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THE ROLE OF SOLAR FORECASTING IN THE MANAGEMENT OF SMALL PHOTOVOLTAIC SYSTEMS: A BIBLIOGRAPHIC REVIEW

EL PAPEL DE LA PREDICCIÓN DE LA RADIACIÓN SOLAR EN LA GESTIÓN DE PEQUEÑOS SISTEMAS FOTOVOLTAICOS: UNA REVISIÓN BIBLIOGRÁFICA

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Abstract

Throughout the last decades an enormous effort has been made to make solar energy an alternative to the use of conventional energy sources. Nevertheless, the use of the solar energy to generate electricity presents a great disadvantage: its integration into the electricity grid. Solar generation is conditioned by weather, being highly intermittent. Currently, the use of solar forecasting is the only way to facilitate the solar energy grid integration. Solar power forecasts are used by grid operators for scheduling of conventional power plant and by solar plants owners to participate in the electricity market. Therefore, the development of accurate solar radiation methods has become a central element for the development of solar energy. In this work a bibliographic review of the solar and PV forecasting methods is conducted. The different methods and techniques are introduced and discussed. Finally, some conclusion on the main advantages and disadvantages are drawn of these methods.

Resumen

La energía solar se está convirtiendo en una alternativa al uso de fuentes de energía convencionales. Sin embargo, la generación eléctrica basada en energía solar presenta una gran desventaja: su integración a la red. La generación solar está condicionada por la meteorología, siendo muy intermitente. Actualmente, el uso de predicciones de la radiación solar es la única forma de abordar el problema. Los operadores de red utilizan los pronósticos de energía solar para programar las centrales eléctricas convencionales y los propietarios de las plantas solares para participar en el mercado eléctrico. Por tanto, el desarrollo de métodos de predicción solar es un campo de trabajo importante. En este trabajo se realiza una revisión bibliográfica de los métodos de predicción de la radiación solar y la energía fotovoltaica. Se presentan y discuten los diferentes métodos y técnicas. Finalmente, se extraen algunas conclusiones sobre las principales ventajas y desventajas de estos métodos.

1.Introduction

Following on the heels of photovoltaic (PV) electricity generation is making rapid inroads in electricity grids worldwide, with growth rates in installed capacity starting from 36.5% for OECD countries over the past decade and installed capacity in these countries reaching 623.2 GW at the end of 2019 (IEA PVPS 2020). In some European countries, PV production already reaches 33.1% [1]of overall power production during clear summer days on a daily basis (IAE 2019). The rapid climb in grid penetration of PV and other variable renewables has prompted research and related initiatives, such as the IEA PVPS Task 14 - High Penetration of PV Systems in Electricity Grids[1].

The integration of solar energy into the electrical network is very important due to the continued growth of consumption. The efficient use of low-energy power for photovoltaic (PV) systems requires reliable prediction(forecast) details. In fact, this combination can provide better service performance if solar radiation variation can be predicted with greater accuracy.

The two main challenges to high penetration rates of PV systems are variability and uncertainty, i.e. The incontrovertible fact that PV output exhibits variability in the least timescales “from seconds to years” and the very fact that this variability itself is difficult to predict.

Forecasting is an important tool for successfully integrating photovoltaic (PV) output power into a grid. The made of accurate weather forecasts for photovoltaic production remains challenging, especially for mass forecasts. Predictable PV power output is essential for many applications, such as micro-grids (MGs), power consumption and management, integrated PV in smart buildings, and renting an electric car. Over the past decade, different studies have been produced on this topic investigating numerical and probabilistic methods, physical models, and artificial intelligence (AI) techniques.

In the last decade, solar radiation and PV forecasting is becoming an important area of research. Two main approaches are often found within the forecasting of PV plant production: indirect and direct. Indirect forecasts firstly predict solar irradiation then, employing a PV performance model of the plant, obtain the facility produced. On the opposite hand, direct forecasts directly calculate the facility output of the plant. Also, many studies only specialize in the prediction of solar irradiation, since it's the foremost difficult element to model and produce other applications aside from solar energy forecasting. Both forecasts (power and irradiation) are approached via similar techniques[2].

This work aims to provide a comprehensive review of recent papers on the subject of solar and PV forecasting, published in the most important journals of the field of meteorology and renewables energies.

To realize this objective, the rest of this report is structured as follows, chapter 2 describe the link between solar and photovoltaic forecasting, chapter 3 gives different forecasting methods for different forecast horizons, and the final chapter we will review in general the solar forecast and the different factors that interacting with it and evaluation of the forecasting error. The architecture chosen, is meant to help the reader to easily understand the different part of the work.

2. The Photovoltaic forecasting and its link to solar forecasting

Different uses of PV forecasts require differing types of forecasts. Forecasts may apply to one PV system, or to the aggregation of huge numbers of systems covering an extended geographical area. Forecasts may specialize in the output power of systems or on its rate of change (also referred to as the ramp rate). Accordingly, different forecasting methods are used. Forecasting methods also depend upon the tools and knowledge available to forecasters, like data from weather stations and satellites, PV system data and outputs from numerical weather prediction (NWP) models[3].Forecasting methods are often broadly characterized as physical or statistical. The physical approach uses solar and PV models to get PV forecasts as presented in the figure 1 reproduced from[3], whereas the statistical approach relies totally on past data to “train” models, with little or no reliance on solar and PV models.

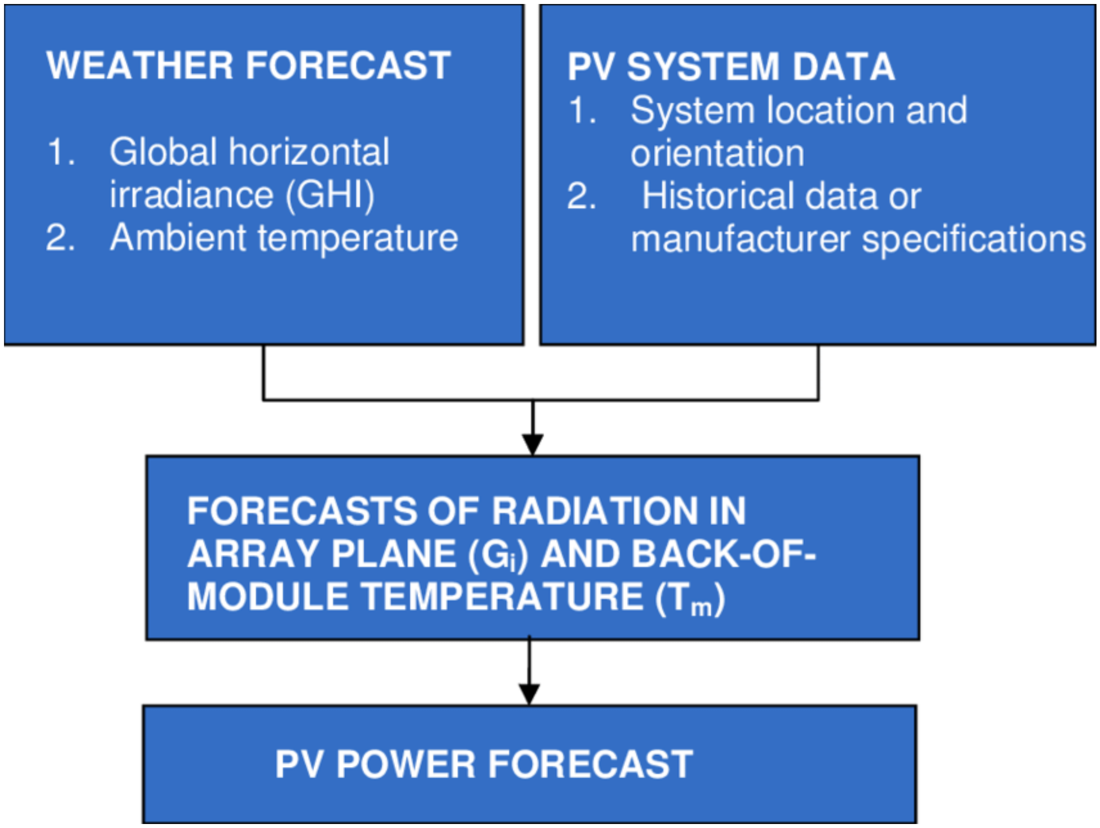

Figure1 Graph of a typical physical approach for generating PV power forecasts from weather forecasts and PV system data.

The basic steps of a typical physical approach are shown in Figure 1 reproduced from[3]. Working upward through the figure, the top product may be a PV forecast as a function of relevant weather variables and PV system characteristics. The most variables influencing PV output power are the irradiance within the plane of the PV array, Gi, and the temperature at the rear of the PV modules (or cells), Tm.

For non-concentrating PV, the relevant irradiance is global irradiance within the array plane, while for concentrating PV it's direct normal irradiance. Other variables, like the angle of incidence of beam irradiance and the spectral distribution of irradiance, are included in some PV models, but high accuracies are obtained with models that don't incorporate these effects. Depending on data availability, PV models can either be fitted to historical data alternatively supported manufacturer specifications[3].

Since neither Gi nor Tm are output by weather forecasts, these must be obtained instead from solar and PV models that calculate these from PV system specifications and weather forecasts, like global horizontal irradiance (GHI) and ambient temperature forecasts. These solar and PV models structure the intermediate step in Figure 1 reproduced from[3]. Tm are often modelled from PV system specifications and from GHI and ambient temperature and, optionally, wind speed. Meanwhile, transposition models to calculate Gi vary in complexity and may make use of only GHI, or of a variety of inputs like albedo, temperature and ratio. For the aim of forecasting Gi, recent works suggests that the selection of the transposition model has little impact on forecast accuracy.

The approach shown in Figure 1 reproduced from[3] concerns one, well-characterized PV system. When PV forecasts must be developed for an outsized number of systems, upscaling methods are needed to generate forecasts covering all systems from forecasts for a limited number of representative systems.

The physical approach with upscaling has been applied as an example by some scientists for PV forecasts over two balancing areas within the German electricity grid. Root mean square errors (RMSEs) for intra-day and day-ahead forecasts of 3.9% and 4.6%, respectively, are achieved with this method over a one-year test period in Germany, where errors are quoted as a percentage of the nominal installed PV power and include night-time values[3].

Meanwhile, purely statistical approaches don't use the solar and PV models that form up the intermediate step in Figure 1. Their start by a training dataset that contains PV power, also as various inputs or potential inputs, like NWP outputs (GHI, Tm, or other), ground station or satellite data, PV system data, and so on. This dataset is employed to train models – like autoregressive or artificial intelligence models – that output a forecast of PV power at a given time supported past inputs available at the time when the model is run[3].

The statistical approach was used as an example to forecast the mean output power of 21 rooftop PV systems in Denmark[3]. Past measurements of the mean power and NWP forecasts of GHI were used as inputs to an autoregressive model with exogenous input (ARX). In this study, they compared three different models: AR with past endogenous data, a Linear Model (LM) with the NWP, and an ARX with both past data and NWP. And the results showed that for 1 h horizons, AR outperformed LM, indicating that the most important variable was solar power. For horizons from 2 to 6 h, the LM slightly outperformed the AR, concluding that both had similar accuracy. Nevertheless, when both groups of inputs were combined in the ARX, they resulted in the best performing model, with an averaged improvement with respect to RMSE of 35%[3].

In two cases where statistical and physical approaches were compared, the statistical approach slightly outperformed the physical. In practice, however, these two approaches are often blended and therefore the division between them isn't sharp. for instance, the physical approach frequently makes use of model output statistics (MOS) methods that compare forecasts to observations over a training period so as to correct forecasts, for example by removing systematic errors. Meanwhile, the simplest statistical approaches make use of the knowledge encapsulated in Figure 1 to pick out input variables judiciously, or to remodel these. as an example, a study calculates clear-sky irradiances within the plane of PV arrays and used this as an input to a statistical model[3].

3. Forecasting methods for different forecast horizons

This chapter is structured as follows. We present a review of forecasting methods, first for forecasting horizons of 0 to 6 hours ahead, and then for longer forecasting horizons, from 6 hours to a few days ahead.

3.1 Solar and PV forecasting from 0 to 6 hours ahead (Intra-day forecasts)

Intra-day forecasts output cover forecast horizons from 15-minutes to 6-hours ahead with a temporal resolution for example of quarter-hour until one hour. Intra-day forecasts are a crucial component of the combination of variable renewable resources into the electrical grid[4].

For solar intra-day forecasting, very different methodologies are preferred, counting on the forecast horizon (Table 1) reproduced from [4].

- Stochastic learning techniques identify patterns in data both within one variable (e.g. autoregression) and between variables or perhaps images. The underlying assumption is that future irradiation is often predicted by training the algorithms with historical patterns.
  - → The simplest stochastic learning technique in generally persistence forecast which is predicated on a current or recent PV power generation plant or radiometer output and extrapolated to account for changing sun angles. Persistence forecast accuracy decreases strongly with forecast duration as cloudiness changes from the present state[4].

- Total sky imagery can be employed to forecast from real-time up to 10-30 minutes ahead by applying image processing and cloud tracking techniques to sky photographs (Figure 2) reproduced from[4]. The reference methods assume persistence of the opacity, direction, and velocity of movement of the clouds. Irradiance is predicted for the present cloud shadow then the cloud shadow is moved forward in time supported cloud velocity and direction[4].
- For satellite imagery, similar methods as in total sky imagery are applied. Clouds reflect light into the satellite resulting in detection and therefore the ability to calculate the quantity of sun rays transmitted through the cloud (transmissivity = 1 – reflectivity – absorptivity). The lower spatial and temporal resolution probably causes satellite forecasts to be less accurate than sky imagery on intra-hour time scales, but extensive comparisons or combinations of the 2 approaches haven't been conducted. Satellite imagery is usually considered the most effective forecasting technique up to a 5-hour forecast range[4].

Technique	Sampling rate	Spatial resolution	Spatial extent	Maximum Forecast horizon	Application
Persistence	High	One point	One point	Minutes	Reference
Whole Sky Imagery	30 sec	10 to 100 meters	Up to 3-8km radius	Dozen minutes	Ramps detection, frequency control
Geostationary satellite imagery	15 min	1 km	65° S – 65°N	5 days	Load following
Numerical weather prediction (NWP)	1 hour	2-50 km	Worldwide	10 days	Unit commitment, regional power prediction

Table 1: Characteristics used for solar forecasting techniques

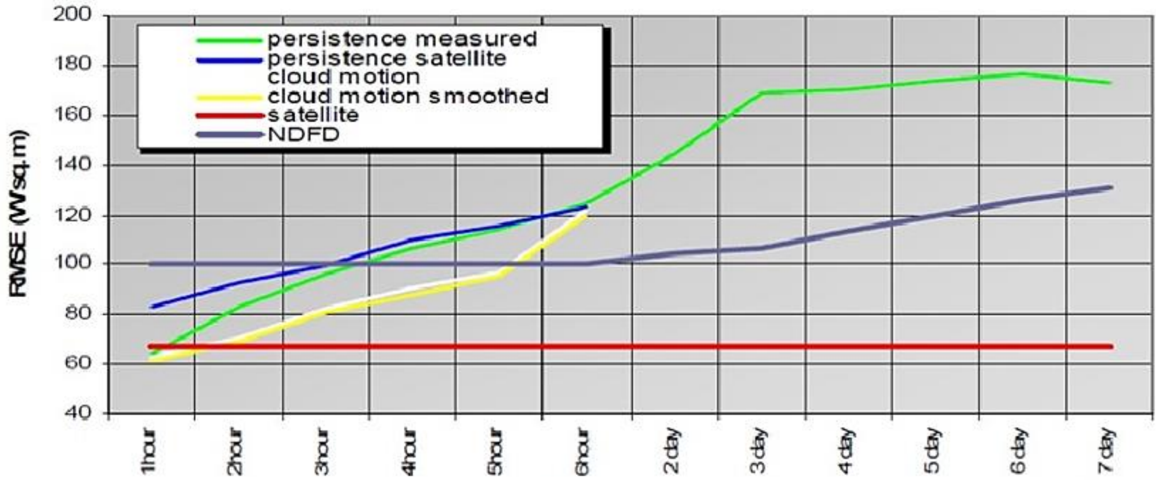

Figure 2: Error of different solar forecasting techniques obtained over a year at seven ground measurement sites.

Figure 2, reproduced from [4], shows the root mean square error (RMSE) of various solar forecasting techniques obtained over a year at seven ground measurement sites. The red line shows the satellite nowcast for reference, i.e. the satellite 'forecast' for the time when the satellite image was taken. Cloud motion forecasts derived from satellite (yellow and white lines) perform better than numerical weather prediction up to five hours ahead. Numerical weather prediction has similar accuracies for forecast horizons starting from 1 hour to three days ahead .

3.1.1 Stochastic Learning Techniques

For very short-term (intra-hour and up to 2 or 3 hours ahead counting on the time-averaging interval) forecasts, stochastic learning techniques without exogenous input (i.e. only the ability plant output is used) is highly competitive in accuracy and comparatively easy to line up, especially when advanced forecasting engines are used [5]. However, the inclusion of relevant exogenous data from sky imagery, satellite, and NWP (in order of accelerating forecast horizon), also as data from other meteorological databases (NWS, NDFD, etc.) can significantly increase accuracy and forecasting skill [5].

- **Time Series Forecasting**

In this section, we introduce linear and nonlinear models that may be applied to a typical "time series" collected from PV systems, so as to estimate future values of the energy production.

A "time series" can be defined as a set of numbers that measures the status of some activity over time. it's the historical values records of some activity, with measurements taken at equally spaced intervals (exception: monthly) with consistency in the activity and also the method of measurement[6].

3.1.2 Linear Models

Linear stochastic difference equation models with random input are often the statistical approach used to forecast time series. These stochastic models use past observations of the time series to predict future values. Such prediction can be used as a baseline to evaluate the possible importance of other variables to the systems.

The most significant of such models is that the already introduced linear autoregressive integrated moving average (ARIMA) model[6]. the fundamental idea behind these models is to seek out a mathematical equation that approximately generates historical patterns. The ARIMA model may be a sort of self-projecting time series model that uses only the time series data of the activity to perform forecasts.

The Box-Jenkins Models are identified as AR (autoregressive), MA (moving average) and also the combination of both is ARMA[6]. AR models express a time series as a linear function of its past values and also the order of the AR models tells the quantity of lagged past values included. MA models include lagged terms on the noise or residuals. Consequently, the ARMA model includes both varieties of lagged terms. The difference between ARMA and ARIMA is that that latter indicates that differencing was already applied to get rid of trends within the time series. ARIMA (p, d, q) defines models with an Autoregressive a part of an order, a Moving average part order, and having applied d order differencing as illustrated within the following equation[6].

$$\left(1-\varphi_1 B-\varphi_2 B^2-\cdots-\varphi_p B^p\right)(1-B)^d\, y_t=c+\left(1-\psi_1 B-\psi_2 B-\cdots\psi_q B^q\right)\varepsilon_t \quad (8)$$

where φs and ψs are the main coefficients to be estimated, c is the constant level, B is the "Backshit" operator and basically characterizes past values and (1-B) symbolizes the differencing operator needed. (1-φ1*B-φ2*B²-…...-φpB^p) refers to the auto-regressive polynomial and ((1-ψ1*B-ψ2*B²-…...-ψqB^q)) denotes the number called the moving average polynomial.

To find the order of the operators (p, q, d), it's common practice to appear at the autocorrelation function (ACF) and partial autocorrelation function (PACF), also as the minimizing information criterion - Akaike's information criterion (AIC) or Bayes information criterion (BIC).

3.1.2.1 Nonlinear Models

The traditional approaches of the Box-Jenkins method assume that the time series within the study are generated from linear processes[6]. Though these linear processes could also be advantageous to know the main points and are easier to clarify and implement, several time series reveal unexplained features during a linear framework. Therefore, and con to traditional statistical methods, nonlinear models like artificial neural networks can capture those structures, are more flexible, and have fewer limitations in estimating the essential relationships between the past values of the time series (inputs) and also the future values (outputs)[6].

3.1.2.2 Solar Energy Forecasting with Artificial Neural Networks

In general, artificial Neural Networks show powerful pattern recognition and pattern classification capabilities and have a large range of applications, in science, business, or industry. What makes artificial neural networks attractive is that the incontrovertible fact that they possess self-adaptive methods that need few a priori model assumptions [6]. Moreover, the relationships among the information are capture and that they are capable of learning from examples and to generalize from experience, no matter the complexity level. Usually, these models correctly infer the unobserved a part of a population after the learning process, though the sample data contains noisy information.

Thus, forecasting is a perfect application area for artificial neural networks since it's performed through estimation of the longer term based on the past steps[6].

The previous section introduced forecasting with artificial neural networks no matter the sector of study. However, this review is curious about assessing the forecasting potential of artificial neural networks applied to the photovoltaic solar forecasting domain, which could be a more modern topic of study. This section identifies relevant studies developed within the field of solar power forecasting with artificial neural networks.

3.1.2.3 Total Sky Imagery

Solar forecasting supported whole sky imagery analysis consists of 4 components[4]:

(1) acquisition of a sky image within the vicinity of the forecast site employing a device like a whole Sky Imager (WSI).

(2) analysis of sky image data to spot clouds (ideally distinguish between thin and thick clouds).

(3) estimation of cloud motion vectors using successive images.

(4) use of cloud location and motion vector data for short-term deterministic or probabilistic cloudiness, irradiance, and power forecasting.

(5) Use of a model to covert cloudiness into solar radiation.

An example is presented in Figure 3b reproduced from[4].

Sky imagery has the advantage of very detailed information about the extent, structure and motion of existing clouds at the time the forecast is formed[4]. These data are often used to generate very short-term (minutes ahead) predictions of future cloud patterns within the vicinity of the solar generation facility. However, the approach at the present doesn't account for cloud development and dissipation or significant changes in cloud geometry. The extrapolation of the cloud patterns is additionally limited to the spatial scale defined by the sector of view of the sky imager. it's possible to increase the spatial scale by using multiple imagers at different locations. Multiple cloud layers with different characteristic motion vectors can also pose a drag since clouds at upper levels could also be partially obscured by clouds at lower levels. the skill will depend, among other things, upon the cloud velocity and therefore the height of the clouds (the ratio of the cloud velocity to the cloud height defines an angular velocity about the WSI which determines the time duration of the cloud being within the field-of-view)[4]. For low and fast clouds, the forecast horizon may only be 3 minutes while for top and slow clouds it's going to be over half-hour, but generally horizons between 5 to twenty minutes are typical. even though cloud size and velocity might be determined accurately, the forecast accuracy depends on the rate at which the cloud field is departing from the evolution defined by the cloud motion vectors (i.e. development, dissipation, etc.)[4].

As an example, at the University of California San Diego[7], sky imagers have recently been specifically developed for solar forecasting applications and have high resolution, high dynamic range, high stability imaging chips that enable cloud shadow mapping and solar forecasting at unprecedented spatial detail (Figure 3a) reproduced from[4]. Such cameras are better ready to resolve clouds near the horizon, which can extend the forecast accuracy, especially for extended look-ahead times[7].

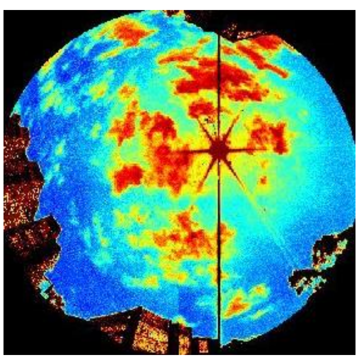

Figure 3a: Ratio of red and blue channel intensity (red-blue-ratio or RBR) on a partly cloudy day from the newly developed UC San Diego solar forecasting sky imager. Areas of high RBR are classified as cloudy.

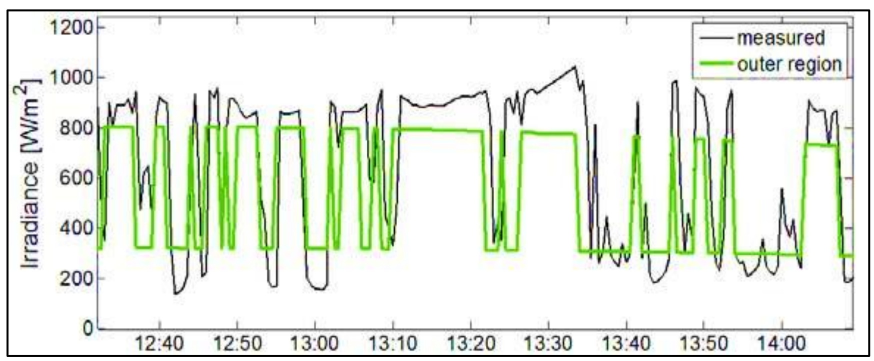

Figure 3b: 30-second GHI ramp forecast from the whole Sky Imager (green) against measurements by a 1-sec GHI station at the UC San Diego campus (black). Timing of cloudy-clear and clear-cloudy ramps on at the moment with cumulus clouds are accurately predicted with the sky imager.

3.1.2.4 Satellite Cloud Motion Vector Approach

The satellite-cloud motion vector approach is conceptually the same as the sky image method; cloud patterns are detected through the employment of visible and/or infrared images from satellite-based sensors flying overhead. The advantage compared to the WSI is that a much larger spatial scale of cloud patterns can be evaluated and that the satellite imagery is continuously available for the whole world. The cloud index (assumed to be proportional to cloud optical depth) are often calculated accurately from the reflectance measured by the satellite. This cloud index method could be a mature approach that has been used extensively in solar resource mapping[4].

Cloud motion vectors is determined from subsequent satellite images. Assuming cloud features don't change between two images, and cloud speed is computed by finding identical features during a successive image.

Conversely, for extended look-ahead times, wind fields from NWP is accustomed improve upon the steady cloud advection vectors from two recent images, but the advantage of the approach has yet to be demonstrated[4]. Classical satellite methods only use the visible spectrum channels (i.e. they only work in day time), which makes morning forecasts less accurate thanks to an absence of time history. to obtain accurate morning forecasts, it's important to integrate infra-red channels (which work day and night) into the satellite cloud motion forecasts[4].

The spatial resolution of geostationary satellite images is 1 km or larger (Meteosat outside high-resolution area) which is much less than ground-based sky images. Hence, with the exception of huge convective clouds, most clouds can't be detected and located directly; one can only conclude that clouds got to be located somewhere within the pixel. Additionally, the time-frequency, download time, and processing of the pictures is slower than that of the sky imager, which implies the forecast can't be updated as frequently. The shortage of high spatial and temporal resolution within the satellite image data reduces the performance of the satellite-based approach relative to the sky imager method for very short-term forecasting lead times. However, the much larger area of coverage implies that the motion of the cloud field is projected forward over longer time periods[4].

Satellite forecasts are shown to outperform Numerical Weather Prediction (NWP) models for short-term forecasts. For 1 h forecasts, the results from persistence and satellite-derived cloud motion are found to get on par, probably because of satellite’s navigation and parallax uncertainties, which tend to mitigate for extended times[4].

3.2 Solar and PV forecasting 6 hours to days ahead

One of the keys uses of solar and PV forecasting is « day-ahead » forecasting of the hourly output power that may be generated by PV systems. These day-ahead forecasts are typically required by about noon for every hour of the following day, which means that day-ahead forecasts must in reality extend a minimum of 36 hours ahead to a couple of days ahead, counting on the timing of electricity markets and of weather forecasts.

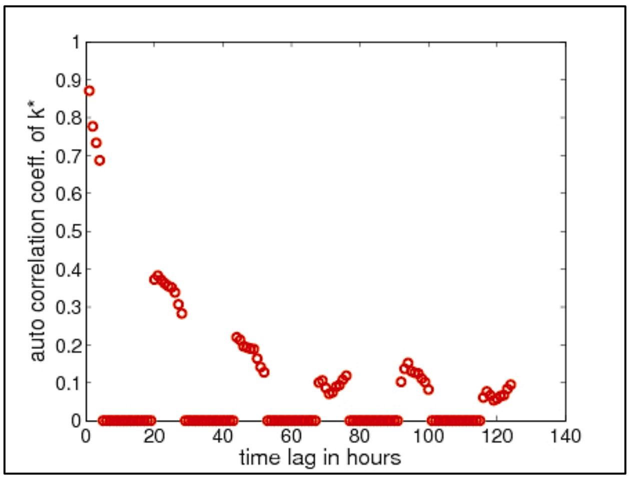

Figure 4 Evolution of the auto-correlation of the clear sky index over several days for Bergen, Norway. The correlation coefficient of an NWP model forecast for the primary forecast day was found to be 0.54.

While key inputs for forecasts within the range of 0 to six hours ahead are past observations, weather forecasts from numerical weather prediction (NWP) models are the key inputs for the day ahead forecasting. This can be illustrated in Figure 4 reproduced from [4], which shows that the autocorrelation of the clear sky index drops rapidly over the course of a couple of hours, limiting the effectiveness of methods based purely on past data and not incorporating dynamics. Methods that include NWP model outputs, therefore, outperform methods based purely on past data after about 2 to three hours ahead for the easiest persistence model to about 3 to five hours ahead for cloud motion vector approaches[4].

3.2.1 Numerical weather prediction models

Numerical weather prediction models are generally based on dynamical equations that predict the evolution of the atmosphere up to many days ahead from initial conditions. The NWP models that underlie all others are global models covering the entire Earth. The model equations and inputs are discretized on a three-dimensional grid extending vertically from the surface of the planet. Since global models are computationally and otherwise intensive, there are only 14 of those currently operational worldwide[8].

Model runs are typically initiated two to four times per day, as an example at 0, 6, 12, and 18 UTC. Their initial conditions are derived from satellite, radar, radiosonde, and ground station measurements that are processed and interpolated to the 3D grid. So as to limit computational requirements, the resolution of worldwide NWP models is relatively coarse, with grid spacings of the order of 40 km to 90 km. Mesoscale or limited area models are NWP models that cover a limited geographic area with higher resolution, which conceive to account for local terrain and weather phenomena in additional detail than global models. Initial conditions for these models are extracted from the worldwide models[8].

The best day-ahead solar and PV forecasts combine NWP forecasts with post-processing of those forecasts so as to boost them or to come up with forecasts that aren't included within the direct model outputs of the NWP, like PV forecasts or direct normal irradiance forecasts.

3.2.2 Improving forecasts through post-processing of NWP models

Forecast improvements are often performed by comparing to measured data during a training period which is employed to develop corrected forecasts. This kind of approach is commonly cited as Model Output Statistics, or MOS.

A number of various MOS approaches are proposed up to now. The subsequent summarizes a number of the key post-processing approaches that are introduced thus far during this rapidly evolving field, and which might be used either singly or in combination.

- **Spatio-temporal interpolation and smoothing**

Since NWP forecasts are generated at discrete grid points, their use at a particular point in space necessitates some sort of interpolation. The easiest method is to use the closest neighbor point on the grid that's closest to the location of interest. Other approaches involve interpolating forecasts from grid points surrounding the purpose of interest. Also, the most effective results are achieved by simply taking an average of forecasts at grid points within a region surrounding the purpose of interest, effectively smoothing the associated forecasts. Also, the most effective results by averaging over areas of about 100 km by 100 km for forecasts supported the ECMWF and GFS global models, and perhaps the optimal results by averaging outputs of the GEM model over larger areas of 300 km by 300 km or more, as shown in Figure 5 reproduced from[4], for the mesoscale forecast model WRF with 10 km resolution.

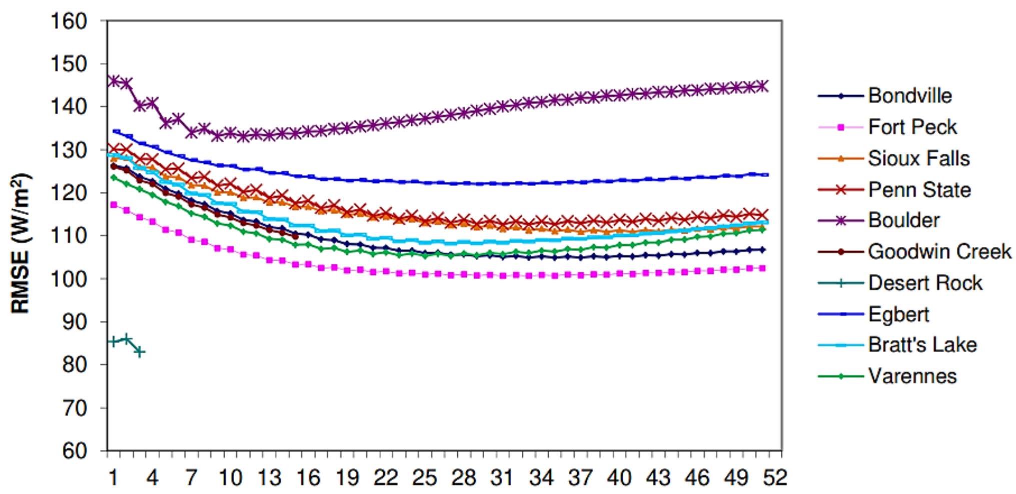

Figure 5 Reduction in root mean square error through averaging of solar forecasts over square grids consisting of N by N grid points.

In addition to spatial interpolation, temporal interpolation must be used when available NWP model outputs have a lower temporal resolution than desired. as an example, used linear interpolation of the clear sky index to interpolate 3-hourly GHI forecasts from ECMWF to an hourly time step.

❖ Model Output Statistics to improve forecasts from a single NWP model

Once point forecasts are generated, these can be improved by comparing to measured data during a training period over which improved models are developed and fitted. This MOS approach works best when forecast corrections are updated in time (recursive) and trained separately over different conditions or regimes, since forecast errors often rely on the time of the day and of the year, on sky conditions, etc. Moreover, NWP models are frequently modified and updated, which necessitates forecast corrections to adapt accordingly. Figure 6, reproduced from [9], shows an example of MOS procedure. Particularly, this figure shows the bias of the forecasts as a function of the clearness index (Kt*) and the solar zenithal angel. The values are used for removing the bias of the forecasts.

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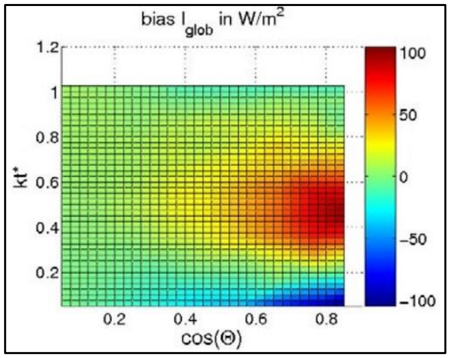

Figure 6 Solar forecast bias as a function of the cosine of the solar zenith angle and of the (forecasted) clear sky index.

Various other MOS-based approaches are developed to forecast GHI or PV power one to many days ahead, including autoregressive methods [9], also as various artificial intelligence methods including artificial neural networks Inputs that are employed by these authors include:

- NWP and other forecasts: GHI, cloudiness, temperature, probability of precipitation, relative humidity, wind speed, and direction.
- Ground station weather measurements (GHI, relative humidity, temperature, vapor pressure, sunshine duration)
- Satellite-based GHI and cloud cover indices
- PV power measurements
- Variables related to solar geometry and time (zenith angle, clear sky irradiance)

For models that need stationary statistic time steps series, the clearness index or the clear sky index are often used, or a PV equivalent of those.

❖ **Combining various NWP models**

One way to enhance solar and PV forecasting is to mix forecasts from different NWP models or from different members in an ensemble forecast, where initial conditions or physical parameterizations are varied within one NWP model to yield probabilistic forecasts. This approach is being actively pursued within the case of wind forecasting, where significant improvements in forecast accuracy are achieved by combining models with weights that rely on prevailing climatic conditions. Within the solar case, slight improvements in forecast accuracy are achieved just by averaging the forecasts from two or three NWP models. Similarly, found an average of three different neural network forecasts based on past observations has been found to outperform the individual ANN forecasts[4].

4.Point forecasts and area forecasts

4.1.1 Upscaling

The representation of the entire power output of all power systems installed at a given area using data from a subset representative of these systems is typically referred to as upscaling. Upscaling techniques are extensively utilized in forecasts of wind energy power output, where generating forecasts for every turbine in the given area, besides requiring normally the availability of detailed data, may be a time-consuming task.

Similar challenges also arise in regional forecasts of photovoltaic power, where specific information for each photovoltaic system installed are often difficult to get, as an example, in areas with large deployments of residential systems. During this case, upscaling techniques also can be applied as they will simplify the calculations and reduce the necessity for extended and detailed characteristics of all photovoltaic systems installed in a given area. In spite of this fact, technical literature regarding regional forecasts of photovoltaic power with upscaling techniques isn't nearly as numerous in the case of wind energy.

In order to represent an entire set of photovoltaic systems using only a subset of these systems, two steps got to be followed. First, the subset must be chosen in such the way that its behavior, regarding power output, is representative of the behavior of the entire set of photovoltaic systems. This characteristic is achieved by selecting the subset distribution of PV systems with the required behavior, or by calculating the required number of randomly selected systems that together will make the subset present characteristics like those of the whole set of systems. The second step in upscaling is to scale the output power of the subset to get the output power of the entire set. This step can include post-processing supported comparing the power output of the chosen subset with the measured power of the entire set.

As indicated above, variety of different approaches is employed in the primary and second steps. As an example, within the start, different errors or correlation parameters can be used to find the required number of randomly selected systems to incorporate within the subset in order to properly represent the whole set. Also, the subset might be assembled not with variety of randomly selected systems but with a distribution of systems selected in order that their characteristics, like location or specifications, are representative of the whole set of installed photovoltaic systems. This was the approach was used, In order to do the upscaling, they matched the spatial distribution of the representative subset to it of the real data set by assigning to every PV system a scaling factor supported its geographic location on a grid with a resolution of 1° x1°. For every grid point, they derived a scaling factor defined because the ratio between overall installed power and installed power of the subset for this grid point; each PV system was then assigned the scaling factor similar to the closest grid point.

4.1.2 Error reduction for area forecasts

Area forecasts of the power output of photovoltaic systems are important for system operators responsible of keeping the balance between demand and provide of power in electricity grids. Area forecasts is done using data from all systems installed in a given area or using an upscaling technique as described within the previous section. The errors of area forecasts are typically significantly less than the corresponding errors of forecasts of single systems. This error reduction was explored, and it gives that the coefficient of correlation between the solar forecast errors at two locations can be modeled with an exponential function of the distance between the 2 stations, with errors decreasing rapidly with increasing station distance initially, and more slowly for distances of about 200 km or more. This effect was modeled in detail in a case of wind. In [4], authors showed that both the dimensions of the geographical area contributed to error reduction, with the reduction from an increased number of stations saturating beyond a particular threshold for a given geographical area.

It is difficult to quantify the error reduction that may be achieved in area forecasts of power output, because the parameters of the exponential functions mentioned above rely on climate diversity within the region, PV system distribution, capacities, etc. Nevertheless, there are case studies available within the technical literature. As an example, a study shows that solar and PV forecast accuracy improves significantly because the size of the geographical area into consideration increases, with a discount in root mean square error (RMSE) of about 64% for a forecast over a neighborhood the dimensions of Germany as compared to a point forecast[4].

In a Japanese case study, they propose a forecast system based in general on irradiance forecasts up to 1 day ahead from the JMA-MSM (Japanese Meteorological Agency Meso-Scale Model)[10]. This model provides forecasts for 0 to 33 hours ahead with a spatial resolution of 5 km x 5 km in Japan. Hourly forecasts of irradiance are obtained with Just in Time modeling. The case study used data from 6 meteorological stations and 11 installed photovoltaic systems, from 4/2003 to 4/2007. The authors found that for a collection of systems in a neighborhood of 100 km x 60 km within the Kanto region in Japan, the mean absolute error (MAE) for the regional forecasts was 22% less than the mean MAE for the purpose forecasts. The error reduction was around 70% (relative error ratio of 0.3) as shown in Figure 7 reproduce from[10] within the Japanese case. Figure 8 reproduced from [10] shows the Kanto region case study using data from 64 PV systems, to reflect the actual fact that Japanese utility companies control the frequency in each region and can require regional forecasts. The "average distance" in Figure 8 is defined because the average of distance among evaluated points. during this case, the error reduction factor reached maximum values of around 0.4 (60% reduction in error) when large numbers of points spread across the Kanto region were considered[10].

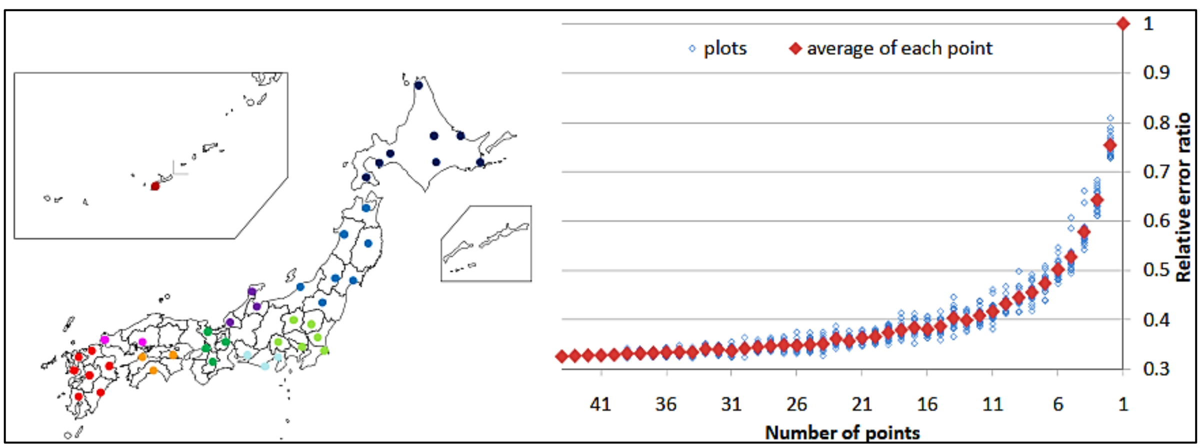

Figure 7 Correlation between average distance and relative error ratio in Japan

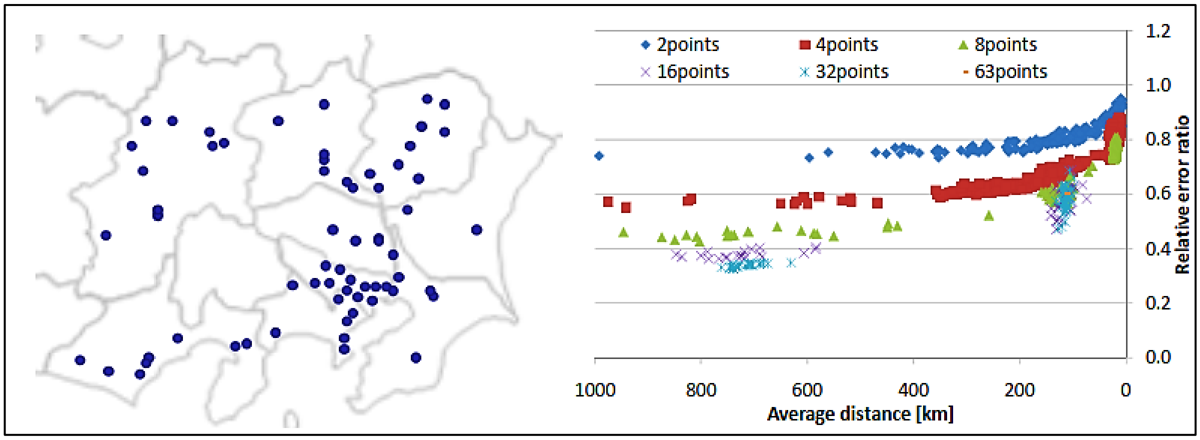

Figure 8 Correlation between average distance and relative error ratio in Kanto region using 64 PV systems' data

5.Forecast accuracy

In this chapter we will review in general the solar forecast and the different factors that interacting with it. And a comparison between the accuracies of various forecasts against a typical set of test data.

5.1 Accuracy metrics and confidence intervals

Various metrics have been proposed and used to quantify the accuracy of solar and PV forecasts. Which metrics are most appropriate depends on the user: system operators need metrics that accurately reflect the costs of forecast errors, while researchers require indicators of the relative performance of different forecast models, and of a single model under different conditions.

Appropriately selecting and specifying the validation dataset over which forecasts will be evaluated is crucial. First, the test dataset should exclude all data that was used to train models and to develop post-processing methods, so that evaluation is performed on independent data ("out-of-sample tests"). Also, data should be screened with appropriate quality check procedures, such as those outlined, to ensure that forecast evaluation reflects forecast accuracy rather than issues with the observations used to test the forecasts. Finally, the test dataset should be appropriately selected and specified alongside evaluation results. Dataset selection should reflect the intended use of the forecasts or evaluation: for instance, system operators and utilities are interested in forecast accuracy overall hours of the day, whereas researchers may wish to exclude the trivial case of forecasting night time irradiance or PV output or to examine accuracy as a function of variables that affect it[4].

Whatever the intended use of forecasts, standardizing performance measures or metrics helps facilitate forecast evaluations and benchmarking. A study has attempted to standardize solar forecast benchmarking and accuracy metrics, also this is often another have proposed standardized measures of wind forecast accuracy. Common metrics proposed by these authors include mean bias error (MBE, or bias), mean square error (MSE) and root mean square error (RMSE), mean absolute error (MAE), and standard deviation (SDE or σ). These are defined as follows[4]:

$$RMSE = (MSE)^{1/2} = (\frac{1}{N}\sum_{i=1}^{N} e_i^2)^{1/2} \tag{1}$$

$$SDE = \sigma = \left(\frac{1}{N-1}\sum_{i=1}^{N}(e_i - \overline{e_i})^2\right)^{1/2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_i| \tag{3}$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N} e_i \tag{4}$$

$$e_i = y_{i,forecast} - y_{i,observed} \tag{5}$$

where y_i, forecast, and y_i, observed are the i_{th} forecast and observation, respectively, and e_i is that the i_{th} error, with $i = 1 \ldots \ldots N$ running through all forecast-observation pairs within the test dataset.

The bias or MBE is that the average forecast error and encapsulates the systematic tendency of a forecast model to under or over-forecast, model output statistics approaches is used to significantly reduce the bias when past observations are available. MAE gives the mean magnitude of forecast errors, while RMSE (and MSE) give more weight to the biggest errors[4].

MSE, SDE and bias are related as follows:

$$RMSE^2 = MSE = MBE^2 + SDE^2 \tag{6}$$

In other words, the quality deviation captures the part of the RMSE that's undue to systematic error and provides a sign of the RMSE that may be achieved once the bias is basically eliminated.

All these metrics are often stated as absolutes, alternatively normalized by dividing by a reference value to facilitate comparisons. as an example, wind and PV forecasts are commonly normalized by dividing by the rated capacity of the PV or wind systems, since this can be an easy and simply accessible reference value. Meanwhile, solar forecasts are often normalized by dividing by the mean irradiance over the test dataset. the various definitions for the reporting of normalized accuracy metrics are summarized, evaluated, and compared[4].

5.2 Benchmarking of forecasts

Since forecast accuracy depends strongly on the placement and period of time used for evaluation and on other factors, it's difficult to judge the standard of a forecast from accuracy metrics alone. More insight is gained by comparing the accuracies of various forecasts against a typical set of test data.

For instance, some simple forecast methods can function benchmarks against which to evaluate forecasts. One very simple, commonly used reference is that the persistence forecast, which basically assumes that “things stay the same”, which within the solar case implies projecting past values of the clear sky or clearness index into the longer term[4]. Other common reference forecasts include those supported climate normal and easy autoregressive methods. regardless of the choice of a reference model, forecasts are compared just by comparing their accuracy metrics, alternatively by calculating the skill score for a given metric, which is defined as:

$$Skill\ score = \frac{Metric_{reference} - Metric_{forecast}}{Metric_{reference} - Metric_{perfect\ forecast}} \tag{7}$$

In other words, the skill score of a forecast compares the advance within the chosen metric with relation to the reference model (numerator) to the current same improvement within the case of an ideal forecast with no errors (denominator). for instance, reported an improvement in RMSE by 36%[11] with reference to persistence, which corresponds to an RMSE skill score with reference to the persistence of 0.36[11].

Benchmarking also can be wont to identify conditions under which forecasts perform relatively well, or poorly. as an example, as mentioned previously, NWP model forecasts underperform persistence for very short forecast horizons of up to about 2 or 3 hours, indicating that NWP forecasts have little skill over these horizons. Similarly, a study has used comparisons to persistence to flag problems with PV forecasts in Germany during the winter and to develop improved algorithms to handle snow[11].

5.3 Factors that influence forecast accuracy

The solar and hence the PV production forecasting accuracy are mainly influenced by the variability of the meteorological and climatological conditions. To a minor extent, accuracy is suffering from uncertainties associated with the various modelling steps that are needed to create energy forecasts out of irradiation forecasts. the maximum achievable accuracy is set mainly by the subsequent factors:

- Local climate and weather conditions
- Single-site or regional forecast
- Forecast horizon
- Accuracy metric used

6.Conclusion

Solar power forecasting becomes an important task as solar energy starts to play a key role in electricity markets. The complexity of issuing reliable forecasts is principally caused by the uncertainty in the solar resource assessment. Moreover, energy markets work within different time frames and, thus, specific forecasts are required for each time horizon. many models appear to issue forecasts as accurate as possible.

This work investigates solar PV power generation forecasting techniques presented to date and describes the characteristics of various forecasting techniques. These approaches are compared together in terms of forecast methodology, time horizon, measurement error. The merits and demerits of different types of forecasting techniques are discussed as well. This work classifies solar PV forecasting methods into 3 major categories, time-series statistical, physical, and ensemble methods.

From the collection of studies shown in this work, the following results and conclusions about solar power forecasting may be stated:

- The forecast horizon where most research has been done is the day-ahead. The reason for this behavior is that most of the energy is traded in day-ahead markets when planning and unit commitment takes place. As energy markets evolve, such as the case of EIM, intra-hour trading will become more important and thus, more research will focus on that time horizon and with a better applicability in electricity markets.

- As the time horizon increases, the proportion of works that use NWP in their models in comparison to those which use other variables also grows.

- The statistical approach was not only used on most occasions, but it also proved superior when put next to the parametric approach. Most recent works used machine learning techniques, thanks to the ease of modeling without the need of knowing PV plant characteristics.

- Spatial averaging reduces the variability of the solar resource and generates regional forecasts that are more reliable than single-site ones. This is caused by the smoothing effect, that cancels errors with opposite signs in different PV plants. Regional forecasting results are also more useful for grid operators, which must handle the production of several distributed plants, whose impact is treated as an ensemble. However, point forecasts are needed by plant operators to assist them in market bidding.

- Traditionally, most of the solar forecasts were deterministic, that is, for every forecast horizon, they provided a single value. Nevertheless, state-of-the-art works are introducing probabilistic forecasts, which enable a better risk assessment and decision making. Compared to load or wind power forecasting, the state of probabilistic solar power forecasting is still immature and several challenges are yet to be solved.

- The economic impact of solar power forecasting has not been analyzed in this work. But recent papers have shown the potential for reducing balancing reserves with improved forecasts, yielding important economic savings, and strengthening the grid. Economic assessments of improved forecasts are system-specific because they greatly depend on the type of energy generators present in each electrical system. Also, reliable forecasts allow avoiding penalties to plant managers caused by deviations between scheduled and produced.

- Classical statistical metrics have been proved to omit important information in the evaluation of forecasting models. New metrics, not only statistical but also to quantify uncertainty, characterize ramps, and value economic impacts are introduced recently, improving the capacity of model assessment. Guidelines for a proper model evaluation have been stated, not only referring to the metrics used but pointing out other crucial aspects for model comparisons as well.

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