolution of 15 minutes and data from 2018 to 2019. Yao et al. organized the training data chronologically, splitting it into 80% for training and 20% for testing over every five days, ensuring the test set is evenly distributed and avoiding training in summer while testing in winter [96].

Solar power generation forecasting in different seasons has been investigated [6]. Hossain et al. utilized hourly historical weather data from Desoto solar farm data and the city of Arcadia in Florida downloaded from the NREL website for the period of 2012-2018. This study employed the K-means algorithm to classify historical irradiance data into distinct dynamic types of the sky for each hour of the day during the same season. Another study referenced as [47] employed a model trained on the SKIPP'D dataset, integrating convolutional layers, Max pooling, batch normalization, filters, and fully connected layers within its architecture. SKIPP'D dataset contains PV power generation data, sky images, and sky videos. However, this model exhibited limitations in accurately forecasting power generation during cloudy conditions, indicating the need for further refinement.

Data preprocessing is key to refining and enhancing the quality of a dataset, significantly impacting the accuracy of predictions. Solar power generation data is often raw and unprocessed, with noisy and missing values that can be addressed through data preprocessing and feature engineering. For instance, partial and Pearson correlation coefficients are used to select the most influential variables for the model [115]. Das et al. handled missing data by filling in gaps with values from corresponding days within the same timeframe, identifying solar irradiance, humidity, and temperature as the most relevant variables from a PV dataset using Pearson's and Spearman's correlation coefficients [57]. Additionally, Xie et al. preprocessed PV data in Oregon using an isolated forest algorithm to detect outliers and Multiple Imputations by Chained Equations (MICE).

Following data preprocessing, an important consideration for achieving the study's objectives is selecting a suitable forecasting horizon for the algorithm. Tables 10 show that studies conducted between 2019 and 2024 indicate that short-term solar power generation forecasting is the predominant focus. For example, Zhou et al. and Pan et al. concentrate on short-term forecasting using various methodologies. While short-term forecasting is prevalent, some studies explore long-term and very short-term forecasting horizons. Long-term forecasting is essential for planning and investment decisions in the renewable energy sector; for instance, Lesmaoui et al. focus on long-term forecasting using SVR, ANN, DT, RF, GAM, and XGBoost. Their results indicate that ANN outperformed the other models for long-term solar power forecasting in Morocco. In contrast, very short-term forecasting is critical for real-time grid operations, as investigated by Piotrowski et al., who demonstrated that MLP achieved higher performance than the other trained models.

A diverse array of forecasting methods have been explored, including physical models, machine learning algorithms, statistical models, and hybrid approaches. Early studies primarily utilized statistical methods such as ARIMA for time series forecasting. For instance, Fara employed ARIMA alongside ANN (Artificial Neural Networks) for short-term forecasting and utilized data location in Romania, proving that ARIMA was more efficient than ANN. Moreover, another investigation deployed the XGBoost algorithm with the UNISOLAR dataset, aiming to analyze the impact of weather parameters on solar power generation [49]. The findings explained that the model trained on data from the summer season yielded the lowest error rates compared to other seasons, underscoring the significance of season-specific training data. Hossain et al. investigated different horizon lengths in different seasons using LSTM NN, and Synthetic weather forecasts achieved higher accuracy. However, this paper proved that autumn and winter achieved the lowest error than spring and summer seasons [84]. Previous studies cited showed that solar power generation forecasting accuracy depends on the weather parameters and affects the research purpose.

In addition, expanding upon the insights gleaned from previous statements, it becomes evident that the efficacy of PV power generation forecasting relies not only on the quality of the datasets employed and forecasting horizon but also on the adaptability of the underlying algorithms. While CNN has shown promise in capturing spatial dependencies within PV datasets, as evidenced by the utilization of convolutional layers in [47], their performance may weaken under certain meteorological conditions, such as cloud cover, as noted in the same study. Furthermore, a significant number of studies employing Long Short-Term Memory (LSTM) networks for solar power generation forecasting [6], [8], [24], [29], [30], [37], [39], [40], [42], [43], [52], [53], [56], [57], [58], [61], [62], [85], [87], [88], [90], [94], [96], [99], [101], [104], [106], [107], [108], [111], [115], [116], [117], [119], [120], [121], [124]. LSTM is popular due to its ability to handle time-series data and learn long-term dependencies. For instance, AlKandari et al. compare LSTM with other methods like GRU and Auto-LSTM, while Chai et al. use LSTM with adaptive hyperparameter adjustment. Besides AI-based methods, hybrid and ensemble learning methods have played essential roles in the recent advances in the past few years. In 2019, ensembled models named T-MLSHM were developed based on deep learning and statistical learning methods [119].

Moreover, a study has developed a hybrid learning which proposed a combined Bi-Directional Long Short-Term Memory (BD-LSTM) model and an Artificial Neural Network (ANN) model [24]. In 2021, a hybrid learning method that integrates Principal Component Analysis (PCA) and Particle Swarm Optimization (PSO) with a Back Propagation (BP) neural network was developed [91]. This combination is aimed at enhancing the accuracy of photovoltaic power generation predictions. The ensemble learning method combines three-dimensional convolution (Conv3D) networks with bidirectional long short-term memory (BiLSTM) networks [37]. This approach is designed to learn the non-linear spatial-temporal relationships between inputs and outputs automatically. In 2024, [116] combined data decomposition, linear models, Transformer models, LSTM networks, and CNN-LSTM architectures, allowing the model to address the complexities of the data involved effectively.

Various metrics are employed to evaluate forecasting models' performance, including MAE, RMSE, MAPE, NRMSE, and R^2. These metrics are crucial for comparing different methods and identifying the best-performing models. As referred to [62] and [97], these metrics assessed the accuracy, reliability, and suitability of forecasting models for solar power generation. In [62], LSTM models were evaluated using MAE, MAPE, RMSE, and R^2, while in [97], nMAPE, nAPEmax, and MBE were used to assess the performance of prediction methods for microgrid applications.

Solar power generation forecasting is rapidly evolving, with continuous advancements in methods and techniques. By carefully considering factors such as dataset selection and quality, forecasting horizon, and evaluation metrics, researchers can select the most appropriate approaches to contribute to the progress of this critical field.

VIII. CHALLENGES AND FUTURE WORK

Accuracy and reliable solar power generation forecasters are necessary in the deployment stage. Besides, there are huge challenges, and future work is needed to improve and innovate in the solar energy area. Challenges and future work are listed below:

1) Weather Conditions: The performance of solar PV systems is heavily dependent on weather conditions, which are subject to change and can affect the accuracy of power forecasts. Preprocessing and selecting variables highly correlated with power generation is recommended for further research.

2) Forecasting Horizons: Select a specific forecast horizon to be studied to accomplish the research's purpose and objective.
3) Data Availability and Quality: The availability and quality of historical PV power generation data and weather forecasts are crucial for training accurate and reliable Machine Learning models. Providing comprehensive dataset sources and descriptions would benefit future research.
4) Model Generalization: Models trained on data from specific locations may not perform well when applied to other locations due to differences in climate and solar PV system configurations. Future work will establish strategies to enhance model generality across various sites while considering climate and solar PV system design variables.
5) Robustness and Versatility: To guarantee dependable performance, looking at the forecasting models' flexibility and robustness is critical.
6) Performance Metrics: Using consistent and accurate performance metrics for fair comparisons between different ML models is challenging, especially when operating on different scales of PV systems. Therefore, future research should focus on selecting suitable objectives and metrics.
7) Hyperparameter Optimization: Optimizing ML model hyperparameters to achieve the best performance can be computationally intensive and time-consuming. Exploring efficient methods through literature review to shorten the process of hyperparameters optimization.
8) Comparison with Existing Literature: Developing standardized benchmarks and methodologies to facilitate meaningful comparisons of ML model performance across diverse studies in the solar power generation field.
9) Suitable Algorithm for the Grid: Implementing the relevant and reliable algorithms on the embedded platform will bring grid dispatching closer to its actual demands.
10) Explore Diverse Algorithms: Testing and validating the hybrid model on other machine learning models and statistical methods. It is necessary to explore techniques that increase the variety within the data used to train the model. This could involve dividing the training data by different parameters or introducing more variation in the data itself. Developing other ensemble techniques that combine multiple models to improve forecasting accuracy.
11) Efficient and Effective Method: Addressing model complexity through a single architecture for extracting diverse features and producing a high-performance model at the same level as hybrid models.

IX. CONCLUSION

The field of solar power forecasting remains dynamic and ever-evolving, driven by the need to employ the potential of renewable energy sources. Over the years, significant strides have been made in developing and applying methods and algorithms to provide accurate and reliable forecasts in this research area. Despite these advancements, one persistent challenge has been the need for real-world deployment on a large scale, specifically for solar power generation forecasting research. This limitation has underscored the importance of establishing robust systems that can facilitate rigorous comparative analyses and benchmarking forecasting methodologies.

In this study, we have attempted to address this challenge by presenting and categorizing forecasting methods, identifying relevant datasets, exploring recent advancements, and comparing their advantages. Purposely empowering researchers in solar power generation forecasting to choose the most effective technique for specific research questions, providing a one-stop resource for navigating this dynamic field. To further expand on this foundational study, future research could involve a more comprehensive review of solar power generation forecasting methods. This in-depth analysis could analyze each classification, including statistical methods. Detailed review for forecasting based on area scales (single, regional), forecast horizon (very short-term, short-term, medium-term, long-term), direct and indirect approaches, deterministic and probabilistic approaches, and time step (hourly, daily, monthly) would be valuable.

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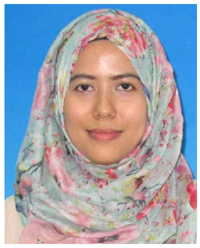

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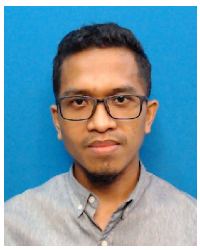

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