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What are the Current Status and Future Prospects in Solar Irradiance and Solar Power Forecasting?

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Abstract-In most of the countries around the world, solar photovoltaic power plants have a cost-competitive structure for providing energy access and for increasing electricity production. However, solar photovoltaic power integration requires the handling of power quality and stability problems due to its non-controllable and intermittent characteristics. At this point, the need for reliable solar irradiance and solar power forecasting is emerged for the optimal modeling and scheduling of solar photovoltaic power plants. For this purpose, this study conducts an exhaustive and up-to-date review of solar irradiance and solar power forecasting methods used in the literature. Although there are a plenty of review papers in the literature, differently, we have created the extensive and comparative literature tables considering very-short term, short-term, medium-term and long-term forecasting periods in this study. Furthermore, we have examined each paper in terms of its input data, forecasting interval, forecasting model, forecasting accuracy and forecasting results. As a result of overall assessments, this study provides complete and considerable information about the current status and future prospects in solar irradiance and solar power forecasting.

Keywords: Solar photovoltaic power plants, solar irradiance forecasting, solar power forecasting, current status, future prospects.

Nomenclature

IMP_{MAE}	Improvement percentage of MAE	**NMAE**	Normalized mean absolute error
IMP_{RMSE}	Improvement percentage of RMSE	**NRMSE**	Normalized root mean square error
MABE	Mean absolute bias error	**R**	Correlation coefficient
MAD	Mean absolute deviation	**R^2**	The coefficient of determination
MAE	Mean absolute error	**rMAE**	Relative mean absolute error
MAPE	Mean absolute percentage error	**RMSE**	Root mean square error
MBE	Mean bias error	**rRMSE**	Relative root mean square error
MdAPE	Median absolute percentage error	**QS**	Quantile score
MRE	Mean relative error	**SDAE**	Standard deviation of AE
MSE	Mean squared error	**SDAPE**	Standard deviation of APE

1. Introduction

Renewable energy meets the energy needs of countries with domestic clean energy resources by reducing the dependence on foreign countries. It also provides the use of sustainable energy by diversifying energy resources and reducing greenhouse gas emissions [1, 2]. Solar, wind, geothermal, biomass and hydroelectric energy sources are the main types of renewable energy. According to the Renewables Global Status Report [3], the global new investment in renewable power and fuels exceeded USD 260 billion in 2016 and the global renewable power generating capacity has seen almost 2,017 GW in total by the end of 2016. Especially, the production capacities based on the energy types have been reached to 1,096 GW for hydropower, 487 GW for wind power, 307.8 GW for solar power, 112 GW for bio-power and 13.5 GW for geothermal power. Among them, solar photovoltaic was observed as the world's leading renewable energy source of additional power generating capacity in 2016. As shown in Figure 1, there has been a tremendous growth in the global capacity and annual additions of solar photovoltaic energy for the last 10 years. These improvements have led to analyse the huge amount of recorded data in solar photovoltaic energy systems by means of the knowledge discovery process in databases.

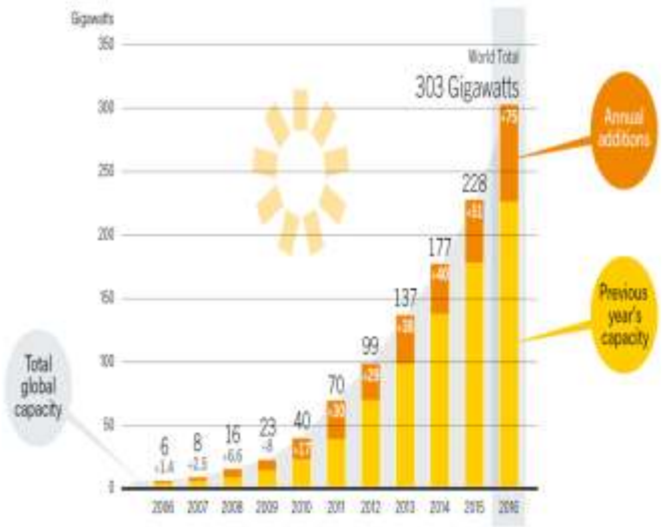

Figure 1. The global capacity and annual additions of solar photovoltaic energy [3]

The knowledge discovery process is based on sorting, searching, summarizing and analysing data in large-scale databases [4, 5]. It contains the steps of data cleaning and integration, data selection and transformation, data mining, pattern evaluation and presentation, as depicted in Figure 2. Each step performs its own task as follows [6, 7]: The data in a database are taken to the data warehouse after data cleaning and integration step, the task-relevant data is constructed by data selection and transformation step, the patterns are uncovered by means of data mining step and finally, useful and meaningful patterns are converted to the knowledge after pattern evaluation and presentation step. Particularly, the inconsistent data is removed in the data cleaning phase and multiple data sources are combined in the data integration phase. The data related to the analysis task is retrieved in the data selection phase and the convenient data form is performed in the data transformation phase. The hidden patterns are searched and the meaningful information is uncovered in the data mining phase. All of interesting patterns are identified in the pattern evaluation phase and the knowledge mined is presented to users with data visualization techniques in the knowledge presentation phase.

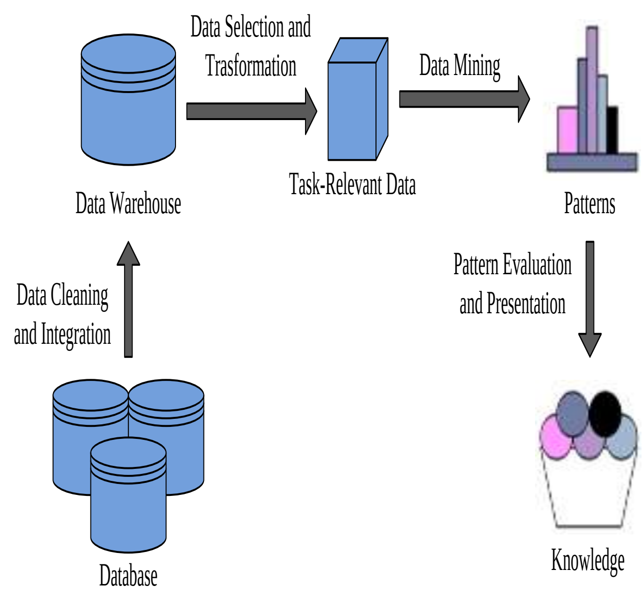

Figure 2. The knowledge discovery process in large-scale databases

Data mining is one of the most important stages of knowledge discovery process in large-scale databases. Intelligent systems, artificial intelligence, machine learning, statistics, etc. are among the disciplines that constitute data mining [8]. Data mining methods are mostly categorized as predictive and descriptive models [9]. Predictive mining aims to develop a model by using the data whose results are known and to predict the results of data whose results are unknown by utilizing the model developed. On the other hand, descriptive mining aims to reveal the relationships in the existing data that can help to make decisions. Classification and regression analysis takes part in the predictive models, while cluster analysis, association rules and sequential patterns are involved in the descriptive models [10]. Bayesian networks, artificial neural networks, support vector machines, decision trees, k-nearest neighbor algorithm, multiple linear and logistic regression models, etc. can be employed for the classification and regression analysis. Agglomerative hierarchical clustering, k-means partitional clustering, Dbscan density-based clustering and Sting grid-based clustering methods can be used for the cluster analysis. In addition, Apriori algorithm has the usage priority in order to obtain the association rules.

Many different applications of data mining methods have been made for solar energy systems, such as electrical efficiency estimation of photovoltaic unit [11], quantifying rooftop photovoltaic energy [12], solar irradiance and solar power forecasting [13, 14], levelized cost prediction [15], reference voltage estimation [16], duty cycle determination of power converter [17], oscillation characteristic modeling [18], etc. Among these application areas, particularly, solar irradiance and solar power forecasting is commonly and predominantly needed for the optimal management of energy flow occurring in solar systems. In this respect, the main objective of this study is to make a comprehensive literature review of forecasting methods of solar irradiance and solar power. In addition, the major contributions of this study are to provide the highly summarized content of the corresponding literature with the easy to understand tables constructed, to evaluate the current challenges to be solved for solar irradiance and solar power forecasting, and to make the crucial proposals need to be considered in future forecasting studies. As a result, the literature review conducted represents a key study for ensuring the literature consistency in solar irradiance and solar power forecasting.

2. Solar Forecasting

Solar forecasting mostly deals with the prediction of solar irradiance and solar power production. Four different time horizons and their purposes used for solar forecasting can be summarized as follows [19, 20]: Very short-term period contains the predictions up to 15 minutes for power balance/quality, reserve capacity planning and load following. Short-term period covers the predictions from 15 minutes to 1 hour for reserve capacity planning, load following and market bidding. Medium-term period contains the predictions from 1 hour to 1 day and long-term period covers the predictions beyond 1 day. Both of them are utilized for market bidding and base-load planning. In the following sub-sections, we investigate solar irradiance and solar power forecasting considering these time horizons.

2.1. Solar Irradiance Forecasting

We examine the solar irradiance forecasting methods in the literature based on very short-term, short-term, medium-term and long-term periods. In each forecasting period, we also focus on input data, forecasting interval, forecasting models, forecasting accuracies and forecasting results of the related study. The content analyses of all studies examined in the scope of solar irradiance forecasting are presented in Tables 1 to 4, elaborately. For instance, in [43], fuzzy logic, artificial neural network and fuzzy-neural network models used solar radiation, sky conditions and temperature data in order to forecast the solar irradiance parameter at 1-h time intervals. The mean absolute percentage errors of these models were achieved as 13.87%, 10.85% and 6.03%, respectively. So, in terms of the forecasting accuracy, fuzzy-neural network model outperformed artificial neural network model, while artificial neural network model surpassed fuzzy logic model.

As a result of overall examination in solar irradiance forecasting, the following meaningful findings and useful proposals are uncovered in this study:

- Solar irradiance, air temperature and sunshine duration are the mostly-used input parameters. Atmospheric pressure, relative humidity and wind speed parameters follow them. In addition, coordinates, sky image, cloud cover, precipitation, wind direction, zenith angle, month and day numbers are used, rarely.
  - ✓ The effects of these parameters on solar irradiance forecasting should be examined and the most influential ones should be utilized for optimizing the forecasting accuracy.
- Artificial neural networks have a wide range of applications in solar irradiance forecasting. Multilayer perceptron, support vector machines, support vector regression and k-means algorithm follow it. In addition, autoregressive modeling, self-organizing maps, extreme learning machine, k-nearest neighbor algorithm and firefly algorithm are also employed for the same purpose.
  - ✓ The forecasting performance of these methods should be compared in detail and according to the results that will be achieved, novel hybrid forecasting methods should be constructed.
- The time horizons usually focus on short-term and medium-term periods. Particularly, 1-h time intervals in short-term period and 1-day time intervals in medium-term period are considered in the forecasting methods.
  - ✓ More studies containing very-short term and long-term periods should be conducted in order to meet the other requirements based on solar irradiance forecasting.
- Root mean square error is the most preferred metric in order to measure the accuracy of solar irradiance forecasting. The coefficient of determination, mean absolute percentage error and mean absolute error also have the usage priorities after it.
  - ✓ All of these accuracy metrics should be computed in the future forecasting studies in order to ensure the literature consistency.
- Artificial neural networks generally provide better forecasting results than autoregressive integrated moving average, autoregressive and linear regression models. On the other hand, they are generally outperformed by support vector machine and support vector regression models.

2.2. Solar Power Forecasting

Similar to the solar irradiance forecasting, we review the solar power forecasting methods in the literature based on very short-term, short-term, medium-term and long-term periods. In each forecasting period, we also concentrate on input data, forecasting interval, forecasting models, forecasting accuracies and forecasting results of the relevant study. The content analyses of all studies reviewed in the scope of solar power forecasting are presented in Tables 5 to 8 in detail. For instance, in [82], solar irradiance, solar cell temperature and solar power output data were used in adaptive feed-forward neural network, dynamic recurrent neural network and radial basis function models for the purpose of forecasting the solar power parameter at 1-h time intervals. The correlation coefficients of these models were accomplished as 0.998, 0.981 and 0.991, respectively. Thus, in terms of the forecasting performance, adaptive feed-forward neural network model surpassed radial basis function model, while radial basis function model outperformed dynamic recurrent neural network model.

As a result of overall review in solar power forecasting, the following beneficial patterns and favourable recommendations are revealed in this study:

- Solar power, solar irradiance and air temperature are the mostly-employed input parameters. Relative humidity and wind speed parameters pursue them. In addition, sky image, cloud cover, precipitation, sunshine duration and air pressure parameters are employed in a seldom manner.
  - ✓ The effects of these parameters on solar power forecasting should be analyzed and the most powerful ones should be utilized for improving the forecasting accuracy.
- Artificial neural networks have a widespread application area in solar power forecasting. Autoregressive integrated moving average modeling, support vector regression and support vector machines pursue it. In addition, ensemble modeling, autoregressive modeling with exogenous inputs, radial basis functions, recurrent neural networks and multilayer perceptron are also used for the similar purpose.
  - ✓ The forecasting achievement of these methods should be compared to each other in depth and in this context, new mixed forecasting structures should be built.
- The time horizons generally concentrate on very-short term, short-term and medium-term periods. Especially, 15-min time intervals in very-short term period, 1-h time intervals in short-term period and 1-day time intervals in medium-term period are regarded in the forecasting methods.
  - ✓ More studies including long-term periods should be dealt in order to fulfill the other necessities based on solar power forecasting.
- Mean absolute error is the most utilized metric in order to evaluate the performance of solar power forecasting. Mean absolute percentage error, root mean square error and normalized root mean square error also have the precedence of usage after it.
  - ✓ All of these performance metrics should be calculated in the further forecasting studies in order to contribute the literature consistency.
- Artificial neural networks in comparison to autoregressive integrated moving average model and seasonal autoregressive integrated moving average model in comparison to support vector machines lead to better forecasting results. Despite that, artificial neural networks are usually surpassed by support vector regression models.

2.3. Common Assessments for Solar Irradiance and Solar Power Forecasting

In the previous sub-sections, solar irradiance forecasting and solar power forecasting are evaluated independently from each other. As a result of considering both forecasting reviews, the following invaluable outcomes are mined in this study:

- There are the studies that do not specify forecasting intervals and forecasting errors. The forecasting intervals should be indicated to enable the time horizon-based evaluations and the forecasting errors should be presented to enable the accuracy-based comparisons.
- There are the limited applications of optimization methods such as genetic algorithm, evolutionary algorithm, particle swarm optimization, Levenberg-Marquardt algorithm, artificial bee colony algorithm, glowworm swarm optimization, coral reefs optimization, etc. In addition to these optimization methods, other new ones such as ant lion, grey wolf, dragonfly, moth-flame, whale, rooted tree etc. optimizers should be adapted to the forecasting processes.
- In addition to RMSE, R^2, MAPE and MAE in solar irradiance forecasting and MAE, MAPE, RMSE and NRMSE in solar power forecasting, their improvement percentages with respect to the persistence method should be given for proper benchmark tests. Since, the persistence method is the most-widely employed reference model in both literatures.
- Each study in the corresponding literatures has its own input data, time interval, accuracy metric and forecasting model. In addition to this case, the usage of persistence method that is the only way to make constructive and effective comparisons is relatively limited in the literature. For these reasons, in this phase, it is not possible to make the exact evaluations about the accuracy performance of forecasting models. However, it can be observed from the literature that hybrid solar predictors frequently provide lower forecasting errors than single solar predictors.
- Lastly, the multi-seasonal data can be used in order to uncover whether the forecasting methods are affected by the seasonal changes. In addition, a common standard database around the world can also be created in order to enable researchers to share their experiences in this field.

In addition to the solar irradiance and solar power forecasting studies in the literature, it should be noted that there are many other studies focusing on the various control strategies for the performance optimization of solar energy systems [95-103].

Table 1. Solar irradiance forecasting methods based on very short-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[21]	Meteorological data	Artificial neural network (ANN)	N/A	R=0.886	ANN
[22]	Daylight hours, temperature, clear-sky and extraterrestrial solar radiation, actual and maximum sunshine duration	Polynomial kernels-based support vector regression (PK-SVR)	N/A	R= 0.889, RMSE=3.3 MJ/m^2	PK-SVR > RBF-SVR
		Radial basis functions-based support vector regression (RBF-SVR)		R=0.887, RMSE=3.4 MJ/m^2	
[23]	Weather data	Multilayer perceptron (MLP)	1-min	N/A	MLP
[24]	Global horizontal, diffuse horizontal and direct normal irradiance	Support vector regression	1-min	rRMSE=6.70%	AR > PM > SVR
		Autoregressive modeling (AR)		rRMSE=3.62%	
		Persistence model (PM)		rRMSE=5.32%	
[25]	Solar irradiance, sky image	Support vector machines-based artificial neural network (SVM-ANN)	5-min	MAE=35.7 W/m^2, MBE=1.20 W/m^2	SVM-ANN
			10-min	MAE=44.2 W/m^2, MBE=2.11 W/m^2	
			15-min	MAE=51.8 W/m^2, MBE=4 W/m^2	
[26]	Direct irradiance, diffuse irradiance, sky images	k-nearest neighbor ensemble model (k-NNE)	5-min	MBE=-2.6 W/m^2, RMSE=78.1 W/m^2	k-NNE
			10-min	MBE=-2.5 W/m^2, RMSE=98.40 W/m^2	
			15-min	MBE=-2.3 W/m^2, RMSE=109.3 W/m^2	
[27]	Solar radiation	Multilayer perceptron	10-min	R=0.89	MLP
[28]	Global horizontal irradiance	Optimized k-nearest neighbor model	15-min	MAE=18.70 W/m^2, IMP_{RMSE}=10.7%	Opt. ANN > Opt. k-NN
		Optimized artificial neural network		MAE=17.60 W/m^2, IMP_{RMSE}=12%	

Table 2. Solar irradiance forecasting methods based on short-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[25]	Solar irradiance, sky image	Support vector machines-based artificial neural network	20-min	MAE=56.8 W/m^2, MBE=5.30 W/m^2	SVM-ANN
[26]	Direct irradiance, diffuse irradiance, sky images	k-nearest neighbor ensemble model	20-min	MBE=-2 W/m^2, RMSE=134.5 W/m^2	k-NNE
[27]	Solar radiation	Multilayer perceptron	20-min	R=0.81	MLP
[28]	Global horizontal irradiance	Optimized k-nearest neighbor model	45-min	MAE=20.90 W/m^2, IMP_{RMSE}=11.4%	Opt. k-NN > Opt. ANN
		Optimized artificial neural network		MAE=20.40 W/m^2, IMP_{RMSE}=10.5%	
[29]	Global horizontal irradiation	Nonparametric bootstrapping method (NBS)	1-h	N/A	NBS
[30]	System configuration, cloud cover, season	Adaptive neuro-fuzzy inference system (ANFIS)	1-h	N/A	ANFIS
[31]	Solar radiation	Autoregressive integrated moving average-based time delay neural network (ARIMA-TDNN)	1-h	N/A	ARIMA-TDNN
[32]	Solar radiation, sunshine duration, wind speed and direction, pressure, humidity, temperature, precipitation	Generalized radial basis functions (GRBF)	1-h	N/A	GRBF
[33]	Global horizontal, diffuse and beam solar irradiation	Artificial neural network	1-h	R^2=0.90, RMSE=21.54%	ANN
[34]	Solar radiation	Linear prediction filters (LPF)	1-h	MBE=17.44 W/m^2, RMSE=68.41 W/m^2	LPF
[35]	Global horizontal solar radiation	k-means-based nonlinear autoregressive neural network (NARNN)	1-h	RMSE=60.24 W/m^2, NRMSE=0.19	k-means-NARNN
[36]	Global solar radiation	Coupled autoregressive-based dynamical system model (CAR-DS)	1-h	MdAPE=7.53%, NRMSE=0.16	CAR-DS
[37]	Extraterrestrial radiation, air temperature, wind speed, wind direction	A soft computing framework using clustering, time series and multilayer perceptron (SCF)	1-h	MAE=23.61 W/m^2, NMAE=2.80	SCF
[38]	Global horizontal irradiance	Artificial neural network	1-h	MBE=3.9 W/m^2, RMSE=77.9 W/m^2	ANN
[39]	Temperature, wind speed, cloud cover, precipitation	k-means algorithm-based Multilayer perceptron (k-means-MLP)	1-h	IMP_{MAE}=5.90%	k-means-MLP
[40]	Numerical weather data	Grouping genetic algorithm-based extreme learning machine (GA-ELM)	1-h	R^2=0.86, RMSE=111.76 W/m^2	GA-ELM
[41]	Solar radiation	Mycielski model	1-h	R=0.88, R^2=0.81, RMSE=13.90 W/m^2	Mycielski-Markov > Mycielski
		Mycielski-Markov hybrid model		R=0.84, R^2=0.83, RMSE=13.49 W/m^2	

[42]	Sun radiation, temperature, weather conditions	Multivariate linear regression (MVLR)	1-h	R^2=0.92	ANN > MVLR
		Artificial neural network		R^2=0.99	
[43]	Solar radiation, sky conditions, temperature data	Fuzzy logic (FL)	1-h	MAPE=13.87%	FNN > ANN > FL
		Artificial neural network		MAPE=10.85%	
		Fuzzy-neural network model (FNN)		MAPE=6.03%	
[44]	Global horizontal irradiation	Autoregressive modeling	1-h	NRMSE=0.272	KF > ANN > AR
		Artificial neural network		NRMSE=0.271	
		Kalman filters (KF)		NRMSE=0.181	
[45]	Zenith angle, azimuth angle, extraterrestrial radiation, diffuse solar radiation, direct solar radiation, global solar radiation	Self-organizing map-based extreme learning machine (SOM-ELM)	1-h	MAE=9.98 W/m^2, MAPE=4.60 %	SOM-ELM > BPNN > ARIMA
		Back-propagation neural network (BPNN)		MAE=12.89 W/m^2, MAPE=6.18 %	
		Autoregressive integrated moving average		MAE=14.90 W/m^2, MAPE=7.70 %	
[46]	Wind speed, relative humidity, sky cover, atmospheric transmissivity	Least-square support vector machine (LS-SVM)	1-h	MAE=33.70 W/m^2	LS-SVM > RBF > AR
		Radial basis functions		MAE=43 W/m^2	
		Autoregressive modeling		MAE=62 W/m^2	
[47]	Month number, day number, number of hours per day, ambient temperature, humidity, sunshine ratio	Artificial neural network	1-h	MAPE=17.15%, RMSE=95.91 W/m^2	FF-RF > RF > FF-ANN > ANN
		Firefly algorithm-based artificial neural network (FF-ANN)		MAPE=13%, RMSE=85.12 W/m^2	
		Random forests (RF)		MAPE=9.78%, RMSE=74.45 W/m^2	
		Firefly algorithm-based random forests (FF-RF)		MAPE=6.38%, RMSE=68.83 W/m^2	
[48]	Solar time series data	k-means algorithm	1-h	RMSE= 58.65 W/m^2, IMP_{RMSE}=1%	Trans. k-means > SOM >k-means++ > k-means
		k-means++ algorithm		RMSE=45.27 W/m^2, IMP_{RMSE}=23%	
		Self-organizing maps		RMSE=37.21 W/m^2, IMP_{RMSE}=37%	
		Transformation-based k-means algorithm (Trans. k-means)		RMSE=20.56 W/m^2, IMP_{RMSE}=65%	
[49]	Temperature, air pressure, relative humidity, solar zenith angle, wind direction, wind speed, precipitation	Support vector machines	1-h	MAPE=28.53%, RMSE=41.28 W/m^2	GSO-LASSO > LASSO > SVM
		Least absolute shrinkage and selection operator (LASSO)		MAPE=20.39%, RMSE=44.87 W/m^2	
		Glowworm swarm optimization-based least absolute shrinkage and selection-operator (GSO-LASSO)		MAPE=13.24%, RMSE=28.05W/m^2	
[50]	Global horizontal irradiance	Empirical mode decomposition-based linear autoregressive and non-linear neural network (EMD-LANNN)	1-h	rMAE=8.82%, rRMSE=11.16%	WD-LANNN > EEMD-LANNN > EMD-LANNN
		Ensemble empirical mode deco.-based linear autoregressive and non-linear neural network (EEMD-LANNN)		rMAE=5.18%, rRMSE=6.19%	
		Wavelet decomposition-based linear autoregressive and non-linear neural network (WD-LANNN)		rMAE=2.76%, rRMSE=3.80%	
[51]	Global horizontal solar irradiance, atmospheric pressure, humidity, air temperature	Decision trees and artificial neural networks (DT-ANN)	1-h	rMAE=21.10%, RMSE=161 W/m^2	SVM-SVR > SVM-ANN > DT-SVR > DT-ANN
		Decision trees and support vector regression (DT-SVR)		rMAE=19.30%, RMSE=163 W/m^2	
		Support vector machines and artificial neural networks (SVM-ANN)		rMAE=18.50%, RMSE=150 W/m^2	
		Support vector machines and support vector regression (SVM-SVR)		rMAE=16.70%, RMSE=147 W/m^2	
[52]	Ground data, satellite-derived data, weather forecast data	Artificial neural network model with ground data (ANN-GD)	1-h	RMSE=110.6 W/m^2, IMP_{RMSE}=7.1%	ANN-GSWD > ANN-GSD > ANN-GWD > ANN-GD
		Artificial neural network model with ground and satellite data (ANN-GSD)		RMSE=105.3 W/m^2, IMP_{RMSE}=11.4%	
		Artificial neural network model with ground and weather forecast data (ANN-GWD)		RMSE=110.3 W/m^2, IMP_{RMSE}=7.4 %	
		Artificial neural network model with ground, satellite and weather forecast data (ANN-GSWD)		RMSE=104.7 W/m^2, IMP_{RMSE}=11.9%	

Table 3. Solar irradiance forecasting methods based on medium-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[28]	Global horizontal irradiance	Optimized k-nearest neighbor model	90-min	MAE=22.60 W/m^2, IMP$_{RMSE}$=15.8%	Opt. k-NN > Opt. ANN
		Optimized artificial neural network	90-min	MAE=22.80 W/m^2, IMP$_{RMSE}$=14.1%	
[38]	Global horizontal irradiance	Artificial neural network	90-min	MBE=8.6 W/m^2, RMSE=93.5 W/m^2	ANN
			2-h	MBE=14.5 W/m^2, RMSE=107.4 W/m^2	
[53]	Solar radiation, temperature, wind speed, wind direction	k-means algorithm-based Bayesian neural networks (k-means-BNN)	2-h	RMSE=85.72 W/m^2, NRMSE=0.533	GTSOM-BNN > k-means-BNN > SOM-BNN
		Self-organizing maps-based Bayesian neural networks (SOM-BNN)		RMSE=90.58 W/m^2, NRMSE=0.586	
		Game theoretic self-organizing maps-based Bayesian neural networks (GTSOM-BNN)		RMSE=82.76W/m^2, NRMSE=0.521	
[39]	Temperature, wind speed, cloud cover, precipitation	k-means algorithm-based multilayer perceptron	2-h	IMP$_{MAE}$=21.10%	k-means-MLP
			3-h	IMP$_{MAE}$=29.30%	
[52]	Numerical weather data	Grouping genetic algorithm-based extreme learning machine	2-h	R^2=0.71, RMSE=165.86 W/m^2	GA-ELM
			3-h	R^2=0.59, RMSE=200.36 W/m^2	
[40]	Ground data, satellite-derived data, weather forecast data	Artificial neural network with ground data	6-h	RMSE=162.8 W/m^2, IMP$_{RMSE}$=28%	ANN-GSWD > ANN-GWD > ANN-GSD > ANN-GD
		Artificial neural network with ground and satellite data		RMSE=157.03 W/m^2, IMP$_{RMSE}$=31%	
		Artificial neural network with ground and weather forecast data		RMSE=148.3 W/m^2, IMP$_{RMSE}$= 34%	
		Artificial neural network with ground, satellite and weather forecast data		RMSE=147.8 W/m^2, IMP$_{RMSE}$=35%	
[54]	Meteorological data	Gaussian process regression (GPR)	1-day	RMSE=3.14 kJ/m^2	GPR
[55]	Global horizontal irradiance	Artificial neural network	1-day	MSE=16.45 W/m^2	ANN
[56]	Temperature, pressure, wind speed, sunlight, radiation	Artificial neural network	1-day	R^2=0.98	ANN
[57]	Altitude, latitude, longitude, clearness index, temperature, humidity, pressure	Artificial neural network	1-day	R^2=0.99, MAPE=2.56%	ANN
[58]	Altitude, latitude, rainfall, number of rainy days, day length, solar radiation	Artificial neural network	1-day	R^2=0.99, MAPE=1.67%	ANN
[59]	Particulate matters, wind speed, temperature, humidity	Multilayer perceptron	1-day	R^2=0.95, MAPE=0.05%, RMSE=0.14 J/cm^2	MLP
[60]	Extraterrestrial radiation, temperature, humidity, wind velocity, precipitation	Artificial neural network	1-day	MBE=357 W/m^2, MAPE=1.36%, RMSE=1589 W/m^2	ANN
[61]	Time, temperature, humidity, solar irradiance	Triple exponential smoothing model (TES)	1-day	MAE=46.08 W/m^2, MAPE=12.22 %	TES
[62]	Precipitation, radiative flux, air pressure, humidity, cloud cover, temperature, radiation	Least-square regression	1-day	N/A	N/A
		Feed-forward neural network		N/A	
[63]	Solar energy	Multilayer perceptron	1-day	MAPE=6.56%	N/A
		Knowledge-based neural network		N/A	
[64]	Average daily solar radiation	Gradient descent algorithm-based artificial neural network (GD-ANN)	1-day	MAPE=86.30%	LM-ANN > GD-ANN
		Levenberg-Marquardt algorithm-based artificial neural network (LM-ANN)		MAPE=85.60%	
[65]	Total ozone amount, total precipitable water, cloud amount, solar irradiance	Classical extreme learning machine (C-ELM)	1-day	RMSE=0.00136 W/m^2	CRO-ELM > C-ELM
		Coral reefs optimization-based extreme learning machine (CRO-ELM)		RMSE=0.00125 W/m^2	
[66]	Temperature, relative humidity, wind speed, sunshine duration	Multilayer perceptron	1-day	R^2=0.82, MABE=360.77 W/m^2	OBS-MLP > MLP
		Optimal brain surgeon algorithm-based multilayer perceptron (OBS-MLP)		R^2=0.83, MABE=356.81 W/m^2	
[67]	Maximum and minimum air temperature, sunshine duration, global solar radiation	Genetic programming (GP)	1-day	R^2=0.76, MAPE=6.46%	FF-SVM > GP > ANN
		Artificial neural network		R^2=0.74, MAPE=6.98%	
		Firefly algorithm-based support vector machines (FF-SVM)		R^2=0.79, MAPE=6.22%	

Table 4. Solar irradiance forecasting methods based on long-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[68]	Altitude, sunshine hour, maximum and minimum temperature	Artificial neural network	1-month	RMSE=4.12 W/m^2	ANN
[69]	Satellite-derived land surface temperature	Autoregressive integrated moving average	1-month	rMAE=7.36%, rRMSE=9.60%	ANN > MLR > ARIMA
		Multiple linear regression (MLR)		rMAE=9.04%, rRMSE=10.23%	
		Artificial neural network		rMAE=4.17%, rRMSE=5.85%	
[70]	Mean relative humidity, mean wind speed, mean station level pressure, mean air temperature, year, month, latitude, longitude, altitude	Gradient descent algorithm-based artificial neural network	1-month	R=0.45, MAE=6.15 W/m^2, RMSE=7.79 W/m^2	LM-ANN > SCG-ANN > RBBNN > GD-ANN
		Levenberg-Marquardt algorithm-based artificial neural network		R=0.95, MAE=0.78 W/m^2, RMSE=1.04 W/m^2	
		Scaled conjugate gradient algorithm-based artificial neural network (SCG-ANN)		R=0.89, MAE=1.30 W/m^2, RMSE=1.71 W/m^2	
		Resilient back propagation algorithm-based artificial neural network (RBBNN)		R=0.71, MAE=2.45 W/m^2, RMSE=3.10 W/m^2	

Table 5. Solar power forecasting methods based on very short-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[71]	Solar power output	Seasonal autoregressive integrated moving average	N/A	NRMSE=0.095	Seasonal ARIMA-SVM > Seasonal ARIMA > SVM
		Support vector machines		NRMSE=0.096	
		Seasonal autoregressive integrated moving average-based support vector machines		NRMSE=0.094	
[72]	Power output, temperature, solar radiation, relative humidity	Artificial bee colony-based multilayer perceptron (ABC-MLP)	5-min	R^2=0.947, MAPE=3.70%	ABC-MLP
[73]	Solar electricity generation	Artificial neural network	5-min	RMSE=35.43 W	ANN
[74]	Solar power, sky image	Artificial neural network	5-min	RMSE=35.50 kW, IMP_{RMSE}=15.10%	ANN > ANN-ARIMA >ANN-kNN
			10-min	RMSE=41.20 kW, IMP_{RMSE}=21.80%	
			15-min	RMSE=42.50 kW, IMP_{RMSE}=26.20%	
		Artificial neural network-based auto-regressive moving average	5-min	RMSE=36.40 kW, IMP_{RMSE}=12.90%	
			10-min	RMSE=44.10 kW, IMP_{RMSE}=16.30%	
			15-min	RMSE=46.40 kW, IMP_{RMSE}=19.40%	
		Artificial neural network-based k-nearest neighbor algorithm	5-min	RMSE=37.10 kW, IMP_{RMSE}=11.20%	
			10-min	RMSE=45.30 kW, IMP_{RMSE}=14%	
			15-min	RMSE=46.40 kW, IMP_{RMSE}=19.40%	
[75]	Solar power, solar irradiance, temperature, humidity, wind speed	Neural network ensemble model (NNE)	10-min	MAE=57.56 kW, MRE=5%	NNE > SVR
		Support vector regression		MAE=64.47 kW, MRE=5.60%	
[76]	Solar power, wind speed, pressure, irradiance, temperature, humidity	Brain project-based evolutionary computing (BPEC)	15-min	MBE=-0.0020, RMSE=0.068 kW, NRMSE=0.18	BPEC
[77]	Solar power, solar radiation, ambient temperature	Autoregressive with exogenous inputs-artificial neural network (ARE-ANN)	15-min	NRMSE=0.09	ARE-ANN

Table 6. Solar power forecasting methods based on short-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[75]	Solar power, solar irradiance, temperature, humidity, wind speed	Neural network ensemble model	20-min	MAE=75.56 kW, MRE=6.57%	NNE > SVR
			30-min	MAE=86.42 kW, MRE=7.51%	
		Support vector regression	20-min	MAE=82.05 kW, MRE=7.13%	
			30-min	MAE=94.13 kW, MRE=8.18%	
[73]	Solar electricity generation	Artificial neural network	35-min	RMSE=54.11 W	ANN
[76]	Solar power, wind speed, pressure, irradiance, temperature, humidity	Brain project-based evolutionary computing	45-min	MBE=-0.0023, RMSE=0.098 kW, NRMSE=0.27	BPEC
[78]	PV power patterns, solar irradiance, ambient temperature	Bio-inspired clustering algorithm (BIC)	30-min	R=0.988, MAE=9.03 kW	BIC
			1-h	R=0.984, MAE=11.31 kW	
[79]	Total precipitation, net solar	Fourier transformation (FT)	1-h	N/A	FT

	radiation, surface thermal radiation, total surface solar radiation				
[80]	Solar power, aerosol index data, temperature, humidity, wind speed	Back propagation neural network	1-h	MAPE=7.04%	BPNN
[81]	Solar power	Autoregressive model	1-h	IMP_{RMSE}=27%	AR-EI > AR
		Autoregressive model with exogenous inputs (AR-EI)		IMP_{RMSE}=35%	
[82]	Solar irradiance, solar cell temperature, power output	Adaptive feed-forward neural network (AFFNN)	1-h	R=0.998, MAPE=2.30%	AFNN > RBF > DRNN
		Dynamic recurrent neural network (DRNN)		R=0.981, MAPE=5.98%	
		Radial basis functions		R=0.991, MAPE=4.67%	
[83]	Solar power output	Autoregressive integrated moving average	1-h	R^2=0.92, MAE=72 kW, IMP_{RMSE}=1%	GA-ANN > ANN > ARIMA
		Artificial neural network		R^2=0.95, MAE=53 kW, IMP_{RMSE}=17%	
		Genetic algorithm-based artificial neural network (GA-ANN)		R^2=0.96, MAE=42 kW, IMP_{RMSE}=32%	

Table 7. Solar power forecasting methods based on medium-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[78]	PV power patterns, solar irradiance, ambient temperature	Bio-inspired clustering algorithm	2-h	R=0.978, MAE=14.67 kW	BIC
[83]	Solar power output	Autoregressive integrated moving average	2-h	R^2=0.86, MAE=102 kW, IMP_{RMSE}=10%	GA-ANN > ANN > ARIMA
		Artificial neural network		R^2=0.86, MAE=89 kW, IMP_{RMSE}=11%	
		Genetic algorithm-based artificial neural network		R^2=0.93, MAE=62 kW, IMP_{RMSE}=35%	
[84]	Horizontal irradiance, temperature, total cloud cover, azimuth angle, solar elevation angle	Ensemble variance deficit model	3-h	N/A	N/A
		Ensemble model output statistics		N/A	
[85]	Solar irradiance, air temperature, cloud amount	Simple linear model (SLM)	3-h	MAE=0.47 kW, RMSE=0.64 kW	TSFM > SLM > GAM
		Takagi-Sugeno fuzzy model (TSFM)		MAE=0.44 kW, RMSE=0.62 kW	
		Generalized additive model (GAM)		MAE=0.64 kW, RMSE=0.64 kW	
[77]	Solar power, solar radiation, ambient temperature	Autoregressive with exogenous inputs-artificial neural network	1-day	NRMSE=0.19	ARE-ANN
[86]	Historical power production, temperature, solar radiation intensity	Particle swarm optimization-based back-propagation neural network (PSO-BPNN)	1-day	MAE=57.30 kW, MAPE=12.48%	PSO-BPNN
[87]	Air pressure, sunshine duration, cloud, wind speed, wind direction, relative humidity, air temperature, solar irradiance, solar power	k-means algorithm-based radial basis functions	1-day	MAPE=10.80%	k-means-RBF
[88]	Weather data	Fuzzy logic-based recurrent neural networks (FL-RNN)	1-day	MAE=0.22 kW	FL-RNN
[89]	Produced power, radiation, precipitation, wind speed, insolation time, humidity, dew temperature	Artificial neural network	1-day	SDAE=37.24 kW, SDAPE=10.24%	MLR > ANN > SVM > k-NN
		Support vector machines		SDAE=48.43 kW, SDAPE=10.34%	
		k-nearest neighbor algorithm		SDAE=52.99 kW, SDAPE=15.39%	
		Multivariate linear regression		SDAE=47.38 kW, SDAPE=9.11%	
[90]	Solar power output	Multivariate adaptive regression splines (MARS)	1-day	MAD=78.70 W, MAPE=28.80%	MARS > SVR > ANN > CART > k-NN
		Artificial neural network		MAD=87.80 W, MAPE=30%	
		k-nearest neighbor algorithm		MAD=82.20 W, MAPE=34.60%	
		Classification and regression trees (CART)		MAD=95.70 W, MAPE=32.60%	
		Support vector regression		MAD=77.30 W, MAPE=29.50%	
[91]	Photovoltaic power output, temperature, precipitation probability, wind direction, wind speed, ultraviolet radiation index	Learning vector quantization, support vector regression and self-organizing map hybrid model (SOM-LVQ-SVR)	1-day	MRE=3.29%, RMSE=350 W	SOM-LVQ-SVR > SVR > ANN
		Support vector regression		MRE=4.01%, RMSE=402.5 W	
		Artificial neural network		MRE=5.41%, RMSE=529.2 W	

Table 8. Solar power forecasting methods based on long-term period

Ref.	Input data	Forecasting models	Intervals	Forecasting accuracies	Forecasting results
[92]	Solar radiation, air temperature	Support vector machines	5-day	MdAPE=7.60%, NRMSE=0.18 (average of both periods)	SVM
			10-day		
[93]	Numerical weather data	Gradient boosting machine (GBM)	1-month	QS=0.01211	GBM
[94]	Solar power output	Evolutionary seasonal decomposition least-square support vector regression (ESD-LSSVM)	1-month	MAPE=7.84%, RMSE=0.16 GWh	ESD-LSSVM > Seasonal ARIMA > LSSVM > ARIMA > GRNN
		Least-square support vector regression		MAPE=14.37%, RMSE=0.21 GWh	
		Autoregressive integrated moving average		MAPE=22.70%, RMSE=0.43 GWh	
		Seasonal autoregressive integrated moving average		MAPE=11.14%, RMSE=0.19 GWh	
		Generalized regression neural network (GRNN)		MAPE=36.02%, RMSE=0.62 GWh	

3. Conclusions

This study elaborates the solar irradiance and solar power forecasting methods used in the literature. As well, their input data, forecasting intervals, forecasting models, forecasting accuracies and forecasting results are discussed in detail. The following widely-existing properties are revealed for solar irradiance forecasting: solar irradiance, air temperature and sunshine duration parameters as the input data, 1-h and 1-day time scales as the forecasting intervals, artificial neural networks as the forecasting models, root mean square errors as the accuracy metrics, support vector machine and support vector regression models as the optimum forecasting performance. In addition, the commonly-encountered features below are uncovered for solar power forecasting: solar power, solar irradiance and air temperature parameters as the input data, 15-min, 1-h and 1-day time scales as the forecasting intervals, artificial neural networks as the forecasting models, mean absolute errors as the accuracy metrics and support vector regression models as the optimum forecasting performance.

In addition to these identifications, the necessities for analyzing the effects of input parameters, constructing novel hybrid methods, making more studies in very-short term and long-term periods and computing all mentioned accuracy metrics are emphasized one by one for both solar irradiance and solar power forecasting. Particularly, in future studies, the adaption of optimization methods into the forecasting processes, the computation of improvement percentages with respect to the persistence reference model, the usage of multi-seasonal input data and the construction of a global standard database will contribute to the studies made in these fields.

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