Classification and Summarization of Solar Irradiance and Power Forecasting Methods: A Thorough Review

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***Abstract*—Solar forecasting is of great importance for ensuring safe and stable operations of the power system with increased solar power integration, thus numerous models have been presented and reviewed to predict solar irradiance and power forecasting in the past decade. Nevertheless, few studies take into account the temporal and spatial resolutions along with specific characteristics of the models. Therefore, this paper aims to demonstrate a comprehensive and systematic review to further solve these problems. First, five classifications and seven pre-processing methods of solar forecasting data are systematically reviewed, which are significant in improving forecasting accuracy. Then, various methods utilized in solar irradiance and power forecasting are thoroughly summarized and discussed, in which 128 algorithms are elaborated in tables in the light of input variables, temporal resolution, spatial resolution, forecast variables, metrics, and characteristics for a more fair and comprehensive comparison. Moreover, they are categorized into four groups, namely, statistical, physical, hybrid, and others with relevant application conditions and features. Meanwhile, six categories, along with 30 evaluation criteria, are summarized to clarify the major purposes/applicability of the different methods. The prominent merit of this study is that a total of seven perspectives and trends for further research in solar forecasting are identified, which aim to help readers more effectively utilize these approaches for future in-depth research.**

***Index Terms*—Hybrid methods, physical methods, preprocessing methods, solar irradiance and power forecasting, statistical methods.**

I. Introduction

In terms of renewable energy, solar energy has become the most popular technology [1], [2], which has been implemented in many countries around the world [3]. Because of its powerful generation capacity, the integration of solar PV power plants with the grid has received increasing attention [4]–[6]. However, the inherent variability of solar power generation has brought major problems to the grid, such as power system instability [7]–[9], voltage surges [10], operation scheduling [11], reserve costs [12], economical dispatch [13], [14], and so on. Therefore, it is critical to employ reliable and accurate solar forecasting to overcome the above effects, which has promoted the booming development of related studies worldwide [15]. In addition, there are two major techniques in predicting the generation of PV plants, e.g., indirect [16] and direct [17]. The former one first predicts solar irradiation, and then obtains the produced power by application of solar irradiation in a performance model of the PV plant [18], [19]. The latter one directly calculates power output of the plant [20]. Meanwhile, other studies only pay attention to solar irradiation forecasting, owing to the fact that it is the hardest component to model [21]–[23].

Although extensive popular techniques in solar forecasting have been presented for the past several years, few reviews have been developed to discuss various solar irradiance and power forecasting strategies, which primarily exist with some limitations, as summarized in Table I.

To address the aforementioned drawbacks, this paper undertakes a thorough up-to-date review. Compared with prior reviews, a systematic one-stop handbook about extensive methods utilized in solar irradiance and power forecasting is thoroughly summarized and discussed [24], [25]. In particular, this paper compiles a comprehensive and systematic summary for a reasonable comparison of various techniques, namely, inputs, forecasting variables, and temporal and spatial resolution. In addition, 128 methods are categorized into four groups, namely, statistical, physical, hybrid, and others.

II. Review Screening of Methods

This review is conducted based on content analysis. The Google Scholar, Baidu Scholar, Bing Scholar, and Web of Science are employed to find relevant articles; the process is carried out using sub-modules, as well as summaries of previous modules [33], [34]. In searching for relevant articles, serval similar keywords are adopted, such as irradiance and PV power prediction, solar irradiance forecasting, solar PV forecasting, and PV power forecasting. Particularly, review

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screening method schematic diagrams, from last decade years, which are illustrated in Fig. 1.

III. Solar Forecasting Data

A. Classification of Input Data

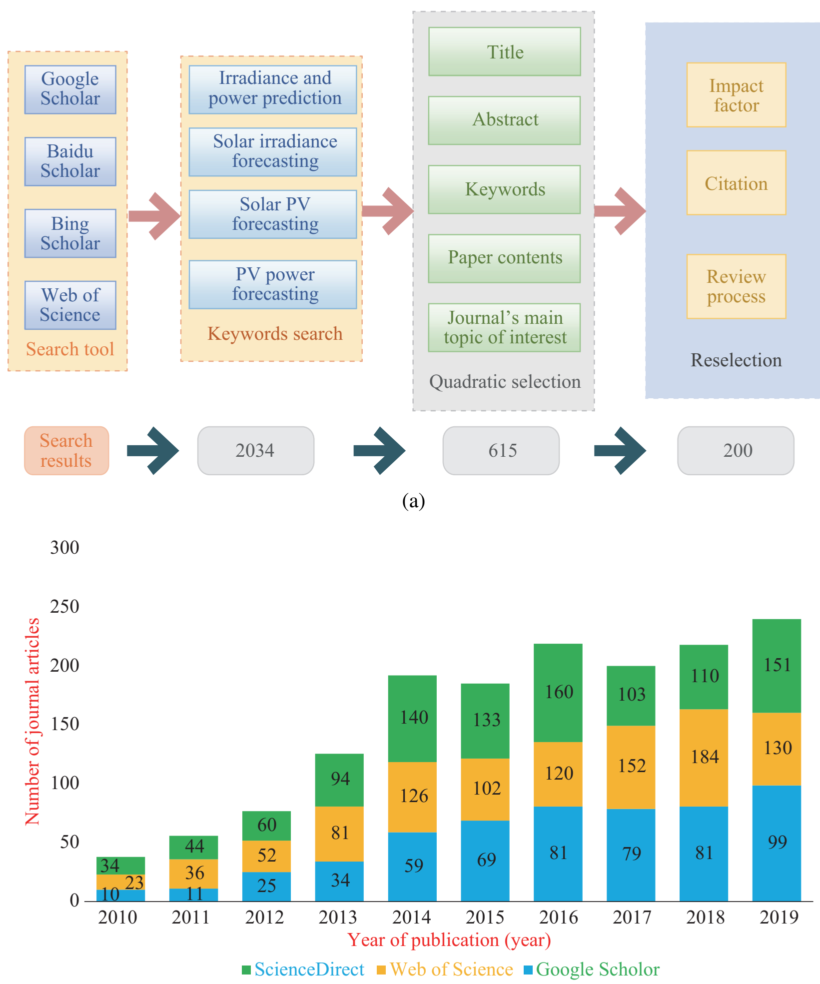
Due to improper selection of prediction model inputs, the forecasting error of different technologies can be increased. Hence, it is necessary to pre-process data to improve prediction accuracy [35]–[37]. Figure 2 classifies various solar forecasting data into five subcategories.

B. Pre-processing of Model Input Data

Through the learning of historical patterns, the pre-processed input data can considerably reduce the computa-

TABLE I
Evaluation of Recent Review Papers

Literature	Year	Content	Limitations
Rich *et al.* [26]	2013	Introduced some related applications of solar energy resources and PV production forecasting methods.	Performance indicators, such as inputs, temporal and spatial resolution, and forecasting variables are ignored.
Diagne *et al.* [27]	2013	Presented recent forecasting methods of solar irradiance and some indications for future applied in small-scale insular grids.	Classifications are obscure or incomplete.
Antonanzas *et al.* [28]	2016	Complied some techniques to produce power forecasts for PV.	Some methods are not fully described.
Utpal *et al.* [29]	2018	Covered a few PV power prediction techniques according to different scales.	Many promising or state-of-the-art technologies are ignored.
Sobrina *et al.* [30]	2018	Analyzed and compared the characteristics and performance of solar power prediction methods.	Lack of effective and detailed data preprocessing methods.
Ahmed *et al.* [31]	2020	Reviewed and evaluated some contemporary forecasting techniques of PV solar power.	Some perspectives and recommendations for future research are ignored or incomplete.
Pazikadin *et al.* [32]	2020	Presented an extensive review on the implementation of Artificial Neural Networks (ANN) on solar power generation forecasting.	Many major forecasting methods along with their classifications are absent.



(b)

Fig. 1. Review screening methods schematic diagram in last decade. (a) Flow diagram and (b) statistical diagram.

tional cost of the prediction model. Numerous techniques have been utilized for pre-processing input data of prediction models [38]–[40]. It should be noted that no one single technique completely outperforms the others.

In reality, these methods are sometimes combined to further improve forecasting performance. In order to provide in-depth analysis for each method, Table II compares applicability and differences of these seven different data pre-processing approaches.

IV. Solar Irradiance and Power Forecasting

A. Temporal Resolution Based Forecast

Researchers have classified solar irradiance and power forecasting according to different factors. However, there is no constant classification criteria for solar forecasting. Most researchers classify solar irradiance and power forecasting based on forecast scales, historical data, and other weather data models and forecasting methods. The major forecast classification is based on time horizon, upon which predictions made for diverse time horizons are significant for different aspects of grid operations [27], [48].

B. Spatial Resolution Based Forecast

Forecasting can be further subdivided into two main approaches, i.e., local forecasts and regional forecasts. Particularly, grid and plant operators are more inclined to use

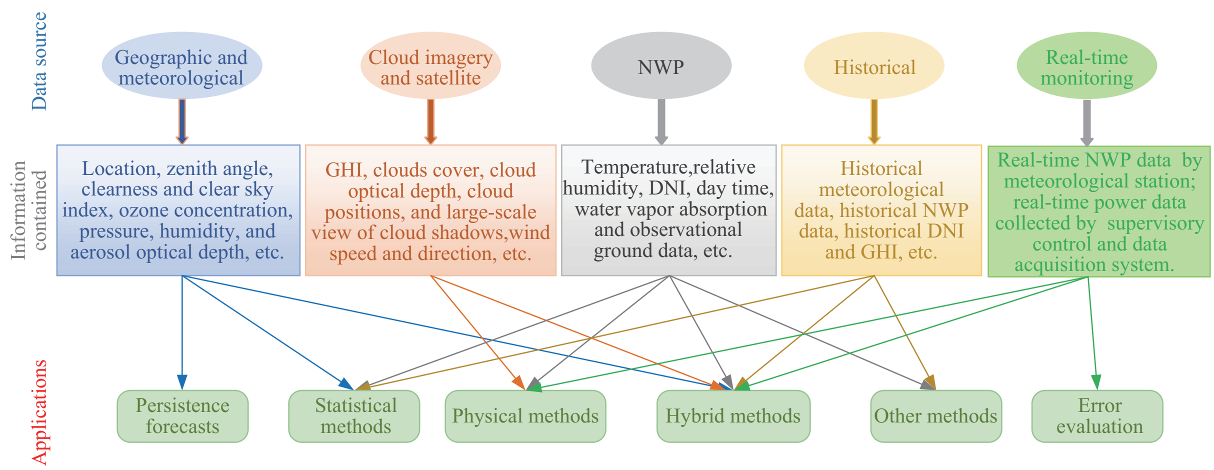


Fig. 2. Classification and summary of input data.

TABLE II
SUMMARY OF SEVEN PRE-PROCESSING METHODS

Method	Year	Applicability	Usage frequency	Implementation difficulty	Computation time	Accuracy improvement	Benefits/Shortcomings
Stationary [41]	2000	Small data with low fluctuation.	**	****	*	**	• Adaptive; • Unable to handle complex data environment.
Trend-free time series [42]	2007	Determine trend of daily solar radiation.	*	*	**	*	• Independent data length; • Relatively trouble-free implementation; • Low robustness.
Clear sky model [43]	2009	Small data with relative low fluctuation.	**	*	***	*	• Fast calculation; • Less calculation burden; • Redundant information included.
Normalization [44]	2012	Medium data with high redundancy.	*	***	***	**	• Adaptive; • Reduced redundant information; • Difficult to distinguish different time-varying components.
Self-organizing map [45]	2014	Medium data with drastic fluctuation.	***	**	***	****	• Especially suitable for nonlinear and non-stationary data environment; • Less computation time; • Low prediction accuracy and low robustness.
Learning vector quantization [46]	2014	Large data with high relevance.	****	***	***	***	• Simple and less computation time; • Prediction accuracy might be regraded.
Wavelet transform [47]	2015	Convert large data into smaller ranges.	****	****	**	****	• Independent on wavelet function and decomposition levels; • Reduced calculation burden; • Difficult to distinguish different time-varying components.

*Note. Larger number of * means a higher rank.

regional forecasts, because of it is more helpful to maintain the balance of supply and demand in the regional power system, while differences between local and regional forecasts are discussed in literature [49]. In addition, distribution of different techniques based on their spatial resolution and temporal horizon are demonstrated in Fig. 3.

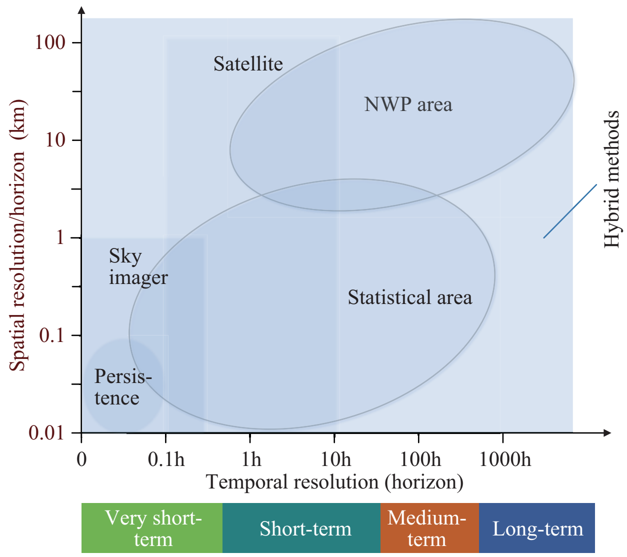


Fig. 3. Distribution of different methods based on spatial resolution and temporal horizon.

C. Model Subject Based Forecast

Based on the model subject, solar irradiance forecasting and solar power forecasting can be classified, as summarized in Fig. 4.

V. Forecasting Methods

A. Statistical Models

A statistical model does not require the system to provide any internal information to the model itself, which is using a basis of learning of forecasting model with historical influential variables [24], [25]. These prediction models attempt to use the difference between the predicted PV output power and the actual measured value to reduce network learning errors. Moreover, their forecasting accuracy is dependent on length and quality of historical input data [29], which are subdivided into

two groups, namely, regressive methods and artificial intelligence (AI) methods. Particularly, with respect to regressive models, these techniques predict the relationship between a dependent variable (solar power output) and some independent variables, which are known as predictors. Here, AI models are described as four subgroups, namely, neural networks (NNs), support vector machines (SVM), extreme learning machine (ELM), and fuzzy logic (FL). In addition, a comprehensive summary of statistical methods for solar irradiance and power forecasting is presented in Table III.

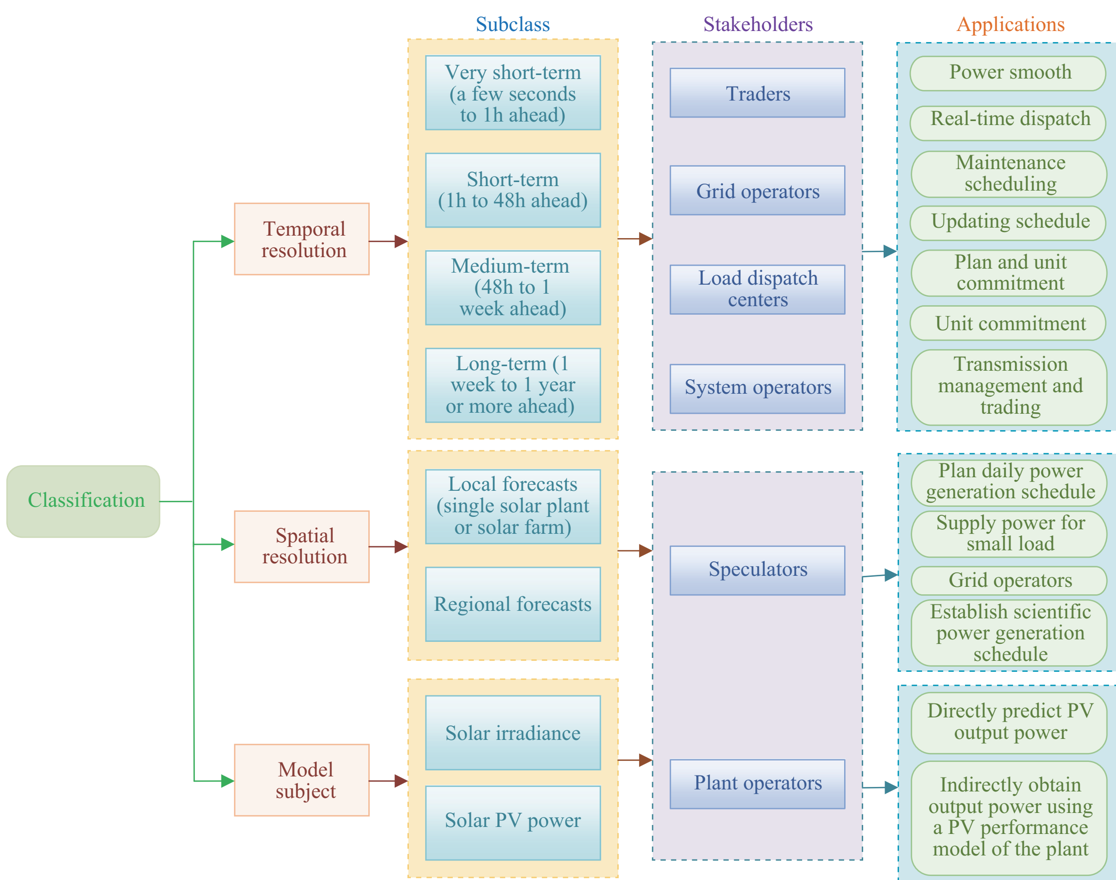


Fig. 4. Classification of solar forecasting based on temporal resolution, spatial resolution, and model subject.

TABLE III
CHRONOLOGICAL SUMMARY OF 25 STATISTICAL METHODS FOR SOLAR IRRADIANCE AND POWER FORECASTING

Method			Year	Temporal resolution	Spatial resolution	Inputs	Forecast variables	Performance metrics	Characteristics
Regressive methods	Linear stationary	AR [43]	2009	Short-term	Regional (21 rooftops PV system)	15-min PV data (1 year)	Hourly P	R^2	• Benchmark model.
		ARX [43]	2009	Short-term	Regional (21 rooftops PV system)	15-min PV data (1 year)	Hourly P	R^2	• Benchmark model.
		MA [50]	2014	Short-term	Regional	Solar irradiance (2 years), historical PV data	Hourly P	RMSE, R^2	• Benchmark model.
		ARMAX [50]	2014	Short-term	Local	Solar irradiance	P	RMSE	• More flexible for practical use of solar power prediction.
		ARMA [51]	2015	Short-term	Local	GHI, DHI, DHI, cloud cover	P	MAE, RMSE	• Very flexible by representing different types of time series.
		VAR [52]	2015	Long-term	Local	Past values of P and T	P	ss	• Quantile score 7.44.
		VARX [52]	2015	Short-term	Regional	Past values of P	P	CRPS	• CRPS improvement of 1.4–5.9% compared with AR model.
	Linear non-stationary	ARIMA [53]	2012	Very-short term	Local (1 MW solar farm)	Past values of P (6 months)	Hourly P	MAPE	• More accurately capture dramatic changes in irradiance related to day-night cycle.
		ARIMAX [53]	2012	Short-term	Regional	Previous solar irradiance (1 year)	Global solar irradiance	R^2, MAE	• Similar to ARMAX.
		SARIMA [54]	2013	Day and Intra-day ahead	Regional (Greek territory)	Solar irradiance (1 year)	P	NRMSE	• Improved prediction accuracy of real PV system.
	Non-linear stationary	NARX [55]	2016	Medium-term	Regional	Solar irradiance, T	P	SDE, RMSE	• Suitable for nonlinear dynamic systems.
		NARMAX [55]	2016	Medium-term	Regional	Solar irradiance, T, sunshine time	P	SDE, RMSE	• Popularly applied in engineering domain, especially in ANN parameterization.
AI methods	NNs	ANN [56]	2010	Very-short term	Regional	Solar irradiance, T, sunshine time (2 years)	P	RMSE, MBE	• No need for more variables or complex calculations.
		ANN based on MLP [57]	2013	Short-term	Local	DNI, mean T (1 year)	GHI	MBE, RMSE, ρ	• Shorter computing time.
		RBN [58]	2013	Short-term	Local	Air humidity, cloud covers, and T (1 year)	P	MAE, RMSE	• Isolation forecast data assists to train.
		Non-linear autoregressive NN [59]	2014	Very-short term	Local	Global solar irradiance, T, P of module (1 year)	P	RMSE, R^2	• Efficient use of solar energy to generate electricity.
		ANN based on explicit approach [60]	2014	Short-term	Local	Latitude, longitude, altitude, monthly and mean hourly relative humidity, total rainfall (1 year)	K_t, DNI, GHI	RMSE, MBE	• Useful for predicting solar irradiance composition at any location.
		BP [61]	2015	Short-term	Local	Historical P data (2 years)	P	MAPE	• Improved prediction accuracy compared with ANN.
		DCNN [62]	2017	Very-short term	Local	Historical P data (1 year)	P	MAPE, RMSE, CRPS	• More concise memory footprints and fewer parameters.
	SVM	SVM with least square [63]	2013	Very-short term	Local	Historical data of atmospheric transmissivity in 2-D form, meteorological parameters (14 years)	P	MAE, MAPE, ρ	• Capture time-varying and nonlinear patterns of solar irradiance data; • High generalization ability.
		SVM [64]	2015	Short-term	Local	Global solar irradiance, DNI, DHI (1 year)	Solar irradiance	RMSE, MRE	• Faster computation; • Reduced error.
		SVR [65]	2016	Short-term	Local	Historical P data, DNI (8 months)	P	RMSE, Bias	• Improved prediction under clear sky and overcast conditions.
	ELM	ELM [66]	2017	Short-term	Regional	Daily mean DNI, T, R_h, W_s, historical P data(12 months)	P	RMSE, R^2, MAPE	• Very fast learning with enhanced performance.
	FL	FL [67]	2013	Short term	Local	Historical solar irradiance data, sky conditions (sunny, rainy and cloudy), T (1 month)	DNI	MAPE	• Forecasting accuracy is poor for a single weather condition.
		GFM [68]	2013	Long-term	Local	n, T, R_h, W_s, atmospheric pressure (2 years)	Solar irradiance	RMSE, MAPE	• Effective modeling structure; • No primary assumptions needed for statistical distributions.

B. Physical Methods

The physical method is based on NWP, using cloud observations through satellite or a sky imager through employing physical data, i.e., air temperature, humidity, day time, water content, etc. [69]

Based on atmospheric numerical dynamic simulation, the NWP model can predict solar irradiance and cloud cover, which then can be subdivided into two groups, namely, global models and regional models [70]. The Sky imager is a digital camera that can provide high-quality sky images from horizontal to horizontal, suitable for cloud detection, cloud height measurement on the ground, and cloud movement determination [71]. The concept of satellite imaging is very similar to the sky imaging model, while the cloud pattern is dependent on visible light and infrared images taken by satellite-based sensors flying overhead [72]. Moreover, a comprehensive summary of physical methods for solar irradiance and power forecasting is given in Table IV.

TABLE IV
CHRONOLOGICAL SUMMARY OF 18 PHYSICAL MODELS FOR SOLAR IRRADIANCE AND POWER FORECASTING

Method			Year	Temporal resolution	Spatial resolution	Input variables	Forecast variables	Performance metrics	Characteristics
NWP	Global model	GFS [73]	2011	Medium-term	Regional	SURFRAD ground measurement data (8 months)	GHI	MBE, RMSE	• Radiant flux attenuation relied on H_2O phase, temperature and particle size.
		ECMWF [73]	2011	Medium-term	Regional	SURFRAD ground measurement data (2 months)	GHI	MBE, RMSE	• Accurately estimate cloudy and clear sky conditions.
	Regional models	RUC/RAP [24]	2009	Short-term	Regional	Water vapor absorption, DNI	DHI, GHI	ρ, R^2	• Wavelength-independent model absorbs/ scatters irradiance only from water vapor.
		NAM [73]	2011	Short-term	Regional	SURFRAD ground measurement data (13 months)	GHI	MBE, RMSE	• Irradiance output applied to NWP can decrease offset and error.
		MM5 [40]	2012	Short-term	Regional	Historical data of hourly energy production, estimate values of weather parameters (1.5 years)	P	RMSE	• Offer forecast values of hourly electrical energy production for allhours of following day.
		WRF [74]	2016	Short-term	Regional	SURFRAD ground measurement data (2 years)	GHI	RMSE, ρ	• Can be completely compressed to meet the requirements for relied on-hydrostatic model.
Satellite imaging	Physical satellite models	GDM [75]	1980	Short-term	Regional (12 meteorological stations)	R_a, water vapor absorption, surface albedo, a cloud threshold, cloud albedo and absorption (3 months)	Global solar irradiance	MBE, ρ	• Consider clear and cloudy conditions separately; • Forecasting accuracy improved by modifying cloud threshold, cloud albedo, and absorption.
		MR [76]	1984	Short-term	Regional	θ_z, cloud top height, cloud optical depth, ground albedo, T, R_h, and W_s (50 days)	Global solar irradiance	RMSE, ρ, R^2	• Clouds own the greatest impact on irradiance reaching ground level.
		MDV [77]	1987	Short-term	Regional	T, R_h and three-layer aerosol column (1 month)	Global solar irradiance	RMSE, MBE	• Ignore change of surface albedo with solar zenith angle.
		DDK [78]	1987	Short-term	Regional	Sky transmissivity factor, gaseous absorption, METEOSAT radiometer data	Global solar irradiance	ρ	• Suitable for both clear and cloudy conditions; • Aerosols with abnormally high concentrations are considered clouds.
	Statistical satellite models	HH model [79]	1978	Short-term	Regional	Visible satellite data: aerosols and dust particles, water vapor, cloud cover	Global solar irradiance	N. S.	• Statistical linear regression based on clearness index and atmospheric absorptivity; • Correct reported digital satellites to determine visible radiation.
		Tarpley & Justus-Paris-Tarpley model [80]	1979	Very short-term	Regional (18 stations)	Mean target brightens, mean cloud brightness, θ	DNI	ρ, SDE	• Focus on three independent cases based on cloud index.
		Perez operational model [81]	2002	Short-term	Regional	k_t, K_t, GHI	Global solar irradiance	ρ, RMSE	• Allow modification based on real-time measurement of snow or ice, as well as correction of solar satellite angle effects for each pixel.
		Cano-HELIOSAT model [82]	2004	Short-term	Regional	Ground albedo, mean albedo of cloud tops	k_t, K_t	ρ, R^2	• Establish simple linear connection between k_t and K_t.
	Sky imagery	TSI [83]	2011	Very short-term	Local	Sky images, sunshine parameters (1 month)	Cloud cover, solar irradiance	ρ, R^2	• Large spatial average power plant; • Inaccurate sky conditions prediction due to uncertainty of cloud motion.
		USI [84]	2014	Very short-term	Local	H_g (28 days)	k_t	ρ, R^2	• No data loss caused by shadow band; • No information loss during image compression; • Higher spatial and intensity resolution.
		Multiple total sky imagers [85]	2015	Very short-term	Local	Various weather and cloud conditions, and DNI (6 months)	GHI, 3-D cloud tracking	MAE, RMSE	• Strong robustness in cloud detection and layer tracking; • Increased visible range to a certain degree.
		Sky camera images [86]	2015	Very short-term	Local	Digital image levels (4 years)	DNI, H_g, DHI	nRMSE	• Only digital image levels used in forecasting.

C. Hybrid Models

It is notable that most researchers focused on single models for solar forecasting. Nevertheless, performance of a single model is not reliably accurate in solar forecasting for different cases. One of the motivations for developing hybrid models is that the forecasting accuracy can often be improved by taking advantage of each method [33].

In this context, a thorough analysis of different hybrid models is undertaken. Particularly, they are classified into six groups based on the employed pre-processing mechanisms, e.g., general ensemble learning approach (GELA), cluster-based ensemble learning approach (CELA), decomposition-based ensemble learning approach (DELA), decomposition-clustering based ensemble learning approach (DCELA), evolutionary based ensemble learning approach (EELA) and residual based ensemble learning approach (RELA), as illustrated in Table V.

D. Other Methods

Up-to-date other methods in solar forecasting, such as post-processing methods and probabilistic forecasts are also

TABLE V
CHRONOLOGICAL SUMMARY OF 72 HYBRID MODELS FOR SOLAR IRRADIANCE AND POWER FORECASTING

	Methods	Year	Temporal resolution	Spatial resolution	Input variables	Forecast variables	Performance metrics	Characteristics
GELA	MTM-ANN [87]	2005	Short-term	Regional (60 meteorological stations)	Latitude, longitude and altitude (10 years)	H_g	RMSE, R^2	• Satisfactory performance compared to AR, ARMA and Markov Chain.
	WRF-MOS-Kalman filter [88]	2014	Very short-term	Regional	Geographical and meteorological data (1 year)	H_g	RMSE, MBE	• Kalman filter boost WRF performance.
	ESSS-ANN [89]	2014	Very short-term	Regional	Different meteorological data driven from satellite images (5 years)	H_g	RMSE, R^2, MBE	• Prediction performance based on images resolution.
	Different Angström-type [90]	2015	Medium-term	Regional	n (10 years)	H_g	R^2, RMSE, MAPE	• Improved performance.
	BFGS-ANN [91]	2015	Short-term	Local (Geostationary meteosat)	T, day time, G_0 (1 year)	H_g	RMSE, MBE, R^2	• Superior to independent model (LLR, CG and ANN) in statistical indicators.
	SVR-GBR-RFR [92]	2016	Medium-term	Regional (7 meteorological stations)	Different meteorological data (2 years)	H_g	MAE	• Enhanced performance compared to stand-alone models.
	B-EKF-MLP [93]	2016	Medium-term	Regional	T, R_h, W_s, n (9 years)	H_g	RMSE, R^2	• Superior to NARX-NN, MLR and winner filters; • Complex processing.
	Mycielski-Markov model [94]	2017	Very short-term	Regional (2 sites)	Sky cover, R_h, W_s (4 years)	H_g	RMSE, MABE	• Complex processing.
	Combining empirical models [95]	2017	Medium-term	Local	G_0, n, daylight hours (4 years)	H_g	RMSE, RAE, MAE, R^2	• Superior to other independent models in statistical indicators.
	HS-MMFF [96]	2018	Very short-term	Local	Six solar features (1 year)	H_g	nRMSE	• Improved forecasting performance.
	CNN-LSTM [97]	2019	Very short-term	Local	Previous half-hourly solar irradiance (12 years)	GHI	MAP, APB, rRMSE	• Accurate results compared with other stand-alone models: CNN, LSTM, DNN, GRU, DNN, and MLP.
	WRF-Kalman Filter [98]	2019	Short-term	Local	k_t (2 years)	GHI	MBE, nRMSE	• Effective for day-ahead forecasting.
	DFT-PCA-Elman [99]	2019	Short-term	Regional (5 sites)	Previous solar irradiance (1 year)	GHI	MAE, RMSE	• Superior to persistence models, ARIMA, PCA-PB, and DFT-PCA-BP.
CELA	Fuzzy c-means Clustering [100]	2012	Short-term	Regional (10 meteorological stations)	Two previous inputs k_t^{t-1} and k_t^{t-2} (2 years)	k_t	RMSE, MBE, MAE	• Satisfactory forecasting accuracy in various European regions.
	K-means-DTW-MWF [101]	2013	Short-term	Local	Six prior inputs of daily global solar irradiance (1 year)	H_g	RMSE	• Outperform ARMA, TDNN, and hybrid ARMA-TDNN.
	K-means-clustering-NAR [102]	2013	Medium-term	Local	Two prior inputs of daily global solar irradiance (2 years)	H_g	RMSE, nRMSE	• Choose the instability and time consumption of k-means of cluster.
	HMM-GFM [103]	2013	Medium-term	Local	16 different combinations of inputs (2 years)	H_g	RMSE, R^2	• Superior to ANFIS and ANN.
	K-means-Kolmogorov-Smirnov-statistic [104]	2014	Short-term	Regional	Previous hourly global solar irradiance (2 years)	k_t	Energy error	• High accuracy.
	GA-GAMMF [105]	2014	Very short-term	Local	Previous global solar irradiance (1 year)	H_g	MAPE, RMSE	• Superior to ARMA, TDNN, and hybrid ARMA-TDNN.
	SOM-SVR-PSO [106]	2015	Very short-term	Local	8 hour of predict data (17 years and 3 years)	H_g	Average lower error	• Superior to ARIMA, LES, SEM, and RW.

TABLE V
CHRONOLOGICAL SUMMARY OF 72 HYBRID MODELS FOR SOLAR IRRADIANCE AND POWER FORECASTING (CONTINUED)

	Methods	Year	Temporal resolution	Spatial resolution	Input variables	Forecast variables	Performance metrics	Characteristics
	K-means-clustering-soft computing [107]	2016	Very short-term	Local	T, R_h, P_r (3 years)	H_g	MAE, RMSE	• SVM-C and SVM-R clustering prediction indicate satisfactory performance.
	TB-K-means-ANN [108]	2016	Very short-term	Regional (11 different regions)	15 different inputs data (9 years)	H_g	MSE, RMSE	• Outperform K-means*, K-means++, K-means, and SOM in accuracy and processing time.
	SOM-OPELM-MISMO [109]	2016	Short-term	Regional (3 different regions)	θ, G_0, H_g, hourly mean DNI, DHI, k_t (4 years)	H_g	RMSE, MAPE, MAE, MBE	• Enhanced performance than SOM-OPELM-DirRec, SOM-OPELM-Recursive, ARMA, and BP neural network.
	T. S. C K-means-MLP [110]	2016	Short-term	Local	T, W_s, W_d, G_0	DNI, GHI	RMSE, nRMSE, MAE, nMAE	• More efficient and accurate compared with K-means*, K-means++, K-means, SOM, and FCM.
	K-means-DTMC [111], [112]	2017	Short-term	Regional	Different meteorological data	H_g	MAE	• Improved performance in different regions; • Complex processing.
	T. M-K-means-MLP [113]	2017	Short-term	Regional	Different meteorological data	H_g	RMSE, MAE	• More accurate and faster compared with K-means*, K-means++, K-means, SOM, and GTSOM.
DELA	WT (DB7)-MLP [114]	2006	Medium-term	Local	Different meteorological data (5 years)	GHI	MAE, MRE	• Employing WT with MLP improves prediction performance than single MLP.
	WT (DB4)-RNN [115], [116]	2014	Short-term	Local	T, R_h, W_d, W_s, rainfall, P_r (7 years)	GHI	RMSE, MAE, R^2	• WT enhances forecasting ability via reducing forecasting error by 6% compared with independent model.
	WT-SVM [117]	2015	Medium-term	Local	T, R_h, n, P_r (13 years)	GHI	MAPE, MABE, RMSE, rRMSE, R^2	• High accuracy compared with ARMA, GP, and ANN.
	Morlet-WT-MLP-ANFIS [118]	2016	Short-term	Local	T, R_h, n, P_r (10 years)	GHI	RMSE	• Novel frequency indicator for prediction.
	WT-ANN [119]	2016	Very short-term	Regional (10 cities)	Different meteorological data (1 year)	GHI	RMSE, R^2	• No unique wavelet applied to all regions.
	WT (DB2)-SVM [120]	2016	Short-term	Regional (3 cities)	Different meteorological data (1 year)	GHI	RMSE, rRMSE, MAE, MAPE	• Improved forecasting performance compared to SVM.
	WT (DB3)-GPR [121]	2016	Short-term	Regional	Previous measurement of k_t (2 years)	GHI	MAE, RMSE, nRMSE, R^2	• High prediction performance against ANN, SVM, GPR, and WA-ANN.
	WT-AR-ANN [122]	2017	Short-term	Local	Different meteorological data (1 year)	GHI	MBE, MAE, RMSE, ss	• Preprocessing methods boost performance of ANN and AR.
	EMD-LMD-LSSVM-VM [123], [124]	2018	Short-term	Local	Different meteorological data (1 year)	GHI	RMSE, MAE, ss	• Obtain better prediction performance compared with other hybrid models such as EMD-LDM-VM.
	MEMD-ACO-RF [125]	2019	Medium	Local	Set of meteorological parameters (23 years)	GHI	MAE, RMSE	• Best accuracy against MEMD-ACO-M5TREE, RF, M5tree, and MPMR.
DCELA	WT-GTSOM-BNN [126]	2015	Very short-term	Regional	T, W_d, W_s (2 years)	GHI	RMSE, rRMSE	• Obtain accurate results against other single model and other decomposition approaches.
	EEMD-LS-SVR-K-means-LS-SCR [127]	2018	Short-term	Local	Different meteorological data (8 years)	GHI	Std. NRMS, Std. MAPE, SDE	• Superior to single models and other decomposition-based models.
	EMD-WA-RE-ANN [128]	2018	Medium-tern	Regional	Previous solar irradiance	GHI	RMSE, MAPE, R^2, ρ	• Satisfactory performance on daily and monthly scale.
EELA	GAO-WNN [129]	2011	Short-term	Regional	T, daily GHI (4 years)	K_t	Relative error	• Applicable to non-stationary behavior of data, quickly providing global optimization.
	PSO-ANN [130]	2012	Medium-term	Regional (41 locations)	Numbers of month, latitude, longitude, altitude, n (42 years)	H_g	MAPE	• Improved performance over empirical models and single ANN.
	MGGP [131]	2013	Medium-term	Regional	Months number, latitude, longitude, altitude, T ratio, mean n (14 years)	K_t	RMSE, R^2	• Enhanced forecasting performance compared to SGGP and regressive methods.
	GA-SA [132]	2013	Medium-term	Regional	$T_{\min}$, $T_{\max}$, R_h, total precipitation and mean n (6 years)	H_g	RMSE, MAPE, ρ	• Improved forecasting performance compared to Angstrom model.
	GA-ANN [133]	2013	Short-term	Regional (83 stations)	G_0, integral Rayleigh optical thickness, Bcs, $\cos\theta$	DNI	MBE, RMSE, ρ	• Accurate forecasting due to high resolution of METESAT satellite images; • Forecasting accuracy relies on satellite resolution.

TABLE V
CHRONOLOGICAL SUMMARY OF 72 HYBRID MODELS FOR SOLAR IRRADIANCE AND POWER FORECASTING (CONTINUED)

	Methods	Year	Temporal resolution	Spatial resolution	Input variables	Forecast variables	Performance metrics	Characteristics
	LGP [134], [135]	2013	Medium-term	Regional	$T_{\min}$, $T_{\max}$, R_h, total precipitation and mean n (5 years)	H_g	RMSE, MAPE, ρ	• Outperform Angstrom model.
	ABC-Angstrom [136]	2013	Medium-term	Regional (4 cities)	Relative moisture, elevation, $T_{\min}$, $T_{\max}$ (4 years)	H_g	R^2	• Satisfactory forecasting ability against SRT.
	BCO-Angstrom model [137]	2014	Medium-term	Regional (7 cities)	Meteorological data (20 years)	H_g	RMSE, R^2	• Improved performance than SRT and PSO.
	CRO-ELM [138]	2014	Short-term	Local	k_t with relative T (1 year	H_g	RMSE, MAE	• Improved results compared to classical ELM and SVR; • Overfitting and weak results.
	RC-GA [139]	2015	Medium-term	Regional (65 locations)	Latitude, longitude, altitude, T, R_h, n, G_0, day length (13 years)	H_g	MAPE	• Sensitive to relative humidity within a few months.
	CS-OP-ELM [140]	2015	Very short-term	Regional	9 inputs meteorological data (8 years)	H_g	RMSE, MRE	• Outperforms ARMA, BP, and OP-ELM.
	SA-ANN [141]	2015	Short-term	Local	$T_{\min}$, $T_{\max}$, R_h, W_s, earth skin temperature (19 years)	H_g	RMSE, MAE, R^2	• Superior to SVM, ANN, GP, and MLSR model.
	FFA-SVM [142]	2016	Medium-term	Local	n, ΔT, R_h, V_p, T_{mean} (14 years)	H_g	RMSE, MAPE, R^2	• Outperforms ARMA, ANN, and GP.
	WRF-GGA-ELM [143]	2016	Very short-term	Local	92 atmospheric inputs (1 year)	H_g	RMSE, R^2	• Outperform single ELM; • Complex processing.
	FFA-RFs [144]	2017	Very short-term	Regional	n, ΔT, R_h, numbers of day, numbers of day time (1 year)	H_g	RMSE, MAPE	• Outperforms ANN, ANN-FFA, and RFs.
	WFR-CRO-SP-ELM [145]	2017	Short-term	Local	12 meteorological data (1 year)	H_g	RMSE	• Outperforms GA-ELM and ELM; • Forecasting performance relies on WRF accuracy.
	CS-SPRQVSR-QRBF [146]	2017	Short-term	Regional (4 regions)	8 meteorological variables (1 year)	H_g	MAPE, RMSE	• Features selection improves forecasting.
	NSMOBA-Combination with machine learning [147]	2017	Medium-term	Regional	12 meteorological factors (19 years)	H_g	MAE, MAPE	• Improved performance of individual model by NSMOBA and superior to PSO and GA.
	ANFIS-ANN-PSO [148]	2017	Very short-term	Local	Different meteorological variables (4 years)	GHI	MAPE, MAE	• Performs well during sunny and cloudy seasons.
	PSO-ANFIS [149], [150]	2018	Medium-term	Local	$T_{\min}$, $T_{\max}$, n, monthly rainfall, k_t (8 years)	H_g	RMSE, MAPE, R^2, ρ	• Improved forecasting performance against ANFIS, ANFIS-GA, and ANFIS-DE.
RELA	ARMA-TDNN [151]	2011	Very short-term	Local	Previous hourly global irradiance data (10 days)	GHI	RMSE, nRMSE	• Outperforms ARMA and TDNN.
	NWP-ARMA-ANN [152]	2012	Short-term	Regional (5 sites)	18 past input data (6 years)	H_g	RMSE, R^2	• Outperforms persistence model and single ANN.
	ANN-ARMA [153]	2013	Very short-term	Local	Exogenous meteorological parameters (9 years)	H_g	RMSE	• Improved performance compared to persistence, ARMA, and clear sky model.
	CARDS [154]	2013	Very short-term	Regional	Previous hourly global irradiance data (5 years)	H_g	MeAPE, MBE, KSI, RMSE	• Outperforms ANN, ARMA, and TDNN.
	ARMA-MLP-Persistence [155]	2014	Short-term	Local	6 sub-variables are constructed from pressure time series (13 years)	H_g	RMSE	• Difficult to combine these three predictors.
	Empirical models-BNN [156]	2014	Short-term	Regional	Daily $T_{\min}$, $T_{\max}$ (1 year)	H_g	RMSE, MBE, MAE	• Outperforms BNN.
	ANN-ARX [157], [158]	2016	Short-term	Local	n, $T_{\min}$, $T_{\max}$ (13 years)	H_g	MABE, RMSE, ρ	• Outperforms ANFIS.
	ARMA-NAR [159]	2016	Very short-term	Regional (three regions)	Different meteorological data (1 year)	H_g	RMSE	• Outperforms single model both in three different regions.
	NARNN-ARMAX [160], [161]	2017	Very short-term	Regional	Exogenous input (19 years)	H_g	RMSE, nRMSE	• Enhanced by three types of daily prediction performance compared to single model.
	SAIRIM-ANN [162]	2017	Medium-term	Regional (three regions)	13 inputs data (26 years)	H_g	RMSE, MAE, MAPE	• Outperforms ARIMA, SAIRIM, and ANN.
	Combining empirical models [163]	2018	Short-term	Regional (20 regions)	n, T, precipitation, vapor pressure, R_h (49 years)	H_g	RMSE, MBE, R^2	• No universal model for all research areas and prediction performance depends on available data.
	LR-MLP-BDT [164]	2018	Short-term	Local	Different meteorological data (3 years)	H_g	MAE, RMSE, nRMSE, rRMSE, R^2	• Inferior to MLP model in terms of forecasting performance.

very crucial [26]. Post-processing methods are often used to optimize the output of NWP models. In particular, although the spatial resolution has increased rapidly in the past few years, detailed local weather characteristics generally cannot be resolved by NWP predictions. In addition, systematic deviations of certain weather conditions may be assigned to global and mesoscale model predictions. Therefore, it may be improved through statistics or other post-processing techniques. Moreover, numerous irradiances forecasting methods contain statistical components [69].

Another latest finding in this field is to take into account the uncertainty of some forecasts. Basically, these forecasting methods provide a single value that is valid for the future. Efforts to integrate the above methods into grid management have shown that, in many cases, probabilistic predictions are more helpful than single-point predictions [165]. Furthermore, a large number of forecasting techniques have been developed to offer point prediction, forecasting intervals, and/or forecasting probability distribution function [166], which are categorized into parametric approaches and non-parametric approaches, as listed in Table VI.

VI. Conclusion

A large number of performance criteria have been presented and utilized to measure precision of solar forecasting methods. It is crucial to complete a fair and comprehensive assessment through suitable criteria to evaluate solar prediction, in consideration of diverse forecasting scales, geographical locations, etc. Therefore, a brief summary of 30 metrics is given in Table VII, while benefits/contributions and shortcomings/limitations of each subcategory for a more practical and reasonable comparison are illustrated in Fig. 5.

Note that accurate solar forecasting is of great significance to solar power systems, which is considerable for power dispatching and power grid security, as well as can bring crucial environmental, economic, and social benefits. Therefore, there have been a series of previous reviews focus on concluding these solar forecasting methods. Nevertheless, existing reviews

TABLE VI
Chronological Summary of 13 Other Models for Solar Irradiance and Power Forecasting

Model			Year	Temporal resolution	Spatial resolution	Input variables	Forecast variables	Performance metrics	Characteristics
Post-processing models		Physical post-processing approaches [167]	2009	Medium-term	Regional	Aerosol forecasts, ground albedo, ozone, water vapor, clouds (5 months)	DNI, H_g	RMSE	• Significantly improves global irradiance and especially direct irradiance forecasts compared with ECMWF forecasts for clear sky situations.
		Temporal interpolation (combined with CSM) [168]	2009	Very short-term	Regional (more than 200 meteorological stations)	Different meteorological data (10 months)	k_t, I_{cs}	RMSE	• Provides a more proper basis for linear interpolation than irradiance.
		Human interpretation of NWP output [169]	2010	Medium-term	Regional	Different meteorological data	Cloud cover, GHI	RMSE	• Prediction can be corrected according to local events or weather conditions; • Hard to predict with NWP or statistical methods.
		MOS (correction from NAM, GFS, ECMWF) [170]	2011	Medium-term	Regional	SURFRAD ground measurement data (1 year)	GHI	MBE, RMSE	• Based on cloud cover variables; • Through location, time and basic forecasting models, solar irradiance can be predicted more accurately.
		Spatial averaging (based on NAM, GFS, WRF) [72]	2011	Short-term	Regional	θ_z, k_t (56 days)	GHI	RMSE, MAE	• Reduced forecasting fluctuations in variable cloud situations; • Increased resolution of NWP model for forecasting accuracy improvement.
Probabilistic forecasts	Parametric	Sky imagery with SVM and ANN sub-models [171]	2015	Very short-term	Regional	Historical data of DNI and sky image	GHI	RMSE, MAE, MAPE	• Variance utilized to construct prediction intervals.
		NWP with extraterrestrial insolation and SVR [172]	2015	Short-term	Regional	R_h, T, P_r, cloudiness, G_0	GHI	PICP	• Normal and Laplacian distribution assumed.
		GARCH [173]	2016	Very short-term	Regional	GHI, I_{cs}	GHI	CRPS	• Prediction interval based modeling.
	Nonparametric	QRFs [174]	2015	Short-term	Regional	R_h, W_s, T, P_r, longitude, latitude, altitude, cloud covers	GHI	N. S.	• All information regarding observations stored.
		GB [175]	2016	Short-term	Regional	GHI, R_h, W_s, T, P_r, W_d, G_0, V_p	GHI	Quantile score	• Learning from errors of prior models; • Linearly combine weak learners, namely, separate variables with limited forecasting information, into an independent forecasting model.
		LUBE [176]	2015	Medium-term	Regional	16 inputs, including calendar variables and historical P	GHI	RMSE	• Basically, according to minimizing forecasting error.
		KDE (with QR) [177]	2016	Short-term	Local	P, T	GHI	ss	• Estimate density of a stochastic variable from unknown density.
		AnEn [178]	2016	Short-term	Regional	GHI, R_h, W_s, T, P_r, W_d longitude, latitude, altitude	GHI	CRPS	• Only requires a physical model.

TABLE VII
SUMMARY OF 30 PERFORMANCE METRICS FOR SOLAR IRRADIANCE AND POWER FORECASTING

Type	Metric	Applicability/Purposes	Equation
Algebraic metrics	Pearson's correlation coefficient [179]	Linear correlation between forecasted and actual value of solar power.	$(\rho)=\frac{\operatorname{cov}(\rho,\hat{\rho})}{\sigma_\rho\sigma_{\hat{\rho}}}$
	Normalized error (nE) [53]	Suitable for assessing normalized forecast errors.	$\mathrm{nE}=\frac{P_{\text{pred}}-P_{\text{meas}}}{\max\left(P_{\text{pred}}\right)}$
	Relative mean absolute error (rMAE) [53]	Suitable for evaluating uniform prediction errors.	$\mathrm{rMAE}=\frac{1}{N}\sum_{i=1}^{N}\left\lvert P_{\text{pred}}-P_{\text{meas}}\right\rvert$
	Mean absolute percentage error (MAPE) [179]		$\mathrm{MAPE}=\frac{100}{N}\sum_{i=1}^{N}\left\lvert\frac{P_{\text{pred}}-P_{\text{meas}}}{P_0}\right\rvert$
	Median absolute percentage error (MdAPE) [180]		$\mathrm{MdAPE}=\text{median}\left(\left\lvert 100\frac{P_{\text{pred}}-P_{\text{meas}}}{P_{\text{meas}}}\right\rvert\right)$
	Relative mean bias error (rMBE) [180]	Applied to assess forecast bias.	$\mathrm{rMBE}=\frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{pred}}-P_{\text{meas}}\right)$
	Standard deviation error (SDE) [180]		$\mathrm{SDE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{pred}}-P_{\text{meas}}-\mathrm{MBE}\right)^2}$
	Root mean square error (RMSE) [181]	Applied to evaluate entire precision of forecasts while penalizing large forecast errors based on a square order.	$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{pred}}-P_{\text{meas}}\right)^2}$ $\mathrm{RMSE}^2=\mathrm{MBE}^2+\mathrm{SDE}^2$
	Coefficient of determination [181]	Represents correlations between real and forecasted values.	$R^2=1-\frac{\mathrm{Var}\left(P_{\text{pred}}-P_{\text{meas}}\right)}{\mathrm{Var}\left(P_{\text{pred}}\right)}$
	Correlation coefficient [182]		$\rho=\frac{\left(\mathrm{Cov}\left(P_{\text{pred}}-P_{\text{meas}}\right)\right)^2}{\mathrm{Var}\left(P_{\text{pred}}\right)}$
	Skill score (ss) or forecasting skill (S) [182]	Define ratio of uncertainty U of solar forecasts to solar variability V.	$ss=1-\left(\frac{U}{V}\right)$ $U=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_{\text{pred, t}}-P_{\text{meas, t}}}{P_{\text{cs, t}}}\right)^2}$ $V=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\Delta k\left(t\right)\right)^2}$
Statistical metrics	Skewness [182]	Measure asymmetry of distribution of forecast errors; A positive/negative skewness causes an over-forecasting/under-forecasting tail.	$\mathrm{skew}=\frac{N}{(N-1)(N-2)}\sum_{i=2}^{N}\left(\frac{\mathrm{nE}-\overline{\mathrm{nE}}}{\mathrm{SD}}\right)^3$
	Excess kurtosis [182]	Measure magnitude of peak of distribution of forecast errors; A positive/negative kurtosis value states a peaked/flat distribution, higher/lower than that of normal distribution.	$\mathrm{kurt}=\left\{\frac{N(N-1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{\mathrm{nE}-\overline{\mathrm{nE}}}{\mathrm{SD}}\right)^4\right\}\cdot\frac{3(N-1)^2}{(N-1)(N-2)}$
	Maximum absolute error (MaxAE) [182]	Applied to the largest forecast error; Larger MaxAE can cause significant economic impact on grid operation	$\mathrm{MaxAE}=\max_{i=1,2,\cdots n}\left\lvert P_{\text{pred}}-P_{\text{meas}}\right\rvert$
	Maximum absolute scaled error (MASE) [182]	No scale and little understanding of outliers; A smaller MASE denotes better forecasting.	$\mathrm{MASE}=\frac{\mathrm{MAE}}{\left(\frac{1}{N}-1\right)\sum_{i=2}^{N}\lvert P_{\text{meas},i}-P_{\text{meas},i-1}\rvert}$
	Kolmogorov–Smirnov integral (KSI) [182]	Evaluate statistical similarity between forecasted and actual solar power.	$\mathrm{KSI}=\int_{x_{\min}}^{x_{\max}}D_n\mathrm{d}x$
	OVER [182]	Characterize statistical similarity between forecasted and actual solar power on large forecast errors.	$\mathrm{OVER}=\int_{p_{\min}}^{p_{\max}}t\mathrm{d}p$ $t=\begin{cases}D_j-V_c & \text{if } D_j>V_c\\ 0 & \text{if } D_j\leq V_c\end{cases}$
	KSD [182]	Ensures a continuous classification of results.	$\mathrm{KSD}=w_1\mathrm{KSI}+w_2\mathrm{OVER}$
	RIO [182]	Offer information from CDFs and distance between pairs.	$\mathrm{RIO}=\frac{\mathrm{KSD}+\mathrm{RMSE}}{2}$
Uncertainty quantification	Rényi entropy [183]	Quantify forecast uncertainty.	$H_\alpha\left(X\right)=\frac{1}{1-\alpha}\log_2\sum_{i=1}^{N}P_i^\alpha$
	Standard deviation [183]		N. S.
Ramp characterization	Swinging door algorithm [183]	Extract ramps in solar power output via identifying start and end points of each ramp.	N. S.
Economic metrics	95th percentile of forecast errors [183]	Represent amount of non-spinning reserves service reserved to compensate for solar power forecast errors.	N. S.
Other metrics	Error estimation [183]	Proportionally correlate to learning error with actual variability of output.	$E=100\sqrt{\sum_{i-1}^{Ni}\frac{\left(P_{\text{meas},i}-P_{\text{pred},i}\right)^2}{\sigma_i^2N_i}}$
	Continuous ranked probability score (CRPS) [184]	Represents fraction of observations at lower/higher level.	$\mathrm{CRPS}=\frac{1}{N}\sum_{i=1}^{N}\int_{-\infty}^{\infty}\left(F_i^{\text{pred}}\left(x\right)-F_i^{\text{meas}}\left(x\right)\right)^2\mathrm{d}x$
	Brier score (BS) [184]	Represents enhancement of base model.	$\mathrm{BS}=\frac{1}{N}\sum_{i=1}^{N}\left(P_n-O_n\right)^2$
	Mean absolute interval deviation (MAID) [184]	Evaluate deviation models between forecasted interval and actual interval.	$\mathrm{MAID}=\frac{1}{2N}\left\{\sum_{i=1}^{N}\left\lvert U_{\text{meas},k,i}^P-U_{\text{pred},k,i}^P\right\rvert+\left\lvert L_{\text{meas},k,i}^P-L_{\text{pred},k,i}^P\right\rvert\right\}$
	Interval coverage probability (ICP) [184]	Average all observations in data set; Higher ICP leads to lower forecast error.	$\mathrm{ICP}=\frac{1}{N\cdot k}\sum_{i=1}^{N}\sum_{j=i+1}^{i+k}c_j\cdot 100\%$ $c_j=\begin{cases}1 & \text{if } P_j\in\left[U_{\text{meas},k,i},L_{\text{meas},k,i}^P\right]\\ 0 & \text{otherwise}\end{cases}$
	Modified version of MAE and MBE [184]	Penalize hourly energy error or daily energy error.	$cv\mathrm{MAE}=\frac{\mathrm{MAE}}{P_{\text{meas}}}$ $cv\mathrm{MBE}=\frac{\mathrm{MBE}}{P_{\text{meas}}}$
	Pinball loss function (L) [184]	Average over target quantiles, time periods and forecast horizons.	$L=\begin{cases}\left(1-\frac{a}{100}\right)\left(q_a-y\right) & \text{if } y<q_a\\ \frac{a}{100}\left(y-q_a\right) & \text{if } y\gg q_a\end{cases}$

on solar forecasting still have various limitations, namely, obscure and incomplete classifications, outdated methods, partial performance indicators, unpromising perspectives and so on, which can be further improved. On the behalf of remedying the aforementioned drawbacks to offer readers comprehensive and systematic guidance for future research in the related field, this paper aims to offer a comprehensive and systematic summary of 128 forecasting methods of solar irradiance and power, which are categorized into four major groups, namely, statistical, physical, hybrid, and others. The following conclusions can be stated:

1) Five classifications of solar data, along with 7 data pre-processing methods which can efficiently improve forecasting accuracy, are thoroughly covered;

2) Six subcategories, along with 30 evaluation criteria, are summarized for a fair and reasonable evaluation for solar forecasting;

3) 128 solar forecasting methods are comprehensively

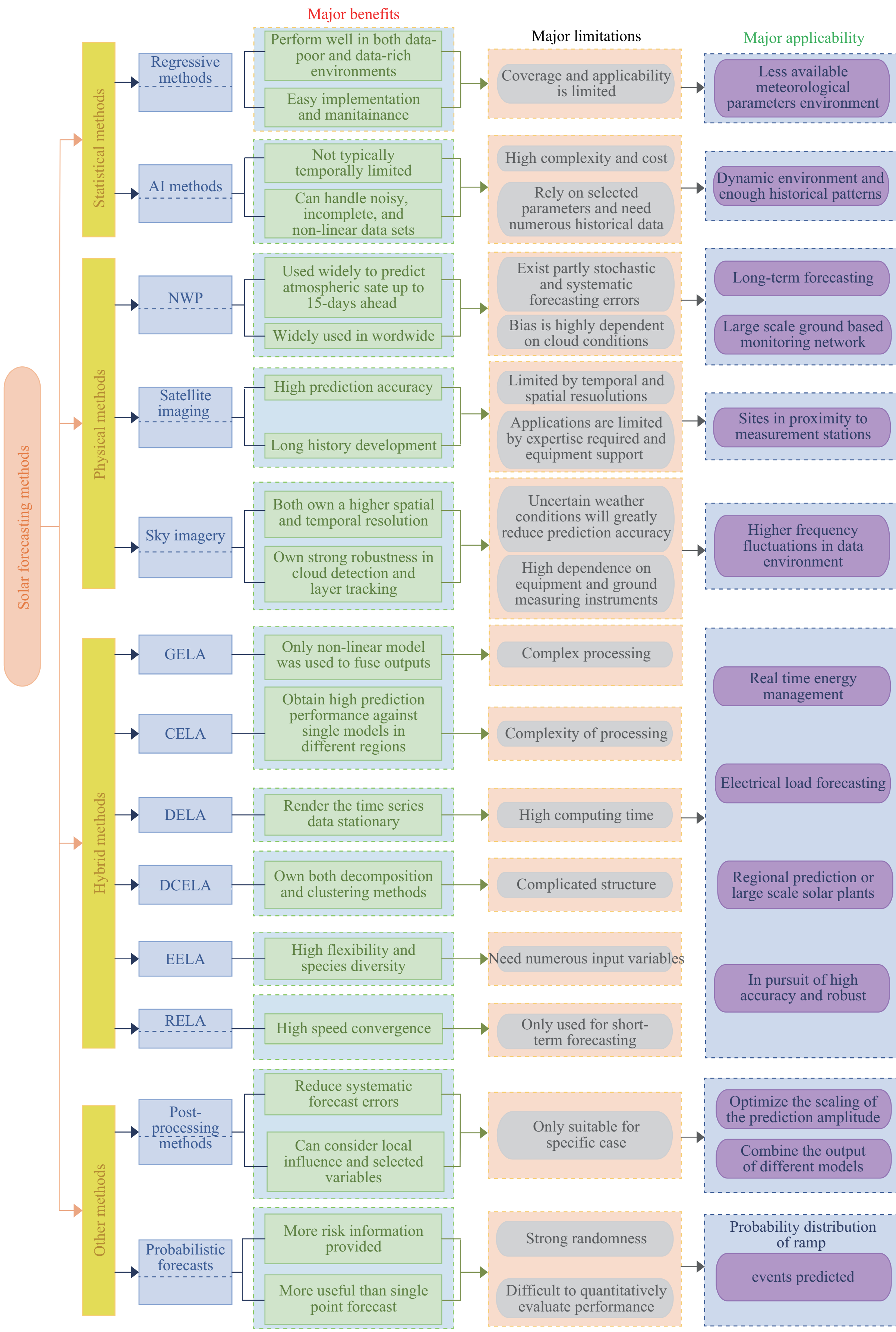


Fig. 5. Comparison of four types of solar forecasting methods.

summarized and compared based on their inputs, temporal resolution, spatial resolution, forecasting variables, metrics, and characteristics, which aims to help readers utilize these methods more effectively for future in-depth research.

The aforementioned methods are all carefully and thoroughly covered and discussed with their application conditions/purposes, such that interested readers or relevant researchers can rapidly and readily find proper models/algorithms to tackle their tasks.

VII. Perspectives

Seven perspectives and trends for further research in solar forecasting are presented here:

1) Independent forecasting methods of conventional solar irradiance and power forecasting are difficult to maintain at a high accuracy rate under different conditions. Thus, hybrid forecasting methods should be further developed to effectively enhance prediction accuracy and performance;

2) Spatial averaging has a potential for improving prediction accuracy without additional measurement data, which is being employed as a promising technique. In addition, regional forecasting results are quite promising for grid operators due to the fact that numerous solar power plants need to operate simultaneously;

3) Probabilistic solar power forecasting is still at an early stage with several challenges remaining to be resolved, which creates a significant potential for future applications;

4) Economic impact of solar forecasting should be further analyzed and discussed. Recent research has indicated a potential to reduce balancing reserves through improving prediction, which can obtain significant economic savings and increase energy efficiency;

5) Pre-processing and post-processing of solar historical datasets need to be considered. An effective and indispensable preprocessing technique, namely weather classification, has been demonstrated through state-of-the-art research. In addition, data-driven approaches are also considered as a hot spot, which can considerably enhance data processing efficiency;

6) Designing proper forecasting models with the optimal number of inputs according to their strong correlation with PV output. Moreover, optimization algorithms are indispensable to help choose the most important input parameters;

7) Owing to its high speed, high bandwidth and low delay, 5th-Generation (5G) technology combining innovative technologies, e.g., big data, cloud computing and AI, can be utilized to significantly improve transmission quality and efficiency of real-time solar data for potential forecasting in different applications.

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