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Review

A Review of State-of-the-Art and Short-Term Forecasting Models for Solar PV Power Generation

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Abstract: Accurately predicting the power produced during solar power generation can greatly reduce the impact of the randomness and volatility of power generation on the stability of the power grid system, which is beneficial for its balanced operation and optimized dispatch and reduces operating costs. Solar PV power generation depends on the weather conditions, such as temperature, relative humidity, rainfall (precipitation), global solar radiation, wind speed, etc., and it is prone to large fluctuations under different weather conditions. Its power generation is characterized by randomness, volatility, and intermittency. Recently, the demand for further investigation into the uncertainty of short-term solar PV power generation prediction and its effective use in many applications in renewable energy sources has increased. In order to improve the predictive accuracy of the output power of solar PV power generation and develop a precise predictive model, the authors used predictive algorithms for the output power of a solar PV power generation system. Moreover, since short-term solar PV power forecasting is an important aspect of optimizing the operation and control of renewable energy systems and electricity markets, this review focuses on the predictive models of solar PV power generation, which can be verified in the daily planning and operation of a smart grid system. In addition, the predictive methods identified in the reviewed literature are classified according to the input data source, and the case studies and examples proposed are analyzed in detail. The contributions, advantages, and disadvantages of the predictive probabilistic methods are compared. Finally, future studies on short-term solar PV power forecasting are proposed.

Keywords: predictive models; weather research and forecasting (WRF); solar irradiance; solar PV power; renewable energy sources

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1. Introduction

The energy crisis, air pollution, global warming, and other environmental issues have stimulated the development of renewable energy, which is expected to account for about 40% of energy consumption by 2030 [1]. Solar PV power generation refers to a power generation device that uses a PV module to directly convert solar energy into electricity energy. This is a novel, highly promising, and comprehensive energy utilization method with the advantages of low environmental pollution, no pollution of air and water resources, no noise pollution, the ability to adapt to local conditions, low installation cost, and on-site consumption when connected to the power grid. It can achieve the coexistence of power generation and consumption and is currently one of the most promising PV technologies. According to Rethink Energy data, in the first three seasons of 2022, the global installed solar energy capacity increased by 54 GW, a year-on-year increase of 37.8%. The total installed capacity in the first nine months of this year was about 142.5 GW. The forecast shows that the annual installed capacity will reach 222 GW [2,3]. According to the latest report from the European Photovoltaic Association SPE, the installed capacity of new devices in the 27 EU countries in 2022 was 41.4 GW, a net increase of 28.1 GW compared to last year, achieving a year-on-year increase of 47%. By 2022, the cumulative installed capacity was expected to reach 208.9 GW. According to the statistical data released by the National Energy Administration of China, the new installed power capacity in 2022 was 87.41 GW, and by 2022, the cumulative installed power capacity was 396.261 GW.

The prediction of power generation was carried out very early due to the early establishment of a large number of solar observation stations in Europe and the United States, more assistance from advanced technology and equipment, and the accumulation of sufficient historical data. The main work involves the use of different predictive models to improve forecasting accuracy, and part of the work is to summarize existing methods or analyze their economic benefits. The methods for realizing PV power generation forecasting are mainly divided into traditional predictive methods in physics and statistics, novel forecasting methods using machine learning, optimization algorithms, and deep learning, as well as hybrid models.

More recently, in artificial intelligence (AI) or neural network (NN) approaches, a new short-term PV predictive method based on the artificial neural network (ANN) or recurrent neural network (RNN) was proposed. This method employs dynamic artificial neural networks to predict solar radiation and temperature, thereby achieving the prediction of the solar power energy output [4–9]. Sudden changes in solar radiation near the surface are extracted from ground-based cloud image sampling technology and are combined with similar day-based and ANN-based approaches to ensure accuracy in solar radiation prediction [10–13]. Lima et al. (2020) used AI methods in a new adaptive topology based on portfolio theory (PT) technology to make short-term predictions of effective solar PV power generation for global solar radiation [14].

Next, some solar PV power generation forecasting models based on machine learning or optimization algorithms, such as the support vector machine (SVM), support vector regression (SVR), extreme learning machine (ELM), gradient boosting decision tree (GBDT), and adaptive boosting learning (ABL), have been proposed [15–33]. These use a large number of satellite images and a significant amount of data. When compared with traditional time series analysis, the forecasting accuracy is significantly improved. Ziyabari et al. (2022) used a novel multi-range attentive gated current residual network (ResAttGRU) model and meteorological data, the clear sky index, and solar Ireland to predict short-term solar radiation [34]. This model also proposes the use of a strong multi-timescale in the proposed architecture, and the GRU can utilize temporal information at a lower computational cost than the popular long short-term memory (LSTM) method. Doubleday et al. (2021) established utility-scale photovoltaic (PV) plants at multiple time horizons based on the Bayesian model-averaging (BMA) algorithm and numerical weather forecasting (NWP) and obtained a probabilistic solar power forecasting model [35].

In addition, deep learning methods, such as the long short-term memory (LSTM) network model, the recursive short-term memory (Rec LSTM) network, convolutive long short-term memory (Conv LSTM), and the multi-step CNN stacked LSTM model [36–56], are used to predict the solar PV output power. Talat et al. (2021) proposed a new multi-layer feed-forward neural network (MFFNN) for solar PV power generation forecasting, considering thermal effects and environmental conditions [57]. The results obtained from the MFFNN-MVO and MFFNN-GA models were studied through environmental temperature, wind speed, and solar irradiance. Jebli et al. (2021) established a multi-layer perceptron (MLP) model, which is a network composed of multi-layer interconnected nodes combined with the clear sky index to achieve the classification of environmental factors. They then optimized the weight of the multi-layer perceptron through the artificial bee colony algorithm to predict solar PV output power. This non-linear forecasting model has a better effect than the linear forecasting model since the output power is intermittent and random [58].

Moreover, some forecasting works have used hybrid and ensemble models. Ma et al. (2021–2022) proposed new forecasting models, such as VMD-LSTM-RVM, CNN-LSTM-MLP, MC-WT-CBiLSTM depth, NARX-CVM, wavelet-adversarial deep, GBRT-Med-KDE model, and TG-A-CNN-LSTM, and implemented interval forecasting for microgrids, providing a good solution for the energy management of microgrids [59–63]. Meng et al. (2021) proposed a new hybrid wavelet-adversarial deep model for power generation forecasting using satellite and global horizontal radiation (GHI) forecasting. This method integrates a wavelet neural network model with a three-stage adaptive modification solution to the DA to improve the algorithm's ability to modify local and global searches, and it provides relatively reliable forecasting results [64]. Wang et al. (2022) proposed a hybrid LSTM-SVR-BO model that combines machine learning methods and statistical methods and conducted comparative tests on multiple time dimensions to better reflect the accuracy of the experimental results. They verified the advantages of the proposed method, which can achieve better forecasting results than a single model [65]. Zhang et al. (2022) proposed the hybrid gradient boosting regression tree–median and kernel density estimation (GBRT-Med-KDE) models. This study proposes a short-term solar power interval prediction method for solar PV power generation, which effectively predicts global solar radiation. This method can obtain more reliable and stable interval forecasting results [66]. Du et al. (2022) proposed a forecasting model based on the theory-guided and attention-based CNN-LSTM (TG-A-CNN-LSTM), which can ignore meteorological data such as temperature and wind speed. In the training process, data mismatch and boundary constraints are introduced into the loss function, and positive constraints are used to limit the output of the model. This model demonstrates better forecasting accuracy, stability, and robustness characteristics for solar PV power generation when compared to a single forecasting model [67]. Furthermore, Ghasvarian Jahromi et al. (2020) conducted forecasting work using statistical methods such as the hidden Markov model (HMM), similarity-based forecasting models (SBFMs), and Kalman filtering (KF) and applied them to the probability forecasting of solar power generation [68,69]. Mutavhatsindi et al. (2021) achieved good results when predicting the production of solar power plants using the quantitative regression average (QRA) regression model based on meteorological data [70–74].

To date, several review papers on solar PV power forecasting have been studied. Maciel, Rajagukguk, et al. (2021) outlined short-term methods for predicting solar PV power generation. In addition to using different forecasting methods to improve forecasting performance, another part of the work is to summarize and analyze the existing PV power generation forecasting methods developed in recent years based on time scales, forecasting models, and output data [75–77]. Wu et al. (2022) summarized machine learning, deep learning, algorithm optimization, and hybrid forecasting models to achieve the modeling and forecasting of meteorological factors. Of these methods, the solar radiant intensity is a key parameter, and its forecasting results will directly affect the output power of PV power stations [78,79]. Furthermore, Sudharshan and Mohamad Radzi summarized 161 and 306 related papers, respectively, and introduced various combinations, influencing factors, issues, limitations, and suggestions for achieving the solar PV power generation prediction of hybrid ANNs, machine learning methods, or algorithm optimization [80,81].

This review work intends to provide a clear and concise understanding of the different predictive models for solar radiation and solar PV power generation forecasting. In order to satisfy the requirements of large-scale solar PV power grid integration and further improve the forecasting accuracy of short-term solar PV power generation, it is necessary to develop a short-term solar PV power forecasting model based on state-of-the-art hybrid AI algorithms to accomplish accurate, robust, and efficient solar PV power forecasting. The main contribution of this paper is a review of the impacts of different irradiance forecasting techniques for solar PV power prediction, as follows:

1. This paper discusses a systematic understanding of the selection and application scope of various prediction models, including Neural Networks (NNs), machine learning models or algorithm optimization, deep learning models, hybrid AI models, and probability models;
2. This paper summarizes the current trends in solar PV power forecasting techniques, including their advantages and disadvantages, and the contributions of various solar

PV power forecasting models. Some important metrics, such as the time resolution, model type, accuracy, and parameters, are presented;
3. These models have different predictive capabilities, and the weights of each model are updated in real time to improve the comprehensive predictive capabilities of the models and have good application prospects for solar PV power forecasting;
4. The paper reviews and analyzes case studies and examples in the literature that accurately predict short-term solar PV power forecasting with uncertainty and stochasticity.

Finally, the paper draws a conclusion and presents the existing issues in the methodologies. Future research directions are suggested.

2. Review of the Development of the Literature on Solar PV Power Forecasting Models

Improving the predictive accuracy of solar PV power generation is conducive to the optimal dispatching of microgrids. This paper analyzes the multi-time-scale optimal dispatching model of microgrids, which can effectively deal with the risks brought about by solar PV power prediction errors to system operation and achieve the optimal dispatching of solar PV microgrid systems. Then, starting from the necessity of improving the predictive accuracy of solar PV power generation, the impact of different predictive accuracies of solar PV output power on the optimal dispatch of microgrids is analyzed, and it is shown that the predictive accuracy of solar PV power generation can be achieved. Optimized scheduling that is more in line with the actual operation shows the practicability and necessity of improving the forecasting accuracy of power generation.

2.1. Forecasting Techniques

Previously, review articles with a wide scope (prediction techniques, sources of input databases, statistical metrics, temporal and spatial coverage, etc.) were produced. In recent years, relevant scholars have conducted theoretical research and practical simulations. This paper presents a comprehensive review of novel techniques for predicting solar PV power generation. Figure 1 shows a predictive model of solar PV power generation. The advantage of these methods (AI or neural networks (NNs), machine learning or optimization algorithms, deep learning, hybrid models, and other statistical analysis methods) is that the amount of training data can be greatly reduced, and they also avoid the excessive weighting of individual data.

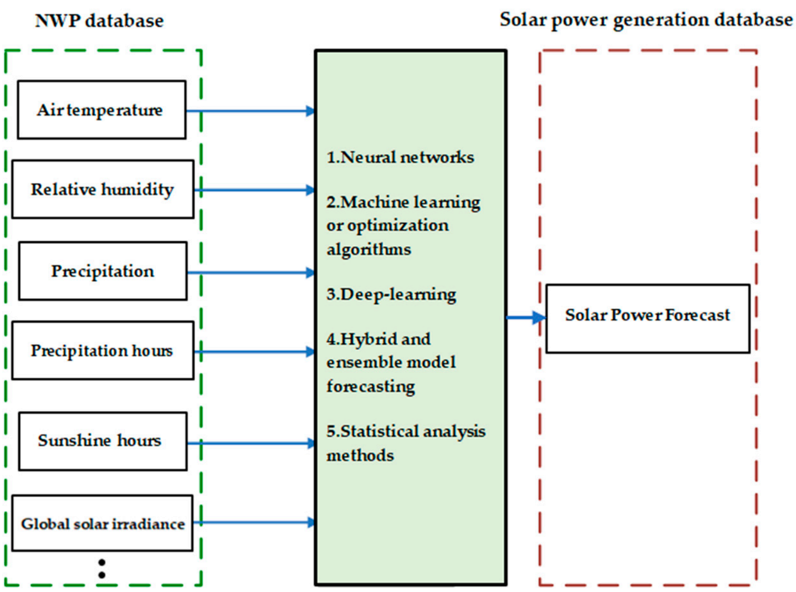

Figure 1. Short-term solar PV power generation prediction model.

2.2. Literature Classification Based on Methods

Modern solar PV power generation forecasting methods mainly include AI neural networks, the support vector machine, wavelet analysis, hybrid and ensemble model forecasting, etc. Neural networks have the characteristics of self-reasoning, self-organization, and information memory. They also have a strong fitting ability, complex mapping ability, fault tolerance, and learning ability and are suitable for dealing with a large number of unstructured and strongly dynamic regular problems. The relationship between solar PV power generation and time is usually random and non-linear because variations in solar radiation are affected by external conditions, such as temperature, relative humidity, rainfall, rainfall hours, sunshine hours, and full-day sunshine. Neural networks (ANNs) are the most frequently used machine learning techniques in short-term solar PV power forecasting. Hybrid predictive models are designed by combining two or three deep learning techniques or combining optimization algorithms with AI methods. They address the aforementioned shortcomings of a single predictive model by finding optimal features, hyperparameters, and training algorithms. The review works on solar PV power generation forecasting for time resolution, model type, accuracy, and the parameters used are presented in Table 1.

Table 1. The model type, accuracy, and parameters for the reviewed works.

Ref	Method	Model Type	Parameter Used	Accuracy
[4]	Neural networks (NNs)	Principal component analysis (PCA), artificial neural networks (ANNs) with the outputs using Mixture DOE (MDOE)	Instantaneous temperature (°C), Instantaneous humidity (%), Instantaneous precipitation (°C), Instantaneous pressure (hPa), Wind speed (m/s), Wind direction (○), Wind gust (m/s), Radiation (KJ/m^2).	MAPE = 10.45%, SD = 7.34 for summer; MAPE = 9.29%, SD = 7.23 for autumn; MAPE = 9.11%, SD = 5.55 for winter; MAPE = 6.75%, SD = 6.47 for spring
[5]	Neural networks (NNs)	Artificial neural networks (ANNs)	Relative Humidity Solar Radiation Temperature Wind speed	RMSE = 86.466 MAE = 8.409
[6]	Neural networks (NNs)	Recurrent neural network (RNN)	Temperature Humidity Wind speed	MRE (%) = 3.87 MAE (kW) = 7.75 nRMSE (%) = 5.69
[7]	Neural networks (NNs)	Artificial neural network (ANN);	National Renewable Energy Laboratory Irradiance, temperature, wind speed, wind pressure	MAPE (%) = 1.8 MSE = 3.19×10^{-10}
[8]	Neural networks (NNs)	Feed-forward backpropagation neural network (FFBPNN) method	Daily average temperature, daily average humidity, daily average wind speed, daily total sunshine duration, daily average Global solar irradiation (GSI)	MAPE = 7.066%, nMAE = 3.629%, nRMSE = 4.673%, and MAE = 5.256%
[10]	Neural networks (NNs)	BP neural network	Cloud-based images, historical data of solar radiation	MAE = 46.1 W MAPE = 7.8%.
[9]	Neural networks (NNs)	Artificial neural network (ANN)	Radiation, temperature, wind speed, humidity	Classification accuracy% = 97.53%
[11]	Neural networks (NNs)	Neural network prediction model	Temp., wind speed, wind direction, humidity, total amount of cloud, insolation	MAPE (%) = 12.94%
[12]	Neural networks (NNs)	The CAE-PCA model	Relative humidity, solar radiation, temperature, wind speed	MAE = 0.0524 MSE = 0.0113 RMSE = 0.1061
[13]	Neural networks (NNs)	Similar day-based and ANN-based approaches	Extraterrestrial radiation Cloud cover factor Temperature	MAPE = 21.37% nRMSE = 30.99%
[14]	Neural networks (NNs)	AI methods based on the portfolio theory (PT)	Solar irradiance Air temperature	MAPE= 4.52%
[15]	Machine learning or optimization algorithms	RNN-LSTM model	Solar radiation, module temperature, ambient temperature	RNN-LSTM (p-si) RMSE = 26.85 RNN-LSTM (m-si) RMSE = 19.78 R^2 = 0.9943
[16]	Machine learning or optimization algorithms	Gradient boosting decision tree (GBDT)	Temperature (°C) Atmospheric pressure (kPa) Relative humidity (%) Wind speed (m/s) Total solar radiation (0.01 MJ/m^2)	MAE (MWh) = 6.02 MAPE (%) = 3.30 RMSE (MWh) = 6.73

Table 1. *Cont.*

Ref	Method	Model Type	Parameter Used	Accuracy
[17]	Machine learning or optimization algorithms	Adaptive extreme learning machine model	(a) Global horizontal irradiance (GHI) (b) Temperature (c) Relative humidity	MAE = 0.2444 MSE = 0.1727 RMSE = 0.3012
[18]	Machine learning or optimization algorithms	Transparent open box (TOB) machine-learning method	Solar radiation, wind velocity, air pressure	RMSE = 1175 MW and R^2 = 0.9804; RMSE = 1632 MW and R^2 = 0.9609
[19]	Machine learning or optimization algorithms	Clouds and sun detection algorithm	Image acquisition, image processing	Sun coverage between 5 and 6 s. Standard error level in the range of 10–20%.
[20]	Machine learning or optimization algorithms	Adaptive boosting Learning model	Solar power (MW), solar irradiance (W/m^2), model temperature (K)	RMSE = 25.77 MAE = 30.28
[21]	Machine learning or optimization algorithms	Extreme learning machine with a forgetting mechanism (FOS-ELM)	PV Data, weather data, noise variance	nRMSE = 0.952, MAPE = 1.549
[22]	Machine learning or optimization algorithms	Regression-based ensemble method	Irradiance, temperature, precipitation, humidity, wind speed	MRE = 4.362%, MAE = 87.242 kW, and R^2 = 0.933
[23]	Machine learning or optimization algorithms	Machine learning (ML)-based	Ambient temperature, relative humidity, wind speed, wind direction, solar irradiation, precipitation	MSE = 0.15.
[24]	Machine learning or optimization algorithms	Spatio-temporal autoregressive model (STVAR)	Global horizontal irradiance (GHI)	rMAE (%) = 13.13, rMBE (%) = −2.99, rRMSE (%) = 21.8
[25]	Machine learning or optimization algorithms	Support vector machine (SVM) and Gaussian process regression (GPR) models	Solar PV panel temperature, ambient temperature, solar flux, time of the day, relative humidity.	RMSE = 7.967, MAE = 5.302 and R^2 = 0.98
[26]	Machine learning or optimization algorithms	Multi-kernel random vector functional link neural network (MK-RVFLN)	Historical solar power data	MAPE (%) = 2.29, RMSE (MW) = 0.738, MAE (MW) = 0.343
[27]	Machine learning or optimization algorithms	An adaptive k-means and Gru machine learning model	Temperature, dew time, humidity, wind speed, wind direction, azimuth angle, visibility, pressure, wind-chill index, calorific value, precipitation, weather type	RMSE = 8.15 MAPE/(%) = 0.04
[28]	Machine learning or optimization algorithms	Choice of random forest regression	Global horizontal irradiation, relative humidity, ambient air temperature, cloud cover, the generation of electricity of more than 20 items	R^2 = 0.94 MAE = 5.12 kWh RMSE = 34.59 kWh
[29]	Machine learning or optimization algorithms	Support vector regression-based model	Power Hourly standard solar irradiance (SSI), Online weather condition (OWC) Cloud cover (CC)	nRMSE = 2.841% MAPE = 10.776%
[30]	Machine learning or optimization algorithms	Hybrid classification-regression forecasting engine	Forecasted/lagged values of weather parameters, lagged solar power values, calendar data	MAE = 0.078 MAPE = 14.1 MSE = 0.014
[31]	Machine learning or optimization algorithms	Frequency-domain decomposition and convolutional neural network (CNN)	PV power data	MAPE = 0.1778 RMSE = 1.1757 R^2 = 0.9438
[32]	Machine learning or optimization algorithms	Regions of interest (ROIs)	Precise cloud distribution information	nRMSE = 5.573 nMAE = 2.362 MASE = 0.644
[33]	Machine learning or optimization algorithms	Adaptive learning neural networks	Solar irradiation, temperature, wind speed, humidity.	RMSE = 143.7483 (W/m^2) MAE = 67.2620 (W/m^2) MBE = 4.5844 (W/m^2)
[34]	Machine learning or optimization algorithms	A novel multi-branch attentive gated recurrent residual network (ResAttGRU)	Clear sky index, Solar irradiance	RMSE = 0.049 (W/m^2) MAE = 0.031 (W/m^2) R^2 = 0.99
[35]	Machine learning or optimization algorithms	Bayesian model averaging (BMA)	Numerical weather prediction (NWP)	SS's of at least 12%
[36]	Deep-Learning	The encoder–decoder LSTM network	Air temperature (°C), Relative humidity (%) Global irradiance on the Horizontal plane (W/m^2) Beam/direct irradiance Diffuse irradiance on the horizontal plane Extraterrestrial irradiation	MAPE (%) = 39.47% RMSE (W/m^2) = 99.22% MAE (W/m^2) = 67.69% nRMSE = 0.27
[37]	Deep-Learning	Deep learning-based adaptive model	Temperature, dew point, wind speed, cloud cover.	nRMSE = 0.3058
[38]	Deep-Learning	Multi-step CNN-stacked LSTM model	Solar irradiance, plane of array (POA) irradiance	nRMSE = 0.11 RMSE = 0.36

Table 1. *Cont.*

Ref	Method	Model Type	Parameter Used	Accuracy
[39]	Deep-Learning	LSTM-dropout model	(a) Cloudy index (b) Visibility (c) Temperature (d) Dew point (e) Humidity (f) Wind speed (g) Atmospheric pressure (h) Altimeter (i) Solar output power.	RMSE = 0.01 MAE = 0.0756 MAPE = 0.05711 R^2 = 0.90668
[40]	Deep-Learning	SCNN–LSTM model	Direct normal irradiance (DNI), solar zenith angle, relative humidity, air mass	nRMSE = 23.47% Forecast skill = 24.51%
[41]	Deep-Learning	Artificial neural network (ANN) and long-term short memory (LSTM) network models	Air temperature, relative humidity, atmospheric pressure, wind speed, wind direction, maximum wind speed, precipitation (rain), month, hour, minute, global horizontal irradiance (GHI)	MAPE = 19.5%
[42]	Deep-Learning	LSTM and ANFIS learning models	Direct and diffuse short-wave radiation, evapotranspiration, vapor pressure deficit at 2 m, relative humidity, sunshine duration, and soil temperature	RMSE = 0.04–0.8 MSE = 0.0016–0.64 MAE = 0.034–0.86
[43]	Deep-Learning	Opaque deep learning solar forecast models	Total column liquid water, total column ice water, surface pressure, relative humidity, total cloud cover, U&V wind component, temperature, surface solar radiation downwards, surface thermal radiation downwards, top net solar radiation, total precipitation.	MAE = 0.050 $\pm$ 0.002 RMSE = 0.098 $\pm$ 0.003
[44]	Deep-Learning	VM-based forecast models	Solar radiation and temperature	Accuracy factor increase of 27%.
[45]	Deep-Learning	A fluctuation pattern prediction (FPP)-LSTM model FPR-LSTM	The ultrashort-term power prediction was performed with the cloud distribution features and historical power data as input	RMSE = 6.675% MAE = 4.768% COR = 0.9055
[46]	Deep-Learning	Long short-term memory (LSTM) network	PV inverter energy meter data logger, Weather data acquisition	RMSE = 0.512
[47]	Deep-Learning	Long short-term memory (LSTM) network	Samples, time steps, features	RMSE = 15.59 kW MAE = 8.36 kW
[48]	Deep-Learning	Convolutional autoencoder (CAE) based sky image prediction models	Precise cloud distribution information	SSIM = 1.012 MSE = 0.712
[49]	Deep-Learning	Long short-term memory (LSTM) neural network	Temperature, relative humidity, wind speed, precipitable water. The approximate numerical solar irradiance	RMSE = 0.71 MW MAE = 0.36 MW MAPE = 22.31%
[50]	Deep-Learning	Recursive long short-term memory network (Rec-LSTM)	General weather information	nRMSE = 15.25% WMAPE = 68.47%
[51]	Deep-Learning	Convolutional long short-term memory (Conv-LSTM)	Multi-point regional data consolidation, 17 sensors were laid on the island of Oahu (Hawaii) covering an area of roughly 1 km^2 from March 2010 to October 2011	RMSE never increases more than 15%
[52]	Deep-Learning	Convolutional neural network (CNN) and LSTM recurrent neural network	General weather information	RMSE = 2.095 MW MAE = 1.028 MW
[53]	Deep-Learning	A spatial-temporal graph neural network (GNN) is then proposed to deal with the graph	Precise cloud distribution information	RMSE = 6.945 k MAE = 3.565 k MAPE = 1.286%
[54]	Deep-Learning	Time-series long short-term memory (LSTM) network, convolutional LSTM (ConvLSTM),	Historical hourly solar radiation	nRMSE = 4.05%
[55]	Deep-Learning	Long short-term memory (LSTM)	Mean solar radiation and air temperature for a region	RMSE = 317.4 MAE = 236.35 MAPE = 2.17
[56]	Deep-Learning	Long short-term memory (LSTM)	Weather temperature (°C) Global horizontal radiation (W/m^2) PV power history data	MAPE =6.02
[57]	Deep-Learning	The multi-layer feed-forward neural network (MFFNN) multiverse optimization (MVO)	Wind speed Solar irradiance Ambient temperature.	nRMSE = 5.95 $\times$ 10^{-3} MSE = 2.16 $\times$ 10^{-5} MAE = 9.44 $\times$ 10^{-5} R^2 = 0.994045813

Table 1. *Cont.*

Ref	Method	Model Type	Parameter Used	Accuracy
[58]	Deep-Learning	Multi-layer perceptron (MLP)	Temperature, humidity, wind speed; wind direction, pressure Solar radiation Solar energy	MAE = 0.03 (J/m^2) MSE = 0.006 (J/m^2) RMSE = 0.08 (J/m^2)
[59]	Hybrid model forecasting	VMD-LSTM-RVM model	Power history data	MAPE (%) = 5.12 RMSE (kW) = 4.80
[60]	Hybrid model forecasting	Covariance matrix adaptive evolution strategies (CMAES) with extreme gradient boosting (XGB) and multi-adaptive regression splines (MARS) models	Wind velocity, maximum and minimum weather humidity, maximum and minimum weather temperature, vapor pressure deficit, evaporation	RMSE = 4.9%
[61]	Hybrid model forecasting	CNN-LSTM-MLP hybrid fusion model	Temperature, rainfall, evaporation, vapor pressure, relative humidity	$r \approx 0.930$, RMSE $\approx$ 2.338 MJm^{-2}day^{-1}, MAE $\approx$ 1.69 MJm^{-2}day^{-1}
[62]	Hybrid model forecasting	MC-WT-CBiLSTM depth model	Global level irradiance, temperature	MAE = 18.13 RMSE = 27.98 R^2 = 0.99 SMAPE = 10.97 MAPE = 15.63
[63]	Hybrid model forecasting	NARX-CVM hybrid model	Temperature, solar radiation, relative humidity, wind speed, pressure	Forecasting skills = 34%
[64]	Hybrid model forecasting	Hybrid wavelet-adversarial deep model	Global horizontal irradiance (GHI)	RMSE = 0.0895, MAPE = 0.0531
[65]	Hybrid model forecasting	Hybrid LSTM-SVR-BO model.	PV power history data	RMSE (MW) = 9.321, MAE (MW) = 4.588, AbsDEV (%) = 0.174
[66]	Hybrid model forecasting	GBRT-Med-KDE model	Wind speed, temperature (Celsius), relative humidity.	MAE = 0.05, RMSE = 0.08, R^2 (%) = 99.75, MAPE = 0.055, SMAPE = 0.028.
[67]	Hybrid model forecasting	Theory-guided and attention-based CNN-LSTM (TG-A-CNN-LSTM)	Neglect the meteorological data, such as temperature and wind speed.	RMSE = 11.07 MAE = 4.98 R^2 = 0.94
[68]	Other statistical analysis methods	Hidden Markov model (HMM)	Solar historical data	nMAE = 2.84, nRMSE = 6.05, MAPE = 13.46 and Correlation coefficient = 0.975.
[69]	Other statistical analysis methods	Similarity-based forecasting models (SBFMs)	Temperature, humidity, dew point, wind speed	RMSE = 15.3% MAE = 826.2 W MRE = 10.8%
[70]	Other statistical analysis methods	Kalman filtering (KF)	Irradiance, temperature, relative humidity, and the solar zenith angle	RMSE = 156.42 (39.88%) nRMSE = 12.71%
[71]	Other statistical analysis methods	Quantile regression averaging (QRA)	Temperature, wind speed, relative humidity, barometric pressure, wind direction standard deviation, rainfall	RMSE = 88.600 MAE = 52.034
[72]	Neural networks (NNs)	Artificial Intelligence (AI) methods—random forest (RF) and deep neural network (DNN)	Ambient temperature (°C) Atmospheric pressure (hPa) Humidity (%) Clouds percentage (%) Wind speed (m/s)	MAE = 338.85 RMSE = 435.44
[73]	Deep learning, Machine learning	The single-graph model	Temperature (°C), Humidity (%), Wind speed (m/s) PV power Global horizontal irradiance (GHI) Diffuse horizontal irradiance (DHI) Direct normal irradiance (DNI)	RMSE (kW) = 0.336 MAE (kW) = 0.177 MAPE (%) = 12.89
[74]	Neural networks (NNs) and Optimization algorithms	Genetic Algorithm programming system (GAPS) and radial basis function (RBF)	Meteorological data, including atmospheric turbidity, relative humidity, and solar irradiance	Sunny RMSE (mw) = 0.9636 Cloudy RMSE (mw) = 4.0123 Rainy RMSE (mw) = 2.9828

2.3. Summary of Forecasting Techniques

A literature review was conducted using (1) the Web of Science, (2) IEEE Xplore, (3) MDPI, (4) Engineering Village, and (5) Google Scholar databases from 2020 to 2023 for publications on short-term solar PV power prediction. In the past three years, the amount of research in this field has significantly increased, which is consistent with the global growth in solar power generation. This indicates that these predictive technologies for solar PV power generation are becoming more important as their penetration rate in the power grid increases. In the initial search for this paper, a total of 217 papers were reviewed and identified using five academic literature databases. A total of 102 relevant articles were identified based on second-review keywords, titles, abstracts, article content, and the journal's main subject of interest. The final 74 papers were selected and analyzed based on reviewing the impact factor, review process, citation, exploration of issues and challenges, and future studies. Based on the temporal resolution, the number of AI methods used in the model, and the accuracy of the model, the performance level of short-term wind power prediction models is evaluated for the reviewed works, recommending prediction models with better performance. These models are mainly divided into five categories: artificial intelligence or neural networks (NNs), machine learning models (MLs) or algorithm optimization, deep learning models (DL), hybrid artificial intelligence models, and probability models. A list of all the papers is presented in the references.

2.3.1. Distribution of Input Data for the Reviewed Works

It was found from the reviewed literature that solar power generation can be predicted through different input source databases, as shown in Figure 1. Figure 2 presents the distribution of the five database input sources, of which the models using meteorological records [81–84] or numerical weather prediction (NWP) [85–87] are dominant, accounting for 49% and 25%, respectively. In several studies, 15% of the power generation information was shared from nearby PV power plants [56,59,88], 6% of the studies used satellite images as the input source data [89,90], and some studies combined with sky images have been very promising. Such studies account for 5% of all studies, although further work is needed to correctly identify cloud layers [72,91–93]. When considering their spatial resolution and the temporal level at which they are applied, NWP, satellite images, and sky images are plotted based on their spatial resolution, while the statistical methods are represented based on their spatial range. If inputs from NWP models or satellite or sky images are input into statistical prediction models, the spatial range of statistical methods will be expanded.

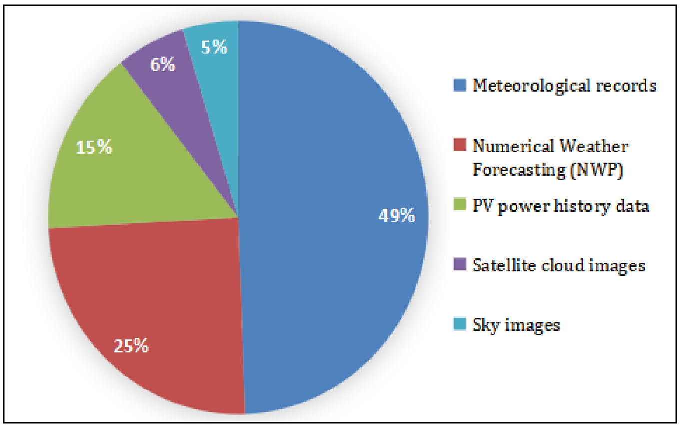

Figure 2. Ratio of input data of the reviewed works.

2.3.2. Distribution of Forecasting Methods for the Reviewed Works

Figure 3 shows the distribution of studies analyzed regarding the techniques used. We found that 16% of all studies included artificial intelligence or neural network (NN) models, 31% included machine learning models or algorithm optimization, 34% included deep learning (DL) models, 13% included mixed artificial intelligence models, and probability models accounted for 6% of all studies. This selection is limited to publications produced in 2020 or later, as the purpose of this work was to focus on the latest trends and developments in solar power energy forecasting. The most common approaches among the papers reviewed were AI techniques, especially deep learning and machine learning or optimization algorithms, which accounted for 34% and 31% of the studies, respectively.

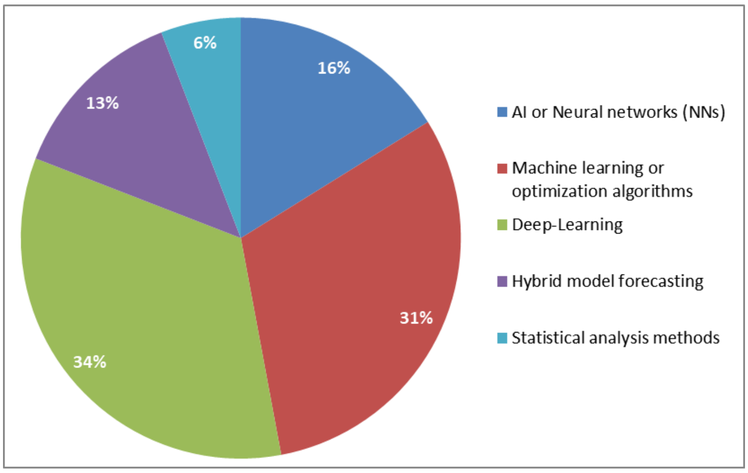

Figure 3. Distribution of forecasting methods used in the reviewed works.

2.3.3. Statistical Metrics for the Reviewed Works

There are many methods to determine errors in solar power generation prediction, and Table 1 uses various statistical metrics to describe the accuracy of different short-term solar power generation prediction models produced in the past three years. In Figure 4, we develop and propose many methods for calculating errors, such as RMSE, MAE, MAPE, nRMSE, R^2, MSE, MRE, nMAE, MBE, SMAPE, MASE, and WMAPE, and attempt to present the error values as completely as possible so that they can be used for the study of future short-term solar power generation prediction, which needs to be improved and evaluated. The most commonly used methods for counting errors in the literature on short-term solar power generation prediction are RMSE, MAE, and MAPE in the respective proportions of 25%, 22%, and 17%.

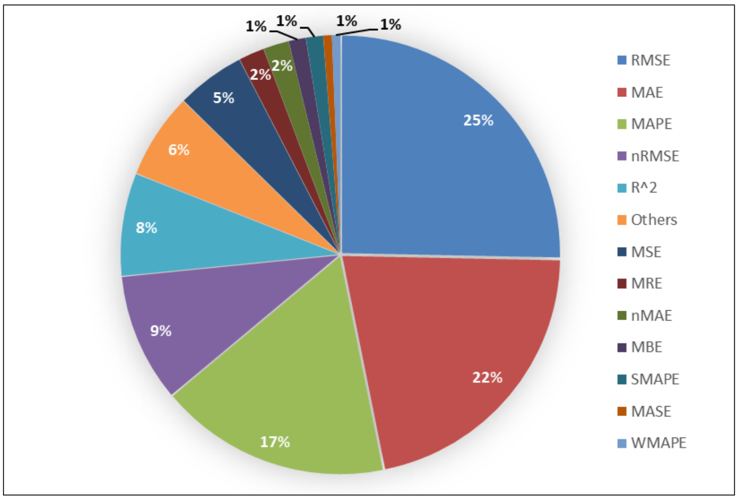

Figure 4. Proportion of statistical metrics for the reviewed works.

The root mean square error (RMSE) is the most commonly used metric since it describes the measurement of the average distribution of errors. The RMSE is a good method for describing prediction errors because it does not consider the difficulty of the predictions made under different meteorological conditions. In addition, most predictive models tend to use some variants of the RMSE to evaluate the performance of their predictive models.

The research on the above short-term solar PV power generation shows that the accuracy of traditional single prediction models, such as BP neural networks [10], SVM [12,25], etc., is far from sufficient. It is easy to fall into local optimal solutions, thereby reducing the prediction accuracy. Deep learning (DL) networks are neural networks with many hidden layers, which can actively and comprehensively grasp the abstract features of samples by using layer-by-layer training and learning methods to form a feature space [86,89]. It overcomes the shortcomings of BP neural networks and SVM, thereby effectively improving the prediction accuracy. In addition, due to machine learning techniques, such as extreme learning machines, where the input weights and hidden layer thresholds can be randomly set, the calculated hidden layer output weights can have significant fluctuations, leading to unstable prediction results. In order to reduce prediction errors, the particle swarm optimization algorithm has a strong global search ability and simple optimization, overcoming the disadvantage of the extreme learning machine model, in which the output weights are prone to random fluctuations [17,19]. A forgetting mechanism or adaptive extreme learning machine is employed to optimize the number of neurons in the hidden layer within a certain range to solve the problem of the poor generalization ability of extreme learning machines [21,87]. Due to the advantages and disadvantages of different prediction models, hybrid prediction methods are used to optimize the data processing results of different models based on specific strategies to obtain better solar PV power generation prediction results and ultimately improve predictive accuracy [92,93]. It was found that hybrid prediction methods have the optimization characteristics of the prediction results. These models fully leverage the advantages of various hybrid prediction models, effectively overcoming the poor adaptability and low prediction accuracy of individual models and providing a more practical reference for the optimization and dispatch of PV microgrids.

2.4. Scientific Contributions and Comparison of Reviewed Works

In the past decade, studies on solar PV power generation prediction have become more and more popular. This paper covers the contribution of the recent progressive solar PV power forecasting technology and explores the advantages and disadvantages of the various solar PV power forecasting models produced in the past three years, as shown in Table 2. These forecasting models have different forecasting capabilities, update the weights of each model in real time, have an improved comprehensive forecasting capability, and have good application prospects for solar PV power generation forecasting.

Table 2. Main contributions, advantages, and disadvantages of reviewed works in terms of solar PV power forecasting.

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[4]	December 2022	The search space and the number of experimental simulations are reduced, selecting parameters in a systematic manner, which can save computational resources and time without lowing statistical reliability.	- Divided the data into four seasons of the year, considering multiple climate variables for each season. - Perform principal component analysis for data reduction of climate variables.	Increasing dimensions of the input vector.
[5]	August 2021	A daily clustering method based on statistical features, such as daily average, maximum, and standard deviation of solar PV power, is adopted in the datasets to address the impact of uncertain weather on the prediction model.	- Established an ensemble model by combining the prediction results of ANN, DNN, SVR, LSTM, and CNN. - Higher stability.	- Time-consuming. - Complex computation process. - Increasing dimensions of the input vector.
[6]	March 2020	- The prediction error for unusual weather conditions is relatively large. - Expanding training samples, subdividing, and performing manual intervention can greatly improve prediction accuracy.	Lowered the chance of overfitting by balancing decision trees.	- Increasing dimensions of the input vector. - Adjusting the parameters of abnormal weather.
[7]	October 2021	- Only a set of dates for the specified prediction period are required as input for the forecasting purpose. - It can predict PV power generation across different time spans.	- Simplified the application of trained artificial neural networks. - Without real-time data on the current weather, it is possible to predict photovoltaic (PV) output.	- Increasing dimensions of the input vector. - Statistics of daily solar energy over the years.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[8]	June 2020	An accurate prediction model and results can be obtained for specific regional meteorological data.	A promising alternative to accurate power prediction for practical PV power plants.	Lowing the prediction accuracy of ANN models due to the chaotic nature of meteorological parameters.
[10]	September 2021	- The movement trajectory of clouds can be evaluated to accurately predict the occurrence covering the sun by calculating the displacement vector of the clouds on the ground cloud images. - Establishing a new 5 min ultrashort-term solar radiation prediction model, which is particularly suitable for predicting sudden changes in near-surface solar radiation in cloudy weather conditions.	- The features of ground cloud images can greatly improve prediction accuracy. - Thirteen features affecting solar radiation near the surface were extracted using digital image processing from ground cloud images.	Ultrashort-term forecasting of cloudy weather is very difficult since there is no rule about clouds blocking the sun.
[9]	March 2020	Determines which regions are more suitable for solar power stations by using the examined model.	Deducted the extra costs of installation and measurement.	Long mathematical processes.
[11]	November 2022	Reduced the input and computational complexity of the neural network model to simplify the hidden layer stage and build a fast and accurate prediction model for PV power generation.	Created a PV power generation prediction model with non-linear correlated variables.	Improvements in the prediction accuracy of performance.
[12]	July 2023	- A preprocessing method and prediction models for various PV sites with abnormal power generation are proposed. - A model combining convolutional autoencoder (CAE) and principal component analysis (PCA) was developed to extract and analyze features of solar data.	When compared the actual power generation of PV devices with the PV power generation predicted by using different Machine learning-based methods.	This database size limits the prediction horizon of the models.
[13]	November 2020	Similar hour-based and hybrid methods have presented better performance than commonly deployed prediction techniques.	The outputs of both solar PV prediction methods are dynamically weighted based on weather types and the MAE.	Increasing dimensions of the input vector.
[14]	January 2020	Creating a hybrid model of four different artificial intelligence prediction methods to obtain the optimal policy for each prediction technique to reduce predictability errors.	Ensemble of artificial intelligence methods into a new adaptive topology based on PT to improve solar PV power prediction.	- Increasing dimensions of the input vector. - Multi-method evaluation.
[15]	March 2022	- An RNN-LSTM algorithm was raised to predict the hour-ahead output PV power of three independent PV power plants annually. - Application of SVR, GPR, and ANN for annual, hour-ahead prediction of PV output power. - RNN with different LSTM frameworks were studied to determine the most implementable model.	- Compared the performance of ANFIS with the proposed RNN-LSTM algorithm. - Better prediction accuracy and results.	It is difficult to adjust the LSTM parameters and determine whether it converges.
[16]	October 2021	Forecasted photovoltaic power generation using historical weather data and different time resolutions.	Suggested a model that only requires a set of dates to specify a prediction period and more inputs.	The modeling would take a longer time due to the large amount of historical data.
[17]	October 2022	The ELM method was employed to ensure faster computing time and more direct microcomputer realization.	FFNN, with the particle swarm optimization algorithm, is used to achieve the search when computing the optimal weight.	Using PSO to select the parameters of adaptive ELM will make the computing time longer.
[18]	June 2020	Assisted power grid operators in better planning the economic dispatch of solar energy grid-connected electricity.	The accuracy of short-term predictions can further be improved by using a longer time period of earlier data.	It is necessary to do more work (usually for several years) on larger datasets to confirm this.
[19]	June 2021	To avoid erroneous optimistic predictions, the predicted power generation should be reduced to avoid affecting the stability of virtual power plants.	Better accuracy and time resolution of irradiance prediction is achieved for the next hour interval.	It is required to acquire the percentage of uncovered sun and cloud images within the next hour.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[20]	November 2021	The proposed model can predict solar PV power generation 10 days ahead.	The proposed model can achieve the best prediction accuracy with minimal error by training with accurate ratios of training and testing.	It is difficult to sharpen the accuracy of an individual model.
[21]	November 2021	Provided time and space compensation, as well as comprehensive power regulation while assisting energy dispatch units in generating strategies, is crucial for the stability and security of the energy system and its continuous optimization.	The proposed method can reduce the training time while improving accuracy.	The degree of uncertainty in photovoltaic power generation is closely related to the chaotic nature of weather conditions.
[22]	June 2022	- Proposed a novel PV prediction model that combines RF models, K-means clustering, and regression-based algorithms with LASSO and Ridge regularization to improve prediction accuracy. - Obtaining the five optimal sets of weight coefficients and which model prediction factors are important.	The integrated prediction models are much more accurate than single prediction models.	Recalculating the weight of each new input sample to improve the accuracy of a single prediction model.
[23]	October 2021	Trained Abha's solar photovoltaic system data using seven famous machine learning algorithms to predict photovoltaic power generation.	Obtaining relatively low prediction error of the algorithms.	The MSE of RF was the worst.
[24]	November 2022	The STVAR model demonstrated good model performance by predicting at a time resolution of 5 min to 1 h.	The prediction system can reduce the cost without installing and maintaining the solar irradiance sensor.	The research limitations of the irradiance prediction model (STVAR model) affect the final PV prediction results.
[25]	November 2021	Machine learning (ML) model is an efficient tool that can predict the power performance of any solar photovoltaic power generation.	The high reliability and accuracy of the GPR prediction model can be verified.	- Square exponential GPR shows worse performance due to the complicated relationship between input parameters and the dielectric coefficient. - Cubic SVM presents worse performance due to the complicated relationship between input parameters and PV module power.
[26]	June 2019	- RVFLN technology enables fast learning and accurate prediction. - Using different kernel functions to obtain better prediction accuracy and combining two optimal kernel functions to obtain more practical solar energy predictions - By utilizing effective optimization techniques for optimization and adjustment, more accurate and shorter time span solar energy predictions can be provided.	Expediting computing time and lowering the complexity of the model.	The selection of parameters using MK-RVFLN affects the accuracy of the prediction model.
[27]	September 2022	Clustering initial training set and day-ahead power forecasting using adaptive k-means.	Gru network has excellent prediction results, better robustness, and fewer errors.	Increasing dimensions of the input vector.
[28]	May 2022	Had better global radiation prediction results.	Proposing seven machine learning models for PV power generation forecasting.	Increasing dimensions of the input vector.
[29]	February 2022	Selecting the SVR-based model parameters using PSO-based algorithms to improve the model performance	Reaching better performance of the forecast algorithm.	Using algorithm bar parameters will lead to longer operation time.
[30]	April 2022	A novel solar PV power prediction method composed of a feature extraction, clustering method, and hybrid classification regression prediction engine.	- The forecasting computation is quicker. - Individual training for each subset is achieved by a prediction engine. - Obtaining the final solar PV power forecasting by using a relevancy-based combination of these two predictions.	- Increasing dimensions of the input vector. - The internal parameters of the subset need to be well selected.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[31]	August 2021	In order to obtain the best frequency demarcation point of the decomposed component, basic data is subtracted from the correlation between the decomposed component and basic data.	Using CNN for low- and high-frequency component prediction and obtaining the final prediction result by additive reconstruction.	Use of FFT for data preprocessing is less applicable than the general data pre-processing method.
[32]	January 2022	Proposed a short-term prediction model for learning cloud motion characteristics from stacked optical flow maps using satellite images as input	- Better performance of the forecast algorithm. - Sky image technology with cloud motion.	- Leading to a heavy computing burden. - Complex computation process.
[33]	November 2020	Proposed a novel method that does not rely on the test data labels during the update process.	This method can dynamically adjust its structural parameters to fit to the latest weather conditions.	- Complex computation process. - Parameter adjustment required.
[34]	February 2022	Modeling data at various time resolutions, extracting hierarchical features, and capturing short-term and long-term dependencies.	A model has been proposed to accelerate the learning process and use shared representations as auxiliary information to reduce overfitting.	- Complex computation process. - Parameter adjustment required.
[35]	January 2021	- In order to reduce the insufficient dispersion of the raw set, BMA's mixture model significantly improves the predictive calibration. - Better than the ensemble model output statistical parameter method in the literature.	- Being the kernel trimming technology of NWP. - The weighted sum for specific probability density functions.	- Increasing dimensions of the input vector.
[36]	June 2022	- High statistical accuracy prediction has been achieved using advanced deep learning-based prediction technology. - Classify solar radiation data from each month of the year to obtain a monthly time series dataset, significantly improving high-performance prediction. - Implemented a combination of recursive multi-step and multi-output prediction strategy	- Use of fixed-sized internal representation in the core of the model, significantly improving short-term solar radiation prediction.	More LSTM parameter settings need to be adjusted.
[37]	May 2022	- As compared to models such as CNN-LSTM and non-clustering-based specific LSTM, the proposed model presented excellent predictive performance. - This model exhibits minor prediction errors for photovoltaic power generation with significant solar radiation variability.	- CB-LSTM exhibits robust performance under different conditions. - As compared to M-LSTM and ST-LSTM, CB-LSTM has better predictive performance for all climatic zones and areas.	- High NRMSE error.
[38]	March 2022	The proposed model combines a stacking structure and drop-out layer to improve the accuracy of the PV prediction model.	The LSTM of multi-step CNN stacking with deep learning algorithms improve the validity of the model as compared with other traditional solar irradiance prediction.	- Complex structure and hardware requirements.
[39]	July 2020	As compared and analyzed in detail with other contemporary ML methods, least absolute shrinkage and selection operator (LASSO), and elastic net (ENET) methods, the effectiveness of the proposed method was verified.	- This prediction model has outstanding accuracy in all selected performance criterion. - The feasibility and practicality of the proposed model have been effectively confirmed.	Failed to reach the accuracy of the proposed prediction model.
[40]	December 2021	- Propose a Siamese CNN model to automatically extract features from continuous sky images. - This model shares some parameters to reduce training time. - The use of SCNN-LSTM effectively combines the time series features of images and meteorological data, improving the prediction accuracy of the model.	The prediction accuracy was promoted by comparing to other models.	In some cloudy or cloudy days conditions, the model prediction accuracy needs to be improved.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[41]	March 2022	Optimized ANN and LSTM prediction models to improve their accuracy.	The ANN and LSTM models in the reduced Input Set and the complete Input Set with seven exogenous variables exhibit the same prediction accuracy.	- Requiring a larger amount of training data. - Higher computational cost and training time for the models.
[42]	March 2022	- The prediction of solar radiation is greatly influenced by parameters such as solar radiation, direct shortwave radiation, scattered shortwave radiation, and temperature. - The prediction of solar radiation is significantly influenced by evapotranspiration, sunshine duration, and humidity.	- Abilities of adaptation. - Non-linearity. - Rapid learning.	Too many solar radiation input parameters.
[43]	August 2022	- Proposed the LSTM-AE model as a benchmark for deep learning solar forecasting. - Ensured higher accuracy and stability of prediction models. - A comprehensive evaluation study was conducted on the performance of prediction models.	A deep learning AE model is an effective method for predicting day-ahead PV power based on NWP due to its highest accuracy.	Using deep learning for each model without NWP, the day-ahead prediction accuracy will sharply decrease, and its upgrade is extremely limited.
[44]	June 2021	- The proposed TESDL model is a short-term prediction algorithm with good generalization ability and robustness - Realizing excellent prediction model accuracy.	Significantly reducing the control costs, initial hardware component costs, and long-term maintenance costs of potential PV power plants.	The whole PV system uses the solar modules with the lowest power to calculate the worst-case power generation performance, and mismatch loss is a major problem.
[45]	September 2022	With historical satellite images as input, the FPP model based on CNN is employed to predict the future PV power fluctuation mode.	Reaching better performance for the prediction algorithm.	- Complex computation process. - Use of cloud computing.
[46]	January 2021	The predicted results can successfully close the expected output and well capture the intra-hour ramping.	Achieving good performance of the prediction algorithm.	It is difficult to adjust the LSTM parameters and determine whether it converges.
[47]	October 2022	Proposed an automatic encoder LSTM model with the best reliability performance.	- Data normalization. - Reaching better performance of the forecast algorithm.	It is difficult to adjust the LSTM parameters and determine if it converges.
[48]	August 2021	Realizing accurate cloud distribution information using ground-based total sky images.	- Particle image velocimetry technology and Fourier phase correlation theory are conducted to establish a benchmark model. - Sky image technology.	- The feature of 3-D CAE models could not find well. - Increasing dimensions of the input vector.
[49]	October 2020	The significance of the proposed synthetic prediction is highlighted to promote the more effective use of public sky prediction types and achieve more reliable PV power generation predictions.	Studied the performance of the proposed model in different seasons with different intraday horizon lengths.	- Complex computation process.
[50]	November 2022	To deal with the scenarios of missing data, an integrated model is proposed for probabilistic PV power generation prediction.	- Addressing data missing scenarios. - Data tolerance.	- Increasing dimensions of the input vector. - Computing time is too long.
[51]	January 2021	In order to predict the solar irradiance at several locations simultaneously, a prediction model trained with several artificial neural networks is proposed.	A family of flexible and robust deep learning models for solar irradiance prediction is proposed.	- Increasing dimensions of the input vector.
[52]	September 2020	A CNN model is proposed to find out the non-linear characteristics and invariant structures in the previous output power data so as to promote the prediction of PV power.	- CNN was used to preprocess the data. - Reaching better performance of the forecast algorithm.	- Increasing dimensions of the input vector - Computing time is too long.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[53]	May 2022	By using bidirectional extrapolation to simulate cloud motion, a directed graph from multiple frames of historical images was generated for predicting PV power.	Proposed a GNN model that is more flexible for different sizes of inputs to handle dynamic ROIs and promote the prediction of PV power.	Increasing dimensions of the input vector.
[54]	December 2021	A novel prediction model is proposed to improve the quality of training data, the size of the data, the meteorological conditions of the location where the data are obtained, and the duration or horizon of the measured solar irradiance.	The accuracy of solar irradiance prediction technology has been greatly improved by training the prediction model with 10-year datasets.	- Complex computation process. - Parameter adjustment required.
[55]	March 2022	A deep learning method based on Long short-term memory (LSTM) algorithm is used to investigate the prediction ability of solar power data.	Proposed multiple prediction models with high suitability.	- Complex computation process. - Parameter adjustment required.
[56]	March 2022	- Utilizing grid search technology to minimize uncertainty. - Comparing the predictive performance of different data segmentation methods from three months to one day.	Comparing the impact of seasonal and periodic variables on time series data and PV output prediction over different time spans (14 days to 5 min)	It is difficult to adjust the LSTM parameters and determine whether it converges.
[57]	August 2021	Optimizing the number of neurons in the hidden layer, weight, and bias of the proposed neural network using MVO and GA algorithms.	Multi-layer Feed-forward neural network (MFFNN) is used to study the accuracy of MFFNN-MVO and MFFNN-GA models.	- Increasing dimensions of the input vector.
[58]	February 2021	The relevance of the studied model in real-time and short-term solar energy prediction was evaluated using appropriate prediction models to ensure optimized management and safety requirements.	Artificial neural networks (ANN) have demonstrated good performance in real-time and short-term predictions.	- Increasing dimensions of the input vector.
[59]	June 2021	Proposed a forecasting model with higher prediction accuracy and relatively small overall fluctuations.	Decomposing the PV power sequence to reduce the complexity and instability of the raw data by the VMD decomposition technology.	Prediction errors and fluctuations are large.
[60]	August 2022	- Providing alternative tools for reliable prediction. - Providing a promising method for predicting daily solar radiation.	The connectivity of machine learning models and optimization algorithms.	Computational complexity
[61]	August 2022	- Proposed a new hybrid DL model, which processes input data with slime mold algorithm (SMA) for feature selection, CNN, LSTM network, CNN, using an MLP for final processing - Obtained a more accurate GSR prediction model.	Proposed a novel DL-based hybrid model that overcomes the above research limitations and produces accurate GSR predictions.	- Incorporating different predictor data decomposition methods. - Complex computation process.
[62]	January 2022	Proposed an MC-WT-CBILSTM hybrid model combined with various AI methods to improve the prediction ability of the model	- Using wavelet transform as input data preprocessing effectively decreases the data complexity. - Raised the forecasting ability of the multi-channel CNN-BiLSTM models.	- The generalization ability for most forecasting methods is poor. - Only achieve good results in a small range.
[63]	April 2022	The short-term solar PV prediction model developed can be applied anywhere.	- The prediction ability of the hybrid model is about 34% of that of the NAR model. - Approximately 42% of the Persistence model.	The proposed prediction model should exclude redundant or irrelevant variables to avoid false results.
[64]	April 2021	A DA prediction model has been proposed with a three-phase adaptive modification solution to improve the algorithm's ability in local and global searches.	Proposed a hybrid deep learning model with a powerful decomposition technology to help reduce data complexity	A long time span has a negative impact on prediction results.

Table 2. *Cont.*

Work	Date of Publication and Location	Main Contribution	Advantages	Disadvantages
[65]	September 2022	In order to better reflect the accuracy of the prediction model, comparative tests were conducted on multiple time dimensions to verify the advantage of the prediction model.	A new prediction model has been proposed, which has an average improvement of about 15% in prediction accuracy and stability as compared to other prediction models.	Adjusting parameters using the BO algorithm increases the time cost of training the model.
[66]	September 2022	An ensemble interval prediction method was proposed for solar power generation prediction to obtain higher-quality prediction intervals than other AI methods	Obtaining more reliable and stable interval prediction results.	The KDE method takes a longer total computing time as compared to other AI methods.
[67]	November 2022	- Data mismatch and boundary constraint are calculated within the Loss function during prediction model training. - Positive constraints are used to limit the output of prediction models.	Demonstrated the stability and robustness of the TG-A-CNN-LSTM model by testing the performance of sparse data prediction models.	It is difficult to adjust the LSTM parameters and determine whether it converges.
[68]	July 2020	Providing better accuracy than other investigated methods for cost computation.	Proposed a novel prediction model that outperforms other investigated methods in terms of accuracy and computational time.	Prediction accuracy can be increased with other new effective techniques.
[69]	June 2020	SBFM predicts PV power at high time resolution by using low time resolution weather variables.	PV power generation prediction with a five-minute time resolution can substantially obtain accurate results.	Increasing dimensions of the input vector.
[70]	August 2021	Generalized a novel prediction model to find the optimal prediction by affine transformation mapping for a given available measurement.	Irradiance, temperature, relative humidity, and solar zenith angle are selected as highly correlated inputs of WRF prediction model.	- Complex computation process. - Parameter adjustment required.
[71]	November 2020	Completed the prediction combination of machine learning models with convex combination and Quantile regression averaging (QRA).	The forecasting performance of Diebold Mariano and Giacomini White tests is remarkable.	- Increasing dimensions of the input vector.
[72]	May 2023	The data set of the proposed new prediction model contains weather features, which is more cost-efficient and more suitable for scenarios where there is no dedicated hardware or hard-to-obtain input features.	The proposed RF and DNN prediction models utilize widely available weather features and operate quite well even in the event of sudden fluctuations in PV output.	Increasing dimensions of the input vector.
[73]	July 2021	The accuracy of the proposed multi-graph model is superior to other benchmark models in the day-ahead prediction cases.	When compared to the deep learning benchmark models, the single- graph prediction model had lower cost regarding training time.	- Increasing dimensions of the input vector. - Longer computing time.
[74]	March 2022	The proposed model and algorithm can lower the dimensionality of the model and improve its prediction accuracy.	Proposed a short-term PV power generation prediction model based on combined fuzzy clustering, a genetic algorithm programming system (GAPS), and radial basis function (RBF) for meteorological data to improve the prediction accuracy.	The parameter numbers of the search window size affect the accuracy of the proposed models.

In the process of predicting solar PV power, each prediction model has its own advantages and disadvantages. Due to the research limitations, it is difficult to achieve high-precision predictions or different types of predictions with a single prediction model. With the continuous increase in the solar PV power grid connection capacity and the increase in the solar PV power penetration power, the State Grid Corporation has implemented increasingly high requirements for the scheduling and prediction accuracy of solar PV power. Based on this, establishing a combined prediction model for solar PV power prediction by integrating the advantages of various prediction models is of great significance for improving the accuracy of solar PV power prediction. Therefore, conducting research on solar PV power prediction based on artificial intelligence algorithms and optimizing prediction models has practical value in engineering for improving the accuracy of solar PV power prediction and the reliability of grid connection scheduling.

3. State-of-the-Art Approaches for Short-Term Solar PV Power Forecasting

The short-term solar PV power forecasting model is discussed in depth, as shown in Figure 5. The latest approaches to short-term solar PV power forecasting developed in the past three years are reviewed to provide an important reference for solar PV power grid integration. In order to improve the accuracy of solar PV power forecasting, this paper gives a detailed overview of the contributions, advantages, and disadvantages of various delivered solar PV power forecasting models, as well as presenting future research work. These advanced forecasting models can be approximately classified into artificial intelligence/neural networks (NNs), machine learning or optimization algorithms, deep learning, hybrid and ensemble forecasting models, and other statistical analysis methods. The proposed novel short-term solar PV power forecasting models provide very useful information for power system operation and control with high renewable energy penetration.

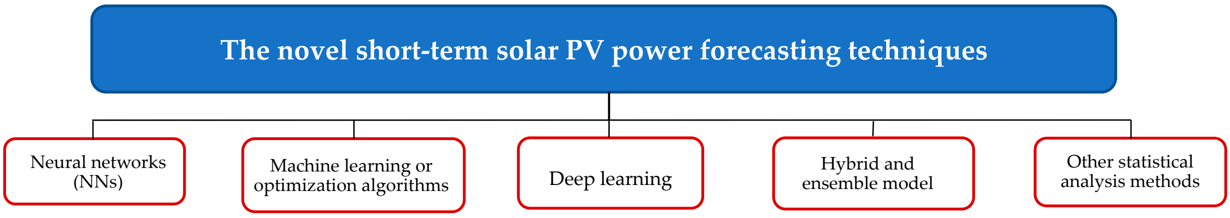

Figure 5. Classification of the novel short-term solar PV power forecasting techniques.

3.1. Insolation Prediction for Solar PV Power Generation

A solar cell is a converter that directly converts solar light energy into electrical energy due to the PV effect. Photodiodes will convert the sun's light energy into electrical energy, which can be connected in series and parallel to form a battery array to increase the output. Equation (1) is given by using least squared curve fitting:

$$P_S = P_{sb} \cdot S^t \cdot k \tag{1}$$

Of these, P_S is the electrical energy obtained from solar energy (kW), which is the record of the solar power plant. P_{sb} is the total capacity of the solar cell (kW), which is a constant value (units: kW), S^t is the global solar radiation (MJ/m^2) obtained by the Central Weather Bureau, k is the design coefficient of solar module (parameters for curve fitting) and in solar PV power generation, and S^t is the main factor affecting the power generation output and is also the main variable used to predict solar PV power generation, making Equation (1) more in line with actual solar power generation. Meteorological data, such as the air temperature, relative humidity, precipitation, precipitation hours, sunshine hours, and global solar radiation, provided by Central Weather Bureau (CWB) Observation Data Inquiry System, were used as input variables for the solar irradiance-related information database; the output variable is the global solar radiation for the solar PV power generation prediction techniques, as shown in Figure 5.

PV Array Model

The PV cell is a p–n junction semiconductor with characteristics similar to diodes. The parameters of the PV cell are modeled, as can be seen in Figure 6. The current source generates the photocurrent, I_{ph}, which is proportional to the solar irradiation. The relation between the array terminal current and voltage is presented in reference [94]. The maximum power point of the photovoltaic (PV) array is variational, so a search algorithm is needed according to the current-voltage (I-V) and power-voltage (P-V) characteristics of the solar cell.

$$V_{PV} = \frac{nKT}{q} \ln\left(\frac{I_{SC}}{I_{PV}} + 1\right) \tag{2}$$

$$I_{PV} = I_{SC} - I_{PVO}\left[\exp\left(\frac{q(V_{PV} + I_{PV}R_s)}{nKT}\right) - 1\right] - \frac{V_{PV} + R_s I_{SC}}{R_{sh}} \tag{3}$$

where R_s is the series resistance, R_{sh} is the shunt resistance, I_{SC} is the light-induced current, n is the diode ideality factor, I_{PVO} is the diode saturation current, and V_T is the thermal voltage. K is the Boltzmann constant (1.38×10^{-23} J/°k), and q is the electronic charge. I_{SC} depends on the irradiance level S and on the array temperature T, while I_{PVO} and V_T depend on T only. The PV array current I_{PV} is a non-linear function of the PV array voltage V_{PV} of the irradiance level S and of the temperature [94,95].

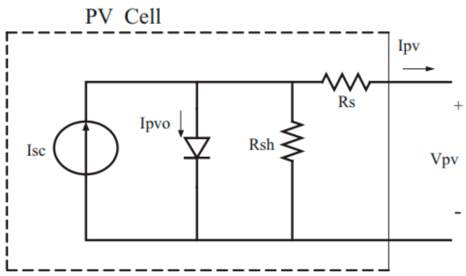

Figure 6. Equivalent circuit of a PV cell [95].

3.2. Data Mining Technique

The data mining technique is used for data processing, and more meaningful data are selected from the database as modeling data, as shown in Figure 7. The problem dealt with by data mining is finding meaningful hidden information in a big database. Power generation forecasts are similar to solar energy.

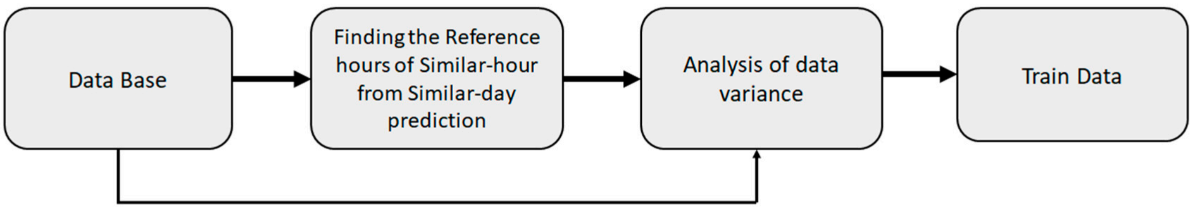

Figure 7. Flowchart of the data mining technique (DMT).

3.3. Hourly Similarity (HS)-Based Method

The reference data selection method based on the hourly similarity (HS) forecasting method introduces the concept of the horizontal axis and the vertical axis of time. The hour of the prediction day to be forecasted is called the prediction hour. Firstly, the prediction day is used to find weather information for the reference day, which is the day before and the next day (the day after). The reference hours are selected from the prediction hour and the reference day. The reference hours are the hours before and after the prediction hour. These reference hours are used as reference data. The reference hours of the hourly similarity prediction method were selected from the hypothetical case demonstration, as shown in Figure 8. Grey is historical data. Yellow represents future data.

Demonstration of how to select reference data; assuming that 12:00 on the prediction day is the prediction hour, the reference hours include 11:00 on the current day, 11:00–13:00 on the previous day, and 12:00–13:00 on the prediction day. A total of six pieces of data are selected for the reference hours (collectively referred to as the reference data).

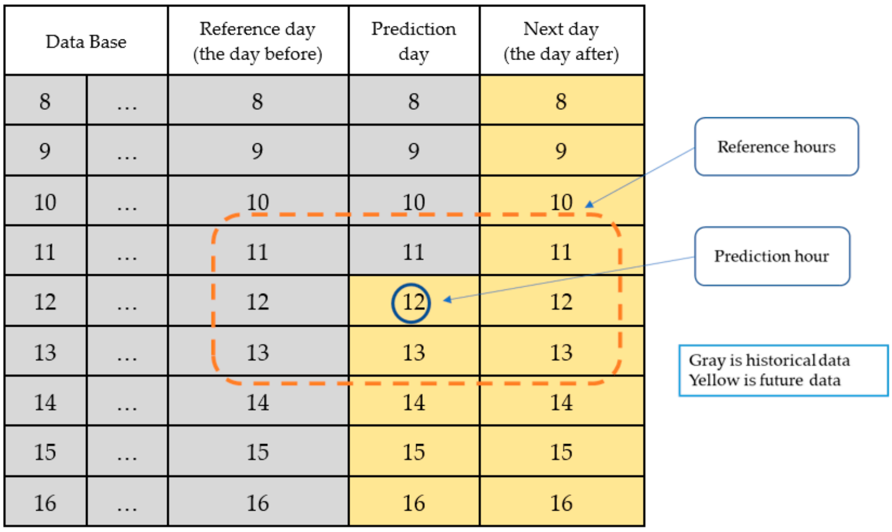

Figure 8. Schematic diagram of the selection of reference data for the similar day prediction method.

Figure 8 shows the data types used in data mining for the similar day prediction method, and the data mining steps are as follows:

Step 1: Select the database range and reference day from the prediction hour.
Step 2: Determine the reference data from the prediction hour and reference day.
Step 3: Normalize the data first and then perform sequence similarity searching for each layer based on the reference hours of each layer. Each reference hour has its own set of sorted data.
Step 4: Integrate a set of data from the same layer, and all the integrated data are modeling data.

As an example, two layers with Layers 1 and 2 can be used for the reference data. The normalization for a particular $\{m, r\}$ is shown in Equation (4):

$$N_{i,k}^{mr} = sqrt\left(\sum_{j=1}^{f}\left(Nr_{d-m,r}^{j} - N_{d-i,k}^{j}\right)^2\right) \tag{4}$$

where $Nr_{d-m,r}$ is a similar hour, $j \in [1, 2, \ldots, f]$ is the input space dimension number, d is the reference data for day, and $m = [0, 1]$ as well as $r \in \{t+1, t, t-1\}$ are the concepts of the horizontal axis and vertical axis of time at a similar hour. $N_{d-i,k}^{j}$ is the original data for hour k in the database, and $i \in [0, 1, 2, \ldots, v]$ is the number of the days with the total number set to v; $k \in [1, 2, \ldots, u]$ is the hour number with $u = 24$. $N_{i,k}^{mr}$ is sequenced for each reference hour and is used to figure out the degree of similarity in the data. L is the number of selections at a similar hour, and $\mathbf{H}_{DMT}$ is the training data selected at a similar hour, as shown in Equations (5) and (6):

$$\mathbf{H}_{DMT}^{m} = sort\left\{\left\{N_{i,k}^{m1}\right\}_{k=1}^{u}\right\}_{i=0}^{v} \tag{5}$$

$$\mathbf{H}_{DMT} = \underset{m}{\cup}\mathbf{H}_{DMT}^{m} = \underset{m}{\cup}\underset{r}{\cup}\underset{1\to L}{sort}\left\{\left\{N_{i,k}^{m1}\right\}_{k=1}^{u}\right\}_{i=0}^{v} \tag{6}$$

After data mining, the modeling data are selected by the hourly similarity (HS)-based prediction method. The modeling data include the training data and test data. The training data are the integrated data obtained after sequencing the data (the sequencing data do not include reference data), and the reference data are used as the test material. The modeling data selected by data mining can be used to train the models of various state-of-the-art approaches for short-term solar PV power forecasting.

3.4. Internet of Things (IOT) Technology

Data obtained from solar PV power generation and several environmental sensors were collected to store in the Raspberry Pi database and corresponding data tables using Internet of Things technology. Through the Raspberry Pi environment, a Python crawler program can be developed to grab the weather forecast information from the local environmental observatory of the Central Meteorological Bureau and store the weather forecast information in the database. Raspberry Pi is also applied to set up the human–machine interface and display it in website form while viewing it remotely via the internet. Furthermore, the collection progress is checked to confirm the hardware operation status and collect the data stably [96–98].

After long-term data collection, the amount of data required for the input layer parameters of the neural network is obtained. Data tables for variables, such as solar PV power generation data and environmental sensor data, are exported from the database management system and are first brought into the model to train the input parameters of the fuzzy neural network while performing data preprocessing. After the data preprocessing is completed, the data are divided into a training group and a test group. The training group data are used to continuously train the internal parameters of the neural network, and then the proposed method is verified by the test group. The feasibility and accuracy of the data collection framework are shown in Figure 9.

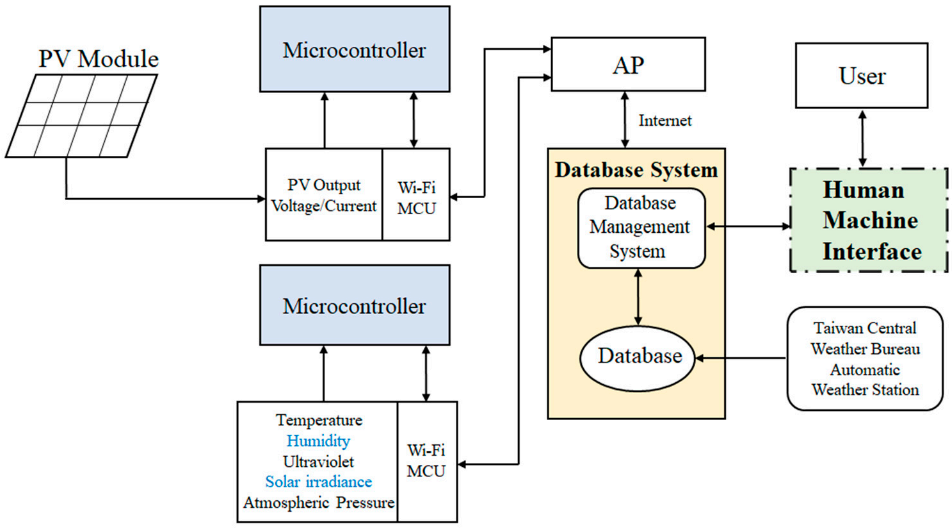

Figure 9. Configuration diagram of the IOT technology prediction system.

3.5. Sky-Image-Based Methods

The automatic identification of clouds, cloud matching, and cloud area corrections based on ground cloud images and the estimation of the cloud movement direction are carried out to allow accurate judgments to be made on clouds that are about to cover the sun and to improve the accuracy and speed of big data feature prediction for solar PV power generation. Next, efficient pixel-sensitive prediction models can be developed based on satellite imagery to track the cloud shape and motion and study satellite measurements and high-resolution cloud images (e.g., images from ground-based sky cameras). In addition, these cloud image information-correlation features have been comprehensively used for classification and prediction while verifying the feasibility of the model using different datasets [99].

Based on dynamic sky images, the characteristics of the cloud layer are extracted to estimate the future cloud movement path by using the object tracking algorithm, and then the cloud cover of the sun is calculated according to the cloud movement path. Finally, the change in insolation is estimated through the long short-term memory (LSTM) network. The paper had the aim of finding a method for predicting the movement path of cloud cover and, at the same time, estimating the sun's shading of cloud piles and forecasting power variation due to the changes in insolation through the long short-term memory (LSTM) network. This information can be provided to power dispatchers or the EMS (energy management system) in advance to allow them to effectively respond to the impact of cloud clusters shading the sun on the grid [100,101].

A schematic diagram of the sky-image-based methods is shown in Figure 10. The system configuration can be divided into three parts, among which D1 is the part used for analyzing the characteristics of all-sky clouds covering the sun and predicting the movement path of cloud clusters; D2 is the part used for extracting the characteristics of ground-based all-sky pyranometers, and D3 is the part used for predicting the solar irradiance and the solar PV power generation. Part D1 in Figure 10 shows the design of a method to predict the moving path of cloud layers through the whole sky image and the moving path of the sun and deduce the moving path of the cloud layers. The moving path of the cloud layer takes into account the moving path of the sun. For sun shading conditions, the predictive path of cloud layer movement is regarded as future information, and the real-time value for the insolation observation of the ground-based all-sky pyranometer is determined in part D2. The input of the intelligent learning network is used to deduce the change in insolation, and the variation in solar PV power generation can be obtained according to the power and insolation curve (PV power curve) of the solar PV module.

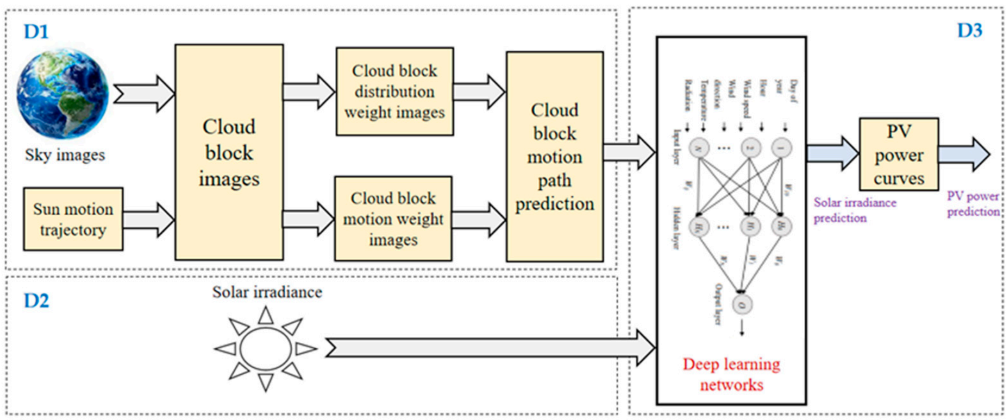

Figure 10. Schematic diagram for sky-image-based methods.

In recent years, various research institutions and scholars have adopted different cutting-edge methods to reduce power fluctuations and randomness in the power prediction of solar power generation, as well as to prevent possible errors and omissions in the original data and allow certain results to be achieved. However, there are still some problems to be solved. First of all, in the future, the sample space can be further expanded, and the diurnal insolation and the dimension of data samples can be increased to predict the diversity of solar data. According to solar power generation data with different characteristics, the prediction model was further optimized to increase the applicability of the model. Secondly, according to the characteristics of the existing hybrid model, the parameter optimization method was further improved to ensure that the prediction model has high prediction accuracy at different time sampling rates, making it suitable for different prediction situations. An overview of future solar PV forecasting studies is given in the next section.

4. Future Studies and Development

As an important subsystem of smart management systems for microgrids, solar PV power generation prediction systems play a vital role in the development of solar energy. Due to the close relationship between solar radiation and meteorological conditions, such as seasons, cloudy and sunny days, and day and night, novel solar PV power output predictive methods have been developed in the past few years to allow for the balanced operation and optimized dispatch of the power grid system. These methods have been used in experiments, and some results have been achieved to solve the intermittent and random power problems associated with solar PV power generation prediction as well as to reduce possible errors and omissions in the original input data. Based on the latest advances in AI neural networks, machine learning, and deep learning methods, this paper examined the temporal resolution, the parameters used, the accuracy, and the research limitations and reviewed the contributions, advantages, and disadvantages of the latest hybrid prediction models for the development of solar PV power generation. However, there are still some issues that need to be improved. The following points describe the main aspects that can be studied further:

(1) Weather variable predictions: Recent investigations only selected meteorological stations based on historical survey data. However, the meteorological information from different regions is inevitably different. Therefore, considering the impacts of the geographical environment, weather, or climate-related factors at the location of the meteorological station can definitely improve the accuracy of solar radiation predictions. In addition, in terms of other meteorological and site determination factors used for solar radiation forecasting, such as the temperature, humidity, precision, pressure, and solar radiation, etc., the impacts of these factors on the prediction results need to be explored, as these could be included as input factors for future meteorological data from the Meteorological Bureau to improve prediction accuracy;

(2) Modeling the prediction algorithms through cloud images: Cloud areas based on ground cloud images are automatically identified, matched, and corrected to estimate the direction of cloud movement and make accurate judgments about clouds that are about to cover the sun. It is necessary to improve the accuracy and speed of feature prediction for big data used for solar PV power generation. Efficient pixel-sensitive prediction models were developed based on satellite images to track the shape and motion of clouds and study satellite measurements and high-resolution cloud images (such as images from ground sky cameras). These correlation features of cloud image information are comprehensively utilized for classification and prediction, for which different datasets are applied to verify the feasibility of the model. New hybrid models or multiple optimization algorithms, including cloud information for predictive models, are also integrated to improve the models and their prediction accuracy;

(3) Solar PV power generation forecasting: Weather forecasting is selected based on data characteristics, and machine learning or optimization algorithms are added to the solar PV power generation prediction model, for example, optimization algorithms with RNN-LSTM, to optimize the superparameters and enhance the prediction accuracy. These deep learning (DL) models or ensemble models (EMs) are implemented for solar PV power generation forecasting to provide more stable power to the grid;

(4) Data preprocessing or data feature analysis: Through data preprocessing and the clustering analysis of initial training sets to predict solar PV power generation, the accuracy of the prediction model is significantly improved. Secondly, the computing cost is reduced, the regression accuracy is significantly improved, and the model's own features are effectively found for predictions through the preprocessing and correlation analysis of input data. When compared with general data preprocessing methods, data preprocessing is further optimized, improving the applicability of FFT methods;

(5) Improvement of inaccurate or missing data: In order to expand the ability of irradiance prediction methods to predict the power capacity of new solar power plants without data, we explored prediction methods that can handle repeated and frequent continuous multi-point data loss, for example, extracting data suitable for the target domain from different data domains or using data from other regions as a supplement when the training data for the target location are insufficient. Therefore, it is

of practical significance to improve short-term solar PV predictions of inaccurate or missing data;

(6) Integration with the power system: Accurate PV power generation forecasting is very important for the scheduling and regulation of power systems after the grid connection, and its results can be integrated into the entire energy management system or utilities to improve grid performance and achieve a higher level of renewable energy integration. Secondly, variation in power generation can have an impact on the voltage and frequency of the power system at any time, solving the problems of economic dispatch, grid integration, and the mismanagement of power management systems caused by the variability of solar energy. Furthermore, based on the basic viewpoint of large-scale or distributed solar PV systems, load forecasting, demand response applications, aggregate capacity prediction, and the dispatch of a large number of distributed solar PV systems can be obtained. When combined with pumped storage power stations, adjustable biomass power stations, or PV battery systems, they can stably transmit solar PV power generation and improve the flexibility of power dispatch.

5. Conclusions

This paper first presented the significance of using solar PV power for energy conservation and emission reduction issues, as well as the technical challenges faced when predicting solar PV power generation. The necessity of developing prediction systems for solar PV power generation and improving the model's accuracy was clarified. Some existing physical and statistical learning methods have deficiencies, such as high modeling costs and large input data requirements when performing predictions, while traditional machine learning methods have trouble processing missing data, are prone to overfitting, and ignore the correlations between attributes in the dataset. This paper further reported on many novel prediction models for PV power generation based on deep learning or hybrid models that integrate multiple meteorological factors such as temperature, relative humidity, rainfall (precipitation), global solar radiation, wind speed, etc. By analyzing the mean square error (MSE) value and the determination coefficient (R-Squared) value, we proved that the proposed method further improves prediction accuracy when compared to previous prediction methods. Secondly, this paper introduced the current situation of solar PV power generation forecasting from a global perspective. Most of these efforts cover the field of short-term PV power generation forecasting, which has grown significantly in the past few years. These advanced solar short-term PV power generation prediction models were classified and compared in terms of temporal resolution, the parameters used, accuracy, and research limitations. In addition, this paper reviewed the latest progress in short-term solar PV power generation based on artificial intelligence methods, emphasizing their contributions to model development, their advantages and disadvantages, and the areas of future study and development. The contributions of this review work are as follows:

(1) The most advanced algorithms for short-term solar PV power generation forecasting were evaluated;

(2) The accuracy, advantages, and disadvantages of various new AI hybrid models were evaluated;

(3) Existing challenges and issues, such as short-term solar PV power generation data diversity, algorithm structure, hyperparametric adjustment, optimization integration, and AI hybrid issues, were explored;

(4) The development and future possibilities of efficient short-term solar PV power generation prediction methods based on artificial intelligence were proposed. Future research directions and challenges for existing short-term solar PV power generation prediction methods were provided;

(5) The impacts of meteorological information and cloud image information in terms of improving data preprocessing or data feature selection and analysis and data

inaccuracies or loss were explored. The distribution of the database input sources, forecasting methods, and predictive error metrics was analyzed, and the effective use of machine learning or optimization algorithms and deep learning models to improve the accuracy of existing models was discussed to increase forecasting accuracy;

(6) It was shown that improving the prediction accuracy of short-term solar PV power generation is beneficial to the optimal scheduling of microgrids and integration with the optimization of power systems.

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Abbreviations

PV	Photovoltaic
AI	Artificial intelligence
ANFIS	Adaptive-network-based fuzzy inference systems
ANN	Artificial neural network
BNN	Backpropagation neural network
CNN	Convolutional neural network
RNN	Regression neural network
LSTM	Long-short term memory
CLSTM	Convolutional long short-term memory
SVM	Support vector machine
SVR	Support vector regression
GBDT	Gradient boosting decision tree
ELM	Extreme learning machine
GHI	Global horizontal irradiance
ABL	Adaptive boosting Learning
TOB	Transparent Open Box
FOS-ELM	Extreme learning machine with a forgetting mechanism
ResAttGRU	Multi-branch attentive gated current residual network
BMA	Bayesian model averaging
Rec_LSTM	Recursive long short-term memory network
STVAR	Spatio-temporal autoregressive model
GPR	Gaussian process regression
MK-RVFLN	Multi-kernel random vector functional link neural network
GRU	Gate recurrent units—a variant of LSTM
Conv LSTM	Convolutional long-term short-term memory
MFFNN	Multi-layer feed-forward neural network
MVO	Multi-verse optimization
GA	Genetic algorithm
MLP	Multi-layer perceptron
VMD	Variational mode decomposition
RVM	Relevance vector machine
CMAES	Covariance matrix adaptive evolution strategies
XGB	Extreme gradient boosting
MARS	Multi-adaptive regression splines

MC-WT-CBiLSTM	Multi-channel, wavelet transform combining convolutional neural network and bidirectional long short-term memory
NARX-CVM	Non-linear autoregressive with exogenous inputs and corrective vector multiplier
LSTM-SVR-BO	Long short-term memory support vector regression Bayesian optimization
GBRT-Med-KDE	Gradient boosting regression tree median-Kernel density estimation
TG-A-CNN-LSTM	Theory-guided and attention-based CNN-LSTM
HMM	Hidden Markov model
SBFM	Similarity-based forecasting model
KF	Kalman filtering
QRA	Quantile regression averaging
MRE	Mean relative error
MAE	Mean absolute error
MASE	Mean absolute scaled error
WMAPE	Weighted mean absolute percentage error
MBE	Mean bias error
MSE	Mean squared error
RMSE	Root mean squared error
MAPE	Mean absolute percent error
SMAPE	Symmetric mean absolute percentage error
nMAE	Normalized mean absolute error
nMBE	Normalized mean bias error
nRMSE	Normalized root mean squared error
R^2	Fitting coefficient

References

1. International Renewable Energy Agency. *Renewable Capacity Statistics*; International Renewable Energy Agency: Masdar City, United Arab Emirates, 2020.
2. Gonçalves, G.L.; Abrahão, R.; Rotella Junior, P.; Rocha, L.C.S. Economic Feasibility of Conventional and Building-Integrated Photovoltaics Implementation in Brazil. *Energies* **2022**, *15*, 6707. [CrossRef]
3. Grazioli, G.; Chlela, S.; Selosse, S.; Maïzi, N. The Multi-Facets of Increasing the Renewable Energy Integration in Power Systems. *Energies* **2022**, *15*, 6795. [CrossRef]
4. Moreira, M.O.; Kaizer, B.M.; Ohishi, T.; Bonatto, B.D.; Zambroni de Souza, A.C.; Balestrassi, P.P. Multivariate Strategy Using Artificial Neural Networks for Seasonal Photovoltaic Generation Forecasting. *Energies* **2023**, *16*, 369. [CrossRef]
5. Gutiérrez, L.; Patiño, J.; Duque-Grisales, E. A Comparison of the Performance of Supervised Learning Algorithms for Solar Power Prediction. *Energies* **2021**, *14*, 4424. [CrossRef]
6. Lateko, A.A.H.; Yang, H.-T.; Huang, C.-M.; Aprillia, H.; Hsu, C.-Y.; Zhong, J.-L.; Phương, N.H. Stacking Ensemble Method with the RNN Meta-Learner for Short-Term PV Power Forecasting. *Energies* **2021**, *14*, 4733. [CrossRef]
7. Bhatti, A.R.; Bilal Awan, A.; Alharbi, W.; Salam, Z.; Bin Humayd, A.S.; Praveen, R.P.; Bhattacharya, K. An Improved Approach to Enhance Training Performance of ANN and the Prediction of PV Power for Any Time-Span without the Presence of Real-Time Weather Data. *Sustainability* **2021**, *13*, 11893. [CrossRef]
8. Bozkurt, H.; MacIt, R.; Çelik, Ö.; Teke, A. Evaluation of artificial neural network methods to forecast short-term solar power generation: A case study in Eastern Mediterranean Region. *Turk. J. Electr. Eng. Comput. Sci.* **2022**, *30*, 2013–2030. [CrossRef]
9. Erduman, A. A smart short-term solar power output prediction by artificial neural network. *Electr. Eng.* **2020**, *102*, 1441–1449. [CrossRef]
10. Hu, K.; Wang, L.; Li, W.; Cao, S.; Shen, Y. Forecasting of solar radiation in photovoltaic power station based on ground-based cloud images and BP neural network. *IET Gener. Transm. Distrib.* **2022**, *16*, 333–350. [CrossRef]
11. Kim, J.; Lee, S.-H.; Chong, K.T. A Study of Neural Network Framework for Power Generation Prediction of a Solar Power Plant. *Energies* **2022**, *15*, 8582. [CrossRef]
12. Park, T.; Song, K.; Jeong, J.; Kim, H. Convolutional Autoencoder-Based Anomaly Detection for Photovoltaic Power Forecasting of Virtual Power Plants. *Energies* **2023**, *16*, 5293. [CrossRef]
13. Moreno, G.; Martin, P.; Santos, C.; Rodríguez, F.J.; Santiso, E. A Day-Ahead Irradiance Forecasting Strategy for the Integration of Photovoltaic Systems in Virtual Power Plants. *IEEE Access* **2020**, *8*, 204226–204240. [CrossRef]
14. Lima, M.; Anderson, F.B.; Carvalho, P.C.M.; Fernández-Ramírez, L.M.; Braga, A.P.S. Improving solar forecasting using Deep Learning and Portfolio Theory Integration. *Energy* **2020**, *195*, 117016. [CrossRef]
15. Akhter, M.N.; Mekhilef, S.; Mokhlis, H.; Almohaimeed, Z.M.; Muhammad, M.A.; Khairuddin, A.S.M.; Akram, R.; Hussain, M.M. An Hour-Ahead PV Power Forecasting Method Based on an RNN-LSTM Model for Three Different PV Plants. *Energies* **2022**, *15*, 2243. [CrossRef]

16. Meng, M.; Song, C. Daily Photovoltaic Power Generation Forecasting Model Based on Random Forest Algorithm for North China in Winter. *Sustainability* **2020**, *12*, 2247. [CrossRef]
17. Alzahrani, A. Short-Term Solar Irradiance Prediction Based on Adaptive Extreme Learning Machine and Weather Data. *Sensors* **2022**, *22*, 8218. [CrossRef] [PubMed]
18. Wood, D.A. Hourly-averaged solar plus wind power generation for Germany 2016: Long-term prediction, short-term forecasting, data mining and outlier analysis. *Sustain. Cities Soc.* **2020**, *60*, 102227. [CrossRef]
19. Radovan, A.; Šunde, V.; Kučak, D.; Ban, Ž. Solar irradiance forecast based on cloud movement prediction. *Energies* **2021**, *14*, 3775. [CrossRef]
20. Babbar, S.M.; Lau, C.Y.; Thang, K.F. Long Term Solar Power Generation Prediction using Adaboost as a Hybrid of Linear and Non-linear Machine Learning Model. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 536–545. [CrossRef]
21. Ramkumar, G.; Sahoo, S.; Amirthalakshmi, T.M.; Ramesh, S.; Prabu, R.T.; Kasirajan, K.; Samrot, A.V.; Ranjith, A. A Short-Term Solar Photovoltaic Power Optimized Prediction Interval Model Based on FOS-ELM Algorithm. *Int. J. Photoenergy* **2021**, *2021*, 3981456. [CrossRef]
22. Lateko, A.A.H.; Yang, H.-T.; Huang, C.-M. Short-Term PV Power Forecasting Using a Regression-Based Ensemble Method. *Energies* **2022**, *15*, 4171. [CrossRef]
23. Mohana, M.; Saidi, A.S.; Alelyani, S.; Alshayeb, M.J.; Basha, S.; Anqi, A.E. Small-Scale Solar Photovoltaic Power Prediction for Residential Load in Saudi Arabia Using Machine Learning. *Energies* **2021**, *14*, 6759. [CrossRef]
24. Mehazzem, F.; André, M.; Calif, R. Efficient Output Photovoltaic Power Prediction Based on MPPT Fuzzy Logic Technique and Solar Spatio-Temporal Forecasting Approach in a Tropical Insular Region. *Energies* **2022**, *15*, 8671. [CrossRef]
25. Zazoum, B. Solar photovoltaic power prediction using different machine learning methods. *Energy Rep.* **2022**, *8*, 19–25. [CrossRef]
26. Majumder, I.; Dash, P.K.; Bisoi, R. Short-term solar power prediction using multi-kernel-based random vector functional link with water cycle algorithm-based parameter optimization. *Neural Comput. Appl.* **2020**, *32*, 8011–8029. [CrossRef]
27. Liu, Y. Short-Term Prediction Method of Solar Photovoltaic Power Generation Based on Machine Learning in Smart Grid. *Math. Probl. Eng.* **2022**, *2022*, 8478790. [CrossRef]
28. Krechowicz, M.; Krechowicz, A.; Lichołai, L.; Pawelec, A.; Piotrowski, J.Z.; Stępień, A. Reduction of the Risk of Inaccurate Prediction of Electricity Generation from PV Farms Using Machine Learning. *Energies* **2022**, *15*, 4006. [CrossRef]
29. Das, U.K.; Tey, K.S.; Idris, M.Y.I.; Mekhilef, S.; Seyedmahmoudian, M.; Stojcevski, B.; Horan, B. Optimized Support Vector Regression-Based Model for Solar Power Generation Forecasting on the Basis of Online Weather Reports. *IEEE Access* **2022**, *10*, 15594–15604. [CrossRef]
30. Nejati, M.; Amjady, N. A New Solar Power Prediction Method Based on Feature Clustering and Hybrid-Classification-Regression Forecasting. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1188–1198. [CrossRef]
31. Yan, J.; Hu, L.; Zhen, Z.; Wang, F.; Qiu, G.; Li, Y.; Yao, L.; Shafie-khah, M.; Catalão, J.P.S. Frequency-Domain Decomposition and Deep Learning Based Solar PV Power Ultra-Short-Term Forecasting Model. *IEEE Trans. Ind. Appl.* **2021**, *57*, 3282–3295. [CrossRef]
32. Cheng, L.; Zang, H.; Wei, Z.; Ding, T.; Xu, R.; Sun, G. Short-term Solar Power Prediction Learning Directly from Satellite Images With Regions of Interest. *IEEE Trans. Sustain. Energy* **2022**, *13*, 629–639. [CrossRef]
33. Sheng, H.; Ray, B.; Chen, K.; Cheng, Y. Solar Power Forecasting Based on Domain Adaptive Learning. *IEEE Access* **2020**, *8*, 198580–198590. [CrossRef]
34. Ziyabari, S.; Du, L.; Biswas, S.K. Multibranch Attentive Gated ResNet for Short-Term Spatio-Temporal Solar Irradiance Forecasting. *IEEE Trans. Ind. Appl.* **2022**, *58*, 28–38. [CrossRef]
35. Doubleday, K.; Jascourt, S.; Kleiber, W.; Hodge, B.-M. Probabilistic Solar Power Forecasting Using Bayesian Model Averaging. *IEEE Trans. Sustain. Energy* **2021**, *12*, 325–337. [CrossRef]
36. Blazakis, K.; Katsigiannis, Y.; Stavrakakis, G. One-Day-Ahead Solar Irradiation and Windspeed Forecasting with Advanced Deep Learning Techniques. *Energies* **2022**, *15*, 4361. [CrossRef]
37. Malakar, S.; Goswami, S.; Ganguli, B.; Chakrabarti, A.; Roy, S.S.; Boopathi, K.; Rangaraj, A.G. Deep-Learning-Based Adaptive Model for Solar Forecasting Using Clustering. *Energies* **2022**, *15*, 3568. [CrossRef]
38. Elizabeth Michael, N.; Mishra, M.; Hasan, S.; Al-Durra, A. Short-Term Solar Power Predicting Model Based on Multi-Step CNN Stacked LSTM Technique. *Energies* **2022**, *15*, 2150. [CrossRef]
39. Mishra, M.; Dash, P.B.; Nayak, J.; Naik, B.; Swain, S.K. Deep learning and wavelet transform integrated approach for short-term solar PV power prediction. *J. Int. Meas. Confed.* **2020**, *166*, 15. [CrossRef]
40. Zhu, T.; Guo, Y.; Li, Z.; Wang, C. Solar Radiation Prediction Based on Convolution Neural Network and Long Short-Term Memory. *Energies* **2021**, *14*, 8498. [CrossRef]
41. Wentz, V.H.; Maciel, J.N.; Gimenez Ledesma, J.J.; Ando Junior, O.H. Solar Irradiance Forecasting to Short-Term PV Power: Accuracy Comparison of ANN and LSTM Models. *Energies* **2022**, *15*, 2457. [CrossRef]
42. Fraihat, H.; Almbaideen, A.A.; Al-Odienat, A.; Al-Naami, B.; De Fazio, R.; Visconti, P. Solar Radiation Forecasting by Pearson Correlation Using LSTM Neural Network and ANFIS Method: Application in the West-Central Jordan. *Future Internet* **2022**, *14*, 79. [CrossRef]
43. Cheng, L.; Zang, H.; Wei, Z.; Zhang, F.; Sun, G. Evaluation of opaque deep-learning solar power forecast models towards power-grid applications. *Renew. Energy* **2022**, *198*, 960–972. [CrossRef]

44. Chang, R.; Bai, L.; Hsu, C.-H. Solar power generation prediction based on deep Learning. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101354. [CrossRef]
45. Wang, F.; Li, J.; Zhen, Z.; Wang, C.; Ren, H.; Ma, H.; Zhang, W.; Huang, L. Cloud Feature Extraction and Fluctuation Pattern Recognition Based Ultrashort-Term Regional PV Power Forecasting. *IEEE Trans. Ind. Appl.* **2022**, *58*, 6752–6767. [CrossRef]
46. Liu, C.-H.; Gu, J.-C.; Yang, M.-T. A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting. *IEEE Access* **2021**, *9*, 17174–17195. [CrossRef]
47. Suresh, V.; Aksan, F.; Janik, P.; Sikorski, T.; Revathi, B.S. Probabilistic LSTM-Autoencoder Based Hour-Ahead Solar Power Forecasting Model for Intra-Day Electricity Market Participation: A Polish Case Study. *IEEE Access* **2022**, *10*, 110628–110638. [CrossRef]
48. Fu, Y.; Chai, H.; Zhen, Z.; Wang, F.; Xu, X.; Li, K.; Shafie-Khah, M.; Dehghanian, P.; Catalão, J.P.S. Sky Image Prediction Model Based on Convolutional Auto-Encoder for Minutely Solar PV Power Forecasting. *IEEE Trans. Ind. Appl.* **2021**, *57*, 3272–3281. [CrossRef]
49. Hossain, M.S.; Mahmood, H. Short-Term Photovoltaic Power Forecasting Using an LSTM Neural Network and Synthetic Weather Forecast. *IEEE Access* **2020**, *8*, 172524–172533. [CrossRef]
50. Li, Q.; Xu, Y.; Chew, B.S.H.; Ding, H.; Zhao, G. An Integrated Missing-Data Tolerant Model for Probabilistic PV Power Generation Forecasting. *IEEE Trans. Power Syst.* **2022**, *37*, 4447–4459. [CrossRef]
51. Prado-Rujas, I.-I.; García-Dopico, A.; Serrano, E.; Pérez, M.S. A Flexible and Robust Deep Learning-Based System for Solar Irradiance Forecasting. *IEEE Access* **2021**, *9*, 12348–12361. [CrossRef]
52. Li, G.; Xie, S.; Wang, B.; Xin, J.; Li, Y.; Du, S. Photovoltaic Power Forecasting with a Hybrid Deep Learning Approach. *IEEE Access* **2020**, *8*, 175871–175880. [CrossRef]
53. Cheng, L.; Zang, H.; Wei, Z.; Ding, T.; Sun, G. Solar Power Prediction Based on Satellite Measurements—A Graphical Learning Method for Tracking Cloud Motion. *IEEE Trans. Power Syst.* **2022**, *37*, 2335–2345. [CrossRef]
54. Obiora, C.N.; Hasan, A.N.; Ali, A.; Alajarmeh, N. Forecasting Hourly Solar Radiation Using Artificial Intelligence Techniques. *IEEE Can. J. Electr. Comput. Eng.* **2021**, *44*, 497–508. [CrossRef]
55. Elsaraiti, M.; Merabet, A. Solar Power Forecasting Using Deep Learning Techniques. *IEEE Access* **2022**, *10*, 31692–31698. [CrossRef]
56. Ahmed, R.; Sreeram, V.; Togneri, R.; Datta, A.; Arif, M.D. Computationally expedient Photovoltaic power Forecasting: A LSTM ensemble method augmented with adaptive weighting and data segmentation technique. *Energy Convers. Manag.* **2022**, *258*, 115563. [CrossRef]
57. Talaat, M.; Said, T.; Essa, M.A.; Hatata, A.Y. Integrated MFFNN-MVO approach for PV solar power forecasting considering thermal effects and environmental conditions. *Int. J. Electr. Power Energy Syst.* **2022**, *135*, 107570. [CrossRef]
58. Jebli, I.; Belouadha, F.-Z.; Kabbaj, M.I.; Tilioua, A. Prediction of solar energy guided by pearson correlation using machine learning. *Energy* **2021**, *224*, 120109. [CrossRef]
59. Ma, Y.; Zhang, X.; Zhen, Z.; Mei, S. Ultra-short-term Photovoltaic Power Prediction Method Based on Modified Clear-sky Model. *Autom. Electr. Power Syst.* **2021**, *45*, 44–51.
60. Goliatt, L.; Yaseen, Z.M. Development of a hybrid computational intelligent model for daily global solar radiation prediction. *Expert Syst. Appl.* **2023**, *212*, 118295. [CrossRef]
61. Ghimire, S.; Deo, R.C.; Casillas-Pérez, D.; Salcedo-Sanz, S.; Sharma, E.; Ali, M. Deep learning CNN-LSTM-MLP hybrid fusion model for feature optimizations and daily solar radiation prediction. *J. Int. Meas. Confed.* **2022**, *202*, 111759. [CrossRef]
62. Pi, M.; Jin, N.; Chen, D.; Lou, B. Short-Term Solar Irradiance Prediction Based on Multichannel LSTM Neural Networks Using Edge-Based IoT System. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 2372748. [CrossRef]
63. Rangel-Heras, E.; Angeles-Camacho, C.; Cadenas-Calderón, E.; Campos-Amezcua, R. Short-Term Forecasting of Energy Production for a Photovoltaic System Using a NARX-CVM Hybrid Model. *Energies* **2022**, *15*, 2842. [CrossRef]
64. Meng, F.; Zou, Q.; Zhang, Z.; Wang, B.; Ma, H.; Abdullah, H.M.; Almalaq, A.; Mohamed, M.A. An intelligent hybrid wavelet-adversarial deep model for accurate prediction of solar power generation. *Energy Rep.* **2021**, *7*, 2155–2164. [CrossRef]
65. Wang, L.; Mao, M.; Xie, J.; Liao, Z.; Zhang, H.; Li, H. Accurate solar PV power prediction interval method based on frequency-domain decomposition and LSTM model. *Energy* **2023**, *262*, 125592. [CrossRef]
66. Zhang, Y.; Hu, T. Ensemble Interval Prediction for Solar Photovoltaic Power Generation. *Energies* **2022**, *15*, 7193. [CrossRef]
67. Du, J.; Zheng, J.; Liang, Y.; Liao, Q.; Wang, B.; Sun, X.; Zhang, H.; Azaza, M.; Yan, J. A theory-guided deep-learning method for predicting power generation of multi-region photovoltaic plants. *Eng. Appl. Artif. Intell.* **2023**, *118*, 105647. [CrossRef]
68. Jahromi, K.G.; Gharavian, D.; Mahdiani, H. A novel method for day-ahead solar power prediction based on hidden Markov model and cosine similarity. *Soft Comput.* **2020**, *24*, 4991–5004. [CrossRef]
69. Sangrody, H.; Zhou, N.; Zhang, Z. Similarity-Based Models for Day-Ahead Solar PV Generation Forecasting. *IEEE Access* **2020**, *8*, 104469–104478. [CrossRef]
70. Suksamosorn, S.; Hoonchareon, N.; Songsiri, J. Post-Processing of NWP Forecasts Using Kalman Filtering with Operational Constraints for Day-Ahead Solar Power Forecasting in Thailand. *IEEE Access* **2021**, *9*, 105409–105423. [CrossRef]
71. Mutavhatsindi, T.; Sigauke, C.; Mbuvha, R. Forecasting Hourly Global Horizontal Solar Irradiance in South Africa Using Machine Learning Models. *IEEE Access* **2020**, *8*, 198872–198885. [CrossRef]

72. Rangelov, D.; Boerger, M.; Tcholtchev, N.; Lämmel, P.; Hauswirth, M. Design and Development of a Short-Term Photovoltaic Power Output Forecasting Method Based on Random Forest, Deep Neural Network and LSTM Using Readily Available Weather Features. *IEEE Access* **2023**, *11*, 41578–41595. [CrossRef]
73. Cheng, L.; Zang, H.; Ding, T.; Wei, Z.; Sun, G. Multi-Meteorological-Factor-Based Graph Modeling for Photovoltaic Power Forecasting. *IEEE Trans. Sustain. Energy* **2021**, *2*, 1593–1603. [CrossRef]
74. Jinpeng, W.; Yang, Z.; Xin, G.; Jeremy, G.; Xin, Z. A Hybrid Predicting Model for the Daily Photovoltaic Output Based on Fuzzy Clustering of Meteorological Data and Joint Algorithm of GAPS and RBF Neural Network. *IEEE Access* **2022**, *10*, 30005–30017. [CrossRef]
75. Maciel, J.N.; Ledesma, J.; Giménez, J.; Junior, O. Hideo Ando Forecasting Solar Power Output Generation: A Systematic Review with the Proknow-C. *IEEE Lat. Am. Trans.* **2021**, *19*, 612–624. [CrossRef]
76. Rajagukguk, R.A.; Ramadhan, R.A.A.; Lee, H.-J. A Review on Deep Learning Models for Forecasting Time Series Data of Solar Irradiance and Photovoltaic Power. *Energies* **2020**, *13*, 6623. [CrossRef]
77. Gupta, P.; Singh, R. PV Power Forecasting Based On Data Driven Models: A Review. *Int. J. Sustain. Eng.* **2021**, *14*, 1733–1755. [CrossRef]
78. Wu, Y.-K.; Huang, C.-L.; Phan, Q.-T.; Li, Y.-Y. Completed Review of Various Solar Power Forecasting Techniques Considering Different Viewpoints. *Energies* **2022**, *15*, 3320. [CrossRef]
79. Benavides Cesar, L.; Amaro e Silva, R.; Manso Callejo, M.Á.; Cira, C.-I. Review on Spatio-Temporal Solar Forecasting Methods Driven by In Situ Measurements or Their Combination with Satellite and Numerical Weather Prediction (NWP) Estimates. *Energies* **2022**, *15*, 4341. [CrossRef]
80. Sudharshan, K.; Naveen, C.; Vishnuram, P.; Krishna Rao Kasagani, D.V.S.; Nastasi, B. Systematic Review on Impact of Different Irradiance Forecasting Techniques for Solar Energy Prediction. *Energies* **2022**, *15*, 6267. [CrossRef]
81. Mohamad Radzi, P.N.L.; Akhter, M.N.; Mekhilef, S.; Mohamed Shah, N. Review on the Application of Photovoltaic Forecasting Using Machine Learning for Very Short- to Long-Term Forecasting. *Sustainability* **2023**, *15*, 2942. [CrossRef]
82. Tu, C.-S.; Tsai, W.-C.; Hong, C.-M.; Lin, W.-M. Short-Term Solar Power Forecasting via General Regression Neural Network with Grey Wolf Optimization. *Energies* **2022**, *15*, 6624. [CrossRef]
83. Lotfi, M.; Javadi, M.; Osório, G.J.; Monteiro, C.; Catalão, J.P.S. A Novel Ensemble Algorithm for Solar Power Forecasting Based on Kernel Density Estimation. *Energies* **2020**, *13*, 216. [CrossRef]
84. Prasad, A.A.; Kay, M. Assessment of Simulated Solar Irradiance on Days of High Intermittency Using WRF-Solar. *Energies* **2020**, *13*, 385. [CrossRef]
85. Alkahtani, H.; Aldhyani, T.H.H.; Alsubari, S.N. Application of Artificial Intelligence Model Solar Radiation Prediction for Renewable Energy Systems. *Sustainability* **2023**, *15*, 6973. [CrossRef]
86. Benti, N.E.; Chaka, M.D.; Semie, A.G. Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects. *Sustainability* **2023**, *15*, 7087. [CrossRef]
87. López-Cuesta, M.; Aler-Mur, R.; Galván-León, I.M.; Rodríguez-Benítez, F.J.; Pozo-Vázquez, A.D. Improving Solar Radiation Nowcasts by Blending Data-Driven, Satellite-Images-Based and All-Sky-Imagers-Based Models Using Machine Learning Techniques. *Remote Sens.* **2023**, *15*, 2328. [CrossRef]
88. Wei, Y.; Zhang, H.; Dai, J.; Zhu, R.; Qiu, L.; Dong, Y.; Fang, S. Deep Belief Network with Swarm Spider Optimization Method for Renewable Energy Power Forecasting. *Processes* **2023**, *11*, 1001. [CrossRef]
89. Moreno, G.; Santos, C.; Martín, P.; Rodríguez, F.J.; Peña, R.; Vuksanovic, B. Intra-Day Solar Power Forecasting Strategy for Managing Virtual Power Plants. *Sensors* **2021**, *21*, 5648. [CrossRef]
90. Dhimish, M.; Lazaridis, P.I. Approximating Shading Ratio Using the Total-Sky Imaging System: An Application for Photovoltaic Systems. *Energies* **2022**, *15*, 8201. [CrossRef]
91. Crisosto, C.; Hofmann, M.; Mubarak, R.; Seckmeyer, G. One-Hour Prediction of the Global Solar Irradiance from All-Sky Images Using Artificial Neural Networks. *Energies* **2018**, *11*, 2906. [CrossRef]
92. Wang, Z.; Wang, L.; Huang, C.; Luo, X. A Hybrid Ensemble Learning Model for Short-Term Solar Irradiance Forecasting Using Historical Observations and Sky Images. *IEEE Trans. Ind. Appl.* **2023**, *59*, 2041–2049. [CrossRef]
93. El Alani, O.; Abraim, M.; Ghennioui, H.; Ghennioui, A.; Ikenbi, I.; Dahr, F. Short term solar irradiance forecasting using sky images based on a hybrid CNN–MLP model. *Energy Rep.* **2021**, *7*, 888–900. [CrossRef]
94. Cheng, Y.M.; Liu, Y.C.; Hung, S.C.; Cheng, C.S. Multi-input inverter for grid-connected hybrid PV/wind power system. *IEEE Trans. Power Electron.* **2007**, *22*, 1070–1076. [CrossRef]
95. Chuang, S.J.; Hong, C.M.; Chen, C.H. Design of intelligent control for stabilization of microgrid system. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 569–578. [CrossRef]
96. Rocha, Á.B.D.; Fernandes, E.d.M.; Santos, C.A.C.d.; Diniz, J.M.T.; Junior, W.F.A. Development of a Real-Time Surface Solar Radiation Measurement System Based on the Internet of Things (IoT). *Sensors* **2021**, *21*, 3836. [CrossRef] [PubMed]
97. Zhou, H.; Liu, Q.; Yan, K.; Du, Y. Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 9249387. [CrossRef]
98. Dosymbetova, G.; Mekhilef, S.; Orynbassar, S.; Kapparova, A.; Saymbetov, A.; Nurgaliyev, M.; Zholamanov, B.; Kuttybay, N.; Manakov, S.; Svanbayev, Y.; et al. Neural Network-Based Active Cooling System with IoT Monitoring and Control for LCPV Silicon Solar Cells. *IEEE Access* **2023**, *11*, 52585–52602. [CrossRef]

99. Dissawa, L.H.; Godaliyadda, R.I.; Ekanayake, P.B.; Agalgaonkar, A.P.; Robinson, D.; Ekanayake, J.B.; Perera, S. Sky Image-Based Localized, Short-Term Solar Irradiance Forecasting for Multiple PV Sites via Cloud Motion Tracking. *Int. J. Photoenergy* **2021**, *2021*, 9973010. [CrossRef]
100. Song, S.; Yang, Z.; Goh, H.; Huang, Q.; Li, G. A novel sky image-based solar irradiance nowcasting model with convolutional block attention mechanism. *Energy Rep.* **2022**, *8*, 125–132. [CrossRef]
101. Kong, W.; Jia, Y.; Dong, Z.Y.; Meng, K.; Chai, S. Hybrid approaches based on deep whole-sky-image learning to photovoltaic generation forecasting. *Appl. Energy* **2020**, *280*, 115875. [CrossRef]