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Posted Date: 23 May 2023

doi: 10.20944/preprints202305.1534.v1

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Article

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 of 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 the balanced operation and optimized dispatch of the power grid system, and reduces operating costs. Solar PV power generation depends on weather conditions, which are prone to large fluctuations under different weather conditions. Its power generation is characterized by randomness, volatility and intermittency. Recently, the demand for further investigation and effective use on the uncertainty of short-term solar PV power generation prediction has been getting increasing attention in many application of renewable energy sources. In order to improve the predictive accuracy of output power of solar PV power generation and develop a precise predictive model, the authors worked predictive algorithms for the output power of a solar PV power generation system. Moreover, since short-term solar PV power forecasting is one of the important aspects for 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 in the reviewed literature are classified according to the input data source used for accurate predictive models, and the case studies and examples proposed are analyzed in detail. The contributions, advantages and disadvantages of the predictive probabilistic methods are compared. Finally, the future studies of short-term solar PV power forecasting is proposed.

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

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 PV module modules to directly convert solar energy into electricity energy. This is a novel and highly promising energy comprehensive utilization method, with the advantages of low environmental pollution, no pollution of air and water resources, no noise pollution, being able 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 54GW, a year-on-year increase of 37.8%. The total installed capacity in the first nine months of this year is about 142.5GW. Forecast shows that the annual installed capacity will reach 222GW [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 41.4GW, a new increase of 28.1GW compared to last year, achieving a year-on-year increase of

47%. By 2022, the cumulative installed capacity is expected to reach 208.9GW. According to the statistical data released by the National Energy Administration of China, the new installed capacity of power in 2022 was 87.41 GW, and by 2022, the cumulative installed capacity of power was 396.261 GW.

The prediction of power generation has been 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 of advanced technology and equipment, and the accumulation of sufficient historical data. The main work is to use different predictive models to improve the 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 the Artificial Intelligence (AI) or Neural Networks (NNs) approaches, a new short-term PV predictive method based on the Artificial Neural Network (ANN) or Recurrent neural network (RNN) has been proposed. This method employs dynamic artificial neural networks to predict solar radiation and temperature, thereby achieving prediction of solar power energy output [4–8,10,12]. Sudden change of solar radiation near the surface are extracted from the ground based cloud images sampling technology combined with the Similar day-based and ANN based approaches ensures accuracy in solar radiation prediction [9,11,13]. Lima et al. (2020) used AI methods in a new adaptive topology based on the 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 Support Vector Machine (SVM), Support Vector Regression (SVR), Extreme Learning Machine (ELM), Gradient boosting decision tree (GBDT), Adaptive boosting Learning (ABL), etc. has proposed [15–33], which use a large amount of satellite images and data. Compared with traditional time series analysis, the forecasting accuracy has significantly improved. Ziyabari et al. (2022) used the a novel multi-range attentive gated current residual network (ResAttGRU) model and meteorological data, clear sky index, and solar Ireland to predict short term solar radiation [34]. This model also proposes a strong multi time scale in the proposed architecture, and GRU can utilize temporal information at a lower computational cost than the popular Long Short Term Memory (LSTM). Doubleday et al. (2021) established a 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 long-term short-term memory (LSTM) network model, recursive short-term memory network (Rec LSTM), convolutive long-term short-term memory (Conv LSTM), multi-step CNN stacked LSTM model, etc. [36–56] are used to predict solar PV output power. Talat et al. (2021) proposed a new multi-layer feedforward 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. Jebley et al. (2021) established a multilayer 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, and then optimized the weight of the multi-layer perceptron through the artificial bee colony algorithm to achieve the prediction of solar PV output power. This nonlinear forecasting model has a better effect than the linear forecasting model since the output power is intermittent and random [58].

Moreover, there are some forecasting works using 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-adversial deep, GBRT-Med- KDE Model, TG-A-CNN-LSTM, etc. and implemented interval forecasting for microgrids, providing a good solution for energy management of microgrids [59–63]. Meng et al. (2021) proposed a new hybrid wavelet-adversial 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

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modification solution of DA to improve the algorithm's ability to modify in local and global search, and has 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 experimental results, and 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) model. 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 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 the better forecasting accuracy, stability and robustness for solar PV power generation compared to a single forecasting model [67]. Furthermore, Ghasvarian Jahromi et al. (2020) proposed some forecasting works using statistical methods such as Hidden Markov model (HMM), Similarity-based forecasting models (SBFMs), and Kalman filtering (KF), and applied them to probability forecasting of solar power generation [68,69]. Mutavhatsindi et al. (2021) achieved good results in predicting the production of solar power plants using the Quantitative Regression Average (QRA) regression model based on meteorological data [70,71].

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 works is to summarize and analyze the existing PV power generation forecasting methods in recent years based on time scales, forecasting models, and output data [72–74]. 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 [75,76]. Furthermore, Sudharshan and Mohamad Radzi summarized 161 and 306 related papers respectively, introducing various combinations, influencing factors, issues, limitations, and suggestions for achieving solar PV power generation prediction of hybrid ANN, machine learning methods or algorithm optimization [77,78].

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. To satisfy the requirements of large-scale solar PV power grid integration and further improve the forecasting accuracy of a short-term solar PV power generation, it is necessary to develop a short-term solar PV power forecasting model based on the state-of-the art hybrid AI algorithms to accomplish accurate, robust and efficient solar PV power forecasting. The main contribution of this paper is to review the impact 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 AI or 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 the advantages and disadvantages, and contributions of various solar PV power forecasting models. Some important metrics as 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 a good application prospect in 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 the existing issues in the methodologies. Future research directions are prospected.

2. Reviews for the development of 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 by Solar PV power prediction errors to system operation and realize 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 accuracy 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. The optimized scheduling that is more in line with the actual operation proves the practicability and necessity of improving the forecasting accuracy of power generation.

2.1. Forecasting techniques

Previously, there were some review articles with a wide scope (prediction techniques, sources of input databases, statistical metrics, temporal and spatial coverage, etc.) In recent years, relevant scholars have conducted theoretical research and practical simulation. This paper works a comprehensive review of the novel techniques for predicting solar PV power generation. Figure 1 shows the predictive model of solar PV power generation. The advantage of these methods as (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 it also avoids excessive weighting of individual data.

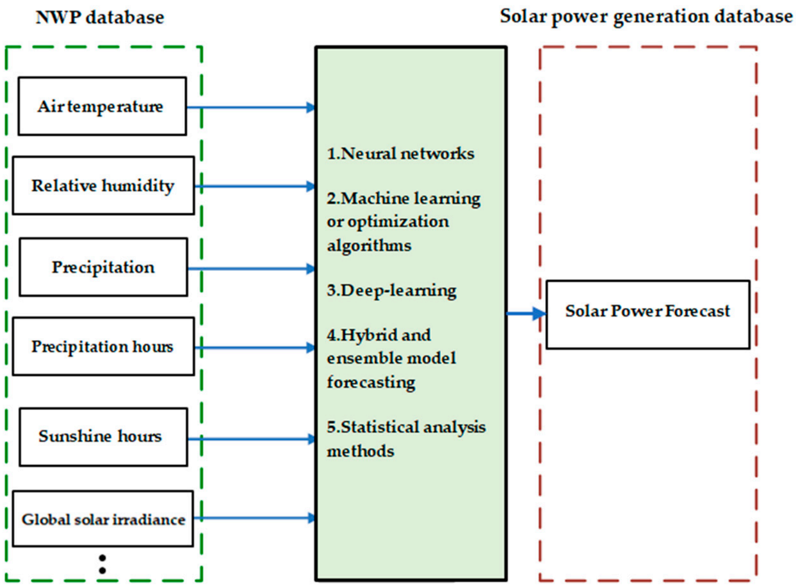

Figure 1. Short-term solar PV power generation prediction model.

2.2. Literature classification based on methods

Modern solar PV power generation forecasting methods mainly include AI neural network, support vector machine, wavelet analysis, hybrid and ensemble model forecasting, etc. The neural network has the characteristics of self-reasoning, self-organization and information memory. It has also strong fitting ability, complex mapping ability, fault tolerance and learning ability, and is 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. The neural networks (ANNs) are the most 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. It addresses the aforementioned shortcomings of a single

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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 parameter used are presented in the Table 1.

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

Ref	Method	Model type	Parameter Used	Accuracy
[4]	AI or Neural networks (NNs)	Principal component analysis (PCA), artificial neural networks (ANN) 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) and Radiation(KJ/m²).	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]	AI or Neural networks (NNs)	Artificial neural networks (ANN)	Relative Humidity Solar Radiation Temperature Wind Speed	RMSE=86.466 MAE=8.409
[6]	AI or Neural networks (NNs)	Recurrent neural network (RNN)	Temperature Humidity Wind Speed	MRE(%)= 3.87 MAE(kW)= 7.75 nRMSE (%)=5.69
[7]	AI or Neural networks (NNs)	Artificial neural network (ANN);	National Renewable Energy Laboratory Irradiance, Temperature, Wind Speed, Wind Pressure	MAPE(%)=1.8 MSE=3.19x10e^{-10}
[8]	AI or Neural networks (NNs)	Feedforward backpropagation neural network (FFBPNN) method	Daily average temperature, daily average humidity, daily average wind speed, daily total sunshine duration, and daily average Global solar irradiation (GSI)	MAPE=7.066%, nMAE=3.629%, nRMSE= 4.673%, and MAE =5.256%
[9]	AI or Neural networks (NNs)	BP neural network	Cloud-based images, historical data of solar radiation	MAE= 46.1W MAPE= 7.8%.
[10]	AI or Neural networks (NNs)	Artificial neural network (ANN)	Radiation, temperature, wind speed, and humidity	Classification accuracy% =97.53%
[11]	AI or Neural networks (NNs)	Neural Network Prediction Model	Temp., wind Speed, wind direction, humidity, total amount of cloud, insolation	MAPE(%) =12.94%
[12]	AI or Neural networks (NNs)	Artificial Neural Network	Relative humidity, solar radiation, temperature and wind speed	RMSE=86.466(W) MAE=8.409
[13]	AI or Neural networks (NNs)	Similar day-based and ANN-based approaches	Extra-terrestrial radiation Cloud cover factor Temperature	MAPE = 21.37% nRMSE = 30.99%
[14]	AI or Neural networks (NNs)	AI methods based on the Portfolio Theory (PT)	Solar irradiance Air temperature	MAPE= 4.52%

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[15]	Machine learning or optimization algorithms	RNN-LSTM Model	Solar radiation, module temperature, and 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/m²)	MAE(MWh)=6.02 MAPE(%)=3.30 RMSE(MWh)=6.73
[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 and 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 range of 10–20%.
[20]	Machine learning or optimization algorithms	Adaptive boosting Learning Model	Solar power (MW), solar irradiance (W/m²) and 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 , and 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 and 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, and the generation of electricity 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, and 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 and 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 multibranch 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, and cloud cover.	nRMSE=0.3058
[38]	Deep-Learning	Multistep CNN-Stacked LSTM Model	Solar irradiance, plane of array (POA) irradiance	nRMSE = 0.11 RMSE = 0.36

[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, and 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, evapo-transpiration, 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 ± 0.002 RMSE=0.098 ± 0.003
[44]	Deep-Learning	VM-based forecast models	Solar radiation and temperature	Accuracy factor increase 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 and 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 and precipitable water. The approximate numerical solar irradiance	RMSE= 0.71MW MAE= 0.36MW 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	RMSE never increases more than 15%

			17 sensors were laid on the island of Oahu (Hawaii) covering an area of roughly 1km^2 from March 2010 to October 2011.	
[52]	Deep-Learning	Convolutional neural network (CNN) and LSTM recurrent neural network	General weather information	RMSE= 2.095MW MAE= 1.028MW
[53]	Deep-Learning	A spatial-temporal graph neural network(GNN) is then proposed to deal with the graph	Precise cloud distribution information	RMSE= 6.945k MAE= 3.565k 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=5.95E-03 MSE=2.16E-05 MAE=9.44E-05 R^2=0.994045813
[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 and evaporation	RMSE=4.9%
[61]	Hybrid model forecasting	CNN-LSTM-MLP hybrid fusion model	Temperature, rainfall, evaporation, vapour pressure, relative humidity	$r \approx 0.930$, RMSE ≈ 2.338 MJm^{-2}day^{-1}, MAE ≈ 1.69 MJm^{-2}day^{-1}
[62]	Hybrid model forecasting	MC-WT-CBiLSTM depth model	Global level irradiance and temperature	MAE=18.13 RMSE=27.98 R^2=0.99

 doi:10.20944/preprints202305.1534.v1

				SMAPE=10.97 MAPE=15.63
[63]	Hybrid model forecasting	NARX-CVM Hybrid Model	Temperature, solar radiation, relative humidity, wind speed, and 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), and 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, and wind speed	RMSE= 15.3% MAE=826.2W 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

2.3. Summary of forecasting techniques

A literature review is conducted using the (1) Web of Science, (2) IEEE Xplore, (3) MDPI, and (4) Google Scholar database from 2020 to 2023 for publications on short-term solar PV power prediction. In the past three years, the number of research in this field has significantly increased, consistent with the global growth of solar power generation. This indicates that these predictive technologies of solar PV power generation are becoming more important as their penetration rate in the power grid increases. These models are mainly divided into five categories: artificial intelligence or neural networks (NN), machine learning models (ML) or algorithm optimization, deep learning models (DL), hybrid artificial intelligence models, and probability models. A list of all papers is presented in the references.

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2.3.1. Distribution of input data for the reviewed works

It is 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 [79–81] or numerical weather prediction (NWP) [82–84] are dominant, accounting for 49% and 25% respectively. In several studies, there was 15% of the power generation information shared from nearby PV power plants [56,59,85], 6% of the studies used satellite images as input source data [86,87], and some studies combined with sky images are very promising, which account for 5% although further work is needed to correctly identify cloud layers [88–91]. 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 statistical methods are represented based on their spatial range. If inputs from NWP models, satellite or sky images are input into statistical prediction models, the spatial range of statistical methods will be expanded.

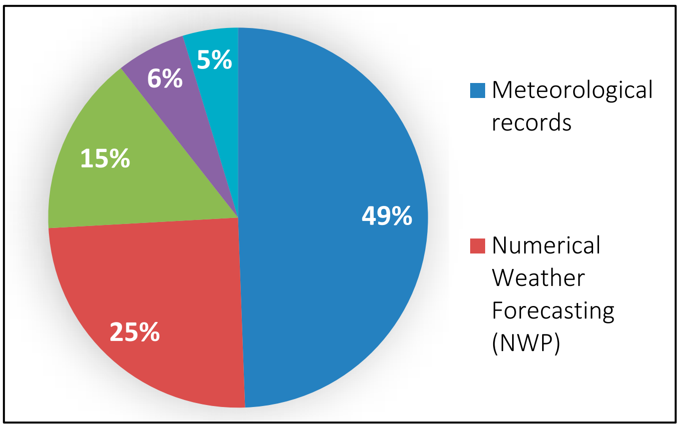

Figure 2. Ratio of input data for the reviewed works.

2.3.2. Distribution of forecasting methods for the reviewed works

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

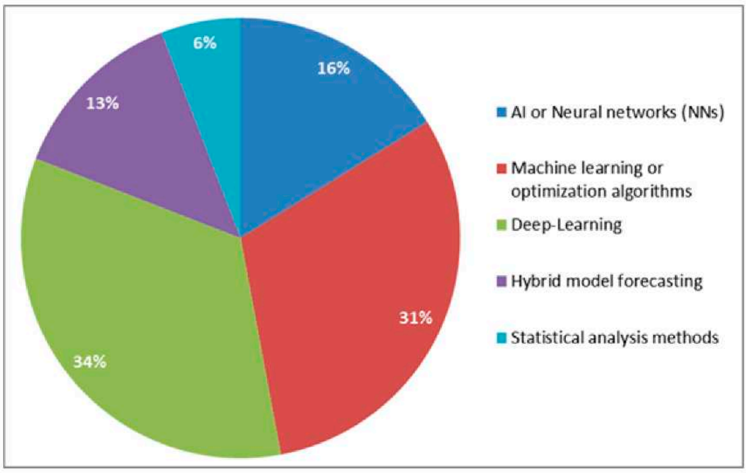

Figure 3. Distribution of forecasting methods for the reviewed works.

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2.3.3. Statistical metrics for the reviewed works

There are many methods to determine errors in solar power generation prediction, and Table 3 uses various statistical metrics to describe the accuracy of different short-term solar power generation prediction models in the past three years. In Figure 4, we have developed and proposed many methods for calculating errors, such as RMSE, MAE, MAPE, nRMSE, R^2, MSE, MRE, nMAE, MBE, SMAPE, MASE, and WMAPE, and attempted to present the error values as completely as possible in this paper for the study of future short-term solar power generation prediction that needs to be improved and evaluated. The most commonly used method for counting error in the literature of short-term solar power generation prediction are RMSE, MAE, and MAPE, with their respective proportions of 25%, 22%, and 17%. The Root Mean Square Error (RMSE) is most commonly used since it describes the measurement of the average distribution of errors. RMSE is a good method for describing prediction errors because it does not consider the difficulties of prediction under different meteorological conditions. In addition, most predictive models tend to use some variants of RMSE to evaluate the performance of their predictive models.

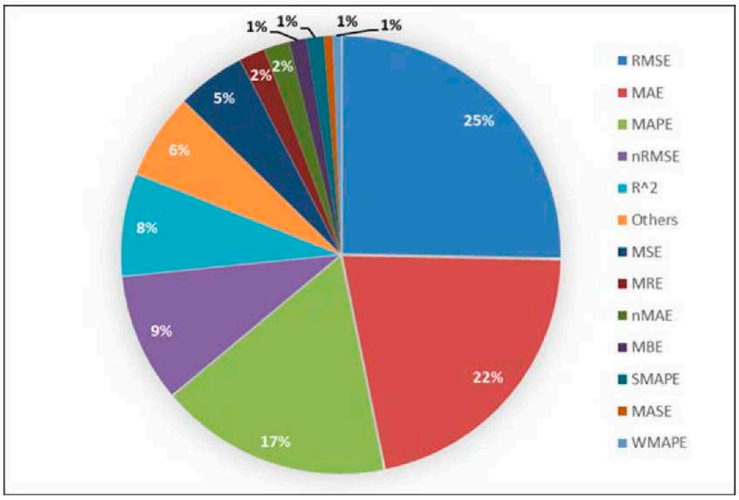

Figure 4. Proportion of statistical metrics for the reviewed works.

The research on the above short-term solar PV power generation shows that the accuracy of traditional single prediction models is far from sufficient, such as BP neural networks [9], SVM, [12,25] etc. It is easy to fall into local optimal solutions, thereby reducing prediction accuracy. Deep learning networks (DL) 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 [83,86]. It overcomes the shortcomings of BP neural network and SVM, thereby effectively improving 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, particle swarm optimization algorithm has strong global search ability and simple optimization, overcoming the disadvantage of the extreme learning machine model that the output weights are prone to random fluctuations [17,19]. A forgetting mechanism or adaptive extreme learning machines is employed to optimize the number of neurons in the hidden layer within a certain range to solve the problem of poor generalization ability of extreme learning machines [21,84]. Due to the advantages and disadvantages of different prediction models, hybrid prediction methods optimize the data processing results of different models based on specific strategies to obtain better solar PV power generation prediction results and ultimately improve the predictive accuracy [90,97]. It was found that hybrid prediction methods have the optimization characteristics of 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, the studies on solar PV power generation prediction have become more and more popular. This paper remarks the contribution of the recent progressive solar PV power forecasting technology, and explores the advantages and disadvantages of various solar PV power forecasting models in the past three years as shown in the Table 2. These forecasting models have different forecasting capabilities, update the weights of each model in real time, improve the comprehensive forecasting capability of the model, and have good application prospects in solar PV power generation forecasting.

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

Work	Date of publication and Location	Main contribution	Advantages	Disadvantages
[4]	December, 2022	The versatility of the proposed approach allows the choice of parameters in a systematic way and reduces the search space and the number of experimental simulations, saving computational resources and time without losing statistical reliability	-The approach separates the data into seasons of the year and considers multiple climatic variables for each period. -The dimensionality reduction of climate variables is performed through PCA.	Increasing dimensions of the input vector.
[5]	August, 2021	To accommodate uncertain weather, a daily clustering method based on statistical features as daily average, maximum, and standard deviation of PV power is applied in the data sets.	-The forecasting results of ANN, DNN, SVR, LSTM, and CNN were combined by the RNN meta-learner to construct the ensemble model. -Higher stability	-Time-consuming; -Complex computation process; -Increasing dimensions of the input vector
[6]	March, 2020	-Forecasting errors are relatively large in unusual weather conditions. -The forecasting precision can be improved by enlarging training samples, performing subdivision, and imposing manual intervention.	Reducing the risk of over-fitting by balancing decision trees	-Increasing dimensions of the input vector; -Adjusting the parameters of abnormal weather
[7]	October 2021	-The proposed model requires only the set of dates specifying forecasting period as the input for prediction purposes. -Being able to predict PV power for different time spans rather than only for a fixed period in the presence of the historical weather data .	-A simplified application of the already trained ANN is introduced -Photovoltaic (PV) output can be predicted without the real-time current weather data.	-Increasing dimensions of the input vector -Statistics of daily solar energy over the years

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[8]	June, 2020	It is more appropriate for meteorological data that belong to a specific region to obtain an accurate forecasting model and results.	Being a promising alternative for accurate power forecasting of the actual PV power plants.	The chaotic nature of meteorological parameters causes a decrease in ANN model forecast accuracy.
[9]	September, 2021	1. By calculating the displacement vector of the cloud on the ground-based cloud images, the moving trajectory of the cloud can be estimated, so as to accurately predict the occurrence of sun occlusion. 2. A new ultra-short-term solar radiation prediction model is designed, and especially suitable for the prediction of sudden change of solar radiation near the surface in cloudy weather conditions. Its time scale is 5 min.	-Combined with the features of ground-based cloud images, the prediction accuracy is greatly improved. -By the digital image processing, 13 features that affect the solar radiation near the surface are extracted from the ground-based cloud images.	In cloudy weather conditions, the ultra-short- term forecasting is very difficult because there are no rules for clouds to block the sun.
[10]	March, 2020	In power plant determination studies, which regions are more appropriate can be determined by using the proposed model.	Extra costs for installation and measurement can be eliminated.	Long mathematical processes
[11]	November, 2022	The amount of input and calculation of the neural network model is reduced to streamline the hidden layer stage, establishing a power generation prediction model capable of fast and accurate prediction.	To create a predictive model including non-linearly related variables.	Improvements in the prediction accuracy of performance.
[12]	July, 2021	Supervised learning algorithms are employed to predict the power generated from meteorological variables since renewable power generation systems present a wide variation due to meteorological conditions.	The actual electricity generation values in the PV installation were compared with the predictions made by different methods (ANN, KNN, LR and SVM).	This database size limits the prediction horizon of the models.
[13]	November, 2020	The similar hour-based approach and the hybrid method have demonstrated better performance than widely employed forecasting techniques	The outputs of both forecasting methods are dynamically weighted, according to the type of the day (sunny, cloudy and overcast) and the MAE.	Increasing dimensions of the input vector
[14]	January, 2020	PT takes advantage of diversified forecast assets: when one of the assets shows prediction errors, these are offset by another asset.	Integration of AI methods in a new adaptive topology based on the Portfolio Theory (PT) is proposed hereby to improve solar forecasts.	-Increasing dimensions of the input vector -Multi-method evaluation

[15]	March, 2022	-A deep learning algorithm (RNN-LSTM) is proposed for hour-ahead forecasting of output PV power for three independent PV plants on yearly basis for a four-year period. -Annual hour-ahead forecasting of PV output power using SVR, GPR and ANN -Different LSTM structures are also investigated with RNN to determine the most feasible structure	-ANFIS is performed to compare with the proposed technique (RNN-LSTM). -Better forecasting accuracy and performance	It is difficult to adjust the LSTM parameters, and determine whether it converges.
[16]	October, 2021	Predicting PV power for different time spans in the presence of the historical weather data.	The proposed model requires only the set of dates specifying forecasting period and multiple inputs .	The modeling would take a longer time due to large amount of historical data.
[17]	October, 2022	The extreme learning machine method uses approximated sigmoid and hyper-tangent functions to ensure faster computational time and more straightforward microcontroller implementation.	Feed Forward Neural Network based PSO completes the search when the optimal weight is calculated.	Using PSO to select the parameters of adaptive extreme learning machine will make the computation time longer.
[18]	June, 2020	Offering potential to assist system operators and regulator in better planning solar and wind power contributions to power supply networks.	Using a longer time period of prior data could lead to further improvements for TOB's short-term forecasting accuracy .	More work is required on larger datasets (i.e., for multiple years) to confirm that.
[19]	June, 2021	Decreasing the predicted amount of generated energy to avoid wrong optimistic predictions to affect the stability of a virtual power plant.	Improving accuracy and resolution of irradiance prediction for the next hour interval.	It is necessary to obtain a curve of the percentage of the uncovered sun with clouds for in the next hour.
[20]	November, 2021	Bringing originality to predicts 10 days ahead solar power generation.	They are trained with accurate ratio of training and testing to have best forecast accuracy with minimal error.	Individual model would not be enough to have sharp accuracy.
[21]	November, 2021	Assisting the energy dispatching unit list producing strategies while also providing temporal and spatial compensation and integrated power regulation, which are crucial for the stability and security of energy systems and also their continuous optimization.	The FOS-ELM approach may expand accuracy while also reducing the training time.	The level of uncertainty in PV generation is strongly related to the chaotic nature of weather schemes.
[22]	June, 2022	-Utilizing a new PV forecasting structure that incorporates K-means clustering, RF models,	The proposed ensemble forecasting strategies are much	Increasing the accuracy by recalculating the

		and the regression-based method with LASSO and Ridge regularization to increase forecasting accuracy. -Determining the five optimal sets of weight coefficients and which model predictors are significant.	more accurate than single forecasting models.	weight of the individual prediction model for each new input sample.
[23]	October, 2021	Seven well-known machine learning algorithms were successfully applied to solar PV system data from Abha to predict the generated power.	The prediction error of the algorithms was relatively low.	RF was the worst in terms of MSE.
[24]	November, 2022	STVAR model showed a good predictive performance for a time scale from 5 min to 1 h.	The design and component sizing of PV power plants.	The strength and limits of the irradiance forecasting model (STVAR model) are consequently imposed on the final PV forecasting results.
[25]	November, 2021	Machine learning (ML) models can be utilized as rapid tool for predicting the suitable performance of the power of any solar PV panel.	Approving the high reliability and accuracy of Matern 5/2 GPR model.	-Squared exponential GPR exhibited poor performance due to the complex relationship between the dielectric permittivity and the input parameters. -Cubic SVM exhibited poor performance due to the complex relationship between the input parameters and the PV panel power
[26]	June, 2019	-The randomness of the RVFLN technique is mitigated for fast learning and accurate forecasting by implementing the kernel matrix -Different kernel functions are investigated to achieve better prediction accuracy and two best kernel functions are combined together to attain more actual solar power prediction -The randomly selected kernel parameters are optimally tuned by an efficient optimization technique, thereby imparting a more accurate shorter time interval solar power prediction.	Reducing computational time and complexity of the model.	MK-RVFLN is the choice of parameters which affects the accuracy of the prediction technique.

[27]	September, 2022	The adaptive k-means is used to cluster the initial training set and the power on the forecast day.	Gru network has better effect, better robustness, and less error.	Increasing dimensions of the input vector
[28]	May, 2022	Horizontal global irradiation and water saturation deficit have a strong proportional.	Development of seven machine learning models for the prediction of PV power generation.	Increasing dimensions of the input vector
[29]	February, 2022	PSO-based algorithm is adapted for the selection of dominant SVR-based model parameters and improvement of performance.	Reaching better performance of the forecast algorithm.	Using algorithm bar parameters will lead to longer operation time.
[30]	April, 2022	A new solar power prediction method, composed of a feature selecting/clustering approach and a hybrid classification-regression forecasting engine	-The forecasting computation is faster by using two subsets. Each of these two subsets is separately trained by a forecasting engine. -The final solar power prediction is obtained by a relevancy-based combination of these two forecasts.	-Increasing dimensions of the input vector -The internal parameters of the subset need to be well selected.
[31]	August, 2021	Raw data is subtracted from the correlation between the the decomposition components and raw data to obtain the optimal frequency demarcation points for decomposition components.	A CNN is used to forecast the low-frequency and high-frequency components, and the final forecasting result is obtained by addition reconstruction.	Use of FFT for data preprocessing is less applicable than the general data pre-processing method
[32]	January, 2022	An end-to-end short-term forecasting model is proposed to take satellite images as inputs, learning the cloud motion characteristics from stacked optical flow maps.	-Better performance of the forecast algorithm. -Sky image technology with cloud motion	-The extremely large sizes of satellite images can lead to a heavy computational burden. -Complex computation process.
[33]	November, 2020.	Unlike existing adaptive iterative methods, the proposed approach does not rely on the labels of the test data in the updating process.	As weather changes, the model can dynamically adjust its structure to adapt to the latest weather conditions.	-Complex computation process; -Parameter adjustment required
[34]	February, 2022	The proposed multibranch ResAttGRU is capable of modeling data at various resolutions, extracting hierarchical features, and capturing short- and long-term dependencies.	Accelerating the learning process, and reduce overfitting by leveraging shared representations as the auxiliary information.	-Complex computation process; -Parameter adjustment required
[35]	January, 2021	-BMA's mixture-model approach mitigates under dispersion of the raw ensemble to	-BMA is a kernel dressing technique for NWP ensembles -	-Increasing dimensions of the input vector

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		significantly improve forecast calibration. -Consistently outperforming an ensemble model output statistics (EMOS) parametric approach from the literature.	A weighted sum of member-specific probability density functions.	
[36]	June, 2022	-A series of experiments applying advanced deep-learning-based forecasting techniques were conducted, achieving high statistical accuracy forecasts. -Solar irradiation data were categorized by each month during the year, resulting in a monthly time-series dateset, which is more significance for high-performance forecasting. -A walk-forward validation forecast strategy in combination with a recursive multi step and a multiple-output forecast strategy was implemented	-Use of fixed-sized internal representation in the core of the model -Significantly improving short-term solar irradiation forecasts.	More LSTM parameter settings require to be adjusted
[37]	May, 2022	-The proposed model showed promising forecasting performance compared to benchmark models such as convolutional neural network (CNN)-LSTM and nonclustering-based site-specific LSTMs. -The model achieved less forecasting error for solar stations having significant solar variability.	-The performance of CB-LSTM was robust under differing conditions. -CB-LSTM achieved better forecasting performance than that of M-LSTM and ST-LSTM for all climatic zones and regions.	-High error in terms of NRMSE in Idukki station.
[38]	March, 2022	The proposed stacked architecture and the incorporation of drop-out layers are helpful for accuracy improvement in the PV prediction model.	The multi-step CNN-stacked LSTM with drop-out deep learning method for improved effectiveness as compared to other traditional solar irradiance forecasting.	-Complex structure and hardware requirement.
[39]	July, 2020	Validating the performance of the proposed approach through a detail comparative analysis with several other contemporary ML approaches such as linear regression (LR), ridge regression (RR), least absolute shrinkage and selection operator (LASSO) and elastic net (ENET) methods	-Outperforming with respect to all selected performance criterion. -Effectively confirming the likelihood and practicality of the proposed model.	It is failed to achieve the accuracy of the proposed WT-LSTM-dropout model.
[40]	December, 2021	-A Siamese CNN was developed to automatically extract the features of continuous total sky images, where the Siamese structure	The prediction accuracy was improved by comparing to other models.	It is required to improve the prediction accuracy, especially

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		reduced the model training time by sharing part parameters of the model; -SCNN-LSTM was used to effectively fuse the time-series features of images and meteorological data to improve the DNI prediction accuracy.		under partly cloudy or cloudy days.
[41]	March, 2022	-Optimizing the prediction performance of the ANN and LSTM models to improve the accuracy rates of these models.	The ANN and LSTM models using the reduced Input Set demonstrated the same prediction accuracy as the seven exogenous variables in the complete Input Set.	-It requires a larger amount of training data -Higher computational cost and training time for the models.
[42]	March, 2022	-The parameters of solar radiation, direct short-wave radiation, diffuse short-wave radiation, and temperature always have a very high degree of influence on solar radiation forecasting. -Evapotranspiration, sunshine duration and humidity showed a remarkable influence in west-central Jordan -Other parameters like cloud cover, snowfall amount, wind speed, and total precipitation amount have no influence in Jordan on the solar radiation prediction.	-Abilities of adaptation -Nonlinearity -Rapid learning	Too many twenty-four solar radiation metrological parameters (inputs to the ML or DL algorithms).
[43]	August, 2022	-These simple improvements can ensure higher accuracy and stability of opaque models. -The LSTM-AE model is proposed as the benchmark of deep-learning solar forecast. -Comprehensive evaluation studies are conducted to evaluate different forecast performances.	The proposed deep-learning AE model is recommend as an efficient method for day-ahead NWP-based PV power forecast due to the highest accuracy.	The day-ahead forecast accuracy will decrease sharply for each model without NWP and its improvement using deep-learning is quite limited.
[44]	June, 2021	-The proposed TESDL short-term prediction algorithm has excellent capacity and robustness for generalization -Achieving an outstanding predictive efficiency.	The costs for control, initial hardware part costs, and extended-lasting maintenance of potential PV farms could be minimized by the proposed TESDL algorithm.	Mismatch losses pose a significant problem since the performance in the worst circumstances of the entire PV array is calculated by the lowest powered solar panel.
[45]	September, 2022	FPP model based on convolutional neural network is used to predict future PV power fluctuation patterns with historical satellite images as input.	Reaching better performance of the forecast algorithm.	-Complex computation process; -Use of cloud computing
[46]	January, 2021	the network forecasting results can successfully approximate to the expected outputs and the intra-hour ramping is well captured.	Reaching better performance of the forecast algorithm.	It is difficult to adjust the LSTM parameters and determine whether it converges.

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[47]	October, 2022	It was observed that the LSTM-Autoencoder model was the best performing one in terms of reliability for the investigated models.	-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	Precise cloud distribution information is mainly achieved by ground-based total sky image.	-Particle image velocimetry and Fourier phase correlation theory are introduced to build the benchmark models. -Sky image technology	-The feature of 3-D CAE models could not find well. -Increasing dimensions of the input vector
[49]	October, 2020	This highlights the significance of the proposed synthetic forecast, and promote a more efficient utilization of the publicly available type of sky forecast to achieve a more reliable PV generation prediction.	The performance of the proposed model is investigated using different intraday horizon lengths in different seasons.	-Complex computation process;
[50]	November, 2022	Proposing an integrated missing-data tolerant model for probabilistic PV power generation forecasting.	-Dealing with data missing scenarios at both offline and online stages. -Data tolerance	-Increasing dimensions of the input vector -Computing time is too long
[51]	January, 2021	Several Artificial Neural Networks are trained as a basis for predicting solar irradiance on several locations at the same time.	A family of deep learning models for solar irradiance forecasting comply with the aforementioned features, i.e. flexibility and robustness.	-Increasing dimensions of the input vector
[52]	September, 2020	The CNN model is leveraged to discover the nonlinear features and invariant structures in the previous output power data, thereby facilitating the prediction of PV power.	-CNN was use to preprocess the data -Reaching better performance of the forecast algorithm.	-Increasing dimensions of the input vector -Computing time is too long
[53]	May, 2022	By simulating the cloud motion using bi-directional extrapolation, a directed graph is generated representing the pixel values from multiple frames of historical images.	GNN is more flexible for varying sizes of input in order to be able to handle dynamic ROIs.	Increasing dimensions of the input vector
[54]	December, 2021	The performance of forecasting models depends largely on the quality of the training data, the size of data, the meteorological condition of the location where the data were obtained, and the duration or horizon of measured solar irradiance.	-Ten-year dataset is a great improvement in the accuracy of the solar irradiance forecast techniques. -It is considered the best result obtained in this work.	-Complex computation process; -Parameter adjustment required
[55]	March, 2022	A deep learning technique based on the Long Short-Term Memory (LSTM) algorithm is evaluated with respect to its ability to forecast solar power data.	Focusing on research and development in multiple models to arrive at predictions with high suitability.	-Complex computation process; -Parameter adjustment required

[56]	March, 2022	-The comparison is then used to minimize uncertainty by implementing grid search technique. -Comparing the effects of different data segmentations (three-months to one-day)	-Varying time-horizons (14-days to 5-mins) to compare the effects of seasonal and periodic variations on time- series data and PV output forecast.	It is difficult to adjust the LSTM parameters, and determine whether it converges.
[57]	August, 2021	The numbers of neurons in the hidden layers, weights, and biases of the proposed ANNs were optimized with MVO and GA.	The multilayer feedforward neural network (MFFNN) was used to investigate its accuracy through the results obtained from MFFNN-MVO and the MFFNN-GA models.	-Increasing dimensions of the input vector
[58]	February, 2021	-The relevance of the studied models was evaluated for real-time and short-term solar energy forecasting to ensure optimized management and security requirements by using an integral solution based on a single tool and an appropriate predictive model.	ANN has shown good performance for both real-time and short-term predictions.	-Increasing dimensions of the input vector
[59]	June, 2021	The prediction model has higher prediction accuracy and relatively small overall fluctuations.	VMD decomposition technology is used to decompose the PV power sequence to reduce the complexity and non-stationarity of the raw data.	Prediction error and fluctuation are large.
[60]	August, 2022	-It can serve as an alternative tool to provide reliable predictions. -Providing a promising method for predicting daily solar radiation as evidenced by the performance at the stations analyzed.	The interchangeability of optimization algorithms and machine learning models.	-Computational complexity
[61]	August, 2022	-Development of a new hybrid DL model, which process the input data with a sequential application of Slime Mould Algorithm (SMA) for feature selection, CNN, LSTM network, CNN and a final processing with a MLP -Overcoming the shortcomings mentioned above to obtain a more accurate GSR prediction.	A novel DL-based hybrid model that overcomes the above limitations and produces accurate GSR predictions.	-Incorporating different design of predictor data decomposition methods. -Complex computation process;
[62]	January, 2022	The various methods combined with the MC-WT-CBiLSTM model have the effect of improving the prediction ability.	-The wavelet transform preprocessing step effectively reduces the data complexity -Improving the prediction ability of the multichannel CNN-BiLSTM model.	-The generalization ability for the most forecasting methods is poor -Only achieve good results in a small range.

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[63]	April, 2022	The development methodology in this work can be applied anywhere.	-The forecasting skills of the hybrid model are about 34% against the NAR model. -About 42% against the Persistence model.	A forecasting model should not be including redundant or irrelevant variables to avoid spurious results.
[64]	April, 2021	Proposing a three-phase adaptive modification solution for DA to increase the algorithm capabilities in both the local and global searches.	The proposed hybrid deep model is equipped by a powerful decomposing mechanism which helps to provide simpler signals with less complexity.	The negative effect of long-time windows on the prediction results.
[65]	September, 2022	-A comparative test is conducted in multiple time dimensions to better reflect the accuracy of experimental results -Verifying the superiority of the proposed method.	The prediction accuracy and prediction stability are improved by about 15% on average compared to the other prediction models.	BO algorithm is used for tuning parameters, which also increases the time cost for training models.
[66]	September, 2022	Proposing an ensemble interval prediction for solar power generation that obtains prediction intervals with higher quality than other methods.	Obtaining more reliable and stable interval prediction results.	The KDE method takes a longer total computational time than other methods.
[67]	November, 2022	-In the training process, data mismatch and boundary constraint are incorporated into the loss function. -The positive constraint is utilized to restrict the output of the model.	The performance of prediction models with sparse data is tested to illustrate the stability and robustness of TG-A-CNN-LSTM.	It is difficult to adjust the LSTM parameters and determine whether it converges.
[68]	July, 2020	-Providing better accuracy than other examined methods -Working with a better computational cost.	Outperforming other examined methods in terms of accuracy and computational time.	Prediction accuracy can be increased with other new effective techniques.
[69]	June, 2020	Similarity-based forecasting models (SBFMs) are advocated to forecast PV power in high temporal resolution using low temporal resolution weather variables.	The PV power generation forecasting for the next day with five-minute temporal resolution can significantly yield accurate results.	-Increasing dimensions of the input vector
[70]	August, 2021	Being generalized to find the optimal prediction given that the available measurements are mapped by an affine transformation.	WRF forecasts of irradiance, temperature, relative humidity, and the solar zenith angle were selected as highly relevant inputs of the model.	-Complex computation process; -Parameter adjustment required

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[71]	November, 2020	Forecast combination of machine learning models is done using convex combination and quantile regression averaging (QRA).	It is found that the predictive performance is significant on the Diebold Mariano and Giacomini -White tests.	-Increasing dimensions of the input vector

3. The 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 of short-term solar PV power forecasting in the past three years are reviewed to provide an important reference in 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 and future research works. These advanced forecasting models can be approximately classified into artificial intelligence/neural networks (NN), 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.

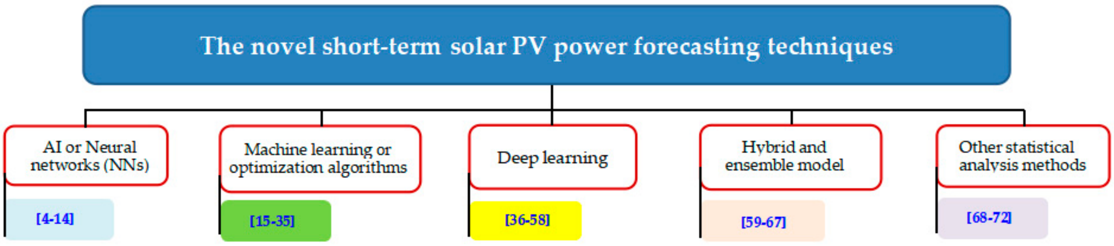

Figure 5. Classification of the novel short-term solar PV power forecasting techniques.

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 output. The simplified solar PV power generation model is represented by equation (3-1):

$$P_S = P_{sb} \cdot S^t \cdot k \qquad (3.1)$$

Among them, P_S is the electric energy obtained from solar energy (W), P_{sb} is the total capacity of solar cells (unit:W), S^t is the accumulated sunlight in an hour ( ), k is the solar module design coefficient (no unit) and in the solar PV power generation, S^t is the Wm^2 main factor affecting power generation output and also the main variable in predicting solar PV power generation. The day-ahead power generation prediction of solar energy is relatively clear and stable, and its influence mainly lies in the amount of solar radiation. Using the meteorological data provided by Taiwan Power Company as input variables of the solar irradiance-related information database, such as air temperature, relative humidity, precipitation, precipitation hours, sunshine hours, and global solar irradiance are provided; the output variable is the solar radiation of the next hour, and the solar radiation of the solar PV power generation in the previous 24 hours is predicted based on the novel short-term solar PV power generation prediction techniques as shown in Figure 5.

3.2. Data mining technique

Data mining technique is used for data processing, and more meaningful data are selected from the database as modeling data. The problem to be dealt with by data mining is to find meaningful

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hidden information in a big database. Power generation forecasts are similar to solar energy. Data mining is used for data processing, and more meaningful data are selected from the database as modeling data, as shown in Figure 6.

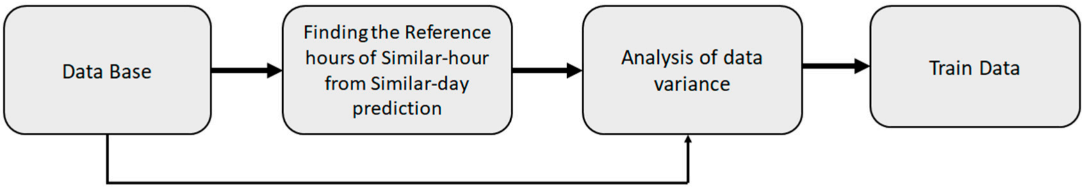

Figure 6. Flowchart of Data mining technique (DMT).

3.3. Hourly-similarity (HS) based method

The reference data selection method based on the hourly- similarity (HS) forecasting method is to introduce the concept of the horizontal axis and the vertical axis of time, which is called the hour of the prediction day to be forecasted as the prediction hour. Firstly, the prediction day is used to find weather information of the reference day as 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 are selected from the hypothetical case demonstration, as shown in Figure 7.

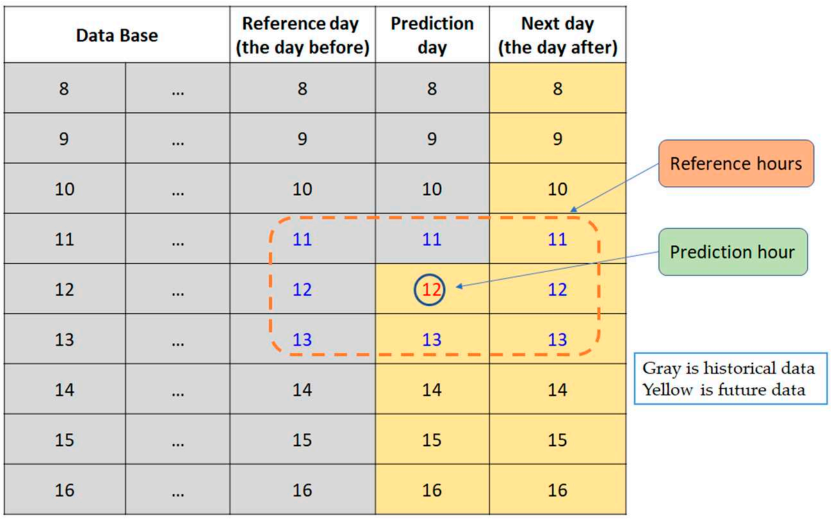

Figure 7. Schematic diagram of selection of reference data for Similar-day prediction method.

Demonstration of how to select reference data: Assuming that 12:00 on the prediction day is the prediction hour, then the reference hours includes 11:00 on the current day, 11-13:00 on the previous day, and 12-13:00 on the prediction day. A total of 6 pieces of data are selected for reference hours (collectively referred to as reference data).

Figure 7 shows the data types in data mining for the similar-day prediction method, and the data mining steps are that

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 hours 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.

The reference data of the hourly-similarity (HS) based prediction method is selected from the hypothetical case demonstration, such as equation (3-2)

$$N_{i,k}^{mr} = sqrt\left(\sum_{j=1}^{f}\left(Nr_{d-m,r}^{j} - N_{d-i,k}^{j}\right)^{2}\right) \tag{3-2}$$

where, $Nr_{d-m,r}$ is the reference data for the similar hour, m=[0, 1] and $r \in \{t+1, t, t-1\}$ is the concept of horizontal axis and vertical axis of time at the similar hour. figures out the degree of similarity of the data. L is the number of selections at the similar hour, and $\mathbf{H}_{DMT}$ $N_{i,k}^{mr}$ is the training data selected at the similar hour, as shown in equations (3-3) and (3-4)

$$\mathbf{H}_{DMT}^{m} = sort\left\{\left[N_{i,k}^{m1}\right]_{k=1}^{u}\right\}_{i=0}^{v} \tag{3-3}$$

$$\mathbf{H}_{DMT} = \bigcup_{m}\mathbf{H}_{DMT}^{m} = \bigcup_{m}\bigcup_{r}\underset{1\to L}{sort}\left\{\left[N_{i,k}^{m1}\right]_{k=1}^{u}\right\}_{i=0}^{v} \tag{3-4}$$

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

3.4. Internet of Things (IOT) Technology

The data of solar PV power generation and several environmental sensor are collected to store in the Raspberry Pi database and corresponding data tables by use the 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. The Raspberry Pi is also applied to set up the human-machine interface, and display it in the website form, while watching it remotely via the Internet. Furthermore, the collection progress is checked to confirm the hardware operation status, and collect data stably [92–94].

After long-term data collection, the amount of data required for the input layer parameters of the neural network has been obtained, data tables such as solar PV power generation data and environmental sensor data are exported from the database management system, and 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 is divided into a training group and a test group. The training group data is 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 is shown in Figure 8.

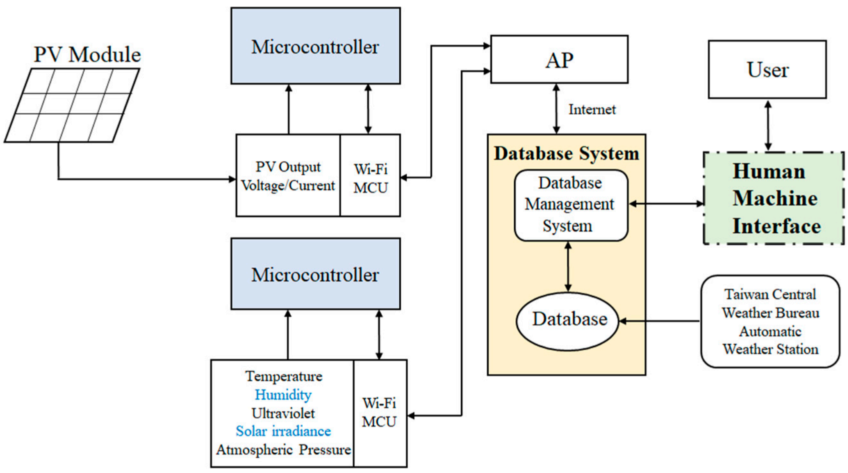

Figure 8. Configuration diagram of the IOT Technology prediction system.

3.5. Sky image-based methods

Automatic identification of clouds, cloud matching, cloud area correction based on ground cloud images, and estimation of cloud movement direction are achieved, so as to make accurate judgments on clouds that are about to cover the sun and 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 cloud shape and motion, study satellite measurements and high-resolution cloud images (e.g., images from ground-based sky cameras). In addition, these cloud image information correlation features are comprehensively used into classification and prediction, while verifying the feasibility of the model by different data sets [95].

Based on the dynamic sky image, the characteristics of the cloud layer are extracted to estimate the future cloud movement path by use of the object tracking algorithm, and then calculate the cloud cover to the sun according to the cloud movement path. Finally, the change of insolation is estimated through the Long Short-Term Memory (LSTM) network. The paper appears with the aim of finding out a method for predicting the movement path of cloud covers, and at the same time estimates the sun's shading of cloud piles, forecasting power variation due to the changes in insolation through the Long Short-Term Memory (LSTM) network so that provides power dispatchers or EMS (Energy Management System) in advance to effectively respond to the impact of cloud clusters shading the sun on the grid [96,97].

The schematic diagram for sky image-based methods is shown in Figure 9. The system configuration can be divided into three parts, among which D1 is the part for analyzing the characteristics of all-sky clouds covering the sun and predicting the movement path of cloud clusters; D2 is the part for extracting the characteristics of ground-based all-sky pyranometers; D3 is the part for predicting the solar irradiance and the solar PV power generation. Part D1 in Figure 9 is to design a predictive method for the moving path of the 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 the future information and the real-time value for insolation observation of the ground-based all-sky pyranometer in part D2. The input of the intelligent learning network is used to deduce the change of insolation, and the variation of solar PV power generation can be obtained according to the power and insolation curve (PV power curve) of the solar PV module.

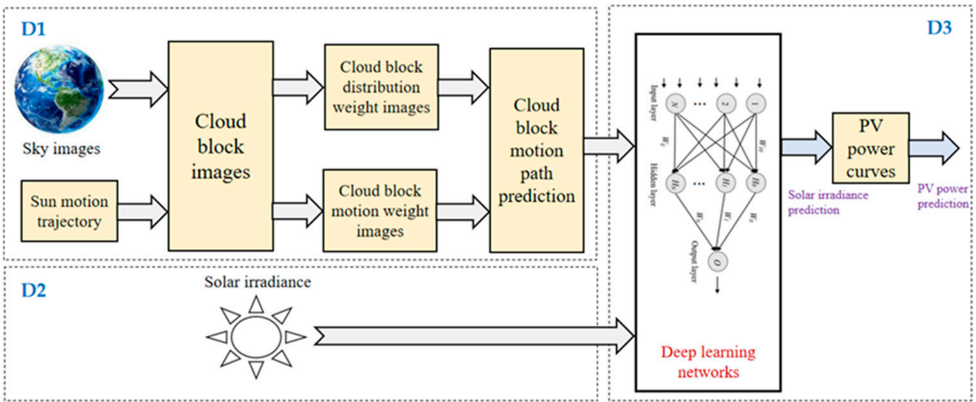

Figure 9. Schematic diagram for sky image-based methods.

In recent years, various research institutions and scholars have adopted different cutting-edge methods to improve the power fluctuations and randomness in the power prediction of solar power generation, as well as the possible errors and omissions in the original data, and achieved certain results. But 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 the solar power generation data with different characteristics, the prediction model is further optimized to increase the applicability of the model.

Secondly, according to the characteristics of the existing hybrid model, the parameter optimization method is further improved to ensure that the prediction model has high prediction accuracy at different time sampling rates, making it suitable for different prediction situations. The overview work for future solar PV forecasting studies will be reported in the next section.

4. Future studies and development

As an important subsystem of smart management systems for micro grids, 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 season, cloudy and sunny days, and day and night, novel predictive methods of solar PV power output have been developed in the past few years 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 in solar PV power generation prediction, as well as possible errors and omissions in the original input data. Based on the latest advances in AI neural network, machine learning, and deep learning methods, this paper examines the temporal resolution, parameters used, accuracy, and research limitations, and reviews the contributions, advantages, and disadvantages of the latest hybrid prediction models to development of solar PV power generation. However, there are still some issues that need to be improved. The following works are the main aspects that can be further studied:

1) In terms of weather variables prediction: Recent investigations only selects a meteorological station based on historical survey data. However, the meteorological information in different regions is inevitably different. Therefore, considering the impact of geographical environment, weather, or climate related factors where the meteorological station is located will definitely improve the accuracy of solar radiation prediction; In addition, additional meteorological and site determination factors such as temperature, humidity, precision, pressure, and solar radiation, etc. for solar radiation forecasting are required to explore the impact of these factors on the prediction results, and even incorporate them as input factors into 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, estimating the direction of cloud movement, and making 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 of solar PV power generation. Next, efficient pixel sensitive prediction models are 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 utilize into classification and prediction for which different data sets 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 model and improve their prediction accuracy.

3) In terms of solar PV power generation forecasting:Weather forecasting is selected based on data characteristics, adding machine learning or optimization algorithms to the solar PV power generation prediction model such as some optimization algorithms with RNN-LSTM to optimize superparameters and enhance its prediction accuracy. These deep learning (DL) models or ensemble models (EM) are implemented for solar PV power generation forecasting to provide more stable power to the grid.

4) Performing data preprocessing or data features analysis: By data preprocessing and 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 its own features are effectively found for prediction through preprocessing and correlation analysis of input data. Compared with general data preprocessing methods, further optimize data preprocessing to improve the applicability of FFT methods.

5) Improvement of inaccurate or missing data: To expand the basis of irradiance prediction methods for predicting the power capacity of new solar power plants without data, we explore prediction methods that can handle repeated and frequent continuous multipoint 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 training data for the target location is insufficient. Therefore, it is practical significance to improve short-term solar PV prediction of inaccurate or missing data.

6) Integration with power system:Accurate PV power generation forecasting is very important for the scheduling and regulation of power systems after 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, variations 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 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 dispatch of a large number of distributed solar PV systems are obtained; Combined with pumped storage power stations, adjustable biomass power stations, or PV battery systems, it can stably transmit solar PV power generation and improve the flexibility of power dispatching.

5. Conclusion

This paper first presents the significance of using solar PV power in energy conservation and emission reduction issues, as well as the technical challenges faced in predicting solar PV power generation. The necessity of developing the prediction systems of solar PV power generation and improving the model's accuracy is 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 problems being difficult to process missing data, being easy to occur overfitting and ignoring the correlation of attributes in the dataset. This paper further reports many of the most novel prediction models for PV power generation based on deep learning or hybrid models that integrate multiple meteorological factors. By analyzing the mean square error (MSE) value and the determination coefficient (R-Squared) value, it is proved that the proposed method has further improved the prediction accuracy compared to previous prediction methods. Secondly, this paper introduces the current study 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 have been classified, and compared in terms of temporal resolution, parameters used, accuracy, and research limitations. In addition, this paper reviews the latest progress for short-term solar PV power generation based on artificial intelligence methods, emphasizing their contributions to model development, their advantages and disadvantages as well as future studies and development. The contributions of this review works are as follows:

(1) Evaluate the most advanced algorithms in short-term solar PV power generation forecasting;

(2) Evaluate the accuracy, advantages, and disadvantages of various new AI hybrid models;

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

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

(5) Explore the impact of meteorological information and cloud image information, improving data preprocessing or data feature selection and analysis, data inaccuracy or loss. The distribution of the database input sources, forecasting methods, and predictive error metrics is analyzed and

 doi:10.20944/preprints202305.1534.v1

effectively utilizing machine learning or optimization algorithms and deep learning models on improving the accuracy of existing models are discussed to increase the forecasting accuracy;

(6) 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.

Author Contributions: W.-C.T. writing-original draft preparation, review and prepared the revised version. C.-S.T. the modeling investigation, conceptualization and application of methodology. C.-M.H. contributed to the project administration, modeling investigation, methodology and prepared the original draft of the manuscript. W.-M.L. supervision and project administration. All authors have read and agreed to the published version of the manuscript.

Funding: The project was funded by Natural Science Foundation of Xiamen, China (project No. 3502Z20227325)

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

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	Multibranch 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 feedforward neural network
MVO	Multiverse 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	Multichannel, wavelet transform combining convolutional neural network and bidirectional long short-term memory

NARX-CVM	Nonlinear 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
SBFMs	Similarity-based forecasting models
KF	Kalman filtering
QRA	Quantile regression averaging
MRE	Mean relative error
MAE	Mean absolute error
MASE	Mean absolute scaled error
WMAPE	Weight 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

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