Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management

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***Abstract*—Due to the challenge of climate and energy crisis, renewable energy generation including solar generation has experienced significant growth. Increasingly high penetration level of photovoltaic (PV) generation arises in smart grid. Solar power is intermittent and variable, as the solar source at the ground level is highly dependent on cloud cover variability, atmospheric aerosol levels, and other atmosphere parameters. The inherent variability of large-scale solar generation introduces significant challenges to smart grid energy management. Accurate forecasting of solar power/irradiance is critical to secure economic operation of the smart grid. This paper provides a comprehensive review of the theoretical forecasting methodologies for both solar resource and PV power. Applications of solar forecasting in energy management of smart grid are also investigated in detail.**

***Index Terms*—Energy management, forecasting models, photovoltaic, smart grid, solar energy.**

I. Introduction

GLOBAL warming and the energy crisis over the past few decades have motivated the use and development of alternative, sustainable, and clean energy sources. Solar energy is inexhaustible and considered as one of the most promising renewable resources for bulk power generation. Photovoltaic (PV) cells are the basic technology for converting solar energy into electric power. By the end of 2014, large capacity PV power generation was installed in Germany (38.24 GW) [1], China (28.05 GW) [2], Italy (18.31 GW), Japan (23.3 GW), U.S.A. (18.28 GW) [1], and Spain (5.39 GW), etc. Among others, Germany is the world's top installer and consumer of PV power [3], [4]. PV power generation has introduced significant economic and environmental interests to the public social awareness, such as reducing emissions of CO_2 as well as creating employment [5].

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PV power is reaching higher and higher penetration level in the smart grid [6]. An important feature of the smart grid is its high ability to integrate renewable energy generation. However, as an intermittent energy source, PV generation introduces significant volatility to the smart grid, which brings severe challenges to system stability [7], electric power balance [8], reactive power compensation [9], frequency response [10], etc.

To ensure secure and economic integration of PVs into the smart grid, accurate PV power forecasting has become a critical element of energy management systems. Accurate forecasting can help improve electric power quality of the electric power delivered to the electricity network and, and thus reduce the ancillary costs associated with general volatility [11]. Since PV power output is directly related to solar irradiance at the ground level, solar irradiance prediction is also equally important to energy management in the smart grid [12]. Moreover, solar prediction with multiple look-ahead times is significant in that it addresses the needs of different operation and control activities, including grid regulation, power scheduling, and unit commitment in both the distribution and transmission grids [13]. Due to the chaotic nature of weather systems and the uncertainties involved in atmospheric conditions such as temperature, cloud amount, dust and relative humidity, precise solar power forecasting can be extremely difficult. A number of forecasting models have been developed for solar resources and power output of PV plants at utility scale level in the past few years.

PV generation forecast methods can be broadly classified into four approaches, i.e., statistical approach, artificial intelligence (AI) approach, physical approach, and hybrid approach. Statistical approaches are based on data-driven formulation using historical measured data to forecast solar time series [14]. AI approaches utilize advanced AI techniques, such as artificial neural networks (ANNs), to construct solar forecasters, which can be also classified into the category of the statistical approach [15]. Physical models are based on numerical weather prediction (NWP) or satellite images that predict solar irradiance and PV generation [16], [17]. Finally, hybrid approaches are combination of the three aforementioned methods [10]. In practice, different forecasting approaches are preferred depending on different scales of prediction horizons to meet the requirements of the decision-making process [18].

This paper reviews the state-of-the-art of PV and solar forecasting methodologies developed over the past decade. The merits and demerits of different types of approaches are discussed from both the theoretical and practical perspectives. The applications of solar forecasting in smart grid management are also investigated.

II. Characteristics of Solar Forecasting

Solar forecasting commonly outputs solar irradiance or PV power. The properties of PV generation are essential to solar energy modeling and forecasting. Some important characteristics of solar forecasting, including related variables and prediction horizon, are clarified in this section. Standardized performance evaluation indices are introduced for developing new solar energy predictors.

A. PV Generation

The forecasted power output of PV generations is affected by many factors including but not limited to the measurement of solar irradiance, reflectivity, estimation of PV cell temperatures, and the efficiency of the inverter. The maximum power output is presented by

$$P_{\mathrm{R}} = \eta S I \left[1 - 0.05(t_0 - 25)\right] \quad (1)$$

where η represents the conversion efficiency (%) of the solar cell array; S is the array area (m^2); I is the solar radiation (kW/m^2); and t_0 is the outside air temperature (°C).

Tracking the maximum power point (MPPT) of a PV array is usually an essential part of a PV system so as to improve the efficiency [19]. The MPPT technique is to automatically find the voltage V_{R} and the current I_{R}, where the PV array operates efficiently to obtain the maximum power output P_{R} under a given temperature and irradiance, as demonstrated in Fig. 1.

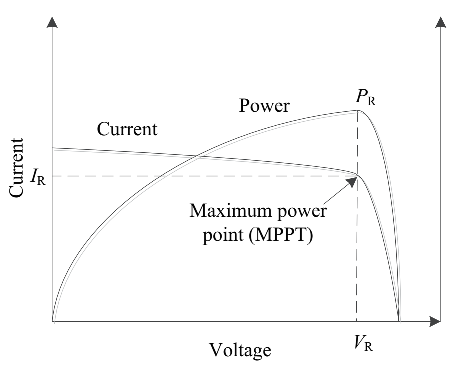

Fig. 1. Characteristic PV array power curve.

B. Major Aspects of Solar Forecasting

The selection of input variables and prediction horizon affects the accuracy of the developed prediction model. In general, the relevant variables available as inputs of the prediction model of solar power include but are not limited to the following factors [20]:

1) historical measurements of PV generation;
2) historical measurements of explanatory variables, such as relevant meteorological variables, including global horizontal irradiance (GHI), temperature, cloud cover, humidity, wind speed, and so on.
3) forecasts of explanatory variables, e.g., NWP.

The most important input is the available observations of solar power for forecasts up to 2 h ahead, while NWPs are the most important input for longer horizons.

From the point of view of practical use, different prediction horizons will correspond to the specific needs of decision-making activities in the smart grid, as follows:

1) Very short-term forecasting (from a few seconds to minutes): Very short-term forecasts can be used for PV and storage control and electricity market clearing, such as 5 minutes for the Australian electricity market [21]. In the smart grid environment, very short-term forecasting of solar power becomes more important than before.
2) Short-term (up to 48–72 hours ahead): Such forecasts are crucial for different decision-making problems involved in the electricity market and power system operation, including economic dispatch, unit commitment, etc.
3) Medium-term (up to one week ahead): Medium-term forecasting would be useful for e.g., maintenance scheduling of PV plants, conventional power plants, transformers, and transmission lines.
4) Long-term (up to months to years): Long-term prediction/estimation can be applied for long-term solar energy assessment and PV plant planning.

Different prediction horizons along with their decision-making activities are shown in Fig. 2. From the perspective of smart grid energy management and power system operations, very short-term and short-term prediction 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. Most studies, therefore, focus on developing advanced models for very short-term and short-term solar forecasting.

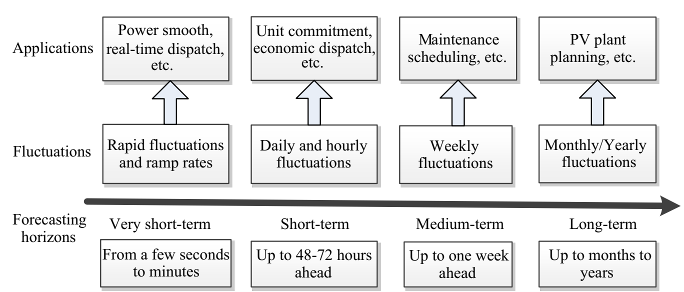

Fig. 2. Forecasting horizons and corresponding decision making activities.

C. Standardizing Performance Measures

Various evaluation indices are proposed and applied to measure the accuracy of solar and PV forecasting. Standardizing performance measures would be helpful for prediction model evaluation and benchmarking. The commonly used indices include mean bias error (MBE), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE), expressed as,

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

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

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

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

where $\hat{X}_i$ and X_i represent the i^{th} prediction and observation value, respectively, and N is the size of the test dataset.

These performance measures have their own characteristics and emphasis. The decision maker can choose the most appropriate one for the prediction evaluation according to the special conditions.

III. Statistical Models

Statistical approaches have been widely used in time series forecasting. In general, statistical approaches are based on historical data. The predictor aims at constructing the relationship between the variables used as inputs for the statistical model and the variable to be predicted.

A. Persistence

The persistence approach is always regarded as a naive predictor, widely used for meteorology-related forecasting [22]. This simple prediction method assumes that the solar power/irradiance in the future X_{t+1} will be the latest measurement X_t, expressed as,

$$X_{t+1} = X_t. \tag{6}$$

Though with significant simplicity, the persistence approach is difficult to be outperformed for the look-ahead times shorter than a few hours. The generalized persistence method is defined, namely, that the future prediction target is the average of the last T measured values, expressed as,

$$X_{t+k} = \frac{1}{T}\sum_{i=0}^{T-1} X_{t-i} \tag{7}$$

which is also known as the moving average. In spite of its simplicity, it is the most popular reference model in short-term forecasting of solar energy as well as wind power [18], [23]. It is reasonable that any newly developed prediction model should perform better than any naïve reference model; otherwise it cannot be meaningful. Persistence forecast accuracy decreases significantly with forecasting horizon [24].

B. ARMA

The auto-regressive moving average (ARMA) is one of the most popular time series forecasting models due to its ability to extract useful statistical properties [25]. Theoretically, it is based on two elementary parts: the moving average (MA) and the autoregressive (AR), expressed as,

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

where X_t is the forecasted solar power/irradiance at time t, p is the order of the AR model, φ_i is the i^{th} AR coefficient, q is the order of the MA error term, θ_i is the j^{th} MA coefficient, and ε denotes the white noise, which is an independent variable with zero mean and constant variance.

ARMA is usually expressed as ARMA(p, q), where p and q are the order of AR and MA, respectively. Mathematically, ARMA(p, q) can be transformed to an AR(p) model when $q = 0$, and an MA(q) model when $p = 0$. The ARMA model is usually applied to auto correlated time series data and has become a popular and practical tool for predicting the future value of a specific time series. ARMA models are very flexible since they can represent several different types of time series by using different orders. They have been proved to be competent in prediction when there is an underlying linear correlation structure in the time series. ARMA is applied to forecasting future solar generation in California based on solar radiation data originating from SolarAnywhere, and shows better performance than the persistence model [24].

C. ARIMA

The major limitation of the ARMA model is that the objective time series must be stationary, i.e., the statistical properties of time series do not change over time. The auto-regressive integrated moving average (ARIMA) model is developed for nonstationary random processes. An ARIMA(p, d, q) model of the nonstationary random process X_t can be expressed as,

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

where L denotes the lag operator defined by $LX_t = Y_{t-1}$, ϕ_i is the AR coefficient, θ_i represents the MA coefficients, ε_t is a white noise that is independent and identically distributed random variables with zero mean, p is the order of AR, d is the number of nonseasonal differences, and q is the MA order. In the case of $d = 0$, ARIMA(p, d, q) is transformed to be an ARMA(p, q) model.

The ARIMA model is the most general class of models for time series prediction. The success of ARIMA is because of its exceptional ability to capture the periodical cycle better than other methods [25]. In [26], input data of ARIMA are transformed to log values to predict solar irradiance.

D. ARMAX

Theoretically, both ARMA and ARIMA cannot involve the process behavior. To consider exogenous inputs, the autoregressive-moving-average model with exogenous inputs

(ARMAX) model is applied, which has proved to be a great tool in time series prediction [27]. ARMAX is actually an extension of ARIMA and can be more flexible for practical use of solar power prediction because it can include external variables such as temperature, humidity, and wind speed. The model can be referred to as ARMAX(p, q, b) with p AR terms, q MA terms and b exogenous inputs terms, defined by,

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

where η_i is the parameters of the exogenous input d_t.

ARMAX is proposed for PV power forecasting and takes into account temperature and humidity as exogenous inputs that can be easily assessed from the local observatory. It achieves better performance than the ARIMA model [28]. A novel multi-time scale data-driven forecast model based on spatio-temporal (ST) and autoregressive with exogenous input (ARX) is developed for a solar irradiance forecast model. Simulation results that use the real solar data of PV sites in California and Colorado demonstrate the proposed model can derive satisfactory results for 1 h and 2 h look-ahead times [29].

IV. Artificial Intelligence Models

AI techniques are being used in various fields, including forecasting, pattern recognition, control, optimization, and so on. Due to the high leaning and regression capabilities, AI techniques have been widely employed for modeling and prediction of solar energy.

A. *Artificial Neural Networks*

Theoretically, multilayered feedforward neural networks (NNs) can be universal approximators and have tremendous capability to approximate any nonlinear mapping to any degree of accuracy [30]. The typical structure of an NN is shown in Fig. 3.

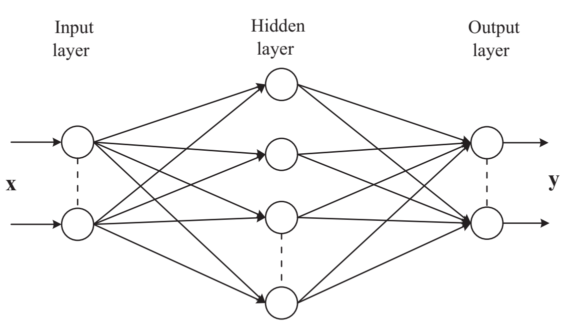

Fig. 3. Typical structure of a feed-forward neural network.

Given a dataset with N distinct samples $\{(\boldsymbol{x}_i, \boldsymbol{t}_i)\}_{i=1}^{N}$ where the inputs $\boldsymbol{x}_i \in \boldsymbol{R}^n$ and the outputs $\boldsymbol{t}_i \in \boldsymbol{R}^m$, the NN with K hidden nodes and activation function $\psi(\cdot)$ for approximating the N samples can be expressed by

$$f_K(\boldsymbol{x}_j) = \sum_{i=1}^{K} \beta_i \psi(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i),\ j = 1, \ldots, N. \tag{11}$$

where $\boldsymbol{a}_i$ denotes the weight vector between the i^{th} hidden neuron and the input neurons, β_i is the weight vector between the i^{th} hidden neuron and the output neurons, b_i represents the threshold of the i^{th} hidden node, and $\psi(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i)$ is the output of the i^{th} hidden node with respect to the input $\boldsymbol{x}_j$.

Theoretically, the parameters of NN can be optimized through different algorithms, among which the back-propagation (BP) algorithm is the most common gradient-based algorithm with the objective function defined by

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

As an alternative to conventional approaches, ANNs have been successfully applied to solar forecasting [31]. A short-term solar irradiance forecasting model has been built based on a BP neural network and time series that avoids over-fitting and is able to reach accurate solar irradiance prediction [32]. Multilayer Perceptron (MLP) is utilized to predict the solar irradiance on the basis of 24 h realistic data from Trieste, Italy [33]. The proposed MLP-model provides reference to grid connected photovoltaic plants (GCPV) and improves the control algorithms of charge controllers.

In [34], a novel PV power forecasting model is proposed based on BP NN, which considers the aerosol index as an additional input parameter to forecast the next 24-h PV power outputs. Experimental results demonstrate that the proposed approach performs better than traditional ANN methods that consider temperature, humidity, and wind speed. In [35], three distinct ANNs are established to fit three typical types of days (sunny, partly cloudy, and overcast) for short-term forecasting of the power generated by a large-scale PV plant located in southern Italy. ANN is applied to predict small solar panel to determine the highest representative of solar prediction horizon for small scale solar power system applications [36]. Bayesian neural network (BNN) is proposed for estimating the daily global solar irradiation with the input parameters of air temperature, relative humidity, sunshine duration, and extraterrestrial irradiation, which has superior performance comparing with classical NN and empirical models [37]. Wavelet based ANN approach is proposed to forecast solar irradiance in Shanghai, indicating that more accurate forecasts can be produced due to the application of wavelet [38].

B. *Other Models*

In addition to ANNs, there are a variety of AI models applied to solar energy forecasting. Radial Basis Function neural network (RBFNN) is used for the prediction of the daily global solar radiation using meteorological data such as air temperature, sunshine duration, and relative humidity [39]. A least-square support vector machine (LS-SVM) based model is proposed for short-term solar power prediction [40]. The LS-SVM model outputs the forecasted atmospheric transmissivity that is converted to solar power and outperforms a reference AR model and RBFNN based model. Several AI techniques including linear, feed-forward, recurrent Elman and Radial Basis Function NNs together with the adaptive neuro-fuzzy inference scheme are proposed for the forecasting of mean hourly global solar radiation [15]. The power production forecasting of a PV system is executed based on insolation forecasting with 24-hour look-ahead time by using weather reported data, fuzzy theory and NN [41]. A weather-based hybrid method for day ahead hourly forecasting of PV power is proposed consisting of classification, training, and forecasting stages [11]. Self-organizing map (SOM) and learning vector quantization (LVQ) are applied to classify the collected historical data of PV power outputs. Support vector regression (SVR) is used to train the input/output data of temperature, probability of precipitation, and solar irradiance. Fuzzy inference is employed to select the trained model for accurate prediction. In [42], the Gamma test (GT) is combined with local linear regression, multi-layer perceptron (MLP), Elman neural network, neural network auto-regressive model with exogenous inputs (NNARX) and adaptive neuro-fuzzy inference system (ANFIS) to successfully reduce trial and error workload. The methodology is then tested on solar radiation at the Brue catchment, UK. A wavelet recurrent neural networks (WRNNs) is proposed for 2-day solar radiation forecast to exploit the correlation between solar radiation and other related variations of wind speed, humidity, and temperature [43]. A hybrid solar radiation prediction model combining fuzzy and neural networks is developed in [44], where future sky conditions and temperature information derived from National Environment Agency (NEA) are classified as different fuzzy sets based on the fuzzy rules.

V. Physical Models

Different from statistical models and AI techniques, physical models utilize solar and PV models to generate solar irradiance/power prediction. The generalized framework of physical approaches is shown in Fig. 4.

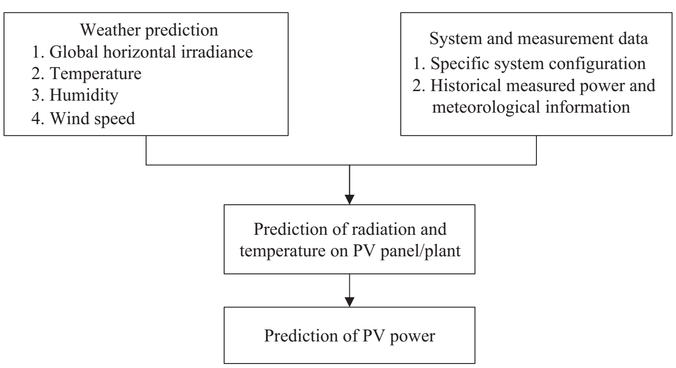

Fig. 4. Typical framework of physical approaches for PV power forecasting.

A. Sky Image-Based Model

The cloud cover and cloud optical depth have critical influence on solar irradiance at the surface level. Determining cloud states would be beneficial for solar irradiance forecasting. Generally, the sky image-based method is based on the analysis of the cloud structures during a given period. Satellites and ground-based sky image approaches have been used for the prediction of local solar irradiance.

Satellites have been used for predicting local solar irradiance conditions. Satellite image based models are based on detecting and recording the cloud structures during some time period and have high spatial and temporal resolution for solar irradiance prediction. Clouds can be detected and characterized from the images to predict GHI relatively accurately up to 6 h ahead. The time series derived from the analysis data of satellite images can be used to detect the motion of cloud using motion vector fields [45]. The short term forecasts of solar irradiance up to 6-h ahead is conducted based on Meteosate satellite images [46]. Similar forecasts are obtained based on the images of the Geostationary Operational Environment Satellite in [18]. An advanced model of estimating ground solar irradiance from satellite (AMESIS) has been developed with better accuracy for the incident solar radiation at the surface based on the spinning enhanced visible and infrared imager (SEVIRI) satellite measurements [17]. The application of new sensors such as SEVIRI can improve the solar prediction accuracy as well as the high spatial and time resolution according to the specific requirements of solar energy applications.

In contrast to the satellite image based method, ground-based sky images can provide a much higher spatial and temporal resolution for solar forecasts, on the basis of a total sky imager (TSI) [47]. It can detect the cloud shadow and thus capture sudden changes in the irradiance, which would be crucial for large-scale PV power plants or distribution network feeders with a high share of PV. If a single TSI is utilized at a site, only short look-ahead time prediction can be achieved because of the designated spatial scale of cloud images and large cloud variability. The forecast horizon varies from 5 to 25 min depending on the cloud images according to [47].

B. NWP-Based Models

Numerical weather prediction has become the most accurate tool for solar irradiation forecasting with look-ahead time longer than several hours. NWP model is able to predict solar irradiance and cloud coverage percentage based on numerical dynamic modeling of the atmosphere. Theoretically, NWP is based on that precise knowledge about the state of the atmosphere at some specific time and the correct physical laws that governing the transition of the atmosphere by the basic differential equations.

In general, NWP provides more benefits than aforementioned prediction models. Satellite imagery models are only suitable for the 1 to 5 h ahead forecast horizon. NWP models are used to predict the state of the atmosphere up to 15 days ahead. There is general consensus that NWPs provide more accurate forecasts than satellite based methods under the look-ahead time beyond 4 hours [46].

Several NMP models can be used in solar forecasting, including European Centre for Medium-Range Weather Forecasts (ECMWF), North American Mesoscale (NAM), Global Forecast System (GFS) and so on [16]. ECMWF is used to predict regional PV power output in Germany with three days look-ahead time [46]. Generally, forecast accuracy has increased for regional forecasts depending on the size of the region. The NAM, GFS, and ECMWF have been validated in GHI forecasts for the continental United States (CONUS) ground measurement data [48]. It has been proved that ECMWF has the highest accuracy in cloudy conditions, while GFS has the best performance in clear sky conditions. A forecasting model based on grid point value (GPV) datasets is proposed for solar irradiance forecasting using relative humidity, precipitation, and three-level cloud covers [49]. Numerical studies have been conducted in Hitachi and four main cities in Japan, indicating the proposed model is reliable.

Nevertheless, NWP models including NAM, GFS, and ECMWF have some inherent limitations. Due to the insufficient spatial resolution, they predict only average value of a grid and cannot precisely predict the value of a given point. In addition, running NWP requires high computation costs, e.g., output frequency is 1 h for NAM and 3 h for GFS and ECMWF. Due to spatial and temporal limitations, the characteristics of most clouds remain unresolved in NWP with prediction horizons less than several hours [29].

VI. Hybrid Models

In practice, various hybrid solar prediction methodologies have been proposed to integrate the merits of different types of prediction models. An advanced model combining ARMA and a nonlinear autoregressive neural network (NARNN) model offers short-term forecasting of hourly global horizontal solar radiation (up to 915 h ahead) and forecasting of a high-resolution solar radiation database (1 s to 30 s scales) with look-head time up to 47,000 s using measured meteorological solar radiation [50]. A novel hybrid model incorporating both ARMA and Time Delay Neural Network (TDNN) is able to forecast hourly solar radiation providing excellent results, where the ARMA model is applied to predict the stationary residual series, and TDNN is utilized to fulfill the prediction [51]. The seasonal auto-regressive integrated moving average method (SARIMA) and the support vector machines method (SVMs) are combined for hourly solar power prediction of a small-scale GCPV plant with 20 kWp [52]. A novel approach combing the clear sky, AR and ARX models and taking NWPs as input is developed to predict hourly solar power with look-ahead time up to 36 h, and tested on 21 PV systems located in a small village in Denmark [14]. A hybrid forecasting model is proposed by the integration of satellite image analysis to obtain a cloud cover index by self-organizing maps (SOM) and a hybrid exponential smoothing state space (ESSS) model together with ANN [21]. It is tested on hourly solar irradiance in Singapore, showing better performance than traditional forecasting models.

VII. Applications in Smart Grid Energy Management

With large-scale penetration of PV power, the negative effects on the distribution network, especially on the energy management of smart grid is drawing a lot of attention [53]–[57], including problems of voltage fluctuation, power flow, grid losses, short-circuit current of distribution networks, and so on [55]. Solar and PV power prediction could provide meaningful guidance for system operators, electricity participants as well as decision makers of electric power planning.

Forecasting models with different prediction periods have been employed for smart grid energy management. Short-time fluctuation of PV outputs can be extremely large, depending on weather conditions, such as cloud passing [58]–[60]. The accurate very short-time PV power prediction model with prediction period from 30 s to several minutes could help to smooth the PV outputs, so as to avoid large fluctuations of voltage and frequency of smart grid.

To limit the ramp rate of PV generations, various strategies have been applied to smooth the PV outputs. An electric double-layer capacitor [61]–[63], battery storage system [64], fast ramping generators [65], and electric vehicles [66] are commonly utilized technologies to absorb the rapid fluctuations of PV generators. Various strategies are proposed in [67], [68] to schedule intraday electric power of smart grids with PV generation integration. As distributed generation (DG) increases in common practice, the PV generators will pose significant influences in the operation of distribution networks, such as network loss minimization, reliability enhancement and distribution network reconfigurations [69], [70]. Intelligent energy management systems with both grid-connected and islanded operations are modeled in [71], [72], which consider the capacity and charging rate of storage, residential load variations, and distribution network electricity price as well.

In the smart grid environment, the development of day-ahead energy management tools for next-generation PV installations, including storage units and demand response, causes flexibility and uncertainty to smart grid operators. In [73], a hierarchical determinist energy management method is proposed to fulfill central energy management of the microgrid and a local power management on the customer side. A price-based day-ahead energy management system with storage system and demand response to cover the fluctuations of the uncertainties of the PV outputs is proposed in [74]. In particular, the local energy management with residential PV system [75] and building-integrated PV microgrid [76] has been widely discussed by researchers. In addition, day-ahead power scheduling is becoming an important part of power systems considering the thermal generators' slow ramp limitation. The effects of forecast accuracy of large-scale aggregated photovoltaic power generation is evaluated in [77]. Day-ahead scheduling of PV generation combined with battery storage in the unit commitment problems are proposed in [78]–[80]. Another application of day-ahead prediction model is the bidding strategy of PV companies participating in the day-ahead electricity markets [81], [82].

VIII. Conclusion

This paper presents relevant research work on developing PV and solar power forecasting approaches. It describes the characteristics of solar forecasting. Forecasting models of PV and solar power are divided in to four classes: statistical models, AI-based models, physical models and hybrid models. The advantages and disadvantages of different types of prediction methodologies are briefly discussed in this paper.

Moreover, the applications of solar forecasting in smart grid energy management are thoroughly investigated. According to the specific applications, the appropriate solar forecasting methodologies can be chosen to ensure the performance.

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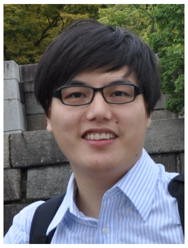

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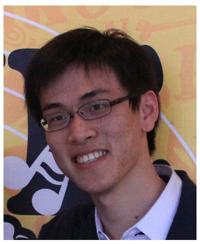

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