Review Article

Solar Photovoltaic Power Forecasting

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The management of clean energy is usually the key for environmental, economic, and sustainable developments. In the meantime, the energy management system (EMS) ensures the clean energy which includes many sources grouped in a small power plant such as microgrid (MG). In this case, the forecasting methods are used for helping the EMS and allow the high efficiency to the clean energy. The aim of this review paper is providing the necessary data about the basic principles and standards of photovoltaic (PV) power forecasting by stating numerous research studies carried out on the PV power forecasting topic specifically in the short-term time horizon which is advantageous for the EMS and grid operator. At the same time, this contribution can offer a state of the art in different methods and approaches used for PV power forecasting along with a careful study of different time and spatial horizons. Furthermore, this current review paper can support the tenders in the PV power forecasting.

1. Introduction

The demand of energy by miscellaneous areas and the worldwide energy exploitation are really highest than any time before. In addition to the uppermost energy demand, oil and other planet's resources in fossil are becoming scarce. In this case, the environmentalists, the socialists, and the economists are supporting the climatic agreements and adopting the clean energy as a solution to retort the global energy demand, the cost effectiveness, and the ecological consequences such as the universal challenge caused by global warming and the greenhouse effect.

In this situation, the clean energy which includes the variable renewable energy, particularly the wind and solar PV, which provides free fuel source to the global energy market, consequently will improve the leveled cost of electricity (LCOE) in the medium and long terms. In this case, the solar PV is in the head of interest by the global investment, and also, Green Banks are leading the low-

carbon energy rebellion, helping to avoid the climate risk and serving the consumer and their concerns. According to the reports by the International Energy Agency (IEA), the solar PV pushed up for more growth, in spite of a decade of acceleration. In this detail, the cumulative solar PV capacity reached 398 GW, which represents around 2% of the global power energy [1]. Despite of the policies and regulation, the innovation, and the corporate commitments, the integration of solar PV in the power grids is suffering from both problems of unpredictability of weather parameters and poor infrastructure grids, which minimize the high penetration of solar PV. In this way, the forecasting techniques can help the rise of solar PV and promise the optimality of energy transition management between intermittent and conventional energies by providing the PV power forecasts in various time and spatial horizons. Subsequently, the PV power forecasting can support the grid operator by providing the future energy generated through the solar PV installations, which can help the planning and scheduling of

the effective unit commitments to meet the market demands. In addition, the PV power forecasting is advantageous for the benefit of new power generation such as the microgrids, in which they are smart, small microgenerations, based on numerous microsources including the solar PV. The microgrids, meanwhile, are a very ambitious technological asset for energy savings. However, their technology must meet certain stringent standards to integrate them into the power grids. The microgrids also need nearly smart regulations and controls. Therefore, the PV power forecasting methods can afford them motivated sustenance, and so, they can help the energy management system (EMS).

This review paper suggests the best strategy for building a PV power forecasting model, which, firstly, includes the analysis of the time horizons that means the time between the present and the future times. Several time horizons are considered by the literature. They include the very short term also called the “now-cast” or “intrahour,” which often begins from nearly seconds and ends in few minutes. 0–6 h which is also considered by the literature, as well as the short term, considers 24 hours or day-ahead forecasts; these time periods are generally expedient for utility scheduling and microgrids. In addition, other time horizons including the medium term, which is planned from several hours to several days, and the long term, which is organized from several days to several months, are used for the engine maintenance. Furthermore, the spatial horizon is revealed in the literature, which is strategic for PV power forecasting since it can display the total space foreseen by a forecasting method. This forecasting horizon, meanwhile, can include the single site and the multisite (regional forecasting) [2]. Secondly, the process of PV power forecasting consists of choosing the accurate methods and approaches of forecasting. In this case, the survey of the literature detailed that the PV power forecasting is possible by the direct and indirect methods. The direct methods consist of estimating directly the quantity of PV power foreseen in a future time horizon. In this situation, the experts suggest the artificial intelligence and machine learning techniques for short-term PV power forecasting [3, 4]. The indirect methods consist of transforming the result of solar irradiation forecasting to the PV power forecasts through the solar PV model [5]. For instance, the literature examination showed three main possible approaches destined for PV power forecasting [6]. They involve the physical performance or real PV model, the statistical approach including the methods of artificial intelligence and machine learning, and the hybrid approach, which consists of the combination of multiple techniques of different approaches or cooperation between techniques of the same approach. Indeed, other approaches exist which include the time series models, regressive models, and probabilistic models.

The objective of this review paper is abridging and expounding the principal components of PV power forecasting design by presenting the insightful analysis of several research publications. To that end, this deep analysis conducted through this review paper has shown a gap in the application of some standard accuracy metrics (SAMs) that are often used to validate the right forecasting method. Such as the research paper by Dong et al.[7] that indicated the

result of Error Maximization-Kalman Filter model implementation which is best in the term of MAPE and does not it really in the term of RMSE. Therefore, the one can find the best result by using a specific metric and does not find it by using another one. In this case, the present review paper opens a way to do the research in the normalization and generalization of standard metrics. The research papers by Vallance et al. and Zhang et al. [8, 9] in the standard accuracy metrics are very helpful for the future research, in which they contain an ensemble of new assessment criteria for enhancing the quality and accuracy of PV power forecasting models. The analysis conducted through these papers showed two new metrics: the first one is called the temporal distortion mix, and the second one is called the ramp metric.

Moreover, this review paper presents a complete study on time horizons by focusing the attention on the short-term PV power forecasting due to the expediency of this time horizon in several applications including the planning and scheduling, the unit commitments, the microgrids, and the electric vehicles (EVs). In addition, this review paper tackles the utility of PV power forecasting in numerous fields, which is the novelty and the value added.

The remainder of this paper is structured as follows: the first section covers the overview of spatial and time horizons, methodologies, and models recently applied for PV power forecasting. The second section recommends the artificial intelligence models and machine learning techniques as the benefit value to the PV power forecasting. The third section puts in a current literature analysis of several research papers conducted in different time and spatial horizons along with a profound study regarding the technical and economic benefits of PV power forecasting in the smart energy. Finally, the last section displays the feasibility study concerning the time utility scale for PV power forecasting.

2. PV Power Forecasting Spatial and Time Horizons

The modelling of PV power forecasting is pertinent when picking up the right time horizon and the resolution of forecasts. Therefore, the time horizons are defined as the time between the present and the future times of forecasting, and they can include the very short term that is considered from few seconds to few minutes, also including the “now-cast” and the “intrahour,” the time horizon of 0–6 h, the short term or day ahead that is considered up to 24 hours, the medium term that starts from several hours to several days, and the long term that begins from several days to several months.

In addition to the time horizons, the spatial horizons are also relevant in the forecasting system design and can be ranged from the single site to the regional area including several PV plants (multisite forecasts) [10].

2.1. Very Short-Term, 0–6 h, and Short-Term Time Horizons.

The time horizons are the key for clustering forecasts. In addition, the forecasts made in various time horizons are

very stimulating in the diverse phases of grid operating, such as maintaining the grid permanency, the scheduling of rotating reserves, load monitoring, unit commitments, and other integrated generations such as microgrid planning.

2.1.1. Very Short-Term Time Horizon. The very short-term time horizon for PV power forecasting, also called the PV power immediate forecasting, covers time scales from few seconds to few minutes. This time horizon, meanwhile, is the key to ensure the grid operator by planning the energy reserves and meeting the consumption demand. This becomes a critical issue when considering stand-alone grid with deprived quality and strong solar penetration. Therefore, the very short-term time horizon is advantageous for controlling the power distribution, and it can help in dropping the number of transformer operations.

In addition, the very short-term time horizon is applicable for particular bids such as the manufacturing applications (e.g., solar airplanes and solar cars). However, this time horizon strongly obeys to the weather parameters such as the clouds' motion which comply with the physical rules; their stormy deportment is stochastic and not simple to model [11]. In this item, several research studies were proposed such as a system based on sky imaging which is used to decide the speed and the stability of clouds by [12]. A useful review paper including deep study of very short-term PV power forecasting with several useful techniques regarding this time horizon is available in [13]. For more literature study and analysis, Table 1 presents a summary of the literature in the very short-term time horizon, and Table 2 corresponds to a current literature review which carried out the methods, time, and spatial horizons and results. As a result, from the literature study, the techniques of artificial intelligence are the most important models for the very short-term time horizon. Nevertheless, this time prospect needs further accomplishment materials and additional advances in the digital technologies such as high-resolution cameras and unconventional satellites.

2.1.2. 0–6 h Time Horizon. The 0–6 h or intraday time horizon generally ranged from zero to six hours (0–6 h). This time horizon was used for both load control and monitoring and the power system operators, particularly for solar energy markets [16]. This time horizon was already revealed by several research papers. In this review paper, we discuss some research papers such as Zhang et al. employed the persistence model of cloud in order to improve the forecasting modelling of PV power, respectively, in one hour-ahead and one day-ahead. This forecasting approach employed the data of past PV power and NWP [9]. The hybrid techniques are also practical for 0–6 h PV power forecasting which consisted of combining multiple techniques to forecast the PV power, as well as the hybrid approach is more powerful in the front of other approaches [32].

Indeed, other references and techniques used in the 0–6 h time horizon are presented in Tables 2 and 3 which

show some precious references regarding the methods, the results, and the data sources.

2.1.3. Short-Term Time Horizon. The weather conditions greatly affect the capacity of solar PV power generation. At the same time, the daily energy produced by PV systems depends on the weather such as the relativeness of PV power to the irradiance in the plane of array, the air temperature, and the wind speed, which themselves depend on the day, the month, the year, and the season. However, this dependability makes the energy planned for grid integration variable, which consequently makes out undesirable scenarios to the electric grids regarding their stability, reliability, and operation scheduling, sideways of the economy losses. For that reason, the forecasting techniques can answer this stropky condition of weather variability and get back the information about the quantity of solar PV power generation in the future time horizons. Therefore, the forecasts from 6 am until the day before are also called short-term forecasts. They cover the times beginning from 6 hours to 48 hours ahead. They are typically practical for planning and unit commitments. In addition, they support the EMS to answer the grid operator demand. However, they are relative to the rent of the PV system, methods, and input data as shown in Tables 2 and 4, which summarize various research studies conducted in the short-term time horizon by focusing on the methods, the inputs, and the results.

In addition to the techniques shown in Tables 2 and 4, other worthwhile research studies were found in the literature such as Das et al. added a review paper in the topic of solar PV power forecasting which consisted of methods used for various time horizons including the short term along with the optimization techniques used for improving the results of forecasting. At the same time, they included genetic algorithm (GA), PSO, grid-search, FOA, firefly algorithm (FF), CO, chaotic ant swarm optimization (CASO), chaotic artificial bee colony algorithm (CABCA), and artificial intelligence [68]. Furthermore, the recent review papers by [3, 4] put on the literature review of recent methods that are used in PV power forecasting which includes the methods of artificial intelligence, machine learning, and deep learning algorithms. These models are considered by this review paper as the boosted techniques for PV power forecasting reliability.

2.2. The Spatial Scale for PV Power Forecasting. The techniques of forecasting used to predict the power produced by a single module or by a solar plant are useful for a single site (city, a rural area) or a regional area (utility-scale solar power system forecasting) [10]. The regional forecasts are practical for providing the grid operator by the information on the future energy and consequently maintaining the balances between supply and demand. In the order to make some differences between the solar forecasting applied to the single and the regional area, the experts suggest the study of variability of PV power in the short-term time horizon. This variability is due to the nature of solar resources and geographical specifications.

TABLE 1: Summary of the literature review in the very short-term time horizon.

References	Methods	Inputs	Best results
[12]	Cloud speed forecast (VOF and CCM forecasting techniques)	PNG images	FS = 0.19
[13]	NWP model, sky images, satellite images, cloud cover, and the time series models	—	—
[14]	SVR-2D	Past PV power and weather data	MRE = 9.65% MAID = 108.33 kW ICP = 73.07%
[15]	Cloud speed persistence	Solar power output data of 96 inverters and cloud motion data	RMSE = 4%
[16]	Machine learning techniques based on ANNs and support vector regression (SVR)	Past data of PV power and weather parameters	—
[17]	Regression tree (RT) method applied for 3 cases (cloudy day, clear day, and yearlong)	Past data of weather parameters and PV power	NRMSE = 13.8 %

Furthermore, the regional forecasts are characterized by the decrease in the error. This error, meanwhile, has an exponential curve of the distance between stations [31]. Subsequently, the process of regional forecasts can include the following: (a) the knowledge of the PV power generation from all PV systems. (b) The knowledge of PV power only at certain PV plants and not at the regional level. (c) The knowledge of the amount of energy produced by only regional sites. (d) If no photovoltaic energy data are available, in this case, it is always possible to use the solar irradiance forecasts and then their conversion to the power through a PV system model.

The literature survey, in the meantime, showed several approaches that tackled the regional forecasts. However, they depend on the data availability. The summation of individual forecasts is still used by da Silva Fonseca et al. [69], whereas Persson et al. presented a nonparametric machine learning approach applied for multisite PV power. In this case, the past data of power generation and relevant meteorological variables related to 42 rooftop installed PV power systems are used to form the forecasting model [10].

In addition, for calculating the installed capacity of PV panels in an area, the following equation can be used:

$$P_{\text{pred}}^{\text{reg}} = \frac{P_{\text{cap}}^{\text{reg}}}{I_{\text{ref}}} K \sum_{i=1}^n A_i I_{\text{POA},i} \quad (1)$$

where I_{ref} is the nominal irradiance, $P_{\text{cap}}^{\text{reg}}$ is the PV power capacity, K is the ratio between the system coefficients, I_{POA} is the irradiance on the plane of array, and A is the accumulation of weights specified to the forecast of solar irradiation that ranges the PV panels correspondingly to a certain tilt angle and orientation; consequently, its form is given by the following equation:

$$\sum_{i=1}^n A_i = 1. \quad (2)$$

3. PV Power Forecasting Approaches and Methods

The selection of convenient forecasting time and/or spatial horizon and the appropriate forecasting approach are primal in

the forecasting process. In this case, the methods are classified into three important approaches: firstly, the physical approach which is based on the PV power model, secondly, the statistical approach which is based on the artificial intelligence and machine learning methods, and thirdly, the hybrid approach, which is based on the mix of the techniques of the same approach or the techniques belonging to the other approaches.

3.1. Naïve Models. The PV power is also foreseeable by the techniques of persistence, also called the naïve models, which are commonly practical as the benchmarking models.

3.1.1. Naïve Persistence. A naïve model assumes that the expected power over the future time horizon is similar to the power in the past time horizon as shown by equation (3). This model, meanwhile, is normally used for the stationary time series. Since the solar time series are not stationary,

$$P_n(T+h) = P(T). \quad (3)$$

In general, the naïve persistence is restricted to very short-term or intrahour applications. This technique involves breaking down of the PV power production into a stationary and a stochastic component. However, the stationary term is typically allied with the production in the clear sky condition, whereas the stochastic term is associated to the cloud that induced the changes in the PV power production [5].

3.1.2. Smart Persistence. A smart persistence model is usually used when the variable is no longer stationary. The mathematical form of a smart persistence model is given by equation (4) which corresponds to the best implementation of this technique:

$$P_i(T+h) = \begin{cases} P_{nc}(T+h), & \text{if } P_{nc}(T) = 0, \\ P_{nc}(T+h) \frac{P}{P_{nc}(T)}, & \text{otherwise,} \end{cases} \quad (4)$$

where $P_{nc}(T)$ is the projected power when the sky is clear. In the periods of low variability and short-term time horizons, the power $P_{nc}(T)$ is very accurate [70].

TABLE 2: Current literature review in the PV power forecasting including the references, methods, time and spatial horizons, and results.

References	Methods	TH	Inputs	Best results
[18]	Persistence, MPL, CNN, LSTM, and LSTM full.	VST	Past PV power data and sky images.	RMSE = 15.3%.
[19]	The component methods including SARIMA, ETS, MLP, STL, TBATS, theta, NWP, MOS, temporal reconciliation (TmpRec), and geographical reconciliation (GeoRec). The combined forecasts including simple averaging, Var, ordinary least squares (OLS), least absolute deviation (LAD), constrained least squares (CLS), subset, AIC, lasso, and Oracle.	ST	Past PV power.	NRMSE = 15.4%.
[20]	Probabilistic forecast based on the Gaussian process (GP) and the reference model based on ARIMA.	0–6 h	Household electricity consumption and past PV power.	NRMSE = 8.2% PINAW: 12.4% PICP: 87.57%.
[21]	GA + PSO + ANFIS compared to BPNN, and LRM.	ST	Past PV power data and NWP data.	NRMSE = 5.48%.
[22]	WT, FNN, ELM, and cascade forward BPNN (NewCF) learned with different learning methods.	ST	Past PV power, air temperature, wind speed, and humidity.	MAPE = 3.10%.
[23]	RF, fuzzy C-means (FCM), sparse Gaussian process (SPGP), and improved grey wolf optimizer (IMGWO).	ST	Past PV power data.	NRMSE = 6.5%.
[24]	Models for clear sky weather: SARIMA, W-SARIMA, RVFL, W-RVFL, and SVR. Models for cloudy/rainy weather: SARIMA-RVFL hybrid model.	VST	PV power data.	RMSE = 9.34%.
[25]	SVM, MLP, multivariate adaptive regression spline (MARS), and SVM-MLP-MARS.	ST	Past PV power, wind speed, wind direction, temperature, relative humidity, GHI, and DHI.	RMSE = 21.41%.
[26]	CNN	VST	PV power and sky images.	RMSE = 2.5 kW.
[27]	CNN, LSTM, and the hybrid model of CNN-LSTM.	ST	Wind speed, temperature, relative humidity, GHI, DHI, wind direction, current phase average, and active power.	RMSE = 0.9 kW.
[7]	Uncertain basis function method (UBF): UBU (uniform), UBG (Gaussian), and UBP (Laplace). Stochastic state-space method (STS): prediction minimization error and expectation maximization and Kalman filter (EM-KF).	VST	Past PV power and solar irradiance.	NRMSE = 8.11% MAPE = 5.81 %.
[28]	CNN with the rectified linear activation function (RLAF), the multiheaded CNN of 4 CNNs, the CNN-LSTM, and the ARMA.	ST	PV power, irradiation, module and ambient temperatures, and wind speed.	RMSE = 0.046 kW.
[29]	CNN, residual network (RN), dense convolutional network (DCNN), theta, ETS, SVR, RFR, physical, MPL, and the hybrid of RN-DCNN.	ST	Past PV power and NWP data.	MSE = 0.152 kW.
[30]	Hoff, Perez, Lave, variability reduction index (VRI)—gene expression programming (GEP) and WT-ANFIS models.	0–6 h	Irradiance data and weather conditions.	RMSE = 9.52 %.
[31]	Similarity algorithm (SA), KNN, NARX, and smart persistence models (SPMs).	ST	Past PV power, air and module temperatures, wind speed, wind direction, humidity, and solar irradiance.	RMSE = 2.3% RMSE = 0% RMSE = 5.9%.

TABLE 3: Summary of the literature review in data sources for the intraday time horizon.

References	Data sources
[16, 33–54]	NWP data
[9, 55, 56]	Endogenous data
[14, 55–58]	Meteorological records
[39, 59, 60]	Records from nearby PV plants
[61]	Past GHI data

A smart persistence model can be separated into stochastic and clear sky PV power production parts as shown by equations (5) and (6) [5]:

$$P(T) = P_{nc}(T) + P_{nl}(T + h), \quad (5)$$

$$P_i(T + h) = P_{nc}(T + h) + P_{nl}(T), \quad (6)$$

where $P_{nl}(T)$ is the stochastic term.

TABLE 4: Summary of the literature review in the short-term time horizon.

References	Methods	Inputs	Best results
[62]	Quantile regression forest (QRF) method and 3 selecting methods, which are previous, KT, and Kolmogorov–Smirnov distance (KS). The result classification is based on the daily clearness index (KTd). At the same time, 3 classes are cloudy, partially cloudy, and clear days.	The past values of power, POA, temperature, wind, and NWP data.	NRMSE = 3.29%.
[63]	Prediction interval centred on the maximum likelihood estimation method, SVR for analysing the relationship between the input data and the NWP data (mesoscale model, GPV-MSM).	The past values of power and NWP of temperature, RH and cloud cover (CC), and extraterrestrial irradiance (EI).	The annual forecast error coverage with prediction intervals = 85–95% and the error aggregation of 1.5%.
[64]	Machine learning with functional analysis of variance (FANOVA), North American mesoscale model (NAM), (NOAA), rapid refresh (RAP), and high-resolution rapid refresh (HRRR).	GHI, DNI, temperature, and wind speed taken from NWP. However, the vertical atmospheric and cloud profiles and surface albedo are used to calculate the DNI.	RAP/HRRR/NAM: MAE is less than 2 MW.
[39]	The gradient boosting (GB) technique for the deterministic prediction technique and K-nearest neighbour (KNN) regression for probabilistic forecasts.	The NWP variables taken from ECMWF and past values of the PV system and from the adjacent PV power plants.	—
[16]	ANN and SVR techniques.	Inverter historical power data, NWP of temperature, wind direction (WD), and solar geometry (SG).	RMSE = 182.6 kWh.
[51]	Probabilistic forecasting based on the voted set of QRF and fixed random forest (RF) methods.	The NWP data and earlier values of power.	—
[65]	The prediction bands based on time series equations and algebraic viewpoint and the test of normality based on the algebraic setting of Jarque–Bera, Kolmogorov–Smirnov, and Lilliefors theories.	The data for one day collected from the rent of two PV systems based in France country.	The mean interval length (MIL), the prediction interval coverage probability (PICP), and the best cooperation between MIL and PICP obtained according to the clear sky index.
[66]	MLP, PHANN, and clear sky radiation model (CSRM) for sunny and cloudy conditions.	Irradiance, temperature, day, and clear sky index.	MAPE = 10%.
[67]	Adaptive-network-based fuzzy inference system (ANFIS) and PSO-ANN models.	One year of input data including actual recorded PV power from the PV system rent in the northeast of Thailand country, solar irradiance, module temperature, and air temperature.	RMSE = 0.1184%.

3.1.3. The Persistence of the Ramp. In the short-term time horizon, the persistence of the ramp is normally practical. Therefore, it is beneficial for prolonging the deviation of the electricity production during the previous second to stay on the forecasting time horizon as shown by equations (7) and (8) [5, 15]:

$$P_r(T+h) = P(T) + k_{ASC}[P_{nc}(T+h) - P_{nc}(T)], \quad (7)$$

where k_{ASC} is the fraction of the current power and that in a clear sky condition

$$P_r(T+h) = P(T) + h[P(T) - P(T-1 \text{ second})]. \quad (8)$$

Furthermore, in the case of clear sky conditions and the clarity clue relations, the readers are invited to check

equations (1) and (2) in the review paper by Antonanzas et al. [5].

3.2. Physical Approach. The conversion of GHI into the PV power is not a technique of forecasting. In the meantime, other variables such as the temperature and wind forecasts are typically coming from NWP models. A physical approach employs the PV system parameters and does not require any further historical data; however, it is totally depended on the NWP models. Therefore, inaccurate NWP data can be a source of errors [71]. For that reason, the MOS are used to escape these errors, but they are strongly relative to the weather forecasts, and they involve the past meteorological data. To deepen the understanding of the PV power

modelling, bookworms are referred to check the research papers by Do et al. and Bessa et al. [71, 72].

In this case, this review paper wants to update the readers by the fresh references available in the physical approach part; however, the literature review does not cover enough research in this section. Furthermore, the analysis of the literature covered by this present review paper does not include the techniques used for the solar irradiance forecasting. To that end, the readers are invited to check out some beneficial references on the solar irradiance forecasting such as [73, 74].

3.3. Statistical Approach. A statistical approach corresponds to the data-driven model. The main process of this approach is often based on the extraction of the relationships for the earlier data in order to forecast the future performance of a PV power plant. The statistical models have the capacity to adjust the systematic errors; consequently, they have shown better performances than the PV performance models [75]. In the meantime, the inputs of models are optimized and organized by an application of optimization algorithms that selects the inputs that give the best results and make a compromise between stress and accuracy. The literature analysis revealed that the statistical approach is commonly used and often provides better results in comparison to the physical approach. Some techniques such as the stepwise regression by Fonseca et al. [76] and the principal component analysis (PCA) by Monteiro et al. [63] presented better results. Furthermore, Tables 2 and 5 offer some worthwhile references related to the application of statistical methods in the solar PV power forecasting.

3.4. Hybrid Approach. A hybrid approach consists of combining the forecasting techniques belonging to the same approach or the mix of techniques belonging to other approaches. Therefore, the combination of models is achievable by many conducts, such as the bagging, strengthening, voting, or stacking. A hybrid forecasting approach, meanwhile, can be realized through a combination of statistical, physical, and probabilistic methods, and it is often used in the literature. In this section, we present to the reader the most combinations found in the literature which are the autoregressive integrated moving average (ARIMA) technique combined with the ANN technique employed by Fonseca et al. [76] and the ANN and NARX models tested by Lorenz et al. [60]. In addition, grouping of the gradient-descent optimization technique and ANNs is used to establish the forecasting model. In this point, the metaheuristic optimization model, called shuffled frog leaping algorithm (SFLA), is developed to check the optimal parameters of ANNs by using the initial individuals found by the gradient-descent optimization method. In the meantime, the past solar power values of 5-, 10-, and 15-minute periods are used to feed the forecasting model. In this study, the forecasting model has given the best results in terms of MAPE [83]. In addition, grouping of ensemble forecasting methods was based on 142 models from six families that are the SARIMA family (36 models), ETS family (30 models), MLP (1 model), STL decomposition (2 models), TBATS family (72

models), and the theta model (1 model). The forecasts, meanwhile, were made by (1) simple averaging, (2) the variance-based grouping, (3) the least squares regression, (4) the least absolute deviation regression, (5) the constrained least squares regression, (6) the complete subset regressions, (7) the Akaike information criterion- (AIC-) weighted subset regressions, and (8) the lasso regression. This study, meanwhile, was established for the one day-ahead operational PV power forecasting and based on both the data diversity and the NWP data. Therefore, the forecasting model has given better results in terms of AIC, NMSE, FS, Kolmogorov-Smirnov test integral (KSI), and NRMSE [19]. At the same time, a research paper proposed a forecasting tool based on time-series models and their analysis which taken into account the nonstandard analysis which corresponds to the infinitely small and infinitely large numbers, this analysis take a time interval $[0,1]$. Furthermore, the Cartier-Perrin theorem is also used for time series analysis. This study, meanwhile, was established for a time horizon of short term and based on the full-year data collected from two sites located at Nancy in the east of France and Ajaccio in Corsica, a French island in the Mediterranean Sea. Consequently, the forecasting process has given a better-quality model in terms of MIL stems from the MRL and the prediction interval coverage probability (PICP) [65].

As a conclusion of this section, the hybrid approach is considered by the literature as the boosted technique for the reason that it takes the advantages from both physical and statistical approaches. For more research studies in this section, Table 2 affords the recent references available in the hybrid forecasting approaches and applied for different time horizons.

3.5. Probabilistic Approach. The probabilistic methods considered by the literature as the advanced approach of PV power forecasting added the concept of limits (upper and lower) in the aim to provide more accurate data by using the probability density function (PDF). The survey of the literature showed many research papers that used the probabilistic methods such as Lorenz Kühnert et al. who used the grouping between the statistical and probabilistic methods to generate the PV power forecasting in the time horizon of 0–6 h ahead. The proposed model, meanwhile, was based on the vector autoregression framework, whereas the parameters of forecasting used in this study were the solar PV power time series and distributed time-series information collected from the smart grid infrastructure. Therefore, the proposed forecasting tool presented better results in terms of RMSE and continuous ranking probability score (CRPS) in which they were susceptible for evolving the grid management functions [59]. Moreover, Sperati et al. developed a model based on the grouping between the statistical and probabilistic approaches which were based on the PDF method. The ANNs, meanwhile, were used to reduce the model bias and to generate the PDF of PV power. At the same time, the variance deficit (VD) and the ensemble model output statistics (EMOS) methods combined with the ensemble prediction system (EPS) were used to produce the skillful probabilistic forecast (SPF) in numerous weather

TABLE 5: The references of the statistical methods used in the forecasting approach.

References	Approaches
[14]	Grid-tie PV power-forecasting model for 0–6 h ahead, also called the 2D-interval forecasts based on SVR-2D, that computes directly the 2D-interval forecasts from the previous historical solar power and meteorological data by using the SVR method. The parameters of the forecasting model were the solar and the weather data that included the solar irradiance, temperature, humidity, and wind speed provided from the “Australian photovoltaic data” for two years sampled for every 1, 5, and 30 min along with the past data of PV power. At the same time, the mean absolute interval deviation (MAID), MRE, and interval coverage probability (ICP) were used to perform the forecasting model accuracy.
[77]	AR model that had comparable performances with the ARMA model to produce the short-term PV power forecasting, and the forecasting parameters include the climate state of previous time samples. Therefore, the forecasting model used for false data injection attacks (FDIAs) detection showed performance results in the security and the control of power grid. To that end, the phase-phase correlation (PPC) was used for evaluating the accuracy of forecasts.
[78]	Cloud and irradiance forecasting of 15 min to 5 hours ahead based on the satellite images and SVM. The 4 years of historical satellite images, meanwhile, were used to learn the model. Consequently, this application showed an improvement for the EMS in terms of RMSE, MRE, and the coefficient of determination R^2 .
[79]	The parametric approach that relied on the mathematical models with several parameters that describe the PV system, whereas the nonparametric approach was based on quantile regression forests with training and forecast stages. In the meantime, the forecasting parameters are the meteorological variables from the NWP models. In this case, this forecasting model showed better results in terms of mean-based error (MBE), RMSE, MAE, and skill scores (SS). Therefore, the forecasting engine has been used for calculating the hourly power delivered to the grid.
[80]	Multilinear adaptive regression splines and persistence method used for the short-term PV power forecasting model. The forecasting parameters, meanwhile, include the weather forecasts from the “US Global Forecasting Service (GFS)” and PV power output data (estimated to 1.3 MW) of a PV power plant located in the Borkum city of Germany country. Therefore, the application of this forecasting model showed better results in terms of R^2 , RMSE, MAE, and MBE, and in this situation, the forecasting process was advantageous for calculating the day-ahead production from a PV power plant.
[81]	A classical statistical method based on neural network modelling. The forecasting model parameters, meanwhile, are the number of sunny hours, length of the day, air pressure, maximum temperature, insolation of the day, and cloudiness. The forecasting model showed better results in terms of Pearson’s linear correlation coefficients, kurtosis, skewness, and RMS, and it was developed to perform the short-term PV power forecasting model.
[82]	A multistep method used for forecasting the PV power in different ranges of time, respectively, 10 s, 1 min, 5 min, 30 min, and 2 hours. The forecasting model, meanwhile, was based on the persistence method and the auto regressive exogenous (ARX) model, which presented better results in terms of RMSE and MAE once trained by the forecasting parameters, which included the data from the NREL radiometer grid, Hawaii (USA), and the Microgen database, East Midlands (UK).

conditions, as well as the persistence ensemble (PE) technique was used as the benchmarking model. In addition, the PV power forecasting model parameters were derived from three solar farms located at different sites in Italy. Therefore, the forecasting model was established for the time horizon of 0 to 72 hours ahead and had given better results in terms of Brier skill score (BSS), relative operating characteristic (ROC) skill score (ROCSS), CRPS, and the missing rate error [53]. In addition, Ayompe et al. added a research paper that consisted of a probabilistic approach used for short-term (24 hours ahead) PV power forecasting. The proposed algorithm, meanwhile, was integrated with the demand-side management (DSM) algorithm. In addition, the performance of forecasting models was confirmed by the cloudiness data that included the cloud classification (low-level clouds, midlevel clouds, and high-level clouds), the weighted relative root mean squared error (WRRMSE), and self-consumed energy, as well as the RMSE, MAE, MBE, and CRPS. Consequently, the probabilistic forecasting model was beneficial for increasing the skilfulness of the DSM algorithm under various load generations in a household [84].

To conclude this section, the probabilistic approach remains as the undeveloped method; however, it needs more growth. For more studies conducted in this section, Table 2 offers the recap of some recent studies in the probabilistic models.

3.6. Regressive Methods. The principal role of the regressive methods is estimating the correlations between dependent variables (PV power) and certain independent variables called forecasters (e.g., solar irradiance and ambient temperature). The time series, meanwhile, can have the linear or nonlinear forms, and they can be stationary or nonstationary, whereas the regression methods such as the support vector machine (SVM) including the supervised methods are used in the classification problems. However, in the regression problems, this technique is known as the vector support regression (SVR). Therefore, this technique is stronger in the capacity of generalization and has the capacity to deal with the nonlinear problems.

Furthermore, the study of the literature showed many related research papers such as the research study conducted by Das et al. which presented a complete and methodical study in the PV power forecasting. They also examined the status of relationships between the input and the output data and the preprocessing of input data [68]. In addition, González Ordiano et al. appended a contribution in the PV power forecasting topic that consisted of the time-series forecasting techniques, probabilistic forecasting techniques of point forecast, and an outline of time horizons [85]. Moreover, Sobri et al. added a clustering of PV power forecasting methods, in which three main categories were distinguished in this paper. They consisted of time-series

models, statistical approaches, physical techniques, and overall methods [6]. In addition, van der Meer et al. proposed a comprehensive study about the practice of Gaussian methods for probabilistic forecasting of the residential electricity consumption, PV power generation, and net demand of the single household [20]. For more references and methods in this section, Tables 2 and 6 offer a recap of recent regressive methods used for PV power forecasting.

3.7. Ensemble Methods. The literature review indicated that this approach sets two kinds of methods that are the competitive and the cooperative. The first method, meanwhile, consisted of making the forecasting by using the individual training of models. The training process is based on heterogeneous data and parameters. The result of forecasting is consequently equal to the average of all forecasting models. The second method consisted of the split of the forecasting process into several subprocesses. Therefore, the selection of the convenient forecasting model is adaptable with the characteristics of each subtask. The forecasting result, meanwhile, corresponds to the sum of all forecasting subprocesses [33, 89].

Furthermore, the survey of the literature showed some concomitant research papers that debated this topic such as the work by Raza et al. which proposed a contribution in the ensemble methods through the multivariate neural network ensemble forecast (MNNEF) methods, including the Bayesian model averaging (BMA) technique, namely FNN, Elman backpropagation network (ELM), and cascade forward backpropagation network (CFN). In this case, the WT is used to smooth the historical of PV power data used to train the MNNEFs ensemble methods. Therefore, this forecasting tool is based on Neural Networks ensembles which generates one day-ahead PV power forecasting, whereas the forecasting parameters considered by this study are the historical PV power, air temperature, wind speed, humidity, and solar irradiance. In addition, the MAPE and R^2 are used to test the forecasting model performances [22]. For more research studies and contributions in the ensemble forecasting techniques, Table 2 provides some recent studies in this field.

3.8. Data Mining Approach. Data mining is defined in simple terms as the process of finding useful patterns in the data. In other terms, it consisted of the knowledge discovery, machine learning, and predictive analytics, in addition to the methods of data exploration, preprocessing, modelling, evaluation, and knowledge extraction [90].

3.8.1. Data Exploration. Data exploration firstly clusters the descriptive statistics that are the process of summarizing the key characteristics in the dataset. The communal metrics used in this process are the mean, standard deviation, and correlation. Secondly, the process of data visualization consisted of projecting the data in a multidimensional space. In the context of data mining, the data exploration,

meanwhile, used both the descriptive statistics and the visualization techniques [90].

3.8.2. Classification. The predictive analytic problems are of two categories: the classification and the numeric prediction problems. In classification or class prediction, the information from the predictors or independent variables is used to categorize the data samples into two or more distinct classes or buckets, but in the case of numeric prediction, the numeric value of a dependent variable is predictable by using the values assumed by the independent variables such as the traditional regression modelling [90].

3.8.3. Fitting Data. The basic idea at the back of fitting function is its practicality for forecasting the value (or class) of a dependent variable. In the meantime, the function of fitting involved several methods. The most common ones are of two categories: the linear regression for the numeric forecasting technique and the logistic regression for the classification technique [90].

3.8.4. Association Analysis. The objective of this class of data mining algorithms is finding usable patterns in the co-occurrences of the items by measuring the strength of the co-occurrence between one item and another [90].

3.8.5. Clustering. The principal role of clustering is simply to capture the possible natural groupings in the data by clustering all meaningful groups' data. The clustering, meanwhile, is usable for describing the dataset and used as a preprocessing step for other predictive algorithms [90].

3.8.6. Time-Series Forecasting Models. The time-series forecasting models are the oldest known predictive analytic techniques including the supervised models that consisted on collecting the data from several different attributes of a system that are used to fit a function in order to predict the desired quantity or target variable, for example, in our case of PV power forecasting, the target variable corresponds to the PV power. Some recommendations for time series models are that, firstly, they needed the choice of the appropriate forecasted variable. However, the presence of the noise component also called the nonsystematic component which is by definition random [90].

3.8.7. Time-Series Analysis Methods. The process of time series forecasting corresponds to the descriptive models or time series analysis and the predictive models. This process is based on the decomposition of the data into a trend component, a seasonal component, and a noise component. The trend and seasonality are also called the systematic components that are predictable. However, the noise component is called the nonsystematic component, and it is random [90].

TABLE 6: The most popular regressive models in the literature.

References	Methods
[86]	Artificial intelligence (AI) techniques including the MLP, NN Delay, recurrent Elman NN, NN radial basic function, ANFIS, adaptive resonance theory (ART), and k -NN techniques.
[59]	Point and probabilistic forecasts based on multivariate models such as autoregressive (AR), vector AR (VAR), and vector ARX (VARX). Therefore, VARX is the most accurate model with NRMSE = 8.5%.
[14]	The techniques of SVM and SVR.
[87]	Nonlinear stationary models including nonlinear-AR exogenous (NARX).
[88]	Random forests (RFs) that are the set of decision RTs. The analysis of the literature in the PV power forecasting showed the best results from RFs in terms of average forecasting for individual trees. In addition, the bagging technique that involved the increasing analysis to understand the complete trees, respectively, with a sample initiated from the entire training set. Nevertheless, the RFs deal with this problematic with a feature encapsulation that involves the choice of an unplanned subgroup of entities at each node. The feature encapsulation, meanwhile, reduced the error of correlation.

3.8.8. Feature Selection Methods. The feature selection methods are simply filters that eliminate some attributes; they are of two categories: filter type and wrapper type. The filter approach is based on selecting the only attributes that meet certain stated criteria, whereas the wrapper approaches randomly selected the feedback of attributes that improve the performance of the algorithm. The filter approach, meanwhile, does not require any learning algorithm. However, the wrapper type is based on the optimization through a learning algorithm [90].

3.8.9. The Quality of a Predictive Model. The survey of the literature showed three best techniques which were used to test the quality of predictive models including the confusion matrices (or truth tables), lift charts, and receiver operator characteristic (ROC) curves. The evaluation of regression models, meanwhile used for numeric predictions, is based on conventional statistical tests [90].

3.8.10. Anomaly Detection. The process of finding the outliers in the dataset is called anomaly detection. The outliers, meanwhile, are the data objects that stand out amongst other data objects and do not conform to the expected performance. The outliers usually bias the forecasting process result [90].

3.9. Machine Learning Approach. The machine learning (ML) approach is actually the advanced algorithm that upholds the use of data at their raw form [91]. In the meantime, the survey of the literature showed several applications of ML in the process of PV power forecasting, as well as model implementation, such as the research paper by Amaro e Silva and Brito who carried out a study in the PV power forecasting for a time horizon of one day ahead. The approach, meanwhile, based on the extreme learning machine (ELM), that is a novel algorithm is used to train the feedforward neural networks. At the same time, this method was used for elaborating three models designed for three weather types (sunny, cloudy, and rainy), whereas the input data are the past PV power records from a PV plant. In order to compare their results, the method ELM was used in this study alongside the BP neural network

technique. The MAPE and NRMSE were used to test the accuracy of models [92]. In addition, Teneketzoglou et al. appended a basic ML approach that consisted of implementing ELM without exogenous inputs. At the same time, the ELM algorithm was used in this study for training a single hidden layer feedforward neural network. The ELM algorithm, meanwhile, used to forecast the PV power for a time horizon of very short term (5 min ahead) was based on 10 historical days of PV power. Subsequently, ELM was excellent in the front of the gradient-based learning method in terms of overtraining and local minima. Furthermore, the proposed model in this study has been compared to the time delay neural network (TDLNN) technique in terms of RMSE and NRMSE [93]. Moreover, Zhang et al. added a study based on the ML approach which consisted of using a mix of probabilistic intervals (PIs) for point forecast and the stochastic gradient boosting machine (SGBM) that are used for total loss function optimization. The association of SGBM, least square error (LSE), and least absolute error (LAE), meanwhile, was used to process the point forecast generation, unlike the PIs with multiple quantiles that were used for both probabilistic and point forecasting. At the same time, the input data of models were based on weather data such as the air temperature, humidity, solar irradiance, and wind speed, along with one year of PV power recorded (from 2012 to 2013); for precision, the time between samples was one minute. Therefore, the model assessment indicates that the SGBM method was very accurate than the ELM method in terms of MAE and RMSE [94]. At the same time, Luo et al. proposed a model of ML that consisted of mix of the fuzzy clustering method along with the grey correlation coefficient algorithm that was used in this study to select the similar days. In the meantime, the ELM method generated forecasts of PV power and was based on historical data of similar days. Furthermore, the GA was engaged in this process to overawe the problem of overfitting. The input data, meanwhile, correspond to the historical similar days of meteorological data including the highest, lowest, and mean value of solar radiation, humidity, and temperature and wind speed of the desired forecasted day. Additionally, the RMSE and MAPE were used in this study for testing the accurateness of forecasting models [95]. In addition, Theocharides et al. appended a recent study in the short-term PV power forecasting based

on ML algorithms that include the ANNs, SVR, and RTs along with the varied hyperparameters and feature methods. The input data of models are the forecasts of weather variables provided by NWP, satellite images, sky images, and other yearly historical data. In the meantime, the MAE, MAPE, RMS, SS, and NRMSE were used for testing the accurateness of models [96]. Moreover, for more techniques and studies in this field, Table 2 provides more information about ML was that used for PV power forecasting in various time horizons.

3.10. Deep Learning Algorithms. The basic idea of the deep learning neural network (DNN) comes from the use of multilayer perceptron that consisted of organizing the nonlinear modules of a given task into multiple layers. They are part of the artificial intelligence techniques, and they have many utilizations in the real life such as in the health care (tumour predictions), in the traffic (vehicle speed prediction), and in the renewable energy (detection of wind turbines fault, etc.). Furthermore, the DNN techniques are practical in the renewable energy forecasting for both PV and wind power. At the same time, they have many pros such as their usefulness in the noisy environment, in which they can filter and extract the data needs. In the meantime, they can display some visual analytic graphics after the training process. In addition, they offer the data discrimination possibility. In addition, they can classify the unstructured data as structured ones by applying some strategies such as deep belief method (DBM) or convolutional neural networks (CNN), as well as they can solve many problems by a near similar manner to the human brain. However, the deep learning algorithms are not far from challenges that are the need to supplement CPUs or GPUs. For the prerequisite of high volume data for the success of such networks, they have the problem with overfitting and suffer from the hyperparameter optimization problem [91].

The analysis of the literature showed some outstanding research studies in the PV power forecasting based on the DNN approach such as the research conducted by Zhang et al. who proposed a study on the deep PV now-casting forecasting model that consisted of PV power forecasting by using the DNN fed by multiple historical sky images. This model was compared to the CNN, long short-term memory (LSTM), and MLP methods [18]. In addition, Lee et al. appended a new study on one day-ahead PV power forecasting based on the DNN algorithm. This research paper, meanwhile, consisted of a question about the usefulness of the short-term memory recurrent neural network algorithm for data pattern recognition. In this case, the TensorFlow tool was used for the training process and based on data provided from multisite PV power. The input data are the total generation, output voltage and current, power factor, wind speed, wind direction, PV module temperature, ambient temperature, and weather information from the Korea Meteorological Administration. Consequently, the forecasting process was used to connect with the EMS [2]. Recently, the review papers by Ahmed et al. and Mellit et al.

[3, 4] offered the detailed studies on PV power forecasting models in which they confirmed that the capacity of deep learning methods is clear in the handling of big data and can afford a better solution for solar PV power forecasting; therefore, they can be considered as the revolutionary methods in this topic. Moreover, for more data about DNN techniques, [97, 98] give a deepen knowledge.

As a conclusion to this part of this review paper, the DNNs are characterized by an important number of neurons in which they suffer from two problems that consist of less fitting when the number of iterations is too few and overfitting when the number of iterations is too many. Therefore, the experts confirmed that the larger the number of hidden layers, the deeper the depth of the DNN. Moreover, the commonly used activation functions in a learning process include sigmoid, tanh, ReLU, and Leaky ReLU. In the meantime, ReLU is typically the most used activation function [99]. For more information about the literature review and the applications of the DNN, Table 2 shows the recap of some recent studies in the DNN and used for PV power forecasting.

4. Study of the Current Literature in the PV Power Forecasting

This section offers a careful study and analysis of the recent literature from the period of 2015 to 2020 of some selected research papers in the PV power forecasting as presented in Table 2. The aim of this table is to bring the reader useful information on the PV power forecasting methods and their corresponding time horizons (THs) alongside the inputs that have been used and the findings. The results found are presented by using the standard average metrics (SAMs). Therefore, this approach can help the reader to pick the PV power forecasting method easily without returning to the main paper.

5. Study of the Current Literature in the PV Power Forecasting Operations

The presence of renewable energy in the electrical systems needs the management, planning, and scheduling of power systems and the grid's power control. Subsequently, the forecasting methods can be used for resolving those problems. In the meantime, this review paper presents the literature review of some applications of PV power forecasting such as follows.

5.1. The Employment of the Forecasting Methods in the Dynamic Economic Dispatch. The forecasting techniques can be useful for the power system management as well as the dynamic economic dispatch (DED). In this case, Mahmoud et al. [100] tackled the DED with solar PV of various profiles' (clear and cloudy) proliferation. Therefore, the Salp swarm algorithm (SSA) method and the LSTM with adaptive moment estimation (ADAM) methods were used in this study. The short-term forecasting utility, meanwhile,

was based on the LSTM-ADAM method and presented the best results for DED. Moreover, Bedawy et al. [101] added a study on voltage regulations and their effect on distributed systems with the solar PV penetration. Consequently, the multiagent system (MAS) was used for voltage sensitivity control. Therefore, this study showed best results in terms of voltage deviation minimization tested for different sun profiles (sunny or cloudy), as well as the IEEE test systems were used for benchmarking utility. Furthermore, Mahmoud and Abdel-Nasser [17] appended 3 case studies relative to the weather states (cloudy day, clear day, and yearlong) in the distribution systems including high solar PV penetration. Therefore, the very short term including times of 1 sec, 30 sec, 1 min, 15 min, 30 min, and 1 hour was considered as the time observation of the distribution systems analysis. In this case, the RT method was used, and consequently, the best result was found for case 1. Therefore, the best numeric results in terms of NRMSE = 0.0138, 0.0141, 0.014, 0.0141, 0.0146, and 0.0153, respectively, for 1 sec, 30 sec, 1 min, 15 min, 30 min, and 1 hour in which they represent good results. In addition, Abdel-Nasser et al. [102] appended a study on the efficient state estimation methods (the estimation of voltages and active and reactive power losses) using the quadratic-based backward/forward sweep (QBBFS) which is a kind of ANNs. As a result, the best outcomes were obtained for NRMSE = 0.0110, 0.0312, and 0.0315, respectively, for the voltages, active, and reactive state estimations. In addition, Mahmoud and Abdel-Nasser [103] presented a research paper concerning the analysis of sequential power flow (SPF) for the active distribution systems including the solar PV. The RT method, meanwhile, was proposed for the voltage estimation. The final algorithm contained the SPF-RT and SPF-RTC with additional correction method. In the meantime, the PV and load data were used for algorithm feeding. Consequently, the best results in terms of NRMSE = 0.000263 and MRE = 0.120477 were found by the SPF-RTC method. Nevertheless, this study neglected the effect of uncertainties of PV and load which can affect the clearness of the final results. Furthermore, Marzband et al. [104] proposed a statistical approach based on the neural network combined with a Markov chain (ANN-MC) method. This technique, for now, presented an advantage for economic dispatch considering the generation, storage, and responsive load offers through the minimization of generation cost and the market-clearing price. Furthermore, the proposed approach of forecasting was used for one day-ahead and very short-term forecasts. This study taken into account the effect of uncertainties, as well as the wind-speed signal considered as the main model parameter. Moreover, Ying et al. [105] proposed a probabilistic approach based on the approximate probability distribution of the light intensity along with the dichotomy method. The proposed approach, meanwhile, was used to obtain the PV power forecasting with the interval [PV min, PV max]. In this case, the forecasting system was based on historical data of light intensity. Therefore, this forecasting model was effective to reinforce the optimality dispatching of the electrical grid.

5.2. The Employment of the Forecasting Techniques in the Planning of Power Systems. The PV power forecasting can be applicable in the planning of power systems. In this situation, Mahmoud et al. [106] proposed an approach for minimizing the power losses in the electrical distribution systems. In the meantime, the RPL formulation, the RPL including distributed generation (DG), and the RPL with multiple DGs were used with the IEEE test systems such as 33-bus and 69-bus for the DG allocation problem. Later, Mahmoud et al. [107] appended an efficient analytical method (EA) for optimal multiple DG installations with the power loss minimization. The method, meanwhile, included the optimal power flow (OPF) algorithm. In addition, the IEEE test systems such as 33-bus and 69-bus were used in this study for testing the RPL formulation, the RPL including distributed generation (DG), and the RPL with multiple DGs. Moreover, Mahmoud and Naoto [108] added a study about the optimal allocation of DGs including the solar PV. In the meantime, the optimal power flow (OPF) method was used for deciding the optimal sizing and the locations, as well as the promising of the best mix of various DGs, consequently reducing the power losses in the electric distribution networks. In addition, Ali et al. [109] proposed the active power curtailment (APC) for determining the optimal oversize of DG inverters as well as the voltage regulation. The approach, meanwhile, passed through the renewable energy sources and the load modelling based on the probability (beta and Weibull PDF) methods. Consequently, the results confirmed that the APC showed the best results and encouraging optimal voltage regulation with minimum total costs, as well as this method is helpful for the optimal inverter oversizing and voltage regulation, especially at different levels of DG penetration. Moreover, Luo et al. [110] added a study concerning the home energy management system (HEMS) with the penetration of renewable energy sources (RESs) such as the solar PV. Therefore, this study meant to minimize the energy cost and the peak-to-average ratio (PAR), and consequently, the proposed methods are PSO and BPSO which showed the best outcome for the energy cost of HEMS (19.7% reduced), and for both the energy cost and PAR, the reduction was 10%.

As a recommendation, the DGs can include the forecasting techniques for planning the nondispatchable energy resources such as the solar PV for power loss recovery. At the same time, the integration of the forecasting techniques can help the HEMS by getting the future data about the peak of power and, therefore, managing the load when there is less production by RESs.

5.3. The Employment of the Forecasting Techniques in the Electric Vehicles. The PV power forecasting can be practical for managing the changing of the electric vehicles (EVs). In this case, Ali et al. [111] added a research paper concerning the optimal day-ahead scheduling of EVs considering the uncertainty of renewable energy source generation and loads. In the meantime, the model of EV was based on the state of charge (SOC), and the PV model was based on the mathematical equations alongside the wind turbine model.

In addition, the IP method was used for interval optimization modelling, as well as the Karush–Kuhn–Tucker (KKT) condition was used for introducing uncertainties. The IEEE 33-bus, meanwhile, was used for testing the results. Consequently, this study proved that the reactive power of PV inverters and the active power of EV are preferable for minimizing the total losses as well as ensuring the voltage security. Furthermore, Ali et al. [112] appended a research paper about the plug-in hybrid electric vehicles (PHEVs). The subject of this study is optimizing the reactive power of PV inverters and the active power of PHEV smart charging, consequently controlling the voltage deviation. Therefore, the sensitivity-based (SB) and the optimization-based (OB) methods were used in this study alongside the SOS. As a result, this study demonstrated that the proposed methods are capable to mitigate the negative impacts of PV. At the same time, the reactive power from the PV inverters can reduce the required capacity of PHEVs reducing the voltage fluctuations and the voltage rise. Later, Ali et al. [113] added a research paper that tackled the problematic of optimizing the reactive power used for charging EV and, at the same time, maintaining the voltage deviations. In this case, the hull moving average (HMA) was proposed for alleviating the voltage fluctuations, as well as the gravitational search algorithm (GSA) was employed for solving the optimization model. Therefore, the IEEE 90-bus and IEEE 33-bus were used for testing the results which effectively improved the voltage deviations and optimized the charging/discharging rate of EVs. Other studies were found in the literature which carried out the EVs such as [114, 115].

Nevertheless, after the careful study and the analysis conducted through the proposed references, we did not see the use of the PV power forecasting; therefore, we recommend future studies for the application of short-term PV power forecasting.

5.4. The Employment of the Forecasting Techniques in the Smart Grids and Microgrids. The forecasting techniques can be helpful for the smart grids as well as the microgrids management. In this item, Wason [21] proposed the hybrid of PV power forecasting methods that was based on grouping the GA, PSO, and ANFIS. In the meantime, the binary GA with Gaussian process regression model based on the fitness function was applied to select the significant parameters of the forecasting model that significantly influence the amount of PV power generation. Therefore, the hybrid algorithm based on GA and PSO is used for optimizing the ANFIS model. This was used for one-day ahead PV power forecasting for a solar PV plant in the Goldwind Microgrid system located at China. Consequently, this PV power forecasting process was practical for the utility of electricity generation from the microgrid with high PV power penetration. In addition, Girbau-Llistuella et al. [116] developed a tool of an innovative EMS that was used to optimize the grid operation based on economic and technical criteria. The EMS, meanwhile, is used to process

the output from the forecasting model which was created by using the parameters such as the demand and renewable generation forecasts, electricity prices, and the status of distributed storages through the network. In addition, the time horizons considered in this study are, respectively, 3 days, 1 day, and 6 hours ahead. Furthermore, Abedinia et al. [117] added a study that consisted of a hybrid model for effective PV power forecasting created by using the VMD method, information theoretic, feature selection, and the forecasting engine (FE) with high learning capability. The feature selection method, meanwhile, was based on the IT criteria and an optimization algorithm. However, the FE was an MPL neural network equipped with a modified Levenberg–Marquardt learning algorithm. The forecasting model was based on the parameters such as the historical data of PV power and historical data of irradiance, weather temperature, and cell temperature. This strategy of forecasting, consequently, showed the best rate return in the Hungarian solar power plant. In addition, Galván et al. [118] added a study that consisted of using the neural networks to create the complex and nonlinear models with the output limits (upper and lower forecasting intervals). In the meantime, the proposed strategy was based on four traditional methods that are delta, Bayesian, bootstrap, and mean-variance. Furthermore, the ANNs, fuzzy logic, and PSO were used as the optimizer tools. Additionally, the effectiveness of this approach was tested by using the hypervolume that was typically used for multiobjective approaches which are employed to evaluate the excellence of the final Pareto fronts. The utility of this study, meanwhile, was the optimization of forecasting models. Moreover, Bao et al. [119] used a hybrid approach that was held in a random fuzzy theory method. The aim of this approach, meanwhile, is optimizing the scheduling model by optimizing the short-term line maintenance of the grid by taking into account the uncertainties of the PV power modelling which were based on the historical data driven out from NASA. In addition, Kroposki [120] tackled the question about the high-level penetration of variable renewable energy in the local grids and how to sustain the equilibrium between the load and the generation at all timescales. Recently, Gomes et al. [121] appended a research paper concerning the microgrid smart management with the peer-to-peer energy transaction model. In the meantime, the multiagent method was used in this study alongside the eight forecasting methods including three methods of baselines, two of weighted arithmetic average forecasts using the last periods, and three of the SVM method. As a result, the microgrid forecasting generation showed best results in terms of MAPE = 7.16% calculated for one week.

As a conclusion to this part, the research and development requirements are mostly in the PV power forecasting topic as shown in Figure 1 that pointed out the need of solar PV power forecasting that is necessary for the utilities of smart grid management, grid operations, and solar market scheduling. The most required time horizon, meanwhile, is the short-term PV power forecasting [5].

FIGURE 1: Development flowchart of different energy forecasts [5].

FIGURE 2: Energy penetration from numerous sources including microgrids with clean energy integration to the power grid.

6. Feasibility Study of PV Power Forecasting Time Horizons

The utility time scale of the short-term PV power forecasting extends to one day ahead. This time horizon, meanwhile, is applicable in the utilities of clean energy management (e.g., PV power trend curve in the near future), the solar energy market that includes planning and scheduling, and unit commitments that have used the PV power forecasting when

the PV plants cogenerate with other sources of power. In the meantime, the short-term PV power forecasting is helpful for the benefit of microgrids which hold the energy-side management system (ESMS) that rules the PV power forecasting algorithms which are used to provide the near upcoming data from the solar PV power plants. Furthermore, the data provided by the forecasting system to the ESMS are useful for the optimization of other generation sources based on fuel, natural gas, and coal by maximizing

FIGURE 3: Research papers discussed by this review paper since 2015 to 2020.

FIGURE 4: Number of publications since 2015 to 2020 for each time horizon returned by Google Scholar research.

the penetration of clean energy in the energy mix as shown in Figure 2.

Furthermore, this review paper is including the time scale from 0 to 6 h that is convenient for the same effectiveness as the short term. In addition, other time horizons such as the very short term were also called the now-cast or online forecasting. This time scale, meanwhile, is useful for the solar PV power monitoring and is usable for the systems that request minimum time forecasting such as the industrial applications. In addition, the very short-term time horizon has been introduced in the solar car industry that was recently developed by the manufacturers (e.g., Toyota manufacturer). Subsequently, the utility of now-cast forecasting in the solar car is its effectiveness to prevent sides including shadows and is also used to provide the weather forecasts [122]. Moreover, the time horizons including the medium term and long term were used in the planning of engine maintenance (e.g., power plants) and for the energy analysis and policy which aided the policy makers to choose the right decisions about the long-term investment return in the energy market.

Additionally, this present review paper provides the research about the time horizons used in the forecasting time utility scale as well as to brighter the time horizon value.

Therefore, two case studies were presented in this review paper: the first one concerns the publications discussed above as illustrated in Figure 3; the second study is based on Google Scholar research platform which provided all studies conducted in the PV power forecasting time horizons since 2015 to 2020. In the meantime, a simple comparison based on Google Scholar research has showed the best-used time horizon in 2019 that is the time horizon of 0–6 h, which returned 17,700 results as shown in Figure 4. To that end, the terminologies used in this website research are short-term photovoltaic power forecasting, very short-term photovoltaic power forecasting, zero to six hours photovoltaic power forecasting, and medium-term photovoltaic power forecasting.

7. Conclusion

This review paper revealed the checkup of several research papers available in the arena of PV power forecasting. After the attending analysis, the literature presented that the solar PV power forecasting depends upon the unpredictable parameters of weather as well as the intrinsic parameters of solar PV systems themselves such as the temperature of PV modules and the irradiance on the plane of PV array. In this case, the study of the forecasting parameters including both variables of weather and PV system can be considered before the modelling such as the use of similarity algorithm which can help the designer to select the best parameters and fast modelling [31]. At the same time, after a careful analysis of methods used to forecast the PV power, this study ascertains the need for developing more skillful methods and approaches in this area alongside the generalization methods that are capable to generalize the forecasting results. Indeed, this review paper suggests the practise of the hybrid models including the methods of artificial intelligence and machine learning such as the deep learning and CNN algorithms alongside the probabilistic models, in which they are efficient methods which are able to improve the accuracy of PV power forecasting models and resolve the complexity of solar PV power forecasting. In addition, there is a need for driving more research studies in the standard accuracy metrics (SAMs). Many research papers in the literature, meanwhile, showed several SAMs that were applied for testing the accuracy of forecasting results by comparing the forecasted data with the measured ones; however, these SAMs needed more generalization in their applications as shown previously in Table 2. Furthermore, the standardization of time horizons needs more research and development.

As a conclusion of this recent review paper, we recommend for the benefit of the industrials and practitioners the integration of PV power forecasting algorithms along with the EMS, the HEMS, and the optimal DG planning and dispatching. The PV power forecasting is also useful in the cases of microgrids and EVs. It provides the necessary information about the PV power available in the future time horizon and going to join the input of PV inverters. Further recommendation concerning the PV power forecasting modelling consisted on the PV power forecasting model for each time horizon which means, for example, a model for

short-term time horizon cannot be used for a time horizon of very short-term. This conclusion is proved through the analysis conducted on research papers [55, 60].

Nomenclature

AR:	Autoregressive	LVQ:	Learning vector quantization
ART:	Adaptive resonance theory	LSTM:	Long short-term memory
AMVs:	Atmospheric motion vectors	LSE:	Least square error
ARMA:	Autoregressive moving average	LS-SVM:	Least square support vector machines
ARX:	AR exogenous	LS-SVR:	Least-square SVR
ARMAX:	ARMA with exogenous variables	MLR:	Multiple linear regression
ARIMA:	AR integrated with MA	MAE:	Mean absolute error
ANN-MC:	Artificial neural network combined with a Markov chain	MOS:	Model output statistics
ANEN:	Analog ensemble	MSE:	Mean square error
ANFIS:	Adaptive-network-based fuzzy inference system	MRE:	Mean relative error
AIC:	Akaike information criterion	MBE:	Mean-based error
BMA:	Bayesian model averaging	MAPE:	Mean absolute percentage error
BSS:	Brier skill score	MLP:	Multilayer perceptron
CC:	Cloud cover	MARS:	Multivariate adaptive regression spline
CASO:	Chaotic ant swarm optimization	MR:	Multivariate regression
CABCA:	Chaotic artificial bee colony algorithm	MIL:	Mean interval length
CI:	Clarity index	MNNEF:	Multivariate neural network ensemble forecasts
CFN:	Cascade forward backpropagation network	MAID:	Mean absolute interval deviation
CNNs:	Convolutional neural networks	MABC:	Multiperiod ABC
CRPS:	Continuous ranking probability score	MM5:	Fifth-generation Penn state
DPC:	Dual-population chaotic	MA:	Moving average
DNN:	Deep learning neural network	NOAA:	National Oceanic Atmospheric Administration
DBM:	Deep belief method	NRMSE:	Normalized root mean square error
DSM:	Demand-side management	NSDE:	Normalized standard deviation of the error
EMOS:	Ensemble MOS	NARX:	Nonlinear AR with exogenous input
EPS:	Ensemble prediction system	NWP:	Numerical weather prediction
ECMWF:	European Centre for Medium-Range Weather Forecasts	PICP:	Prediction interval coverage probability
ELM:	Elman backpropagation network	PDF:	Probability density function
EI:	Extraterrestrial irradiance	PE:	Persistence ensemble
ELMs:	Extreme learning machines	PINAW:	Prediction interval normalized average width
EMS:	Energy management system	PCA:	Principal component analysis
FF:	Firefly algorithm	POA:	Plane of array irradiance
F-FNN:	Feedforward neural network	PHANN:	Physical hybridized artificial neural network
FDIAs:	False data injection attacks	PPC:	Phase-phase correlation
GP:	Gaussian process	QR:	Quantile regression
GB:	Gradient boosting	QRFs:	Quantile regression forests
FCM:	Fuzzy C-means	RPS:	Ranked probability score
GA:	Genetic algorithm	RH:	Relative humidity
GSO:	Genetic swarm optimization	ROC:	Relative operating characteristic
GTNN:	GHI-temperature neural network	RMSE:	Root mean square error
GBRT:	Gradient boosted regression trees	RFs:	Random forests
GPU:	Graphic processing unit	RMS:	Root mean square
GRNN:	Generalized regression neural network	SPF:	Short-term probabilistic solar power forecasts
GEMS:	Global energy management system	SOM:	Self-organized map
HIRLAM:	High-resolution limited area model	RTs:	Regression trees
IMGWO:	Improved grey wolf optimizer	SSE:	Sum squared error
ICP:	Interval coverage probability	SG:	Solar geometry
IA:	Immune algorithm	SR:	Stepwise regression
KSI:	Kolmogorov-Smirnov test integral	SAM:	Solar advisor model
KNN:	K-nearest neighbours	SFLA:	Shuffled frog leaping algorithm
LAE:	Least absolute error	SDE:	Standard deviation of error
		SAMs:	Standard accuracy metrics
		SVM:	Support vector machine
		SMA:	Simple moving average
		SGBM:	Stochastic gradient boosting machine
		SGBQR:	Stochastic gradient boosting quantile regression
		SS:	Skill scores
		SSO:	Shark smell optimization

SARIMA:	Seasonal ARIMA
SPF:	Skillful probabilistic forecast
SPGP:	Sparse Gaussian process
SVR:	Support vector regression
TDLNN:	Time delay neural network
VD:	Variance deficit
TCWB:	Taiwan Central Weather Bureau
VARX:	Vector ARX
VMD:	Variational mode decomposition
VAR:	Vector AR
WT:	Wavelet transform
WRFM:	Weather research and forecasting model
WRRMSE:	Weighted relative root mean squared error
VST:	Very short term
ST:	Short term
0–6 h:	Zero to six hours
PINAW:	Prediction interval normalized average width
MABC:	Multiperiod ABC.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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