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Review

Recent Trends in Real-Time Photovoltaic Prediction Systems

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Abstract: Photovoltaic power forecasting is an important problem for renewable energy integration in the grid. The purpose of this review is to analyze current methods to predict photovoltaic power or solar irradiance, with the aim of summarizing them, identifying gaps and trends, and providing an overview of what has been achieved in recent years. A search on Web of Science was performed, obtaining 60 articles published from 2020 onwards. These articles were analyzed, gathering information about the forecasting methods used, the horizon, time step, and parameters. The most used forecasting methods are machine learning and deep learning based, especially artificial neural networks. Most of the articles make predictions for one hour or less ahead and predict power instead of irradiance, although both parameters are strongly correlated, and output power depends on received irradiance. Finally, they use weather variables as inputs, consisting mainly of irradiance, temperature, wind speed and humidity. Overall, there is a lack of hardware implementations for real-time predictions, being an important line of development in future decades with the use of embedded prediction systems at the photovoltaic installations.

Keywords: forecast; photovoltaic energy; machine learning; deep learning; prediction; forecasting; real time; artificial neural network

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1. Introduction

In recent years, there has been an increasing interest in renewable energy development as a response to global warming and environmental problems [1]. In this context, solar photovoltaic installations and their growth are of great importance. The use of photovoltaic (PV) systems on city rooftops can help to increase self-sufficiency, and they are safe and do not produce noise or other disruptions [2]. However, because of the need to balance electricity generation with demand in real time, accurate forecasting of PV production is required for better integration of this resource in the grid [3]. Real-time predictions are required in different fields (e.g., energy, health, and finances) to process information as data are received continuously. This helps in taking action and making decisions with information that is constantly updated.

However, the dependance of PV generation on environmental conditions makes prediction a challenging problem [4]. The amount of energy generated depends especially on irradiation on the panel, which depends on the hour, season, and climatic conditions (cloud coverage and precipitations). Therefore, in recent decades, different methods and approaches have been proposed, from traditional statistical and physics-based models to machine learning and deep learning models.

Physical models are methods that use meteorological data as input in equations to calculate the solar irradiation and output power [5]. For example, numerical weather prediction (NWP) [6] is used to forecast the weather by using numerical methods that simulate the atmosphere's behavior. NWP uses mathematical equations that describe the physical processes occurring in the atmosphere, such as thermodynamics, fluid mechanics, and heat transfer. These models incorporate data from various sources, such as weather stations and satellites, to provide initial conditions for the computation. Typically, NWP output is used to feed other analytical models which calculate irradiation or PV power on the panels [7]. Other physical models use sky images to predict the movement of the clouds [8].

Statistical models make predictions based on previous values of the time series [7]. Auto-Regressive Integrated Moving Average (ARIMA) model time series [9] are a combination of autoregression (AR), differencing (I), and moving average (MA) terms. Autoregression predicts values depending on previous values; moving average makes predictions based on previous errors; and differencing removes the trend and seasonality to make the model stationary. The model used can be a combination of only some of the terms, like ARMA models [10]. Although these models provide forecasting information, their use is limited due to the lack of capacity to model complex nonlinear behaviors. Persistence model considers that the predicted value will not change with respect to the previous value in the series [11]. ARIMA and persistence models are typically used as a benchmark reference for the models proposed in the studies, consisting mainly of machine learning techniques [7]. However, other mathematical approaches can be used for PV forecasting as well [12].

Machine learning (ML) is a field in Computer Science that uses big sets of data to model complex functions or relationships [13]. In recent years, it has increased its application in many fields thanks to the developments in computational capacity and data processing. There are several techniques depending on the problem to solve. They can be divided into Supervised Learning, Unsupervised Learning and Reinforcement Learning [13]. In Supervised Learning, the models are fed with labelled data to find the relationships between features. Some typical algorithms are linear and polynomial regression [14], logistic regression [13], support vector machine [3], decision trees [3] or random forest [15]. These algorithms can be used for different tasks depending on the complexity of the problem. While linear or polynomial regression are well fit for simple mathematical functions, other tools such as random forests or support vector machines can model very much more complex problems where the relevant physics are not well understood or imply nonlinear mathematical equations.

Deep learning (DL) [16] is a branch of the machine learning field that makes use of artificial neural networks (ANN) [17] to model complex, nonlinear behaviors in different fields. Inspired by the functionality and structure of the human brain, these models are composed of computational units called neurons that are interconnected in multiple layers. Each neuron receives inputs from other neurons, computes a weighted sum and applies an activation function to produce an output that is transmitted to the next neurons.

There are several architectures, depending on the connections, types of neurons and activation functions. Feedforward ANN are the most basic, consisting of an input layer, one or more hidden layers, and an output layer. The information goes from the input layer to the output, with the hidden layers processing the relationships in the data. In recurrent neural networks (RNN) [18] the output of the neurons is connected to their own input and the input of the neurons of the same or previous layers. This feedback gives the network the ability to handle complex relationships between past and future observations. There are other types of architectures, like convolutional neural networks (CNN), encoder-decoders, or transformers, that can be used for different goals.

Additionally, ensemble models [19] combine several individual models in a way that the prediction of all models is processed to increase the total accuracy of the ensemble. The models that conform the ensemble can be different and even from different fields, like a neural network and an ARIMA series; or they can be the same, like bagging and boosting methods. Random forest can be considered an ensemble method, as it aggregates several decision trees to perform inference. Nevertheless, it is typically considered a traditional ML algorithm and is broadly used in the literature.

Finally, hybrid models [7] combine physical models with machine learning or deep learning methods, with the aim of combining the best features of both fields.

The purpose of this review is to analyze the recent trends in photovoltaic prediction systems, identifying gaps and providing a critical overview on what has already been achieved and which are the important aspects to be covered in future decades. A specific focus is provided on real-time prediction, with the aim of approaching real installations for democratization of the technology.

2. Materials and Methods

2.1. Data Sources

A search was performed on the Web of Science website [20]. This website provided access to the following databases: the Web of Science Core Collection, the BIOSIS Citation Index, BIOSIS Previews, Current Contents Connect, the Derwent Innovations Index, the KCI-Korean Journal Database, MEDLINE, the Russian Science Citation Index and the SciELO Citation Index. The search was performed using the topic searching field. The following terms were used: prediction OR forecasting AND energy OR photovoltaic OR solar power OR renewable AND real time. Furthermore, only articles published since 2020 (included) were considered.

2.2. Study Selection

This selection returned 195 publications that were screened, finding that 60 articles were in scope of this review (see Figure 1). These articles focused on photovoltaic power or solar irradiance prediction, providing models, and comparing them with already established techniques. The rest of the articles focused on other topics like energy management or load forecasting.

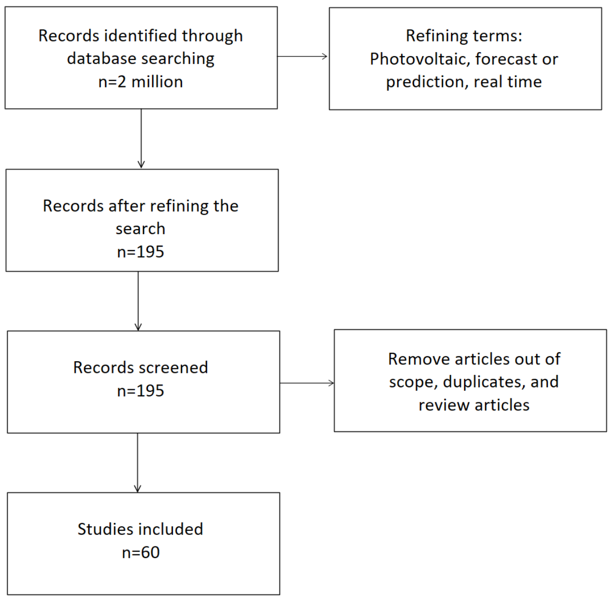

Figure 1. Diagram showing the study selection process.

2.3. Data Analysis

The 60 articles included in this review were analyzed in a specific template developed for this purpose. In that template, the following information was included: authors, year, type of method, model, forecast horizon, prediction objective, input parameters, time step, actual application, and hardware implementation.

3. Results

The main attributes of the articles selected for this review are summarized in Table 1. Hereafter, a description of the main conclusions related to the field of expertise, time horizon and time division, models used, and its objectives is provided.

Table 1. Summary of the articles included in this scoping review. In Field, ML: machine learning, DL: deep learning, ST: statistical, EN: ensemble, PH: physical and HY: Hybrid. In Horizon and Time Division: h: hour, d: day, w: week, and m: month. In parameters, Ir: irradiance, temp: temperature, w.speed: wind speed, and w.dir: wind direction. In Metrics, RMSE: root mean squared error, MAE: mean absolute error, and MAPE: mean absolute percentage error.

Article	Year	Field	Model	Horizon	Prediction	Parameters	Time Division	Metrics
Ahn et al. [18]	2021	DL	LSTM	5′–3 h	Power	Ir, temp, w.speed, humidity	5′, 30′	nRMSE, nMAE
Aljanad et al. [21]	2021	DL	ANN	1 d, 3 d	Irradiance	Temp, w.speed, w.dir, humidity, pressure	5 s, 1′	RMSE, MAE, MAPE, MSE
Almaghrabi et al. [22]	2021	DL	CNN	1 d	Power	Power	30′	RMSE, MAE, MRE
Almaghrabi et al. [12]	2022	ST	Wavelet transform	24 h	Power	Power	30′	RMSE, MAE, MRE, RAE, RRSE, R2
Anand et al. [23]	2020	ST	SPES	1 h	Power	Ir, w.speed	1 h	RMSE, MAE
Bozorg et al. [24]	2020	ST	Bootstrapping	24 h	Power	Ir, temp, pressure, cloud cover, precipitation	1 h	NPS, AACE
Bozorg et al. [25]	2021	ST	Bootstrapping	1 h	Power	Ir, temp, pressure, cloud cover, precipitation	1 h	NPS, AACE
Bozorg et al. [26]	2020	ST	Persistence	10′	Power	Power	10′	RMSE, MAE, nMAPE, MdAPE
Cannizzaro et al. [27]	2021	ML, DL, EN	CNN, RF, LSTM	15′–24 h	Irradiance	Ir, temp, w.speed, humidity, pressure, cloud cover	15′	RMSE, MAE, nRMSE, R2
Carriere et al. [28]	2020	ML	Analog Ensemble	30′–36 h	Power	NWP variables, satellite images	30′	RMSE, CRPS
Cordeiro-Costas et al. [29]	2022	ML, DL	RF, XGB, SVR, ANN, RNN, CNN	1 h	Power	Ir	1 h	nRMSE, nMBE, R2
Dimovski et al. [3]	2020	ST, ML, DL	Persistence, MLR, SVM, DT, RF, ANN	1–72 h	Power	Ir, temp, precipitation, w.speed	1 h	nRMSE, nMAE, nMBE

Table 1. *Cont.*

Article	Year	Field	Model	Horizon	Prediction	Parameters	Time Division	Metrics
Dong et al. [30]	2019	ST	Uncertain basis functions, stochastic model	$1'$–$50'$	Irradiance, Power	Irradiance, Power	$1'$, $5'$, $50'$	nRMSE, MAPE
Duman Altan et al. [31]	2021	ST, DL	SARIMA, ANN	-	Power	Ir, temp, w.speed, angle	1 h	MAPE, R2
Farah et al. [10]	2021	ST	Fourier series, ARMA	$7'$	Power	Power	$1'$	nRMSE, nMAE
Gao et al. [32]	2020	DL	CNN, LSTM	1 h	Irradiance	Irradiance	$1'$	nRMSE, RMSE, MAE, FS
Ghimire et al. [33]	2022	DL	CNN, MLP	1 d	Irradiance	Temp, humidity, precipitation, vapor pressure	1 d	RMSE, MAE, MBE, rRMSE, MAPE, SS
Goh et al. [34]	2022	DL	ANN	-	Power	Ir, temp	$30''$	RMSE, MAE, R2
Haupt et al. [35]	2020	HY, EN	NWP, ANN, RF	$15'$–$345'$	Irradiance	NWP	$15'$	RMSE
Hosseini et al. [36]	2020	DL	GRU	$15'$–3 h	Irradiance	Ir, temp, w.speed, w.dir, humidity, zenith angle, cloud coverage	1 h	RMSE, MAPE
Huertas-Tato et al. [37]	2019	ML, EN	SVM, smart persistence, Satellite, NWP	$15'$–6 h	Irradiance	Irradiance	$15'$	RMSE, rRMSE, rMAE, BIAS
Khortsriwong et al. [38]	2023	DL	RNN, CNN, LSTM, GRU	1 d, 1 w	Power	Ir, temp, w.speed	$5'$	RMSE, MAE, MAPE
Kumar et al. [17]	2021	DL	ANN, RNN	1 h, 1 d, 1 w	Power	Ir, temp, w.speed	1 h	RMSE, MSE, MAPE, R2
Kumari et al. [39]	2020	EN, DL	XGBF-DNN	1 h	Irradiance	Ir, temp, w.speed, humidity	1 h	RMSE, MBE

Table 1. *Cont.*

Article	Year	Field	Model	Horizon	Prediction	Parameters	Time Division	Metrics
Kumari et al. [40]	2021	DL	CNN, LSTM	1 h	Irradiance	Temp, w.speed, humidity, pressure, cloud cover, precipitation, zenith angle, dew point, cloud type	1 h	RMSE, MAE, R
Lauria et al. [41]	2022	ST	Caputo derivative	1′–10′	Power	Power	1′, 5′, 10′	RMSE, MAE, nMAPE, rRMSE
Lee et al. [42]	2020	ML, EN	Boosting, bagging, RF	1 h	Irradiance	Temp, w.speed, humidity, cloud cover, dew point temp	1 h	RMSE, MAPE, R2
Leva et al. [43]	2020	DL, ST	ANN, persistence, PHANN (hybrid)	30′–24 h	Power	Ir, temp, humidity, w.speed, w.dir,	1′, 1 h	nRMSE, NMAE, WMAE, EMAE, OMAE
Mehazzem et al. [44]	2022	ST	STVAR	1′	Irradiance	Irradiance	1′	rRMSE, rMAE, rMBE
Mubarak et al. [15]	2022	ML, EN	LASSO, RF	1 h	Power	Ir, temp, w.speed	1 h	RMSE, MSE, MAE, R2
Munshi [4]	2022	ST	Statistical	30′–120′	Power	Ir, temp	10′	RMSE, MAE
Nkounga et al. [45]	2021	DL	ANN	30′–6 h	Irradiance	Ir, temp, humidity, pressure	10′	nRMSE, RMSE, R
Oprea et al. [46]	2020	DL	ANN	30′	Power	Ir, temp, w.speed, w.dir, humidity, dew point temp	10′	PELI, PPLI
Pahmi et al. [47]	2021	DL	ANN	-	Power	Ir, temp, humidity, voltage, current	-	RMSE, R2
Pattanaik et al. [48]	2020	DL	ANN	1 m	Power	Ir, temp	1 m	MS, SS
Perera et al. [14]	2022	ML, ST, EN	Persistence, ARIMA, SVR, MLR	5′–3 d	Power	Power	1′, 5′, 1 h, 1 d	MASE

Table 1. *Cont.*

Article	Year	Field	Model	Horizon	Prediction	Parameters	Time Division	Metrics
Polimeni et al. [11]	2021	DL, ST	Persistence, ANN	30′–24 h	Power	Power	1′, 1 h	nRMSE, NMAE
Puah et al. [49]	2020	DL	ANN	1 h	Irradiance	Irradiance	1′	RMSE, MASE
Rafati et al. [50]	2020	DL	MLP	15′	Power	Power	15′	RMSE, MAE, MRE
Rai et al. [51]	2022	DL	CNN, LSTM, attention	5′	Power	Ir, temp, w.speed, w.dir, pressure	5′	MSE, MAE
Raj et al. [19]	2023	ML, EN	RF, GBM	1′	Power	Ir, temp, w.speed, humidity	1′	nRMSE, RMSE, MAE, R2
Rodríguez-Benítez et al. [8]	2019	ST, PH, HY	Smart persistence, Satellite, NWP	15′–6 h	Irradiance	Irradiance	1′	RMSE, rRMSE, rMAE, BIAS
Rosato et al. [52]	2021	DL	CNN, LSTM	3 d, 1 w	Power	Temp, w.speed, w.dir, humidity, pressure, turbulence	1 h	RMSE
Salamanis et al. [7]	2020	PH, ST, ML, DL, HY	Physical, persistence, ARIMA, SVR, GBT, ANN, LSTM, hybrid	15′–180′	Power	Temp, w.speed, cloud cover	15′	RMSE, MAE, MAPE, WRSE
Schreiber et al. [6]	2022	DL	Autoencoder, CNN	24 h	Power	NWP variables	1 h	nRMSE, RMSE
Shboul et al. [53]	2021	DL	ANN	1 h	Irradiance	Angle, cloud cover	1 h	MAPE, R
Simeunovic et al. [54]	2021	DL	LSTM, transformer, ANN	6 h	Power	NWP variables	15′	nRMSE, nMAE
Simeunovic et al. [55]	2022	DL	ANN	4–6 h	Power	Power	15′	nRMSE, nMAE
Solano et al. [56]	2022	ML, EN	SVR, XGBT, CatBoost, ensemble	1–3 h	Irradiance	Ir, w.speed, dry bulb temp, pressure, humidity	1 h	RMSE, MAE, MAPE

Table 1. *Cont.*

Article	Year	Field	Model	Horizon	Prediction	Parameters	Time Division	Metrics
Stüber et al. [5]	2021	ML, DL, PH, EN	FFNN, LSTM, RF, physical, ensemble	1 d	Power	Ir, temp, w.speed	1 h	s, mm
Succetti et al. [57]	2020	DL	LSTM, CNN	1–3 d	Power	Ir, Temp, w.speed	1 h	MAE
Theocharides et al. [58]	2021	DL, ML	Bayesian NN, SVR, RT	1 d	Power	Ir, temp, pressure, NWP	1 h	nRMSE, MAPE, RMSE, nMBE, SS
Theocharides et al. [59]	2020	DL	ANN	1 d	Power	Ir, temp, w.speed, w.dir, humidity	1 h	nRMSE, MAPE, SS
Theocharides et al. [60]	2021	DL, EN	Bayesian NN	1–5 h	Power	Ir, temp, angle	1 h	nRMSE, MAPE
Tovar et al. [61]	2020	DL	CNN, LSTM	10′–180′	Power	Ir, temp, w.speed, humidity, pressure	10′	RMSE, MAE, MSE
Wai et al. [62]	2022	DL	LSTM	4 h	Power	Ir, temp	1 h	nRMSE, nMAE
Walch et al. [63]	2020	ML, PH, EN	RF, ELM-E, physical	1 h	Power	Ir, temp, albedo	1 h	MSE
Wang et al. [64]	2020	DL	ANN (DXNN)	1′–90′	Irradiance	Ir, temp, w.speed, w.dir, humidity, sun altitude	1′–90′	MAE, RMSE, R2
Zang et al. [65]	2020	DL	CNN, LSTM	1 h	Irradiance	Temp, w.speed, w.dir, humidity, precipitation, zenith angle, dew point temp	1 h	nRMSE, RMSE, nMAE, MAE, R
Zjavka [66]	2023	DL	Differential NN	24 h	Irradiance	Ir, w.speed	30′	RMSE

3.1. Forecasting Horizon

It is the time length for which the power is predicted. There is a large variability in the chosen horizon between articles (see Figure 2a). A total of 9 articles consider short horizons, from one minute up to one hour, while 19 articles present horizons between 1 and 6 h. Nine studies make predictions for the day ahead, and there are three studies that consider longer horizons up to one week, and one study considers one month [48]. In this article, the monthly production is taken to forecast the next month power in one step. A total of 17 studies present several horizons, ranging from one minute to one week. Finally, there are three articles that do not state what horizon was considered. Considering all the horizons presented, the two most frequently chosen options are one hour and one day ahead.

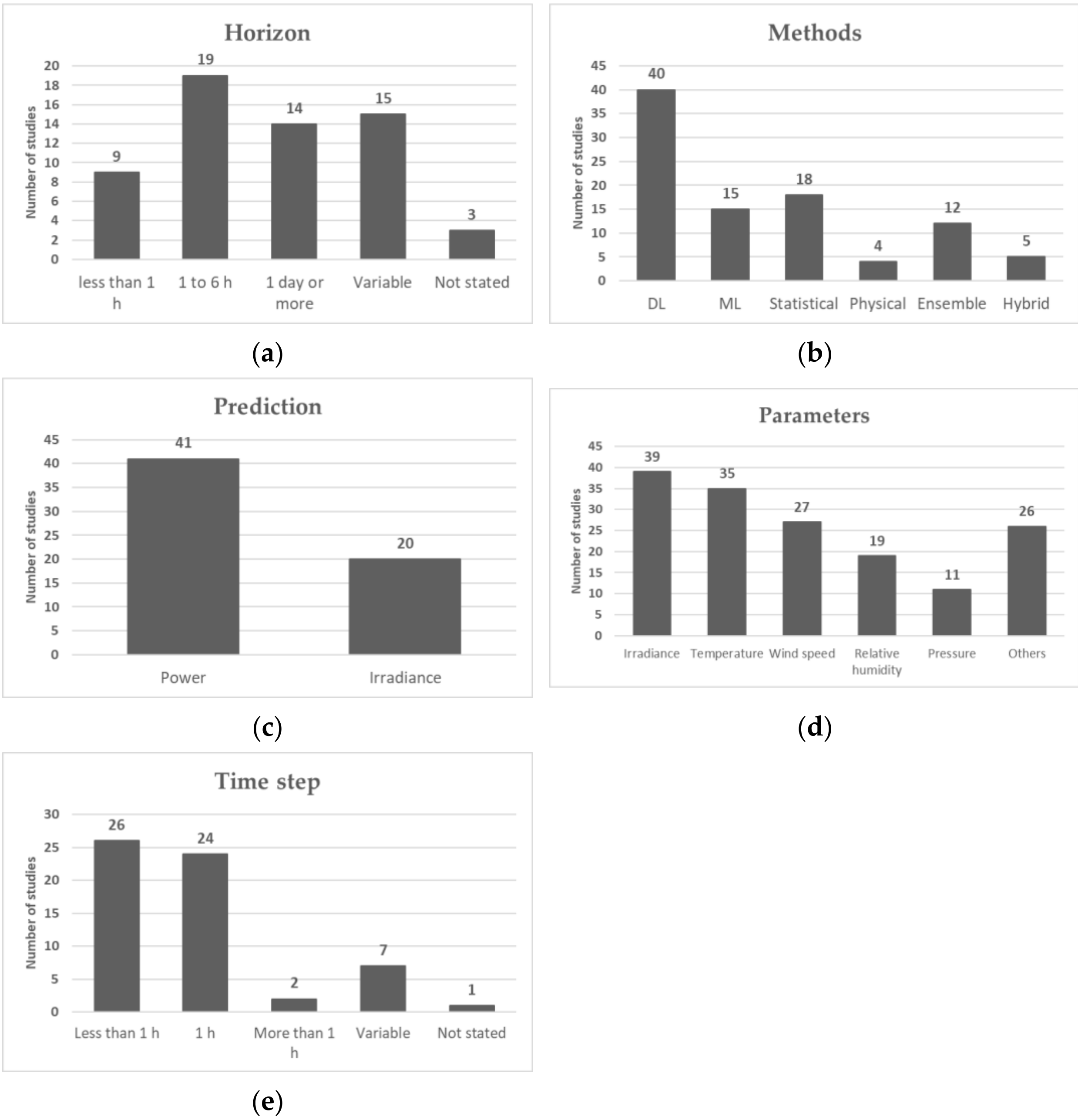

Figure 2. Results of characteristics highlighted in this review and frequency in the articles. (**a**) time length of forecasting horizon, (**b**) field of the predictive system, (**c**) parameter that is forecasted, (**d**) features used as input, (**e**) time division of the system.

3.2. Field and Models

Taking into consideration the forecasting method, 40 out of 60 articles provide deep learning models, while 15 include some traditional machine learning algorithm (see Figure 2b). A total of 18 articles developed some statistical model, like ARIMA or persistence, while 4 developed a physical model, like Sky Image or NWP. Finally, 12 studies present some type of ensemble method, and 5 papers develop a hybrid model. Most articles develop more than one model to compare between them and consider other well-established techniques as a benchmark reference. Regarding the deep learning models, 18 articles use RNN, mainly consisting of LSTM networks. Nevertheless, other types of recurrent networks are also used, like GRU, bidirectional LSTM or traditional RNN. A total of 11 studies present some type of CNN and 17 focus on feed forward ANN like the Multi-Layer Perceptron (MLP). Nine articles consider more specific architectures like the transformer or autoencoder. Out of all the deep learning models, RNNs make 32%, being the preferred architecture for this task. Additionally, some of the articles use different types of layers, mixing CNN and RNN in a single model [33]. With respect to machine learning algorithms, eight studies use random forest and six support vector machines, being the two most frequently used options in this field. The remaining papers consider decision trees, linear regression with regularization techniques like LASSO, or more specific algorithms [28]. The hybrid models present a physical method whose outputs feed a DL or ML algorithm. The ensemble models consist of several algorithms gathered through some boosting or bagging method, like gradient boosting machine [19]. With respect to the statistical approaches, four studies present some variation of ARIMA methods, six present a persistence-based model, while nine develop a different mathematical approach. These nine articles propose methods based on wavelet transform, Fourier series, and bootstrapping, among others.

3.3. Prediction Objective

A total of 40 studies predict PV power generation, while 19 forecast the solar irradiance as a previous step to calculate the power (see Figure 2c). One study forecast both power and irradiance. This shows that only 33% of the articles develop a predictive method for irradiation, with PV power having more prominence in the research. These results show that the produced power is more relevant for photovoltaic integration in the grid and actual installations.

3.4. Input Parameters

With respect to the parameters used as input, they consist of weather variables that are obtained from meteorological stations at the place of the PV installation or from meteorological agencies (see Figure 2d). Some of the articles include weather forecasts or use another predictive system like NWP to calculate the inputs. The number of features considered depends on the article. All the articles analyzed take into account the time series of the predicted parameter (power or irradiance), except for the physical approaches that only consider weather data. Most of the studies also include temperature, irradiance, humidity and wind speed. A total of 26 articles include more features like cloud coverage, wind direction, precipitation, pressure, or dew point temperature. Finally, nine studies only use the power past series to forecast the next values, while four studies use only the past irradiance to predict future values. All the data-driven models require the prediction objective series (power or irradiance) to train the algorithm, using more features to capture the dynamics of the system with more accuracy. Only five papers use NWP variables but do not state what parameters are used to feed the forecasting model.

Considering the dataset size used for training and evaluation of the data-driven models, there is a large variation between articles. The smallest dataset size is one month, chosen by 3 articles, while one study takes 55 years of historical data. A total of 12 studies selected datasets smaller than a year. Nine articles took 1 year of data, and eight considered 2 years. Additionally, 16 articles used bigger datasets, consisting of several years of data.

These datasets range from 3 to 55 years, although most of them consist of 3 to 7 years, with only 4 studies using more than 10 years of data. Finally, there are 14 studies that do not state the size of the dataset. Apart from the time length, the size of the dataset depends on the length of the time steps considered.

3.5. Purpose of the System

A total of 28 articles develop a model for a specific installation, while the rest make models for general PV forecasting purposes. All the studies that focus on actual installations use the data from the installation and local weather measures. The 16 studies that develop models for general forecasting use data from actual installations as well. While the goal of developing a model is its general applicability, using data from a specific plant is needed to validate the results or train a machine learning or deep learning algorithm.

3.6. Time Discretization

Regarding the temporal division of the data collection and output forecast, 24 of the 60 studies consider 1 h; 26 articles use smaller intervals, mostly between 1 and 30 min, while 2 studies have longer time steps of 1 day and 1 month (see Figure 2e). Finally, seven papers consider a variable time division, depending on the horizon which varies as well. Only 1 article does not state the temporal step.

Most of the articles obtain the data with a small temporal resolution, between several seconds and 10 min. However, due to the longer horizons considered, averaging measures for longer periods is recommendable to decrease the computational cost of the models. The time resolution is chosen according to the horizon, as using small intervals for very long horizons is not practical due to the cost, while the forecasting horizon cannot be shorter than the temporal steps, as the limit is the prediction of one step ahead. The articles that change both horizon and resolution take longer steps as the horizon is extended.

3.7. Hardware

Only 19 articles out of 60 specified the hardware used in the research. A total of 14 of those articles used a personal computer, while 1 system was developed using a cloud service. Only four studies presented a hardware-based model for real-time predictions at the PV installation place. However, due to the focus on the development of the predictive models, the hardware implementation is not extensively explained. Although most of the studies do not specify any hardware used for the development and utilization of the forecasts, all of them seem to use a computer for the whole research process.

Another parameter to evaluate the accuracy of the models is the computational time required to train and evaluate them. This time depends heavily on the hardware used, which varies from one study to another. For this reason and considering that the computational time is not stated in most of the articles analyzed, it has not been considered as a relevant measure.

3.8. Accuracy

There are several metrics that are used to evaluate the accuracy of the models. The ones most broadly used are root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). However, the different metrics cannot be used for comparison as they calculate errors differently; and some metrics, like RMSE, are sensitive to the data used, which differs from one article to other. To avoid this, some studies present normalized metrics, such as nRMSE or nMAE. This lack of standardization limits the quantitative evaluation of the performance of all the models. Nevertheless, some articles using the same metric can be compared, and the set of models presented by individual articles can be compared and analyzed to understand what works best for a particular task.

4. Discussion

The advance in ML and DL in recent years has made PV prediction methods more broadly used. Different types of artificial neural networks are the more recent and frequent methods. Most of the articles present some machine learning or deep learning algorithm, along with traditional models (such as persistence or ARIMA) generally used for comparison [28]. Hybrid and ensemble methods, usually including a machine learning model, are proposed for an improvement in accuracy. The results show that combining several models and data provides the best results, although it increases the computational cost of the model. Other machine learning algorithms are very spread too, like support vector machines and random forests, while several articles use only traditional methods like ARIMA or physical models.

The increasing use of neural networks has provided a large number of possible architectures and configurations. This can be seen in all articles presented in this manuscript, as most of the studies applying deep learning models try different configurations in order to find the one that captures the physical behavior better. However, RNNs and specifically LSTM networks [18,27,38,51,52,54,57,61,62] are the ones used most often. These types of networks are usually applied to time series forecasting due to their ability to capture temporal dependencies thanks to their recurrent nature. Articles comparing RNNs with other types of ANNs show that the RNNs can get more accuracy when predicting. CNNs are very common for PV prediction as well, especially in combination with other types of networks like RNNs or feed-forward networks (FFNN). In [38] the authors tried different types of recurrent networks, including RNN, LSTM, GRU, and combinations with convolutional layers. The results showed that using bidirectional LSTM and GRU cells, and CNN layers, yielded the best results. Nevertheless, the best model changed depending on the weather conditions and forecasting horizon. This implies that some architectures offer advantages for this task, and GRU and LSTM networks may capture temporal patterns better. However, the large number of studies using different network architectures shows that good results can be achieved with any type of network if the data and hyperparameters are well tuned, and some articles use specific architectures designed for the research. In [18] the authors compare different configurations of RNN, changing the number of layers and time steps; and in [27] they compare different CNN. This shows the need to continue researching in order to find the network that performs the task best.

The machine learning algorithms most frequently used are support vector machines and random forests. These methods are very common in many applications due to their ability to generalize and model nonlinear functions, and they are well established in the field of machine learning. Other papers [3,14,15] propose some type of linear regression model or decision trees or develop a different algorithm [28]. The results show that there are not big differences with respect to the models used.

Regarding the results, hybrid or ensemble methods seem to be the best in terms of accuracy. The drawback of these models is the bigger computational cost. If the PV installation includes embedded hardware with the forecasting method, the size of the model is limited by the hardware.

Considering the rapid developments in the field of machine learning and deep learning, the trends in PV forecasting have been analyzed. However, as this review only considers three and a half years, a change in accuracy, data, or models has not been observed in recent years. This could be due to the limitations imposed by the physics of the problem (accurate weather predictions), and the relatively short time span of this review.

Due to the chaotic nature of the weather [4], and the dependency of PV generation on the environment, long-term forecasting cannot be done with accuracy [38]. This makes predictions for the day ahead the habitual option for grid management applications. The forecast range from a few hours to one day is used to adapt the load to the demand, which helps to improve PV penetration [3]. Long-term forecasting can be used for trend analysis and planning. The articles that try different horizons show that increasing the horizon implies a fast decrease in prediction accuracy [27]. In general, horizons of a few hours produce good results and can be used by grid operators to manage the energy production [3].

The parameters used as input for the prediction vary with the type of model and data origin, but most of the articles use weather variables consisting of temperature, relative humidity, wind speed and direction and solar irradiation. The production of the panel is correlated with the irradiation it receives, so it is the most used feature. Temperature also has influence in the energy generation, and wind speed, direction, and relative humidity are used to predict the atmospheric behavior to improve the accuracy. While some studies include more variables, like pressure, precipitation, cloud coverage or dew point temperature, it does not have a big impact on the results [46]. These parameters are taken from several sources. Some articles take information from sensors close to the installation for which the predictions are made, while others use weather agencies forecasted values or use the prediction of a physical model like NWP. Additionally, some studies use meteorological data from open databases. With respect to the dataset size, it does not seem to have a strong effect on the predictions, and some articles choose online learning when datasets are small. Models developed with smaller datasets get results as good as articles using 6 or 7 years of data.

Although the most relevant information is the generated power, solar irradiation is strongly correlated with it. For this reason and considering that irradiation is more directly dependent on physical variables, it is chosen in some studies [27,30,33,44,45,53,56,66] as the prediction objective. However, most of the articles analyzed forecast PV power. Due to the data-driven nature of machine learning algorithms, forecasting power avoids the need of further modelling and correlating with irradiance.

With respect to the hardware used, all studies seem to have been developed and used on personal computers or stations, with only four articles taking into account the production of the model on an embedded system at the PV installation location. For an extensive use of the forecasts this could be further investigated in the future. It would allow the system to have more autonomy and make predictions without relying on external computers.

Taking into consideration the accuracy metrics, the lack of a standard measure that can be used independently of the data and results makes quantitative analysis a difficult task. The use of the same metrics for all articles within the field could help improve the research, allowing to understand the results better.

The most used metric by the articles (28 out of 60) is the RMSE, which is proportional to the data used and has the same units (W/m^2 for irradiance and W for power). This makes RMSE not suitable for comparison between articles using different datasets. Other metrics like MAE, used by 23 studies, have the same problem. A total of 18 articles use normalized RMSE, and 11 consider MAPE, both of which give percentual errors. These metrics can be used to compare results of different articles, but there is another issue that prevents an accurate quantitative analysis. The articles that provide metrics for different conditions show that there are parameters that influence the accuracy of the forecasts more than the election of a model. The horizon is the most important feature, which varies significantly throughout the articles. The data used to train and test the models also have a strong relevance. On [38], the most accurate model differs depending on the weather. The climatic characteristics of the place strongly influence the forecasts, as some locations have more unpredictable conditions than others. All these variables imply that to get a good quantitative analysis of which models perform better, a standardized testbench should be designed, making use of the same dataset, time horizons, and evaluation metrics.

The influence of the horizon on accuracy can be observed in the articles that consider different horizons. On [60], the nRMSE increases from 3.49% at forecasting 1 h ahead to 7.92% at 5 h ahead. On [11], an increase on nRMSE can be observed as well between the different horizons: 30 min (3%), 3 h (16%), and one day (17%). This shows that accuracy is high for very short-term predictions (a few minutes ahead), but it drops quickly with longer time lengths. On [45], the nRMSE increases from a 21% at the horizon of 30 min to a

33% at 6 h. On [43], the accuracy drops from 2.6% nRMSE predicting one hour ahead to 11.7% predicting 24 h ahead.

Regarding the input variables, on [36] the results show an increase in accuracy when more weather variables were included, from 17% MAPE to 10%. On [7] the results show an important drop in accuracy due to the presence of clouds. They also show big differences between seasons, having the best forecasts for spring. On the developed LSTM model, the MAPE decreases from 3% for sunny days in spring to 22% for cloudy days. The drop in accuracy due to the increase in the horizon is more important for cloudy days than for sunny days. This happens because predicting the presence and movement of clouds is harder with longer time spans, while sunny days lead to more stable energy generation. This study also shows that there is not a model that clearly outperforms the rest. Comparing several deep learning, machine learning, statistical and hybrid models, the results show that some models perform better for some season, horizon, or type of day. This illustrates that ensemble models perform better because some algorithms perform slightly better in some conditions, and the inclusion of several decisions can give better predictions than those of an individual model.

5. Conclusions

This review shows that the field of deep learning is the most frequently used for PV forecasting in recent years. There is a great variety of methods that can be applied to this task, and the results depend on several variables. Different algorithms, like random forests or ANN architectures, can give comparably good results. While ensemble methods give better results, they can be computationally expensive, and hybrid methods depend on inputs from external models like clear sky radiation model or numerical weather prediction. Traditional statistical methods are still broadly used for PV prediction, with new developments like the inclusion of Fourier series [10] or Wavelet transform [12], while physical approaches are not typical, due to the complexity of the atmospheric behavior. This shows that there is not an algorithm that outperforms the rest and to develop a good prediction model the combination of a method, input features and data selection is required. On the other hand, there is not a broad hardware implementation of these predictive systems, although many of them consider real-time forecasting. To conclude, the best option in terms of accuracy is the use of an ensemble method, with several base models to contribute to an averaged prediction. The use of different models as base learners can also help improve the robustness of the ensemble.

Further work should focus on data and features selection, and the effect on different configurations and models. Another field for future research is the embedding of these techniques on hardware for autonomous predictions and more integration of PV power in the grid. Finally, implementing the same metrics, and considering normalized measures, could improve the analysis of results with different studies. Further, validating results on the same data, considering standard horizons or including similar inputs could help compare different articles' models.

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