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Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management

Dheeresh Upadhyay[1] and Lokesh Kumar[2]

[1]Department of Electrical & Electronics Engineering, Mangalayatan University, Aligarh, UP

[2]Faculty of Engineering & Applied Sciences, Usha Martin University, Ranchi, Jharkhand

E-mail: dheeresh.upadhyay@mangalayatan.edu.in

Abstract

As a result of the current climate and energy crises, the production of renewable energy sources, such as solar power, has seen a huge increase. Photovoltaic (PV) generation in the smart grid is increasing at a rapid rate. Sunlight may be intermittent and changeable due to cloud cover, airborne dust levels, and other meteorological characteristics affecting the solar source at ground level. Large-scale solar power brings major hurdles to intelligent grid energy management because of its inherent unpredictability.. The smart grid's economic functioning relies heavily on accurate solar power/irradiance predictions. The theoretical forecasting methods for solar resources and PV electricity are thoroughly examined in this work. The use of solar forecasts in smart grid energy management is also being studied in depth.

Key words: Energy management, forecasting models, pho-tovoltaic,smartgrid,solarenergy.

INTRODUCTION

Renewable energy production is easily integrated into the system. There are several issues with the smart grid that arise from the intermittent nature of PV production, including system stability [7], electric power balance [8], re-active power compensation [9], and frequency response [10].

Accurate PV power forecasting has become a vital component of energy management systems in order to enable the safe and cost-effective integration of PVs into the smart grid. Improved electric power quality and reduced ancillary costs associated with general volatility may be achieved by accurate fore-casting of the energy network. Predicting ground-level solar irradiance, which is directly connected to PV power generation, is critical to smart grid energy management [12]. It is also important to note that solar prediction with numerous look-ahead durations is vital since it covers the demands of a wide range of diverse activities in the grid, comprising grid regulation, power scheduling, and unit commitment. Accurate solar power forecasting is challenging because of the erratic nature of weather systems and the inherent uncertainty in factors like temperature, cloud cover, dust, and relative humidity. There have been a number of utility-scale PV plant forecasting models created in the last several years.

Statistical, AI, physical, and hybrid techniques may all be used to predict PV production. Artificial neural networks (ANNs) and other sophisticated AI methods, such as data-driven formulation based on historical measurements, may be used to build solar forecasts that fall within the statistical approach category as well [15]. Solar irradiance and PV production may be predicted using numerical weather prediction (NWP) or satellite pictures [16, 17]. Finally,

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hybrid techniques combine the three previously stated methodologies. A variety of forecasting methods are used based on the size of the prediction horizon in order to suit the needs of decision-making.

This report examines the most recent advances in PV and solar forecasting methods. A variety of techniques to problem solving are compared and contrasted from theoretical and practical viewpoints. In addition, solar forecasting is examined in the context of smart grid management.

I. SOLAR FORECASTING CHARACTERISTICS A frequent outcome of solar forecasting is solar irradiance or PV.

Solar energy forecasting and modelling relies heavily on PV generation parameters. This section explains some of the most significant characteristics of solar forecasting, such as associated variables and the prediction horizon. The development of novel solar energy predictors will be aided by the use of standardised performance assessment metrics.

A. PV Generation

Solar irradiation, reflectance, calculation of PV cell temperatures, and inverter efficiency all have an impact on the predicted power output of PV generations. In order to determine the maximum power output, we use:

$$P_R = \eta SI[1-0.05(t_0-25)] \qquad (1)$$

S denotes the solar array's surface area (in square metres), I represents solar radiation (in kilowatts per square metre), and t0 refers to the outside air temperature (in degrees Celsius).

An important aspect of a solar power system is monitoring and optimising the maximum power point (MPPT) of a PV array [19]. For a given temperature and irradiance, a PV array may be set to run most effectively when its voltage VR and current IR are automatically calculated, as shown in Figure 1.

Aspects of Solar Forecasting That Are Significant

The created prediction model's accuracy is affected by the input variables and the prediction horizon it uses. However, these are only a few examples of characteristics that may be used as inputs to the solar power forecast model.

2) historical data on the production of PV power;

Second, historical observations of explanatory factors, such as significant meteorological variables, such as GHI (global horizontal irradiance), temperature and cloud cover.

Explanatory factors, such as NWP predictions, are also included.

For short-term predictions, solar power measurements are the most essential input, whereas NWPs are the most critical input for longer-term forecasts.

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According to practical application, the smart grid's decision-making activities need the employment of multiple forecast horizons.

For PV and storage management and energy market clearing, very short-term projections, including such 5 minutes for the Australian power market [21], may be employed. With the advent of smart grids, accurate short-term forecasts of solar power will be even more critical.

These projections are critical for a variety of energy market and power system decision-making issues, such as economic load dispatch, unit commitment, and so on.

To schedule maintenance on PV plants, traditional power plants, transformer, and transmission lines, medium-term forecasting might be valuable.

For long-term solar energy evaluation and PV plant design, it is possible to use long-term prediction/estimation.

As demonstrated in Fig. 2, several forecasting horizons and decision-making processes are shown. Very short-term and short-term predictions of solar power are particularly useful for activities such as PV plant operations, real-time unit scheduling, storage control, automatic generation control (AGC), and electricity trading from the perspective of smart grid energy management and power system operations. As a result, the majority of research focuses on building more complex models for estimating solar activity in the very short term and near term.

Fig. 1.

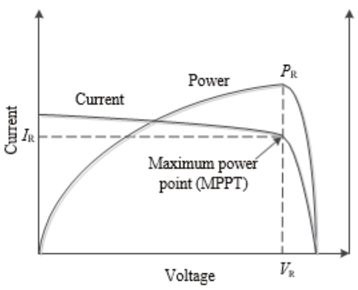

Fig. 1. Characteristic PV array power curve.

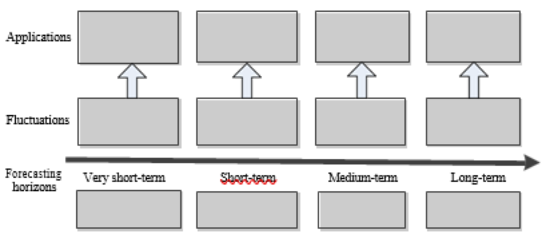

Fig. 2. Forecasting horizons and corresponding decision making activities.

A. StandardizingPerformanceMeasures

The precision of solar and PV predictions may be measured using a variety of assessment metrics. Predictive model assessment and benchmarking might benefit from standardising performance indicators. MBE, MAE, MSE, and RMSE are some of the most often used indices, which are stated as follows:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left[\hat{X}_i - X_i\right] \qquad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{X}_i - X_i\right| \qquad (3)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{X}_i - X_i\right)^2 \qquad (4)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{X}_i - X_i\right)^2} \qquad (5)$$

N is the number of observations in the test dataset, and X I and Xi represent each prediction and observation, respectively. Measures like this have their own unique qualities and focus. Depending on the specifics, the decision maker may choose the best one for the prediction assessment.

III. STATISTICAL MODELS.

Time series forecasting has long relied on statistical methods. His torical data is the foundation for most statistical methodologies. With the help of the predictor, the statistical model's inputs and the predicted variable may be connected. Perseverance, to begin with. The persistence technique is commonly employed in meteorology forecasting [22] and is usually viewed as a naïve prediction. It is assumed that the solar energy in the future Xt+1 will be the current measurement Xt, stated as, Xt+1=Xt in this basic prediction approach (6) If you're looking forward more than a few hours, the persistence strategy is almost impossible to beat. Xt+k = 1 T T X1 i=0 Xti (7), commonly known as the moving average, is a definition of the generalised persistence method: the future prediction objective is the arithmetic mean of the last T measured values. For short-term forecast of solar and wind power, it is the most often used reference model [18, 23]. To be significant, a new prediction model must outperform a reference model that has been around for a long time. As the forecasting horizon becomes longer, the accuracy of the persistence prediction degrades dramatically [24].

ARMA Time series forecasting methods that may extract important statistical features such as the auto-regressive moving average (ARMA) are widely used. Using a moving average (MA) and an autoregressive (AR) model, it may be described as follows:

$$X_t = \sum_{i=1}^{p}\varphi_i X_{t-i} + \sum_{i=1}^{q}\theta_i \varepsilon_{t-i} \qquad (8)$$

The predicted solar energy at time t is represented by the variable Xt. The AR model's coefficients are represented by the numbers in the following format: (Xt, p, MA, q, I j) where each number represents an AR model coefficient. The MA error term is represented by the number q. For ARMA, the order of AR and MA is often represented as ARMA(p, q). AR(p) may be converted into an AR(p) model when the q parameter is 0, and an MA(q) model when the p parameter is 0.

To forecast the future value of a certain time series, the ARMA model has become a popular and effective method for autocorrelation analysis. ARMA models can represent a wide variety of time series by varying the order in which the data is arranged. When the time

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series has a linear correlation structure, they are capable of making accurate predictions. When used to estimating future solar power in California using data from Solar Anywhere, ARMA outperforms the persistence model [24].

The C. ARIMA name If you are interested in using this method, you must ensure that the underlying time series is stationary, which means that the statistical features of time series do not vary. For non-stationary random processes, the auto-regressive integrated moving average (ARIMA) model is created. The nonstationary random process Xt has an ARIMA(p, d, q) model stated as:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \quad (9)$$

In this equation, L stands for the lag operator, which is defined as LXt=Yt1, where I is the AR coefficient, I is the MA coefficient, t is a random variable with zero mean, and p is the AR order, d is the number of nonseasonal differences, and q is the MA order. The model ARIMA(p, q) is changed to an ARIMA(p,q) model when d is equal to zero. In terms of time series forecasting, ARIMA is the most generic class of models available to researchers. By capturing the monthly cycle more accurately than other approaches, ARIMA has become one of the most widely used techniques in financial analysis. In order to estimate sun irradiance, the ARIMA input data are converted to log values in [26]. The ARMAX, DANIEL Both ARMA and ARIMA are theoretically inaccessible to process activity. Autoregressive-moving average model with exogenous inputs (ARMAX) is used to account for exogenous inputs in time series prediction. Armax may be used for solar power prediction since it incorporates external factors like temperatures, dampness, and wind speed, making it more versatile than ARIMA. There are three types of exogenous inputs in this model: AR terms (for p), MA terms (for q), and an exogenous input term (for b).

$$X_t = \sum_{i=1}^{p}\varphi_i X_{t-i} + \sum_{i=1}^{q}\theta_i \varepsilon_{t-i} + \sum_{i=1}^{b}\eta_i d_{t-i} \quad (10)$$

Temperature and humidity are taken into consideration as exogenous inputs in ARMAX, which is intended for PV power forecasting and which can be simply measured by the local observatory. Compared to the ARIMA model, it performs better. Spatiotemporal (ST) and autoregressive (ARX) data-driven prediction models have been created for a solar radiation forecast model. For 1 and 2 hour look-ahead intervals, simulation results using actual solar data from PV installations in California and Colorado show that the suggested model may provide excellent results.

I. MODELS OF ARTIFICIAL INTELLIGENCE

Forecasting, pattern classification, control, optimization, and so on are only some of the applications of AI. In order to analyse and forecast solar energy, AI approaches have been frequently used because to their great leaning and regression capabilities.

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A. Neural networks that are artificial

It is theoretically possible to use multilayered feedforward neural networks (NNs) to approximate any nonlinear mapping to any degree of precision. Figure 3 depicts a NN in its usual configuration.

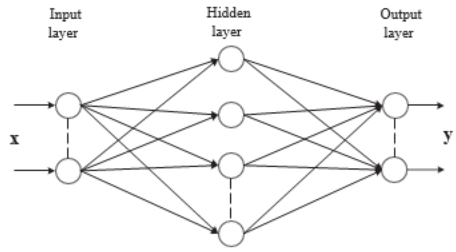

Fig. 3. Typical structure of a feed-forward neural network.

The NN with K hidden nodes and activation function () for approximating the N samples may be described as follows given a dataset with N different samples (xi, ti) N

$$f_K(x_j) = \sum^{K} \beta_i \psi(a_i \cdot x_j + b_i), j = 1, \ldots, N. \qquad (11)$$

Ai is the weight vector between a hidden neuron and its input neurons, I is the weight vector between a hidden neuron and its output neurons, bi is the threshold of a hidden node, and (aj + bj) is the output of the hidden node with regard to the input xj, which is represented by ai. Backpropagation (BP) is the most popular gradient-based approach for optimising the parameters of NNs, with the objective function specified as follows:

$$C = \sum_{j=1}^{N} \left(\sum_{i=1}^{K} \beta_i \psi(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i) - \boldsymbol{t}_j \right)^2. \qquad (12)$$

ANNs have been effectively used in solar forecasting as an alternative to traditional methodologies [31]. Overfitting has been avoided in this model of short-term solar irradiance forecasting, which is based on a BP neural network and time series [32]. It is possible to estimate the sun irradiation from Trieste, Italy, using a Multilayer Perceptron (MLP). Grid-connected photovoltaic plants (GCPV) are used as a point of reference in the MLP-model, which also helps charge controller control algorithms.

[34] proposes the use of the aerosol index as an extra input parameter to anticipate the next 24 hours of PV power outputs based on the BP NN model. Traditional ANN approaches temperature and air, moisture, and wind speed are shown to be inferior to the suggested method. A large-scale photovoltaic (PV) facility in southern Italy uses three different ANNs to model three different sorts of days (sunny, partly cloudy, and overcast) for short-term electricity forecasts. For small-scale solar power system applications, an ANN is used to estimate the highest representative of the sun prediction horizon [36]. In comparison to standard NN and empirical models, the Bayesian neural network (BNN) presented for predicting daily global solar irradiation with input data of air temperature, relative humidity, sunlight length, and extraterrestrial irradiation shows improved performance [37]. The use of

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wavelet-based ANN to estimate solar irradiance in Shanghai has been suggested, and the results show that more precise forecasts may be created [38].

A. Other Models.

The use of artificial intelligence (AI) in solar energy forecasting is not limited to neural networks (ANNs). Solar radiation may be predicted using meteorological data such air temperature, daylight length, and relative humidity [39]. Radial Basis Function neural network (RBFNN) For short-term solar power forecasting, an LS-SVM-based model has been developed [40]. When it comes to predicting solar power output, the LS-SVM model beats a reference AR model and an RBFNN-based model. Many artificial intelligence (AI) strategies have been suggested for the prediction of mean hourly global solar radiation, such as linear, feed-forward, recurrent Elman and Radial Basis Function NNs and the adaptive neuro-fuzzy inference scheme[15]. Insolation forecasting using a 24-hour look-ahead period, weather reported data, fuzzy theory, and neural networks (NN) are used for PV system power output forecasting [41]. We present a weather-based hybrid technique that includes categorization, training, and forecasting phases for day-ahead hourly PV power forecasting [11]. Classification of historical data on PV power outputs is accomplished using SOM and LVQ, two algorithms developed by the authors of this paper. The input/output data of temperature, likelihood of precipitation, and sun irradiance are trained using support vector regression (SVR). For accurate forecasting, fuzzy inference is used to pick the trained model from a pool of possible candidates. [42] combines the Gamma test (GT) with local linear regression, multi-layer perceptrons (MLP), neural network auto-regressive model with exogenous inputs (NNARX), and adaptive neuro-fuzzy inference system (ANFIS) to successfully minimise trial and error workloads. The approach is then evaluated on solar radiation in the Brue catchment in the United Kingdom. In order to take advantage of the link between solar radiation and other relevant variables in wind speed, humidity, and temperature, WRNNs (wavelet recurrent neural networks) have been suggested for 2-day solar radiation forecasting [43]. Fuzzy rules are used to classify future sky conditions and temperature information from the National Environment Agency (NEA) into multiple fuzzy sets in order to create a hybrid solar radiation prediction model [44].

I. PHYSICALMODELS

Physical models use solar and PV models to create predictions of solar irradiance and power, as opposed to statistical models and AI methodologies. Fig. 4 depicts a broad physical approach framework.

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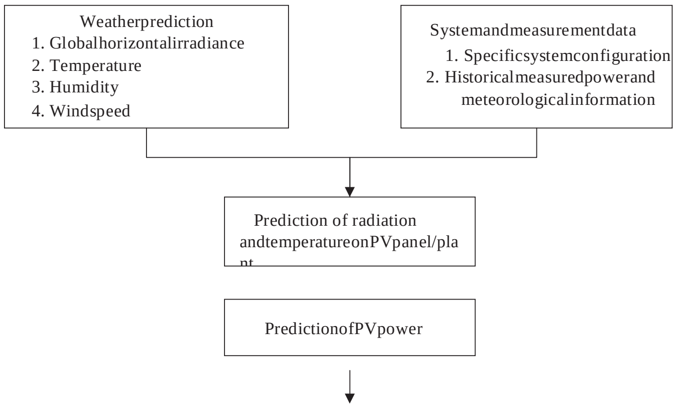

Fig.4.TypicalframeworkofphysicalapproachesforPVpowerforecasting.

A. SkyImage-BasedModel

It is vital to understand how cloud cover and optical depth affect solar irradiance at the surface. Solar irradiance forecasting might benefit by determining cloud conditions. An investigation of cloud patterns over time is the basis for the sky image-based technique. Predictions of local sun irradiance have been made using satellites and land sky imaging techniques.

Solar irradiance conditions may be predicted using satellites. Models that use satellite images to identify and record cloud patterns over a certain period of time are very accurate in their ability to forecast solar irradiance. GHI forecasts may be made up to six hours in advance by analysing photographs of clouds. Motion vector fields [45] may be used to identify cloud motion using time series acquired from satellite image analysis data. Meteosate satellite photos are used to predict solar irradiance up to six hours in the future [46]. [18] photos from the Geostationary Operational Environment Satellite provide similar projections. The SEVIRI satellite's spinning enhanced visual and infrared imager (SEVIRI) observations have been used to construct a more sophisticated model for predicting ground solar irradiance (AMESIS) [17]. The use of novel sensors like SEVIRI may increase the accuracy of solar forecasts as well as the high spatial and temporal precision required for specialised solar energy applications.

Ground-based sky photos, using a total sky imager (TSI), can give far greater spatial and temporal resolution for solar predictions than satellite images can [47]. For large-scale PV power plants or feeders with a high percentage of PV irradiance, it can detect cloud shadow and hence record abrupt changes in irradiance. Since cloud pictures are designed for a small spatial scale and are very variable, short look-ahead time predictions are only possible if just one TSI is used. According to [47], the predicted horizon might range from 5 to 25 minutes depending on the cloud pictures.

Models based on the NWP

With a look-ahead period of more than a few hours, numerical weather prediction has become the most accurate technique for solar irradiation forecasting. Using a numerical

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dynamic model of the environment, the NWP model can forecast solar irradiance and cloud cover percentages Fundamental differential equations regulate the transition of the atmosphere and, thus, NWP is theoretically predicated on accurate knowledge of the condition of the atmosphere at specified times.

For the most part, NWP is superior than traditional forecasting methods. Only models based on satellite images are adequate for forecasts of the next 1 to 5 hours. Up to 15 days in advance, NWP models can forecast the weather. When it comes to long-term forecasting, there is generally agreement that NWPs are more accurate than satellite approaches [46].

With the advent of NMP models like the European Centre for Medium-Range Weather Forecasts (ECMWF), the North American Mesoscale Forecast System (NAM), and others, solar forecasting is now possible [16]. The three-day look-ahead period of the ECMWF is used to anticipate regional PV power production in Germany [46]. Generally, regional predictions have improved in accuracy as the size of the area increases. GHI projections for the continental United States (CONUS) are based on the NAM, GFS, and ECMWF [48]. For clear skies, it's been shown that ECMWF has the maximum accuracy, while GFS has the best performance for hazy skies. For solar irradiance forecasting, a model based on grid point value (GPV) information is suggested utilising relative humidity, rain, and three-level cloud cover [49]. The suggested approach has been validated mathematically in Hitachi and four other major Japanese cities. NWP models like as NAM, GFS and ECMWF do have some inherent limitations. Insufficient spatial resolution prevents them from accurately predicting the value of a specific location. The calculation expenses of operating the NWP are also substantial, since the output frequency is one hour for NAM and three hours for GFS and ECMWF, respectively. The features of the majority of clouds in NWP remain mostly undetermined due to time and space constraintsforecasting timescales of a few hours or less [29].

I. HYBRID MODELS.

Hybrid methods have been suggested to combine advantages from several solar forecast models in practise. Short-term forecasting of hourly global horizontal solar radiation (up to 915 hours ahead) and forecasting of a high-resolution solar radiation database (1 s to 30 s scales) with look-head time up to 47,000 seconds are both possible with an advanced model that combines ARMA and a nonlinear autoregressive neural network (NARNN) [50]. In order to forecast hourly solar radiation, an unique hybrid model including both ARMA and Time Delay Neural Network (TDNN) has been developed, where the ARMA model is employed to predict the stationary residual series, and TDNN is utilised to complete the prediction [51]. A 20 kWp GCPV plant uses a combination of the seasonal auto-regressive integrated moving average technique (SARIMA) and the support vector machines method (SVMs) to forecast hourly sun output [52]. A new method for predicting hourly solar power with a look-ahead duration of up to 36 hours has been devised and tested on 21 PV systems in a small town in Denmark [14]. Self-organizing maps (SOM) and a hybrid exponential smoothing state space (ESSS) model with ANN are presented as part of a hybrid forecasting

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model for cloud cover via satellite image analysis [21]. It has been shown to outperform more typical forecasting algorithms using hourly solar irradiance data in Singapore.

I. APPLICATIONSINSMARTGRIDENERGYMANAGEMENT

There is a lot of attention paid to the negative impacts of PV power on the distribution network, notably on the energy management of the smart grid, which includes issues of voltage fluctuations, current flows, grid losses, short-circuit current, and so on [55]. Forecasts for PV and solar energy might bring

System operators, electricity participants, and planners of electric power planning will benefit from this advice.

Various forecasting models have been used for smart grid power management. PV outputs may experience considerable short-term fluctuations due to meteorological conditions like cloud passage [58]–[60]. In order to minimise major variations in the voltage and frequency of the smart grid, an accurate short-term PV power forecast model with a prediction period of 30 seconds to several minutes is needed.

Various methods have been used to reduce the pace at which PV generation increases. Some typical solutions for absorbing the quick fluctuations of PV generators include a double-layer electric capacitor [61]–[63], battery storage systems, fast ramping generators, and electric cars [65, 66]. Smart grids with PV generating integration may use a variety of scheduling algorithms, such as those outlined in [67], [68]. Distributed generation (DG) will have a substantial impact on the operation of distribution systems, including network loss reduction, reliability improvement, and distribution network reconfigurations, as PV generators become more commonplace [69, 70]. [71], [72] model intelligent energy management systems that take into account storage capacity and charging rate, home load changes, and distribution network power pricing in grid-connected and islanded operations.

Developing day-ahead energy management tools for next-gen PV installations, such as storage units and demand response, is a challenge for smart grid operators in the smart grid environment. Using a hierarchical determinist energy management strategy proposed in [73], the microgrid's central energy management may be completed, as can the customer's local power management. For PV production changes and uncertainties, [74] proposes a day-ahead energy management system that is based on pricing with a storage system and demand response. Research has centred on the use of PV systems in homes and buildings, as well as building-integrated PV microgrids [75, 76]. In addition, due to the sluggish ramp constraint of thermal generators, day-ahead power scheduling is becoming more critical in power systems. On a large-scale aggregated solar power production, the consequences of forecast accuracy are assessed in [77]. In the unit commitment dilemma, day-ahead scheduling of PV generation paired with battery storage is presented in [78–[80]. The bidding technique of PV businesses engaging in day-ahead power markets is another use of the day-ahead prediction model [81], [82].

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II. CONCLUSION

This study focuses on the development of PV and solar power forecasting methods. In this context, solar forecasting properties are described. Four types of PV and solar power forecasting models are available: statistical, AI-based, physical, and hybrid. Different kinds of forecasting approaches are briefly covered in this study, along with their benefits and drawbacks. Furthermore, solar forecasting applications in smart grid power management are fully examined. The right solar forecasting methods may be used to assure performance based on individual applications.

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