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Review

Investigating the Power of LSTM-Based Models in Solar Energy Forecasting

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Abstract: Solar is a significant renewable energy source. Solar energy can provide for the world's energy needs while minimizing global warming from traditional sources. Forecasting the output of renewable energy has a considerable impact on decisions about the operation and management of power systems. It is crucial to accurately forecast the output of renewable energy sources in order to assure grid dependability and sustainability and to reduce the risk and expense of energy markets and systems. Recent advancements in long short-term memory (LSTM) have attracted researchers to the model, and its promising potential is reflected in the method's richness and the growing number of papers about it. To facilitate further research and development in this area, this paper investigates LSTM models for forecasting solar energy by using time-series data. The paper is divided into two parts: (1) independent LSTM models and (2) hybrid models that incorporate LSTM as another type of technique. The Root mean square error (RMSE) and other error metrics are used as the representative evaluation metrics for comparing the accuracy of the selected methods. According to empirical studies, the two types of models (independent LSTM and hybrid) have distinct advantages and disadvantages depending on the scenario. For instance, LSTM outperforms the other standalone models, but hybrid models generally outperform standalone models despite their longer data training time requirement. The most notable discovery is the better suitability of LSTM as a predictive model to forecast the amount of solar radiation and photovoltaic power compared with other conventional machine learning methods.

Keywords: solar irradiance forecasting; renewable energy; photovoltaic power forecasting; long short-term memory; hybrid model; deep learning

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1. Introduction

The primary focus of the energy industry in recent years has been on reducing carbon emissions by shifting to renewable energy sources. Excessive carbon emissions negatively affect the environment, leading to further global warming and climate change. Additionally, industrialization has substantially accelerated the growth of the world's demand for energy, causing the supply of nonrenewable energy sources, such as coal, natural gases, and petroleum, to be increasingly constrained. Given this circumstance, many countries have crafted and subsequently implemented policies and strategies associated with the energy sector. In 2015, the USA and China jointly issued a statement addressing climate change. The statement emphasized new domestic policy commitments aimed at achieving 100% dependency on renewable energies [1]. Furthermore, the European Union plans to use renewable energy sources to generate 30% of electricity by 2030 and 100% of electricity by 2050 [1,2].

Among the promising renewable energy types, solar energy is the most recognized and widely used around the world. This situation is especially true among countries with developed economies [2]. Regarding the incorporation of renewable energy sources into grids, the majority of studies have concentrated on the development of photovoltaic (PV) systems rather than the incorporation of other forms of renewable energy, such as wind energy, biomass, and other forms. However, the characteristics of solar energy, such as uncertainty, fluctuation, and randomness, may lead to dynamic instability and unpredictability of solar PV power output [3,4]. Given this difficulty, techniques for accurately predicting the amount of solar irradiance should be pursued to provide important decision support to power-dispatching systems. More importantly, the search for appropriate methods can considerably minimize the running cost of power systems [5].

Solar energy is gaining popularity as a renewable energy source due to its environmental benefits and abundance. However, integrating solar energy into the power grid is challenging due to its intermittent and uncertain nature. To accurately forecast solar irradiance and PV power output, it is crucial to consider parameters such as spatial and temporal correlations, which affect the accuracy of the predictions. Spatial correlations refer to the relationship between the geographical location of PV systems and the weather patterns of that region. On the other hand, temporal correlations refer to the time-series relationship of the solar irradiance and PV power output data. Other parameters, such as cloud cover, atmospheric conditions, and the time of day, can also influence the forecasting accuracy. Therefore, incorporating these parameters into forecasting models is crucial.

In forecasting studies, there are several major techniques that have been applied, such as statistical methods, physical methods, machine learning methods, and ensemble methods [4,6]. Commonly, the performance of each technique depends on the forecast horizons and input parameters. Forecasting analysis parameters such as spatial–temporal (spatial and temporal refer to space and time, respectively) correlation play a main role in improving the accuracy and require large-scale datasets [7]. Further investigations of spatial and temporal correlation, which combines with other solar data sources, are important for solar energy forecasting such as PV power generation forecasts [8,9] because having a large size of the dataset may lead to high accuracy despite its complexity.

Several studies have demonstrated the ability of long short-term memory (LSTM) methods to improve the forecasting accuracy of time-series statistical techniques. Nonetheless, to the best of our knowledge, no research has been conducted to comprehensively review LSTM either as a standalone model or as part of a hybrid model with respect to solar irradiance forecasting and PV power forecasting. The aim of this study is to analyze LSTM and hybrid models (i.e., those with LSTM) and compare their performance with those of other solar irradiance forecasting and PV power forecasting techniques as a means of gaining insights into their various mechanisms and applications. The main contributions of this review are as follows:

- Analyze and compare the relevant papers that have been proposed and discussed LSTM models on solar irradiance prediction.
- Identify better models among standalone and hybrid models of LSTM to predict solar irradiation and PV power by comparing the features of prediction parameters.
- Discuss in depth regarding the characteristics and mechanism of LSTM and how it is able to integrate with other methods to improve the performance of solar prediction accuracy.

The remainder of the paper is organized as follows: Section 2 describes the previous studies about solar irradiance and PV power forecasting techniques. Sections 3 and 4 present an in-depth discussion of the history of LSTM and hybrid models. Section 5 summarizes the evaluation metrics used to demonstrate the performance of the forecasting models. Section 6 provides an examination of relevant published studies in terms of several characteristics. Section 7 summarizes the findings of this study.

2. Related Works

Technological advancements have contributed significantly to the adoption of machine learning (ML) and ensemble methods for forecasting solar irradiance with high accuracy.

Among them, deep learning (DL) algorithms have enabled the mining of multilayer information from PV power series in addition to improving forecasting accuracy [10,11]. However, extant models underestimate the effects of weather on PV power output, and they cannot effectively capture the short-term variations in PV power across different climates. Significant fluctuations in solar PV power output occur on cloudy and wet days, and historical PV data representing these days cannot be used for forecasts. Interestingly, hybrid DL models may be used to solve these problems [11].

Guermoui et al. [12] compared different hybrid models according to their respective characteristics and ranked their performance. They classified the hybrid models into six types: general ensemble learning, cluster-based ensemble learning, decomposition-based ensemble learning, decomposition–clustering-based ensemble learning, evolutionary-based ensemble learning, and residual-based ensemble learning. In their study, the hybrid models outperformed the standalone models. However, the performance comparison was somewhat insufficient because the models were reviewed by simply focusing on their various characteristics using metric assessments.

Kumari et al. [13] reviewed standalone models (i.e., LSTM, convolutional neural network (CNN), gated recurrent unit (GRU), recurrent neural network (RNN), and deep neural network (DNN) models), and a hybrid model (CNN–LSTM), which have been recently used to forecast solar irradiance in terms of their working mechanisms and benefits and drawbacks. According to their simulation results, LSTM outperforms the other standalone models as evidenced by its low root mean square error (RMSE). However, the performance of solar irradiance forecasting can be further improved by integrating LSTM into a hybrid model (i.e., CNN–LSTM); this hybrid model is superior even to the standalone models in terms of error reduction. Kumari et al. [13] suggested comparing CNN–LSTM with other hybrid models.

Rial et al. [14] comprehensively reviewed DL models in terms of their ability to forecast the time-series data of solar irradiance and PV power. They examined published studies pertaining to three standalone models (RNN, LSTM, and GRU) and a hybrid model (CNN–LSTM) to assess each model's contributions. They also compared the performance of the models in terms of their characteristics, such as accuracy, input data, forecasting horizon, season and weather type, and training time. The results of their performance analysis showed that LSTM outperforms the other standalone models in terms of RMSE. However, the hybrid model (CNN–LSTM) obtained the highest accuracy among the models studied in terms of forecasting solar irradiance and PV power. Meanwhile, Tawn and Browell [15] focused on the accuracy of very short-term solar power forecasting by examining several approaches, including image-based, probabilistic, and ML methods. Different assessment metrics, such as the mean absolute error (MAE) and RMSE, were used to evaluate the performance of the forecasting models.

Ahmed et al. [16] assessed state-of-the-art models used for PV solar power forecasting. Their input correlational analysis showed that solar irradiance is strongly linked to PV production, further suggesting the urgent need to study weather and cloud motion. They found that normalization, wavelet transform, and generative adversarial networks, which are used for network training and forecasting, are the best approaches to clean forecasting data. They also highlighted the ability of genetic algorithms and particle swarm optimization to optimize inputs and network parameters. Then, they reviewed the use of established performance measures (MAE, RMSE, and mean absolute percentage error (MAPE)) and recommended the incorporation of economic utility indicators. Finally, on the basis of their evaluation and comparative results, they classified the modeling methodologies into physical, statistical, artificial intelligence (AI), ensemble, and hybrid approaches.

Wang et al. [17] explored the use of AI for solar energy prediction—a topic that is rarely reviewed—by examining previously published studies that attempted to review the contributions of different models. Undeniably, their research has contributed considerably to the taxonomic research of existing AI-based solar power prediction models. In their study, taxonomy is defined as the systematic grouping of solar energy forecasting methodologies, optimizers, and forecasting frameworks based on their differences and similarities. In AI systems for solar energy prediction, ML, DL, and fuzzy logic are all commonly used. Their work showed that the performance of a predictive model (i.e., DL-based LSTM, with low RMSE) is better than those of other models. Meanwhile, Dodiya and Shah [18] proposed the use of DL in the development of solar PV energy. Some of the DL models they investigated were the multilayer perceptron (MLP), CNN, LSTM, GRU, RNN, support vector machine (SVM), and deep RNN–LSTM. They also discussed the application areas, model types, and MAPEs and summarized the related studied models.

LSTM models has also been applied on various domains in terms of prediction models. Noman Khan et al. [19] proposed a forecasting model to predict the renewable energy (RE) generation for short-term horizons. The proposed model was an AB-Net model, a hybrid model of autoencoder (AE) and bidirectional long short-term memory (BiLSTM). The input data deployed were solar and wind power generation data. For the solar dataset, the input variables for the 3 years and 10 months data were inclined irradiance, surrounding temperature, and surface temperature, while the input variables of the wind dataset were power, wind speed, wind direction, surface air pressure, air temperature, and air density. The performance of the proposed model for both solar and wind datasets have outperformed the fine-tuning metaheuristic algorithm (FTMA), which was used for comparative study. Other than that, a short-term electricity load prediction model has been studied by Fath et al. [20], where the prediction accuracy was obtained by evaluating the performance of several ensemble learning algorithms and deep learning methods. The household power consumption dataset was used as input for the proposed model. From the result, multiple LSTM (M-LSTM) has outperformed other models such as LSTM and BiLSTM for different horizons: minutely, hourly, daily, and weekly.

In summary, the studies cited above generally discussed the LSTM model and related hybrid models in various domains; as illustrated in Table 1, some of these studies failed to provide enough details about the models. Nonetheless, as the LSTM model has been demonstrated to be capable of predicting solar power, the standalone and hybrid models of LSTM, as well their uncovered and partially covered criteria (see Table 1), should be further investigated.

Table 1. Summary of related works of solar energy predictions.

Ref.	Criteria			
	LSTM	**Hybrid Model**	**Evaluation Metrics**	**Analysis of Past Studies**
[8]	X	–	√	X
[9]	–	√	√	X
[10]	√	–	√	√
[11]	–	–	√	√
[12]	X	–	√	√
[13]	–	√	√	√
[14]	–	–	–	√

Note: X means not covered, − means partially covered, and √ means fully covered.

3. LSTM

The feed-forward neural network (FFNN), also known as MLP, is a fundamental type of deep learning architecture. In Figure 1, we can see the structure of the MLP with its three layers, namely, the input layer, hidden layer, and output layer. The input layer receives the input data, the hidden layer processes the input and produces an intermediate representation, and the output layer produces the final output. This figure helps to illustrate the basic structure of the MLP, which is important to understand as it forms the basis for more complex deep learning models. MLPs are utilized frequently in power systems as a method for protecting transmission lines, detecting faults in transformers, and monitoring online voltage stability [21].

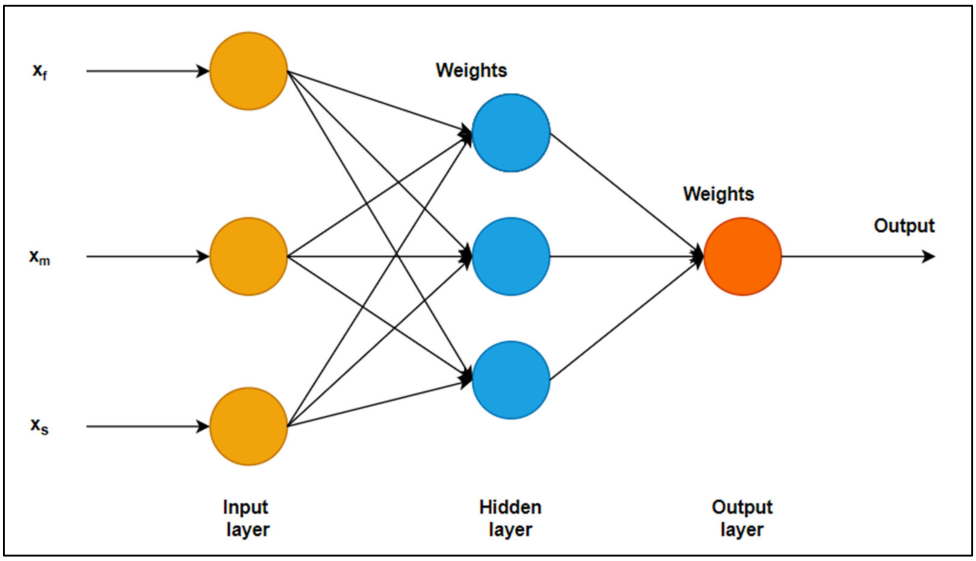

Figure 1. FFNN model [22].

In the context of forward neural networks (FNNs), data travels from the input layer to the output layer via the hidden layers arranged between them, as shown in Figure 1. Figure 2 illustrates the information being sent linearly from one side of the diagram to the other side, but the lines never return to any particular node or layer. In addition, a certain node only receives input once, and never again after that. This pattern of information sharing indicates that an FNN involves memory loss, with only the most recent input and training instructions remembered. Thus, unless prior information is supplied, the strategy supplied by FNNs is not beneficial for forecasting or prediction.

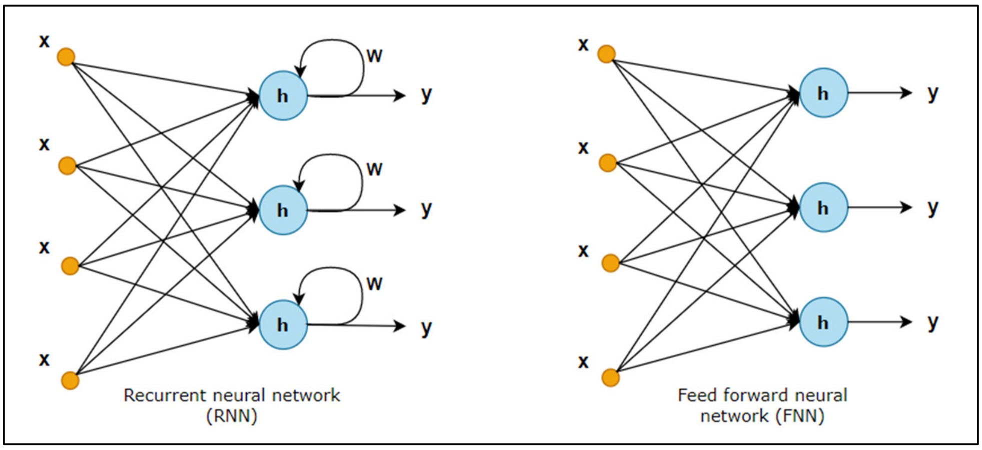

Figure 2. RNN vs. FNN [19]. x: input, y: output, w: h: hidden layer, w: loop.

Figure 2 shows a comparison between RNNs and FNNs, with loops shown in the hidden layers (blue circles) of the former. In the hidden layers, information is repeated several times, implying memory gain, as shown in Figure 3. The decision regarding the handling of data is determined based on the current state input and the prior output. For example, the irradiation data of a particular date or time can be anticipated by inputting the result from the previous time step into the current time step [14,21]. This scheme can also be adopted for other data types. Furthermore, in contrast to FFNNs, RNNs are more similar to human synapses, as humans tend to learn in progressive sequences rather than random sequences [23]. Thus, the RNN is the optimal choice for predictive models.

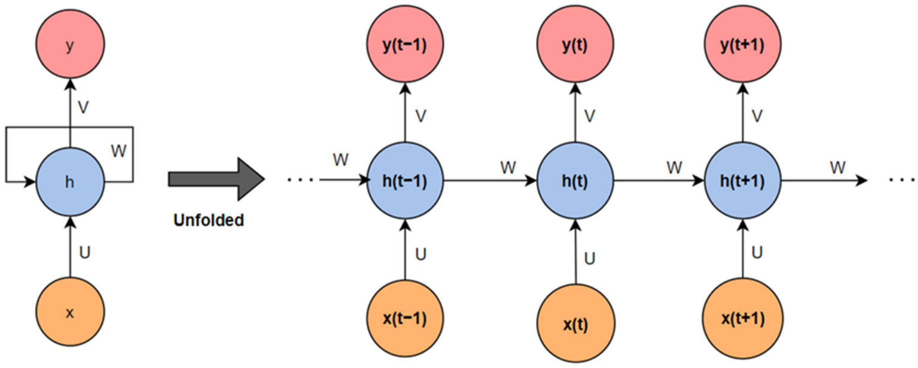

Figure 3. Structure of an RNN with unfolded architecture [19].

LSTM is a type of RNN. Therefore, similar to the RNN, an LSTM network can perform calculations with a sufficient number of network elements. Figure 4 shows the structure of the LSTM cell, which consists of three different gates: the forget gate, input gate, and output gate. The memory cell, which acts as a collector of state information, is the distinguishing element of LSTM networks. When the input gate is triggered, new information is collected in the cell; by contrast, when the forget gate is triggered, previous information is erased. In the feedback loop, the sigmoid function determines which information should be forgotten or retained in the memory cell, and the hyperbolic tangent function controls the input and output to the cell. The combination of these functions allows the LSTM to selectively remember or forget information, making it effective in handling time-series data and generating predictions. In LSTM networks, the latest cell is propagated to the final step only when the output gate is triggered. This LSTM-specific cell behavior prevents the gradients trapped in the cell from rapidly disappearing; this feature implies the better performance of LSTM in handling time-series data and generating predictions compared with other RNN designs [24].

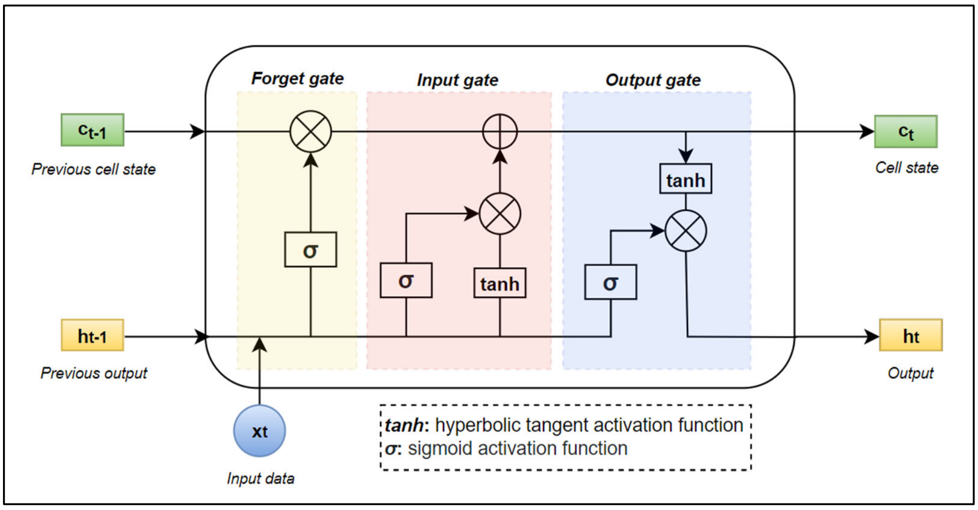

Figure 4. Structure of internal LSTM cell [25].

4. Hybrid Models

A hybrid model combines a DL model with another DL model. In this study, a hybrid model refers to LSTM combined with other DL or ML methods to improve forecasting accuracy. Hybrid models involve two important characteristics: spatial features and temporal features. Most of the studies in the literature we reviewed used LSTM and combined it with CNN to forecast solar irradiance and PV power. CNNs can be regarded as FFNNs. Figure 5 shows the CNN structure, which consists primarily of a convolutional layer, a pooled layer, and a fully connected layer [14]. In the convolutional layer, the convolution operation is deployed to extract features from previous layers [26]. Through this process, an activation function is used to generate the output of feature maps. To reduce the parameters of the CNN, the mean and maximum values of pooling for the selected area in feature maps are evaluated in the pooling layer [22,26]. Then, the combination of the feature maps obtained after going through the process in convolutional and pooling layers generates the input data for the fully connected layer [26]. Lastly, the output can be obtained through the calculation of final output vector [26].

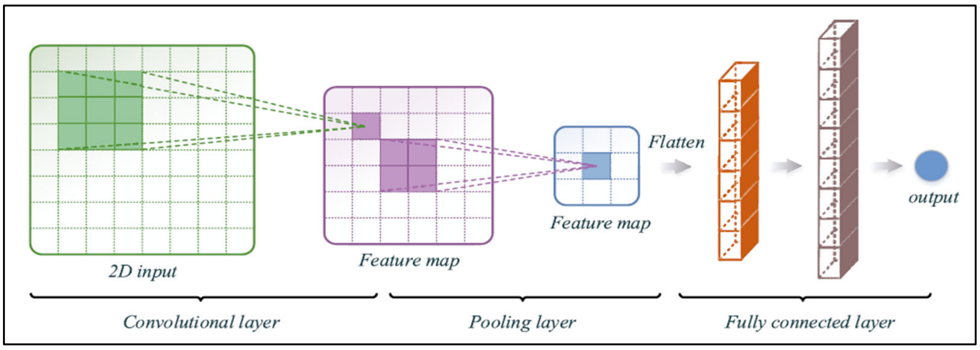

Figure 5. Basic structure of a CNN [26].

Take CNN–LSTM and LSTM–CNN as examples of hybrid models. The arrangement of the two inputs (i.e., spatial and temporal features) for extracting historical data differs between the two hybrid models, as shown in Figures 6 and 7. The LSTM network is commonly used to extract temporal feature information from historical data, whereas the CNN is used to extract spatial feature information.

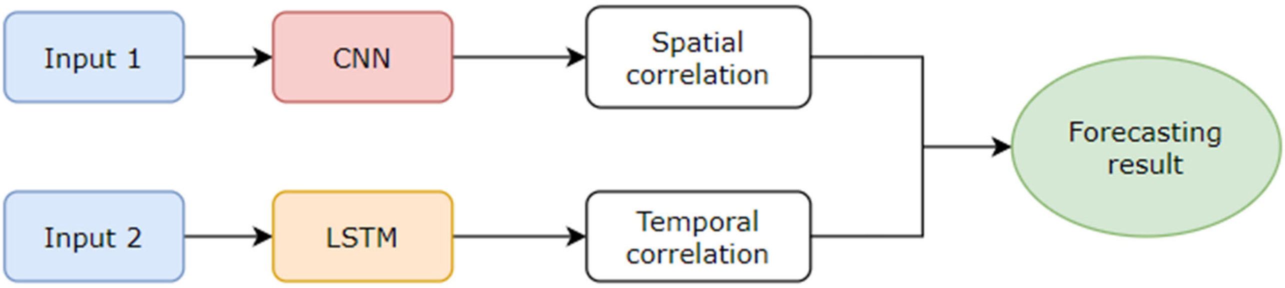

Figure 6. Structure of CNN–LSTM.

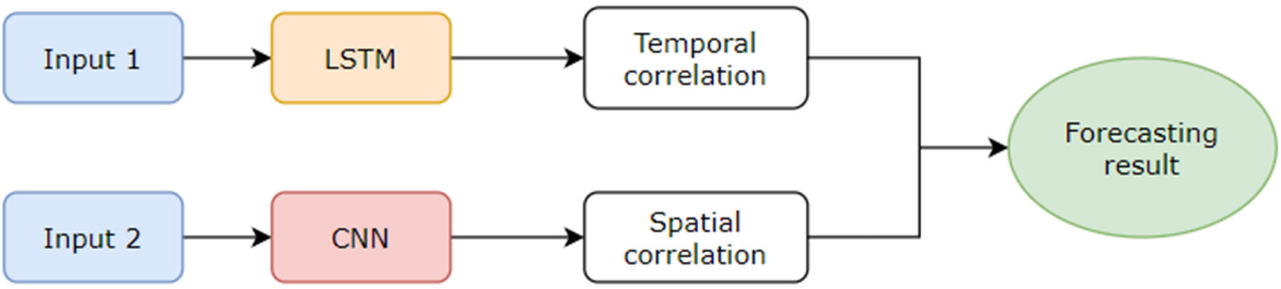

Figure 7. Structure of LSTM–CNN.

5. Evaluation Metrics

In the forecasting domain, evaluation metrics play a crucial role in describing the performance of DL models. Measurements provide feedback about prediction accuracy, and they enable models to be improved until a desired level of accuracy is achieved [27]. Numerous evaluation measures are available for determining predictive accuracy. Table 2 presents the evaluation measures typically used in sun irradiation and PV power forecasting. In the formulas, X_{pred}, X_{meas}, and n denote the projected values at each time point, the measured values at each time point, and the sample size of a period, respectively.

Table 2. Evaluation metrics.

Evaluation Metric	Equation
Error	$Error = X_{pred} - X_{meas}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert X_{pred} - X_{meas}\right\rvert$
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert \frac{X_{pred}-X_{meas}}{X_{meas}}\right\rvert \times 100$
MBE	$\frac{1}{n}\sum_{i=1}^{n}\left(X_{pred} - X_{meas}\right)$
rMBE	$\frac{\sum_{i=1}^{n}\left(X_{pred}-X_{meas}\right)}{\sum_{i=1}^{n}X_{meas}} \times 100$
rRMSE	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{pred}-X_{meas}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}X_{meas}} \times 100$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{pred} - X_{meas}\right)^2}$

MAE quantifies the average size of error in a set of forecasts based on the absolute value. When the absolute sign is eliminated, the evaluation metric becomes the mean bias error (MBE), which captures the average prediction bias, whose positive and negative values represent overprediction and underprediction, respectively [28]. Meanwhile, RMSE is used as a metric to quantify the departure from the measurement. The lower the RMSE, the better the prediction.

MAPE is a well-known forecasting metric for assessing prediction accuracy, as it can explain the forecast variability of real-world datasets [16]. When mean values differ by location or system, directly comparing the assessment metrics may result in miscalculations. In these instances, percentage-based or relative measures, such as MAPE and relative RMSE (rRMSE), provide much more accurate information [28]. The smaller the values of MAE and MAPE, the better the performance of the prediction algorithm [16].

6. Analysis of Past Studies

In this section, the characteristics necessary for solar irradiance forecasting and PV power forecasting are discussed. The characteristics investigated in this work are accuracy, types of input data, forecast horizon, type of season and weather, and training time.

6.1. Accuracy

The accuracy of DL models in forecasting solar irradiance and PV power can be evaluated using performance metrics. Most of the past reviews applied the error metrics of RMSE, MAE, MAPE, and so on. In the present review, the performance of standalone and hybrid LSTM models are evaluated based on RMSE, which is the most accessible error metric in the published papers. Tables 3 and 4 present the reviewed studies related to solar irradiance forecasting and PV power forecasting, respectively.

Table 3. Solar irradiance forecasting.

Ref.	Forecast Horizon	Time Interval	Model	Input Parameter	Historical Data Description	Error Metrics
[1]	Ahead by 1 h	Hourly	LSTM–CNN	• Temperature • Wind speed • Wind direction • Relative humidity • Precipitation • Solar zenith angle • Dew point • Pressure • Cloud type • Clear-sky global horizontal irradiance (GHI) • GHI	1 January 2015 to 31 December 2019 (5 years)	*Average RMSE:* Los Angeles: 57.983 W/m^2 San Diego: 47.826 W/m^2 San Francisco: 66.023 W/m^2
[29]	• Ahead by 15 min • Ahead by 30 min • Ahead by 45 min • Ahead by 60 min • Ahead by 75 min • Ahead by 90 min	Hourly	MSCA–CLSTM	GHI	2018 (1 year)	*Average RMSE:* Columbus: 0.0177 W/m^2 San Antonio: 0.0183 W/m^2 Detroit: 0.0183 W/m^2
[30]	• Ahead by 15 min • Ahead by 30 min • Ahead by 45 min • Ahead by 60 min • Ahead by 75 min • Ahead by 90 min	15 min	CNN–LSTM	• Average solar irradiance • Average ambient temperature • Average relative humidity	1 January 2016 to 1 January 2017	*RMSE (6 steps):* 5.79–34.89 W/m^2
[31]	Multiple forecast horizon (1 day to 8 months)	30 min	CLSTM	GSR	1 January 2006 to 31 August 2018	*RMSE (W/m^2):* 1 day: 8.189 1 week: 16.011 2 weeks: 14.295 1 month: 32.872

Table 3. *Cont.*

Ref.	Forecast Horizon	Time Interval	Model	Input Parameter	Historical Data Description	Error Metrics
[26]	Ahead by 1 h	Hourly	CNN–LSTM	• GHI • Dew point temperature • Solar zenith angle • Wind speed • Wind direction • Precipitable water • Relative humidity • Temperature	1 January 2006 to 31 December 2012	***Average MAE:*** Dallas: 41.88 W/m^2 San Jacinto: 52.00 W/m^2 Zapata: 43.66 W/m^2 Moore: 37.26 W/m^2 Lamb: 37.20 W/m^2
[32]	Ahead by 1 h	Hourly	CEEMDAN-CNN–LSTM	Solar irradiance	6 year data	***Average RMSE:*** 38.49 W/m^2
[33]	Ahead hourly every day	Hourly	LSTM	• Temperature • Dew point • Humidity • Visibility • Wind speed • Weather type	• March 2011 to August 2012 • January 2013 to December 2013 (30 months)	***RMSE:*** 76.245 W/m^2
[34]	Ahead by 1 h	Hourly	LSTM	• Wind speed • Wind direction • GHI	2000 to 2014	***Average 24-h RMSE:*** 80.0 W/m^2

Table 4. PV power forecasting.

Ref.	Forecast Horizon	Interval Data	Model	Input Variables	Historical Data Description	Size PV Power (kW)	Error Metrics
[35]	• Ahead by 7.5 min • Ahead by 15 min • Ahead by 30 min	7.5 min	CNN-ALSTM	• PV power • PV module temperature • Current • Voltage	October 2014 to September 2018	N/A	***Overall RMSE:*** 7.5 min: 1.30 15 min: 1.40 30 min: 2.04

Table 4. *Cont.*

Ref.	Forecast Horizon	Interval Data	Model	Input Variables	Historical Data Description	Size PV Power (kW)	Error Metrics
[36]	• Ahead by 10 min • Ahead by 30 min • Ahead by 60 min • Ahead by 90 min • Ahead by 120 min • Ahead by 150 min • Ahead by 180 min	10 min	5D CNN–LSTM	• Active power generated • Average phase current • AC voltage generated • Direct radiationGlobal radiation • Diffuse radiation • Temperature • Humidity • Wind speed • Barometric pressure	1 year data (2019–2020)	1.70	***RMSE:*** 10 min: 0.0830 30 min: 0.2257 60 min: 0.4593 90 min: 0.7289 120 min: 1.0588 150 min: 1.4438 180 min: 2.0570
[37]	1 day	15 min	BCLSTM + IFFS	Numerical weather prediction (NWP) data	1 January 2017 to 31 December 2018 (2 years)	N/A	***RMSE:*** 0.1075 kW
[38]	• Ahead by 7.5 min • Ahead by 15 min • Ahead by 30 min • Ahead by 60 min	7.5 min	ALSTM	• PV power • PV module temperature	October 2014 to September 2018	20.0	***Overall RMSE:*** 7.5 min: 1.39 15 min: 1.60 30 min: 1.81 60 min: 2.09
[10]	Ahead by 1 h	5 min	WPD–LSTM	• PV power output • GHR • Diffuse horizontal radiation • Ambient temperature • Wind speed • Relative humidity	1 June 2014 to 12 June 2016	26.5	***Average RMSE:*** 0.2357

Table 4. *Cont.*

Ref.	Forecast Horizon	Interval Data	Model	Input Variables	Historical Data Description	Size PV Power (kW)	Error Metrics
[39]	N/A	5 min	LSTM–CNN	• Current phase average • Active power • Wind speed • Weather temperature, Celsius • Weather humidity • Global horizontal radiation • Diffuse horizontal radiation • Wind direction	Half-year data (53,280 samples)	N/A	***RMSE:*** 0.621
[40]	Ahead by 1 h	Hourly	PCA–LSTM	The dataset has 49 features • Temperature • Humidity • Sun exposure angle • Light amplitude • Time • Season and other characteristics	The first 24 historical data points	N/A	***NRMSE:*** 0.0472%
[41]	• Ahead by 15 min • Ahead by 30 min • Ahead hourly • Ahead daily • Ahead weekly • Ahead monthly	15 min	Auto-LSTM	• PV power • Weather data	2014–2015 (2 years)	1.30	***Daily forecasting RMSE:*** Smart meter 1: 4.4414 Smart meter 2: 7.1925
[42]	Ahead hourly	15 min	LSTM	PV power	13 January 2010 to 29 January 2010	20,000	***RMSE (ahead by 1 h):*** 0.841

Table 4. *Cont.*

Ref.	Forecast Horizon	Interval Data	Model	Input Variables	Historical Data Description	Size PV Power (kW)	Error Metrics
[43]	Ahead by 1 h	Hourly	DRNN–LSTM	• PV power • Temperature • Humidity • Wind speed	1 January 2018 to 1 February 2018	106.60	***RMSE:*** 7.536
[44]	Ahead by 1 day	Every 1 min or 5 min	LSTM	PV power	One month	N/A	***Average RMSE:*** 0.512
[45]	Ahead by 1.5 h	15 min	Stacked LSTM	PV power	1 September 2016 to 31 January 2019 (84,768 observation)	N/A	***RMSE:*** 0.09394
[46]	Ahead by 1 h	Hourly	LSTM-FC	• Temperature • Humidity • Weather • Wind direction • Wind speed	1 January 2018 to 31 December 2018	N/A	***RMSE:*** 2.5605
[47]	Ahead by 1 day	5 min	EMD-SCA-LSTM	• PV power • GHI • Relative humidity (RH) • Diffuse horizontal irradiance (DHI) • Air temperature (AT)	1-year data (2017)	5.83	***RMSE: 0.5283 kW MAE: 0.3063 kW R^2: 0.9210***

6.2. Types of Input Data

The two types of models for providing input data in solar irradiance forecasting and PV power forecasting are the endogenous and exogenous models [14]. Each of the two models requires different types of input data; however, inadequate selection of input data may magnify the forecasting error [45]. The differences between the endogenous and exogenous models are explained with examples below.

For the exogenous model, a hybrid CNN–LSTM model was proposed for short-term global horizontal irradiance (GHI) prediction, i.e., ahead by 1 h [26]. The datasets of 34 locations in TX, USA, were applied to the proposed model for training and testing uses, in which the locations represent different climate zones. The input parameters were hourly GHI, dew point temperature, solar zenith angle, wind speed, wind direction, precipitable water, relative humidity, and temperature. The MAE, nMAE, RMSE, nRMSE, and R results indicate that CNN–LSTM outperforms the other models, namely, the standalone persistence model, SVM, artificial neural network (ANN), CNN, and LSTM models, and the hybrid CNN–ANN and ANN–LSTM models.

Jalali et al. [29] proposed the GHI forecasting model in designing the automated deep CNN–LSTM architecture to specifically produce the hybrid MSCA–CLSTM model. They used the endogenous model with the GHI dataset covering the whole year of 2018 and the three locations of Columbus, Detroit, and San Antonio, USA, with intervals of 1 h for each dataset. In their work, 75% of the data were allocated for training and the remaining 25% of the data were applied to the test set. Then, the performance of MSCA–CLSTM was analyzed and compared with those of other methods, such as the auto-LSTM, XGBF–DNN, LSTM, CLSTM, DWT–CLSTM, MEA–ANN, and SCA–CLSTM models. The prediction accuracy of CNN–LSTM was higher than those of other models in terms of MAE, RMSE, and Pearson metrics.

Using PV power and meteorological data as inputs, Zhou et al. [47] proposed the hybrid model of LSTM with empirical mode decomposition (EMD) and a sine cosine algorithm (SCA) to predict the PV power output. The application of EMD and SCA reduces the impact of the noise data and enhances the accuracy and stability of the proposed model, respectively. Using one year of data from 2017, the input parameters selected were PV power, GHI, RH, DHI, and AT. In this research, there were five case studies that were compared on their performance, where each case study has different input variables. The performance of case study that consists of PV power output and GHI is better than other case studies in terms of RMSE and MAE values of 0.5283 kW and 0.3066 kW, respectively. The proposed model, EMD-SCA-LSTM was then applied to predict the PV power output using PV power and GHI as inputs. The proposed model has outperformed other prediction models such as LSTM, Gaussian process regression with active learning (AGPR), and EMD-SCA-ELM, with an RMSE value of 0.5283 kW.

6.3. Forecast Horizon

The forecast horizon is significant in predicting the solar irradiance and PV power output in the future, as each forecast horizon affects the accuracy of the entire forecast. The models or forecasting techniques to be adopted depend on the requirement of the forecast horizon range [48]. Forecasting horizons can be categorized into four types [2,45]:

1. Very short-term forecast (ahead by 1 min to several minutes);
2. Short-term forecast (ahead by 1 h or several hours to 1 day or 1 week);
3. Medium-term forecast (ahead by 1 month to 1 year); and
4. Long-term forecast (ahead by 1–10 years).

Bhatt et al. [30] proposed three different DL models to forecast short-term solar irradiance. The proposed hybrid CNN–LSTM model employed the sliding window technique to convert the input variables into 12-step lag datasets for training the model. A comparative analysis of CNN, LSTM, and CNN–LSTM was performed with 15 min intervals for all six time-step horizons, i.e., ahead by one step (15 min) up to six steps (90 min). As shown in Table 5, CNN–LSTM outperforms the standalone models in terms of MAE, RMSE, MAPE, and R^2. The values of the error metrics increased with the progression of step time. Thus, the hybrid model is better than the standalone models.

Table 5. Summary of error metrics for LSTM, CNN, and CNN–LSTM.

Step Ahead	MAE (W/m^2)			RMSE (W/m^2)			MAPE (%)			R^2		
	LSTM	CNN	CNN–LSTM	LSTM	CNN	CNN–LSTM	LSTM	CNN	CNN–LSTM	LSTM	CNN	CNN–LSTM
1	6.61	6.51	3.83	10.43	9.82	5.79	10.19	11.29	7.50	0.998	0.998	0.999
2	12.15	11.69	7.32	20.46	18.09	11.71	51.74	37.45	19.64	0.993	0.994	0.997
3	18.39	16.73	10.61	31.12	26.41	18.18	28.62	52.21	31.87	0.984	0.988	0.994
4	24.16	21.81	13.68	40.33	34.53	23.48	70.51	91.84	50.08	0.974	0.979	0.99
5	31.21	27.26	17.01	52.5	43.11	29.25	30.99	52.79	55.47	0.957	0.969	0.985
6	36.89	32.38	20.07	62.27	50.99	34.89	44.81	127.29	59.28	0.942	0.957	0.979

6.4. Type of Season and Weather

Because each season and weather type significantly affects the solar radiation rates, the performance of forecasting models may also be influenced. Li et al. [10] performed 1 h ahead PV power forecasting at 5 min intervals and subsequently proposed wavelet packet decomposition (WPD) integrated with LSTM. They broke down the original PV power series into sub-series by employing WPD. After categorizing the LSTM networks into four independent networks, each of the independent LSTM networks was developed for the sub-series representing each of the four seasons. Then, to improve the accuracy of the proposed model, they applied the linear combination method to multiple single networks. Finally, the performance of the proposed model was compared with those of the benchmark models, namely, LSTM, RNN, GRU, and MLP. Table 6 shows the results of their work. The low MBE, MAPE, and RMSE scores of WPD–LSTM indicate that their proposed model outperforms the benchmark models across different seasons and weather in the 1 h ahead category.

Table 6. Error metrics of PV power forecasting across different seasons and weather.

Season	Types of Weather	Error	WPD–LSTM	LSTM	GRU	RNN	MLP
Winter	Sunny (Day 1)	MBE (kW)	−0.0055	−0.0058	0.1588	−0.0085	−0.0284
		MAPE (%)	1.7526	1.7744	2.1019	2.633	5.5833
		RMSE (kW)	0.2466	1.2541	1.2399	1.2468	1.1944
	Cloudy (Day 2)	MBE (kW)	0.1127	−0.0497	0.0184	−0.0901	0.2429
		MAPE (%)	1.7365	0.1276	1.9913	2.7622	6.1295
		RMSE (kW)	0.1773	1.1279	0.2206	0.2868	0.6075
	Rainy (Day 3)	MBE (kW)	−0.0214	−0.1913	0.1651	−0.3158	−0.0495
		MAPE (%)	6.7328	8.4150	10.8690	9.3110	10.7191
		RMSE (kW)	0.4374	2.2336	2.0876	2.1223	1.9916
Spring	Sunny (Day 4)	MBE (kW)	0.1425	−0.0239	0.0377	−0.0240	0.3277
		MAPE (%)	2.0973	1.3243	2.0199	3.1087	6.8559
		RMSE (kW)	0.2250	0.1643	0.2456	0.3431	0.7173
	Cloudy (Day 5)	MBE (kW)	−0.0675	0.1165	0.5523	0.0711	−0.2168
		MAPE (%)	8.1383	15.3881	14.9651	13.0762	15.4708
		RMSE (kW)	0.1453	0.2759	0.6452	0.4222	0.3312
	Rainy (Day 6)	MBE (kW)	0.0566	0.2304	0.5502	0.0674	0.1121
		MAPE (%)	3.8080	9.9553	14.8235	11.3013	8.3763
		RMSE (kW)	0.2807	0.8107	1.0036	0.8604	0.7572

Table 6. *Cont.*

Season	Types of Weather	Error	WPD–LSTM	LSTM	GRU	RNN	MLP
Summer	Sunny (Day 7)	MBE (kW)	0.0481	0.1115	0.2936	−0.1382	0.3617
		MAPE (%)	2.6031	8.4936	10.8292	8.8545	10.8997
		RMSE (kW)	0.2664	0.9701	1.0748	0.8514	1.0822
	Cloudy (Day 8)	MBE (kW)	0.0183	0.2012	0.5218	−0.0583	0.1048
		MAPE (%)	3.4360	13.0028	11.8370	14.8472	11.5344
		RMSE (kW)	0.2382	0.8398	0.9323	0.8812	0.7810
	Rainy (Day 9)	MBE (kW)	−0.0127	0.0924	0.4668	−0.2068	−0.3127
		MAPE (%)	3.8936	9.8571	12.5799	16.0052	14.7068
		RMSE (kW)	0.1253	0.3009	0.5805	0.4993	0.4479
Autumn	Sunny (Day 10)	MBE (kW)	−0.0799	−0.2050	0.0959	−0.1813	0.2752
		MAPE (%)	2.0367	7.4015	8.3304	7.8951	8.3189
		RMSE (kW)	0.1929	0.7395	0.8029	0.7778	0.7495
	Cloudy (Day 11)	MBE (kW)	0.0049	0.1174	0.5692	−0.1111	0.1729
		MAPE (%)	3.7923	5.0279	9.9234	7.0087	14.4850
		RMSE (kW)	0.2576	1.0540	1.2110	1.1365	1.0643
	Rainy (Day 12)	MBE (kW)	0.0029	−0.0799	0.1202	−0.3103	0.3244
		MAPE (%)	4.3427	8.3508	9.3104	7.3294	14.8202
		RMSE (kW)	0.3903	2.4216	2.3687	2.4275	2.4343

Gao et al. [32] conducted hourly predictions of solar irradiance by using the complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) and CNN–LSTM models. CEEMDAN was used to break down the historical data into a set of constitutive series for extracting data features. Six-year datasets from four locations (Los Angeles, Denver, Hawaii's Big Island in the USA, and Tamanrasset, Algeria) were collected and used as input data. The four datasets were divided into the training set (4 years), validation set (1 year), and testing set (1 year). Season affects the accuracy of solar irradiance forecasting; thus, the dataset in their work was divided into four seasons prior to the prediction. Thereafter, five different CEEMDAN-CNN–LSTM models were compared. CEEMDAN-CNN–LSTM V was selected as the proposed model because of its ability to jointly utilize CNN and LSTM to process the frequency features and time features. The average RMSE, nRMSE, and MAE of the proposed model were 38.49 W/m^2, 17.23%, and 20.50 W/m^2, respectively. The forecasting performance of the proposed model was better under different climatic conditions compared with those of the other models (Table 7).

Table 7. Average RMSE, nRMSE, and MAE across four seasons.

Season	Indicator	Methods									
		C-C-L	C-L	C-S	C-B	C-A	LSTM	SVM	BP	ARIMA	Per.
Spring	RMSE (W/m^2)	42.87	56.76	64.97	64.46	79.88	79.63	84.62	82.20	112.46	126.76
	nRMSE (%)	17.88	25.46	29.15	28.92	35.84	35.72	37.96	36.87	50.45	56.87
	MAE (W/m^2)	22.80	37.74	36.09	35.98	41.84	42.21	51.09	41.87	63.77	76.89
Summer	RMSE (W/m^2)	47.60	55.15	58.73	65.07	82.44	70.62	73.09	70.94	110.09	125.63
	nRMSE (%)	17.34	21.68	23.09	25.58	32.41	27.76	28.72	27.89	43.28	49.39
	MAE (W/m^2)	26.80	36.76	37.60	39.44	43.09	39.12	41.14	35.66	65.76	80.06

Table 7. *Cont.*

Season	Indicator	Methods									
		C-C-L	**C-L**	**C-S**	**C-B**	**C-A**	**LSTM**	**SVM**	**BP**	**ARIMA**	**Per.**
Autumn	RMSE (W/m^2)	37.59	47.19	47.76	50.86	69.79	54.86	59.71	55.49	103.07	122.39
	nRMSE (%)	17.65	19.59	19.83	21.11	28.98	22.78	24.79	23.04	42.79	50.81
	MAE (W/m^2)	19.66	29.59	27.79	29.01	36.14	27.28	38.96	28.38	60.32	75.99
Winter	RMSE (W/m^2)	25.97	38.19	46.82	45.31	50.23	47.26	54.24	48.27	81.98	107.96
	nRMSE (%)	15.73	19.60	24.04	23.26	25.79	24.26	27.85	24.78	42.09	55.42
	MAE (W/m^2)	13.25	22.14	28.33	23.69	25.65	20.18	32.44	21.86	41.92	64.54
Annual	RMSE (W/m^2)	38.49	49.87	55.10	57.07	71.72	64.37	68.93	65.57	102.61	121.75
	nRMSE (%)	17.23	21.85	24.14	25.00	31.42	28.20	30.20	28.73	44.96	53.34
	MAE (W/m^2)	20.50	31.56	32.45	32.03	36.68	32.20	40.90	31.95	57.94	74.64

C-C-L: CEEMDAN–CNN–LSTM; C-L: CEEMDAN–LSTM; C-S: CEEMDAN–SVM; C-B: CEEMDAN–BPNN; C-A: CEEMDAN–ARIMA; Per.: persistence.

6.5. Training Time

Training time is one of the most important indicators for evaluating the accuracy levels of solar irradiance forecasting and PV power forecasting. The different DL models vary in their processing time for achieving their respective best performances [14], especially between the time required by standalone and hybrid models. In this section, several models are compared to determine which among them is more efficient in predicting PV power in terms of training time.

Kejun et al. [39] proposed the use of LSTM–CNN in PV power forecasting. A half-year dataset with 5 min time intervals and consisting of 53,280 samples from the Alice Springs PV system was utilized by the proposed model. Then, the accuracy of LSTM–CNN was compared with that of LSTM, CNN, and CNN–LSTM. Their results showed that the hybrid LSTM–CNN model outperformed the other models, with MAE, RMSE, and MAPE of 0.221, 0.621, and 0.042, respectively. In general, the operating times of hybrid models are longer than those of standalone models because more time is needed to extract data, enabling much higher prediction accuracy. As shown in Table 8, the proposed LSTM–CNN has lower training and running times compared with CNN–LSTM in the hybrid model category. For the standalone model, LSTM has a lower training time compared with CNN, but the running time of LSTM is slightly longer than that of CNN.

Table 8. Training and running time for each model.

	LSTM	**CNN**	**CNN–LSTM**	**LSTM–CNN**
Training time (s)	70.490	787.494	983.701	871.606
Running time (s)	5.439	5.425	8.692	7.196

Tovar et al. [36] proposed a hybrid model in the form of a five-layer CNN–LSTM model to forecast PV power in the short term. A one-year dataset, from 2019 to 2020, of Temixco, Morelos, México, with 10 min intervals was used for the proposed model. About 80% of the data were used for training, and the remaining portions were employed to forecast PV power. The forecast horizon range was set to be ahead by 10 and 180 min. Then, the proposed model was compared with the other competitive benchmark and hybrid models, including the Ridge and Lasso linear regression methods, five-layer LSTM, and two-layer CNN–LSTM. Their performance analysis showed the suitability of the five-layer CNN–LSTM to accurately forecast short-term PV power, with MSE, RMSE, and MAE of 0.006897, 0.08304, and 0.05193, respectively. However, the time processing of the proposed model was longer than those of the other models (Table 9).

Table 9. Time processing.

Model	Time (s)
5D LSTM	9.1394
2D CNN–LSTM	8.0362
5D CNN–LSTM	69.1148

7. Future Directions

Deep learning models are more accurate than other ML models in predicting solar irradiance and PV power. According to the literature we reviewed, LSTM is mainly used in predicting solar irradiance and PV power in the very short-term and short-term forecast horizons. However, there are several challenges for this review as listed below:

- In terms of comparing and analyzing the available source code, not all the reviewed papers provided the data source codes; it is recommended for future works to find the data sources to describe the data and analyze their differences.
- Regarding performance evaluation, it is difficult to compare accuracy efficiently between the prediction models due to several main factors such as different evaluation metrics used, weather conditions of selected regions, forecasting horizons, size of input parameters, and so on. Thus, it is suggested to find specific research papers that discuss or review similar factors as mentioned, to compare the performance effectively.
- This paper has mostly reviewed very short-term and short-term forecast horizons for solar irradiance and solar power forecasting (Tables 3 and 4). For future work, it is recommended to expand the review on medium-term and long-term forecast horizons by applying various combinations of DL and ML models to enhance the existing hybrid models.

8. Conclusions

This review introduced DL models for estimating solar irradiance and PV power generation. Separate evaluations were conducted for PV power and solar irradiance due to their distinct output values. Solar irradiance can be compared across locations and measured in power per unit area, while PV power production is influenced by solar panel size and efficiency. DL models have advantages over traditional ML models for forecasting time-series data. They have the potential to improve solar energy forecasting for more efficient use of solar power. LSTM, CNN–LSTM, and LSTM–CNN models are widely used for predicting solar energy, offering advantages over traditional ML models for time-series forecasting. However, determining the best model for predicting solar irradiance and PV power is challenging due to each model's unique strengths and weaknesses. Overall, DL models show promise for improving solar energy forecasting, but careful evaluation is necessary to identify the most suitable model for each task. The findings derived from this work can be summarized as follows:

- In terms of predicting solar irradiance, hybrid models outperform standalone models. In particular, the evaluation measures of hybrid models are significantly lower than those of standalone models. Among the hybrid models, CNN–LSTM requires complex input data, such as images, because it includes a CNN layer.
- When evaluating model performance, training time must be considered. Because hybrid models must extract two types of feature (i.e., spatial and temporal features), they take a longer time to process data compared to standalone models.

- The prediction accuracy for models that run a large batch size of data is lower when compared to other prediction models that use small data batch sizes. This is because more data are required to be extracted, and there is a more complicated process to produce the most accurate prediction.

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