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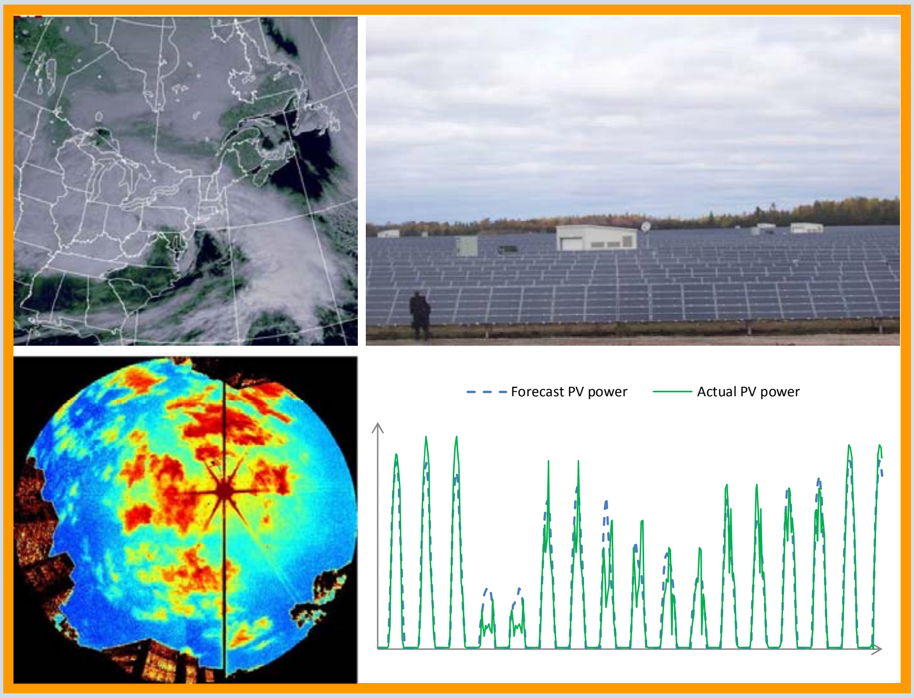
Photovoltaic and Solar Forecasting:

State of the Art



PVPS

PHOTOVOLTAIC
POWER SYSTEMS
PROGRAMME

Report IEA PVPS T14-01:2013

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IEA PVPS Task 14, Subtask 3.1
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Foreword

The International Energy Agency (IEA), founded in November 1974, is an autonomous body within the framework of the Organization for Economic Co-operation and Development (OECD) that carries out a comprehensive programme of energy co-operation among its 23 member countries. The European Commission also participates in the work of the Agency.

The IEA Photovoltaic Power Systems Programme (IEA-PVPS) is one of the collaborative R & D agreements established within the IEA and, since 1993, its participants have been conducting a variety of joint projects in the applications of photovoltaic conversion of solar energy into electricity.

The mission of the IEA PVPS program is: To enhance the international collaborative efforts which facilitate the role of photovoltaic solar energy as a cornerstone in the transition to sustainable energy systems by:

1. ensuring sustainable PV deployment,
2. improving PV performance and reliability, and
3. assisting in designing new market structures and regulations which will be suitable for the widespread adoption of unsubsidised PV.

The overall program is headed by an Executive Committee composed of one representative from each participating country, while the management of individual research projects (Tasks) is the responsibility of Operating Agents. By mid 2012, fourteen Tasks had been established within the PVPS program.

The overall goal of Task 14: “High Penetration of PV Systems in Electricity Grids” is to promote the use of grid-connected PV as an important source in electric power systems at the higher penetration levels that may require additional efforts to integrate dispersed generators. The aim of these efforts is to reduce the technical barriers to achieving high penetration levels of distributed renewable systems.

The current members of the IEA PVPS Task 14 are: Australia, Belgium, Canada, Switzerland, China, Germany, Denmark, Spain, Israel, Italy, Japan, Portugal, Sweden and the United States of America.

This report describes the state of the art of solar and photovoltaic forecasting models used to facilitate the integration of photovoltaics into electric systems operation, and reduce associated uncertainties. The report represents, as accurately as possible, the international consensus of the Task 14 experts on the subject. Further information on the activities and results of the Task can be found at: http://www.iea-pvps.org.

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Executive summary

The field of solar and photovoltaic (PV) forecasting is rapidly evolving. The current report provides a snapshot of the state of the art of this dynamic research area, focusing on solar and PV forecasts for time horizons ranging from a few minutes ahead to several days ahead. Diverse resources are used to generate solar and PV forecasts, ranging from measured weather and PV system data to satellite and sky imagery observations of clouds, to numerical weather prediction (NWP) models which form the basis of modern weather forecasting. The usefulness of these resources varies depending on the forecast horizon considered: very short-term forecasts (0 to 6 hours ahead) perform best when they make use of measured data, while numerical weather prediction models become essential for forecast horizons beyond approximately six hours. The best approaches make use of both data and NWP models. Examples of this strategy include the use of NWP model outputs in stochastic learning models, or the use of measured data for post-processing NWP models to correct systematic deviations between NWP model outputs and measured data.

Benchmarking efforts have been conducted to compare the accuracy of various solar and PV forecast models against common datasets. Such benchmarking is critical to assessing forecast accuracy, since this accuracy depends on numerous factors, such as local climate, forecast horizon and whether forecasts apply to a single point or cover a wide geographic area. In the latter case, which is often the main interest of electric system operators, higher accuracies can be achieved since random errors at distant locations tend to be largely uncorrelated and to partially cancel out.

1. Introduction

Following on the heels of wind power, photovoltaic (PV) electricity generation is making rapid inroads in electricity grids worldwide, with growth rates in installed capacity ranging from 34% to 82% for OECD countries over the past decade and installed capacity in these countries reaching 63.6 GW at the end of 2011 (IEA PVPS 2012). In some European countries, PV production already reaches 30% of overall power production during clear summer days on a regular basis (EPIA 2012). The rapid growth 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*.

The two main challenges to high penetration rates of PV systems are *variability* and *uncertainty*, i.e. the fact that PV output exhibits variability at all timescales (from seconds to years) and the fact that this variability itself is difficult to predict. The current report addresses the second issue, uncertainty, and the method used to address it: photovoltaic forecasting.

This report is structured as follows. Section 2 discusses the link between weather forecasts and PV forecasts. Section 3 presents a review of forecasting methods, first for forecasting horizons of 0 to 6 hours ahead (Section 3.1) and then for longer forecasting horizons, from 6 hours to a few days ahead (Section 3.2). Section 4 specifically examines upscaling, which is used to forecast the output of a large number of PV systems by making use of a representative subset of well-characterized systems. Section 5 examines forecast accuracy – how well forecasts perform, and what factors influence forecast quality. Finally, Section 6 presents the results of an IEA PVPS Task 14 survey of solar and PV forecast models worldwide, illustrating the concepts explored in the previous sections with concrete examples.

2. Photovoltaic forecasting and its link to solar forecasting

Different uses of PV forecasts require different types of forecasts. Forecasts may apply to a single PV system, or refer to the aggregation of large numbers of systems spread over an extended geographic area. Forecasts may focus on the output power of systems or on its rate of change (also known as the ramp rate). Accordingly, different forecasting methods are used. Forecasting methods also depend on the tools and information available to forecasters, such as data from weather stations and satellites, PV system data and outputs from numerical weather prediction (NWP) models.

Forecasting methods can be broadly characterized as *physical* or *statistical*. The physical approach uses solar and PV models to generate PV forecasts, whereas the statistical approach relies primarily on past data to "train" models, with little or no reliance on solar and PV models.

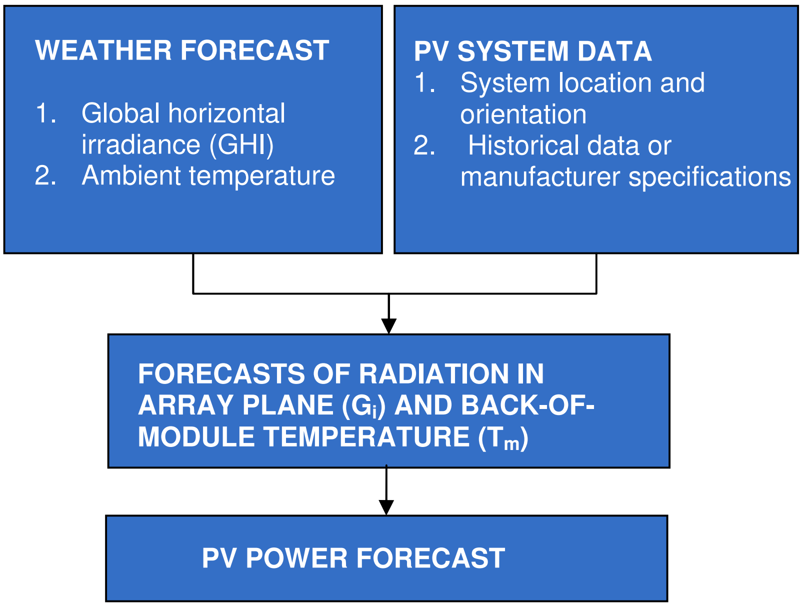

Figure 1: Sketch of a typical physical approach for generating PV power forecasts from weather forecasts and PV system data.

Basic steps of a typical physical approach are shown in Figure 1. Working upward through the figure, the end product is a PV forecast as a function of relevant weather variables and PV system characteristics. The main variables influencing PV output power are the irradiance in the plane of the PV array, G_i, and the temperature at the back of the PV modules (or cells), T_m. For non-concentrating PV, the relevant irradiance is global irradiance in the array plane, while for concentrating PV it is direct normal irradiance. Other variables, such as the incidence angle of beam irradiance and the spectral distribution of irradiance, are included in some PV models, but high accuracies have been obtained with models that do not incorporate these effects. Depending on data availability, PV models can either be fitted to historical data (see e.g. Pelland et al., 2011) or else based on manufacturer specifications (see e.g. Lorenz et al., 2011b).

Since neither G_i nor T_m 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, such as global horizontal irradiance (GHI) and ambient temperature forecasts. These solar and PV models make up the intermediate step in Figure 1. T_m can be modelled from PV system specifications and from GHI and ambient temperature and, optionally, wind speed (see e.g. Lorenz et al., 2011b). Meanwhile, transposition models to calculate G_i vary in complexity and can make use of only GHI, or of a range of inputs such as albedo, temperature and relative humidity. For the purpose of forecasting G_i, recent work by Pelland et al. (2011) suggests that the choice of the transposition model has little impact on forecast accuracy.

The approach shown in Figure 1 concerns a single, well characterized PV system. When PV forecasts must be developed for a large number of systems, upscaling methods (see Section 4.1) are used to generate forecasts covering all systems from forecasts for a limited number of representative systems.

The physical approach with upscaling has been applied for instance by Lorenz et al. (2011b) to generate PV forecasts over two balancing areas in the German electricity grid. Root mean square errors (RMSEs) for intra-day and day-ahead forecasts of 3.9% and 4.6%, respectively, have been achieved with this method to date 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 (Lorenz et al., 2011a).

Meanwhile, purely statistical approaches do not use the solar and PV models that make up the intermediate step in Figure 1. Their starting point is a training dataset that contains PV power, as well as various inputs or potential inputs, such as NWP outputs (GHI, T_m or other), ground station or satellite data, PV system data and so on. This dataset is used to train models – such as autoregressive or artificial intelligence models – that output a forecast of PV power at a given time based on past inputs available at the time when the model is run.

The statistical approach was used for instance by Bacher et al. (2009) to forecast the average output power of 21 rooftop PV systems in Denmark. Past measurements of the average power and NWP forecasts of GHI were used as inputs to an autoregressive model with exogenous input (ARX).

In two cases where (pure) statistical and physical approaches were compared (Huang et al., 2010; Kudo et al., 2009), the statistical approach slightly outperformed the physical. In practice, however, these two approaches can be blended and the division between them is not sharp. For instance, the physical approach frequently makes use of model output statistics (MOS) methods that compare forecasts to observations over a training period in order to correct forecasts, for example by removing systematic errors. Meanwhile, the best statistical approaches make use of the knowledge encapsulated in Figure 1 to select input variables judiciously, or to transform these. For instance, Cai et al. (2010) calculated clear sky irradiances in the plane of PV arrays and used this as an input to a statistical model.

3. Forecasting methods for different forecast horizons

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

Intra-day forecasts are an important component of the integration of variable renewable resources into the electric grid (Jones 2011). For example, in California (the state with by far the largest amount of installed solar power in the US, the independent system operator CAISO uses the following forecasts:

- **The day ahead (DA) forecast** is submitted at 05:30 on the day before the operating day, which begins at midnight on the day of submission and covers (on an hourly basis) each of the 24 hours of that operating day. Therefore, the day ahead forecast is provided 18.5 to 42.5 hours prior to the forecasted operating day. The vast majority of conventional generation is scheduled in the DA market.
- **The hour ahead (HA) forecast** is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. [Note that the CAISO HA forecast is really a 1.75 to 8.75 hour ahead forecast. We will use 'intra-day' here to identify 0 to 6 hour ahead forecasts in contrast to the 'day ahead' discussion in Section 3.2.

CAISO also is considering the implementation of intra-hour forecasts on 5 minute intervals; a similar intra-hour forecast is already implemented by the Midwest Independent System Operator (ISO). The US Federal Energy Regulatory Commission (FERC) has issued a Notice of Proposed Rulemaking requiring public utility transmission providers to offer all customers the opportunity to schedule transmission service every 15 minutes, and requiring providers with variable renewables on their systems to use power production forecasting. Similar day-ahead schedules are applicable throughout the different power exchange markets in Europe. In summary, intra-day forecasts are currently of smaller economic value than DA forecasts but with increasing solar penetration and the expected accuracy improvement of intra-day compared to DA forecasts substantial market opportunities will likely materialize.

For solar forecasting, very different methodologies are preferred, depending on the forecast horizon (Table 1). For a more in-depth discussion see an upcoming book (Kleissl, 2013):

- Stochastic learning techniques identify patterns in data both within one variable (e.g. autoregression) and between variables or even images. The underlying assumption is that future irradiation can be predicted by training the algorithms with historical patterns.
    - The simplest stochastic learning technique is the persistence forecast which is based on current or recent PV power 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 current state.
- Total sky imagery can be used to forecast from real time (*nowcast*) up to 10-30 minutes ahead by applying image processing and cloud tracking techniques to sky photographs (Figure 3). The published methods assume persistence in the opacity, direction, and velocity of movement of the

clouds (Chow et al. 2011). Irradiance is predicted for the current cloud shadow and then the cloud shadow is moved forward in time based on cloud velocity and direction.

- For satellite imagery, similar methods as in total sky imagery are applied. Clouds reflect light into the satellite leading to detection and the ability to calculate the amount of light 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 two approaches have not been conducted. Satellite imagery is commonly considered the best forecasting technique up to 5 hour forecast range (Perez et al. 2010).

Table 1 Characteristics of solar forecasting techniques.

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

Day-ahead forecasting using NWP and stochastic learning techniques is extensively described in Section 3.2. NWP models can also be applied intra-day, but they will not be considered here, since the techniques described in this section typically achieve superior performance for forecast horizons of about 0 to 5-6 hours ahead, as shown in Figure 2.

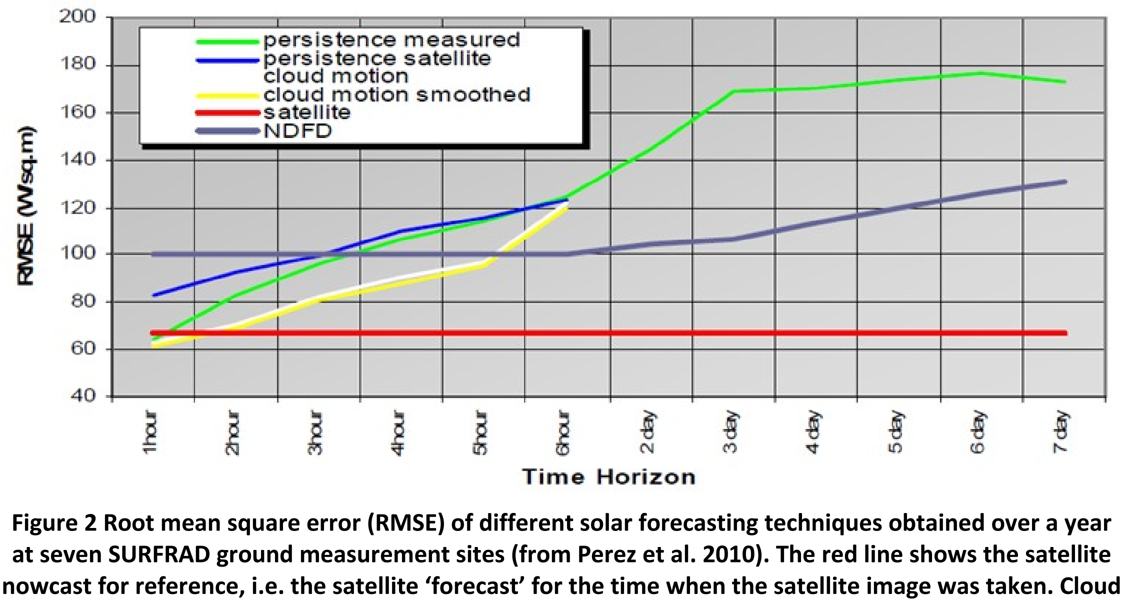

Figure 2 Root mean square error (RMSE) of different solar forecasting techniques obtained over a year at seven SURFRAD ground measurement sites (from Perez et al. 2010). The red line shows the satellite nowcast for reference, i.e. the satellite 'forecast' for the time when the satellite image was taken. Cloud motion forecasts derived from satellite (yellow and white lines) perform better than numerical weather prediction (NDFD) up to 5 hours ahead. Numerical weather prediction has similar accuracies for forecast horizons ranging from 1 hour to 3 days ahead. From Perez et al. (2010).

3.1.1 Total Sky Imagery

Solar forecasting based on whole sky imagery analysis consists of four components: (1) acquisition of a sky image in the vicinity of the forecast site using a device such as a Whole Sky Imager (WSI) (Shields et al., 1998); (2) analysis of sky image data to identify 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 cloud cover, irradiance, and power forecasting. A method to accomplish this is described in detail in Chow et al. (2011) and in Ghonima and Kleissl (2012) and an example is presented in Figure 3b.

Sky imagery has the advantage of very detailed information about the extent, structure and motion of existing clouds at the time the forecast is made. These data can be used to generate very short-term (minutes ahead) predictions of future cloud patterns in the vicinity of the solar generation facility. However, the approach at present does not account for cloud development and dissipation or significant changes in cloud geometry. The extrapolation of the cloud patterns is also limited to the spatial scale defined by the field of view of the sky imager. It is possible to extend the spatial scale by using multiple imagers at different locations. Multiple cloud layers with different characteristic motion vectors may also pose a problem since clouds at upper levels may be partially obscured by clouds at lower levels. The actual look-ahead time for which this method has significant skill will depend, among other things, upon the cloud velocity and 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 in the field-of-view). For low and fast clouds the forecast horizon may only be 3 minutes while for high and slow clouds it may be over 30 minutes, but generally horizons between 5 to 20 minutes are typical. Even if cloud size and velocity could 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.).

At the University of California San Diego, sky imagers (USIs) have recently been specifically developed for solar forecasting applications and feature high resolution, high dynamic range, high stability imaging chips that enable cloud shadow mapping and solar forecasting at unprecedented spatial detail (Figure 3a). Such cameras are better able to resolve clouds near the horizon, which will extend the forecast accuracy especially for longer look-ahead times.

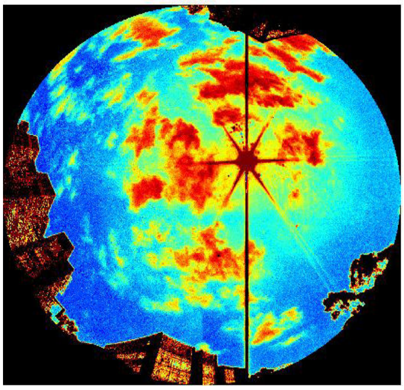

Figure 3a: Ratio of red and blue channel intensity (red-blue-ratio or RBR) on a partly cloudy day from the newly developed UC San Diego solar forecasting sky imager. Areas of high RBR are classified as cloudy.

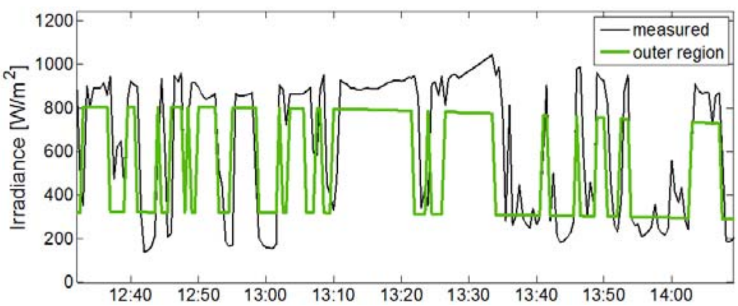

Figure 3b: 30 second GHI ramp forecast from the Total Sky Imager (green) against measurements by a 1 sec GHI station at the UC San Diego campus (black). Timing of cloudy-clear and clear-cloudy ramps on this day with cumulus clouds are accurately predicted with the sky imager.

3.1.2 Satellite Cloud Motion Vector Approach

The satellite-cloud motion vector approach is conceptually similar to the sky image method; cloud patterns are detected through the use 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 detected and that high quality satellite imagery is continuously available for the entire world. The cloud index (assumed to be proportional to cloud optical depth) can be calculated accurately from the reflectance measured by the satellite. This cloud index method is a mature approach that has been used extensively in solar resource mapping (e.g. Cebecauer et al. 2010, Perez et al. 2002).

Cloud motion vectors can be determined from subsequent satellite images. Assuming cloud features do not change between two images, Leese et al. (1971) cloud speed is computed by finding the same features in a successive image. Hamill and Nehrkorn (1993) applied the same method and showed the forecast with a backward trajectory technique outperformed the persistence forecast. Hammer et al. (1999) developed a statistical method based on conditional probabilities to predict cloud cover and solar radiation up to 2 hours ahead. Lorenz et al. (2004) used a similar method that minimizes the mean square pixel differences and forecasts solar radiation up to 6 hours ahead.

Satellite derived motion vectors have been used also to improve the results from numerical models. Velden et al (1998) showed that the Geostationary Operational Environmental Satellites (GOES) multispectral wind information had a significant positive impact on the numerical model derived forecasts for tropical cyclone tracks. Bedka and Mecikalski (2005) improved the Velden et al. (1998) algorithm to derive motion vectors including both synoptic-scale and mesoscale flows; such mesoscale flows are important in applications that monitor the rapid evolution of (convective) clouds in near–real time. Mecikalski et al. (2009) pointed out that problematic scene types for both synoptic and mesoscale processing methods are deep convection, thin cirrus, and multilayered clouds. Bosch et al. (2013) demonstrated that cloud motion vectors can be estimated from ground-based irradiance measurements.

Conversely, for longer look-ahead times, wind fields from NWP can be used to improve upon the steady cloud advection vectors from two recent images (Miller et al. 2011), but the benefit of the approach has yet to be demonstrated. Classical satellite methods only use the visible spectrum channels (i.e. they only work in day time), which makes morning forecasts less accurate due to a lack of time history. To obtain accurate morning forecasts, it is important to integrate infra-red channels (which work day and night) into the satellite cloud motion forecasts (Perez et al. 2010b).

The spatial resolution of geostationary satellite images is 1 km (GOES) or larger (Meteosat outside high resolution area) which is much less than ground-based sky images. Hence, with the exception of large convective clouds, most clouds cannot be detected and located directly; one can only conclude that clouds have to be located somewhere within the pixel. In addition, the time frequency, download time and processing of the images is slower than that of the sky imager, which means the forecast cannot be updated as frequently. The lack of high spatial and temporal resolution in the satellite image data reduces the performance of the satellite-based approach relative to the sky imager method for very short look-ahead times. However, the much larger area of coverage means that the motion of the cloud field can be projected forward over longer time periods.

Satellite forecasts have been shown to outperform Numerical Weather Prediction (NWP) models (Perez et al., 2010) for short-term forecasts. Perez et al. (2010) conclude that for forecasts up to 5 hours ahead satellite-derived cloud motion-based forecasting leads to a significant improvement over National Digital Forecast Database (NDFD) forecasts. For 1 h forecasts the results from persistence and satellite-derived cloud motion are found to be on par, probably due to satellite's navigation and parallax uncertainties, which tend to mitigate for longer times.

3.1.3 Stochastic Learning Techniques

For very short-term (intra-hour, and up to 2 or 3 hours ahead depending on the time averaging interval) forecasts, stochastic learning techniques without exogenous input (i.e. only the power plant output is used) can be highly competitive in accuracy and relatively easy to setup, especially when advanced forecasting engines are used (see, e.g., Pedro and Coimbra, 2012). However, inclusion of relevant exogenous data from sky imagery, satellite, and NWP (in order of increasing forecast horizon), as well as data from other meteorological databases (NWS, NDFD, etc.) can significantly increase accuracy and forecasting skill, as described in Section 2. For a review of earlier stochastic learning and the general use of artificial intelligence methods in solar forecasting, see Mellit (2008). More recently, new forecasting algorithms that go beyond the use of simple pattern recognition algorithms have gained attention. These more comprehensive stochastic learning techniques attempt to remove the opinion of the modeller in the optimization of the topology, initial weights and coefficients of the neural networks through a Master Optimization Process (MOP) that is usually evolutionary in nature. The MOP "evolves" the topology of the various artificial neural networks (ANNs) (number of neurons, layers, initial weights, size of the training set, etc.) by scanning the whole solution space of the training set with an evolutionary optimization scheme such as a Genetic Algorithm (GA). This multi-objective, multi-layer optimization determines the best topologies and the best sections of the training set for each microclimate under study, and may or may not include dynamic input selection for exogenous variables through Gamma tests (Marquez and Coimbra, 2011). Because of their robust and versatile nature, these hybrid schemes outperform persistence, conventional regression (ARMA, ARIMA, f-ARIMA, etc.) and pattern recognition methods (kNN, ANN, etc.), producing higher-fidelity forecasts with or without exogenous variables at various horizons (Pedro and Coimbra, 2012; and Marquez et al., 2012).

3.2 *Solar and PV forecasting 6 hours to days ahead*

One of the key uses of solar and PV forecasting is « day-ahead » forecasting of the hourly output power that will be generated by PV systems within an area managed by an electricity system operator or utility. These day-ahead forecasts are typically required by about noon for each hour of the next day, which implies that day-ahead forecasts must in fact extend at least 36 hours ahead to a few days ahead, depending on the timing of electricity markets and of weather forecasts.

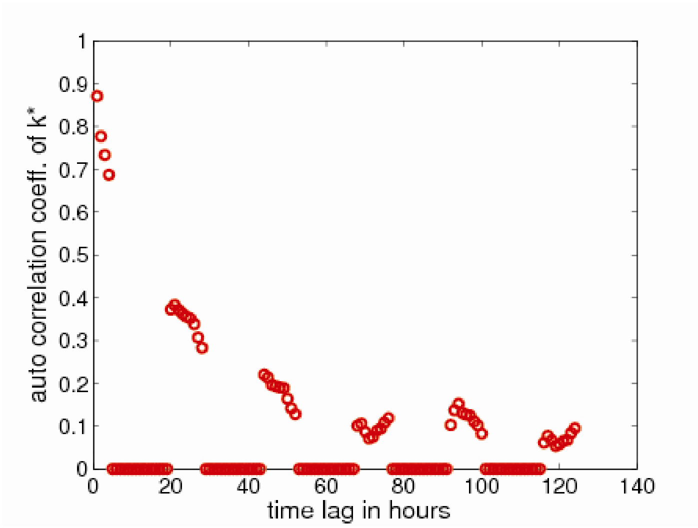

Figure 4 Evolution of the auto-correlation of the clear sky index over several days for Bergen, Norway. The correlation coefficient of a NWP model forecast for the first forecast day was found to be 0.54. Reproduced from (Beyer et al., 2009).

While key inputs for forecasts in the range of 0 to 6 hours ahead are past observations (see 3.1), weather forecasts from numerical weather prediction (NWP) models are the key inputs for day ahead forecasting. This is illustrated in Figure 4, which shows that the autocorrelation of the clear sky index drops rapidly over the course of a few 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 3 hours ahead for the simplest persistence model to about 3 to 5 hours ahead for cloud motion vector approaches (Perez et al., 2010).

3.2.1 Numerical weather prediction models

Numerical weather prediction models are based on dynamical equations that predict the evolution of the atmosphere up to several days ahead from initial conditions. The NWP models that underlie all others are global models covering the whole Earth. The model equations and inputs are discretized on a three-dimensional grid extending vertically from the surface of the Earth. Since global models are computationally and otherwise intensive, there are only 14 of these currently in operation worldwide (Traunmüller and Steinmaurer, 2010).

Model runs are typically initiated two to four times per day, for 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. In order to limit computational requirements, the resolution of global NWP models is relatively coarse, with grid spacings of the order of 40 km to 90 km (Traunmüller and Steinmaurer, 2010). Mesoscale or limited area models are NWP models that cover a limited geographical area with higher resolution, and that attempt to account for local terrain and weather phenomena in more detail than global models. Initial conditions for these models are extracted from the global models.

The best day-ahead solar and PV forecasts combine NWP forecasts with post-processing of these forecasts in order to improve them or to generate forecasts that are not included in the direct model outputs of the NWP, such as 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 used to develop corrected forecasts. This type of approach is often referred to as Model Output Statistics, or MOS.

A number of different MOS approaches have been proposed to date. The following summarizes some of the key post-processing approaches that have been introduced so far in this rapidly evolving field, and which can 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 specific point in space necessitates some form of interpolation. The simplest method is to use the nearest neighbour point on the grid that is closest to the location of interest. Other approaches involve interpolating forecasts from grid points surrounding the point of interest. According to Lorenz et al. (2009a), the best results are achieved by simply taking an average of forecasts at grid points within an area surrounding the point of interest, effectively smoothing the associated forecasts. Lorenz et al. (2009a), and later Mathiesen et al. (2011) obtained best results by averaging over areas of about 100 km by 100 km for forecasts based on the ECMWF and GFS global models, while Pelland et al. (2011) found 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. For the mesoscale forecast model WRF with 10 km resolution Müller and Remund (2010) found an optimal smoothing of 10 x 10 pixels for Switzerland.

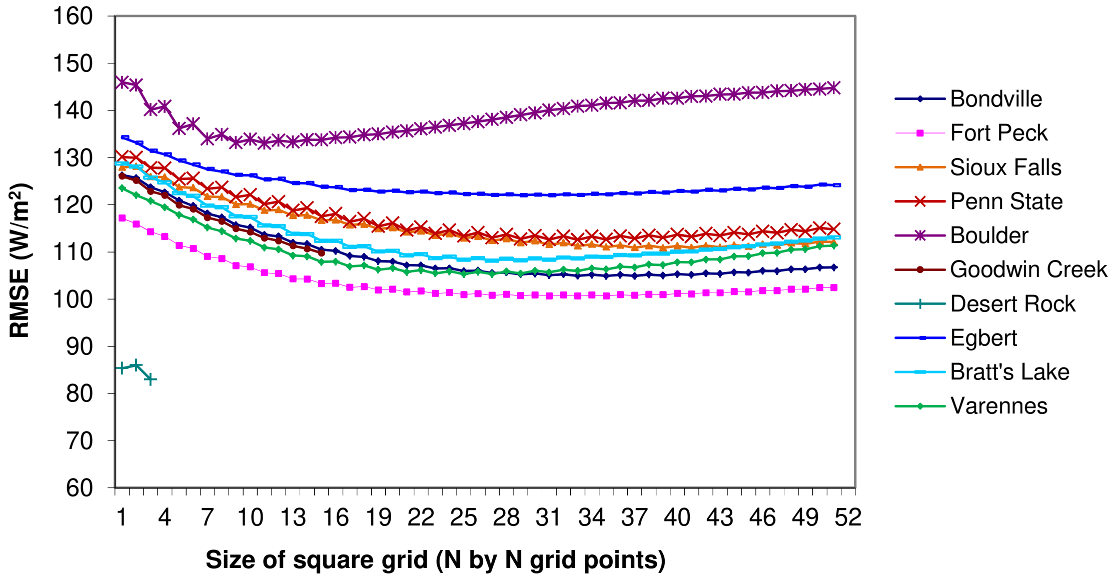

Figure 5 Reduction in root mean square error through averaging of solar forecasts over square grids consisting of N by N grid points.

In addition to spatial interpolation, temporal interpolation must be used when available NWP model outputs have a lower temporal resolution than desired. For instance, Lorenz et al. (2011b) 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 have been 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 depend on the time of the day and of the year, on sky conditions, etc. (see Section 5.3). Moreover, NWP models are frequently modified and updated, which necessitates forecast corrections to adapt accordingly.

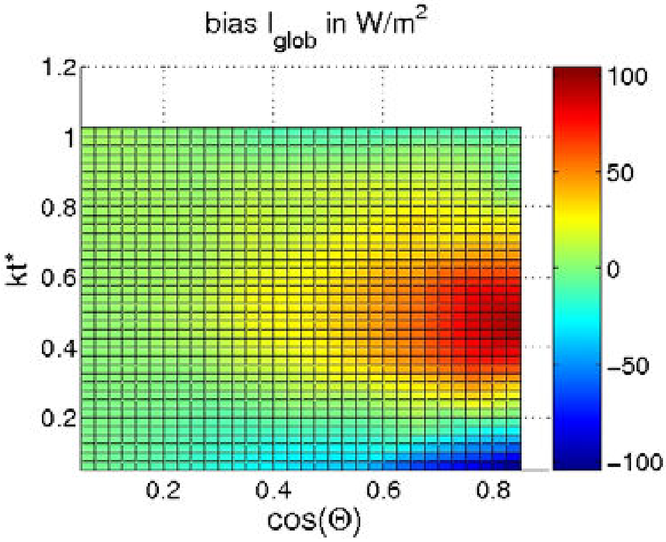

Figure 6 Solar forecast bias as a function of the cosine of the solar zenith angle and of the (forecasted) clear sky index. Reproduced from (Beyer et al., 2009).

One simple but powerful type of MOS is the correction of systematic forecast errors, or bias removal. This was applied for instance by Lorenz et al. (2011b) to solar forecasting in Germany: GHI forecast bias was computed as a function of sky condition (forecasted clear sky index) and of the position of the sun (cosine of the solar zenith angle), with the bias computed over a moving 30-day training window using measurements at several ground stations in Germany. As shown in Figure 6, the underlying ECMWF forecasts were found to have the strongest bias for intermediate values of the clear sky index, corresponding to variable cloud conditions. A similar procedure was applied by Mathiesen et al. (2011) for the US and different bias structures were found for different NWP models. Bias removal was also developed by Pelland et al. (2011) for GHI forecasts in North America, using a Kalman filter linear in GHI and a 30 to 60 day moving training window. Both approaches have the most impact when applied to area forecasts, where bias makes up a larger proportion of the root mean square error, since non-systematic errors from individual points tend to cancel out to some extent (see section 4.2).

Other MOS approaches forecast GHI from various NWP outputs and past observations. For instance, Perez et al. (2007) forecasted GHI using cloud cover forecasts from the US NDFD, which does not output GHI forecasts. They reached forecast accuracies comparable to MOS-corrected GHI forecasts from other mesoscale NWP models that forecast GHI directly. Meanwhile, Marquez and Coimbra (2011) found improvements over Perez's approach to GHI forecasting by using four or more NDFD forecast variables to generate GHI (and DNI) forecasts rather than just one variable. They used a Gamma Test to select the most relevant NDFD forecast outputs and trained their models using genetic algorithm search and artificial neural networks (ANNs). Huang et al. (2010) also found performance improvements by including more than one NWP forecast output into their ANN-based PV forecasts.

Various other MOS-based approaches have been developed to forecast GHI or PV power one to several days ahead, including autoregressive methods (Bacher et al., 2009; Cai et al., 2010), as well as various artificial intelligence methods including artificial neural networks (Cao and Lin, 2008; Chaouachi et al., 2010; Mellit et al., 2010; Huang et al., 2010; Yona et al., 2008), grey models with ANN (Wang et al., 2011) and support vector machines (Shi et al., 2011). Inputs that have been used by these authors include:

- NWP and other forecasts: GHI, cloud cover, temperature, probability of precipitation, relative humidity, wind speed and direction
- Ground station weather measurements (GHI, relative humidity, temperature, vapour 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 require stationary time series, the clearness index or the clear sky index are often used, or a PV equivalent of these.

Combining various NWP models

One way to improve solar and PV forecasting is to combine forecasts from different NWP models or from different members in an ensemble forecast, where initial conditions or physical parameterizations are varied within a single NWP model to yield probabilistic forecasts. This approach is being actively pursued in the case of wind forecasting, where significant improvements in forecast accuracy have been achieved by combining models with weights that depend on prevailing weather conditions (Ernst et al., 2009). In the solar case, slight improvements in forecast accuracy have been achieved simply by averaging the forecasts from two or three NWP models (Perez, 2011). Similarly, Chaouachi et al. (2010) found that an average of three different neural network forecasts based on past observations outperformed the individual ANN forecasts.

4. Point forecasts and area forecasts

4.1 *Upscaling*

The representation of the total power output of all power systems installed in a given area using data from a subset representative of those systems is usually known as *upscaling*. Upscaling techniques have been extensively used in forecasts of wind energy power output, where generating forecasts for each wind turbine in a given area, besides requiring the availability of detailed data, can be a time-consuming task.

Similar challenges also arise in regional forecasts of photovoltaic power, where specific information for every photovoltaic system installed can be difficult to obtain, for example, in areas with large deployments of residential systems. In this case, upscaling techniques can also be applied as they can simplify the calculations and decrease the need 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 is not nearly as numerous as it is in the case of wind energy.

In order to represent a complete set of photovoltaic systems using only a subset of those systems, two steps need to be followed. First, the subset must be chosen in such a way that its behaviour, regarding power output is representative of the behavior of the complete set of photovoltaic systems. This characteristic can be achieved by selecting as the subset a distribution of PV systems with the desired behavior, or by calculating the necessary number of randomly selected systems that together will make the subset present characteristics similar to those of the complete set of systems. The latter approach was investigated by Lorenz et al. (2008), who found that a subset of 150 randomly selected systems presented a measure of error (a normalized version of the RMSE) similar to that of a complete set of 500 systems installed in Germany. The second step in upscaling is to scale the output power of the subset to obtain the output power of the complete set. This step can include post-processing based on comparing the power output of the selected subset with the measured power of the complete set. In order to do that, Lorenz et al. (2008) normalized the power output values of the subset and of the complete set by their respective total nominal power, allowing for a direct comparison between the values of the subset and the values of the complete set.

As indicated above, a number of different approaches can be used in the first and second steps. For example, in the first step, different errors or correlation parameters could be used to find the necessary number of randomly selected systems to include in the subset in order to properly represent the complete set. Also, the subset could be assembled not with a number of randomly selected systems but with a distribution of systems selected so that their characteristics, such as location or specifications, are representative of the complete set of installed photovoltaic systems. This was the approach taken in Lorenz et al. (2011), where in order to do the upscaling, they matched the spatial distribution of the representative subset to that of the real data set by assigning to each PV system a scaling factor based on its geographic location on a grid with a resolution of 1° x1°. For each grid point they derived a scaling factor defined as 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 corresponding to the nearest grid point.

4.2 *Error reduction for area forecasts*

Area forecasts of power output of photovoltaic systems are important for system operators in charge of keeping the balance between demand and supply of power in electricity grids. Area forecasts can be done using data from all systems installed in a given area or using an upscaling technique as described in the previous section. The errors of area forecasts are typically significantly lower than the corresponding errors of forecasts of single systems. This error reduction was explored by Lorenz et al. (2009), who found that the correlation coefficient between the solar forecast errors at two locations could be modelled with an exponential function of the distance between the two stations, with errors decreasing rapidly with increasing station distance at first, and more slowly for distances of about 200 km or more. This effect was modelled in detail by Focken et al. (2002) in the case of wind: They showed that both the size of the geographic area and the number of stations or systems considered contributed to error reduction, with the reduction from an increased number of stations saturating beyond a certain threshold for a given geographic area.

It is difficult to quantify the error reduction that can be achieved in area forecasts of power output, as the parameters of the exponential functions mentioned above depend on climate diversity within the region, PV system distribution, capacities, etc. Nevertheless, there are case studies available in the technical literature. For example, Lorenz et al. (2009) show that solar and PV forecast accuracy improves significantly as the size of the geographic area under consideration increases, with a reduction in root mean square error (RMSE) of about 64% for a forecast over an area the size of Germany as compared to a point forecast. Similarly, Pelland et al. (2011) found that the RMSE for the forecast of the average irradiance of 10 ground stations across Canada and the U.S. was about 67% lower than the RMSEs of the irradiance at individual ground stations.

In a Japanese case study, Suzuki et al. (2010) propose a forecast system based on irradiance forecasts up to 1 day ahead from the JMA-MSM (Japanese Meteorological Agency Meso-Scale Model). 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, which is one of the black-box models described in Section 3. 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 set of systems in an area of 100 km x 60 km in the Kanto region in Japan, the mean absolute error (MAE) for the regional forecasts was 22% lower than the average MAE for the point forecasts. The authors also evaluate an error reduction factor in Suzuki et al. (2011) using the full Japanese area, with a “relative error_ratio” defined as the ratio of MAE to the MAE of a point forecast (relative error ratio of 1 for a point forecast). The error reduction was around 70% (relative error ratio of 0.3) as shown Figure 7 in the Japanese case. Figure 8 shows the Kanto region case study using data from 64 PV systems, to reflect the fact that Japanese utility companies control the frequency in each region and will require regional forecasts. The “average_distance” in Figure 8 is defined as the mean value of distance among evaluated points. In 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.

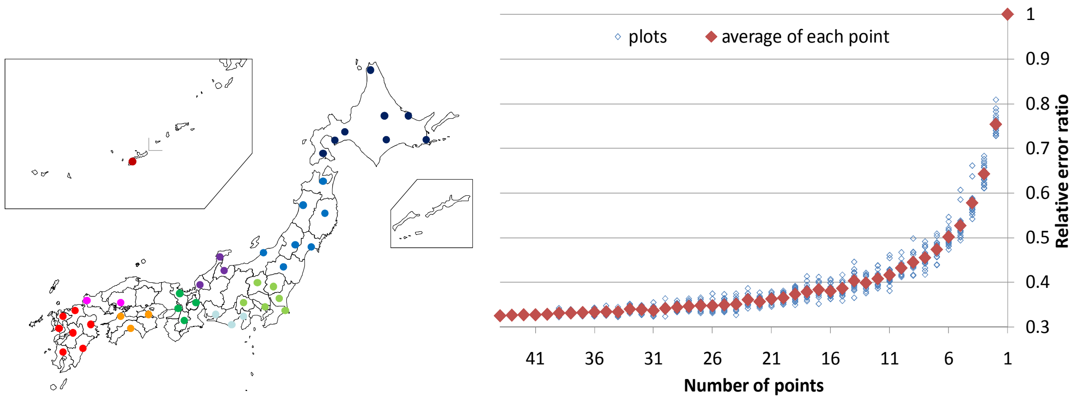

Figure 7 Correlation between average distance and relative error ratio in Japan

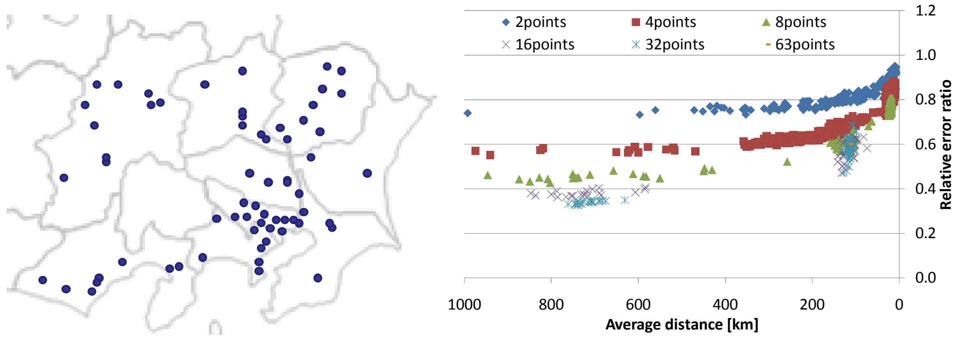

Figure 8 Correlation between average distance and relative error ratio in Kanto region using 64 PV systems' data

5. Forecast accuracy

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 (e.g. clear vs. cloudy skies – see section 5.3).

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 by Hoyer-Klick (2008), 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 over all 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 (see 5.3).

Whatever the intended use of forecasts, standardizing performance measures or metrics helps facilitate forecast evaluations and benchmarking. Beyer et al. (2009) have attempted to standardize solar forecast benchmarking and accuracy metrics, while Madsen et al. (2005) 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:

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

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

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |e_i| \quad (3)$$

$$MBE = \frac{1}{N} \sum_{i=1}^{N} e_i \quad (4)$$

$$e_i = y_{i,forecast} - y_{i,observed} \quad (5)$$

where $y_{i,forecast}$ and $y_{i,observed}$ are the ith forecast and observation, respectively, and e_i is the i^{th} error, with i=1,…,N running through all forecast-observation pairs in the test dataset.

The bias or MBE is the average forecast error, and encapsulates the systematic tendency of a forecast model to under or over-forecast. As discussed in 3.2.2.2, model output statistics approaches can be used to significantly reduce the bias when past observations are available. MAE gives the average magnitude of forecast errors, while RMSE (and MSE) give more weight to the largest errors. Madsen et al. (2005) argue that large errors are disproportionately costly, so that RMSE better reflects the costs of forecast errors to system operators than the MAE.

MSE, SDE and bias are related as follows:

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

In other words, the standard deviation captures the part of the RMSE that is not due to systematic error, and provides an indication of the RMSE that can be achieved once the bias is essentially eliminated.

All these metrics can be stated as absolutes, or else normalized by dividing by a reference value to facilitate comparisons. For instance, wind and PV forecasts are commonly normalized by dividing by the rated capacity of the PV or wind systems, since this is a straightforward and easily accessible reference value. Meanwhile, solar forecasts are often normalized by dividing by the average irradiance over the test dataset. In Hoff et al. (2012), the different definitions for the reporting of normalized accuracy metrics are summarized, evaluated and compared.

Forecast evaluation and accuracy metrics provide one way of generating confidence intervals (also known as prediction intervals) for forecasts. Adding confidence intervals to forecasts builds into the forecast an indicator of its expected accuracy: single, deterministic forecast values are replaced by distributions or ranges of values that can be expected. Such confidence intervals for solar forecasts have been developed by Lorenz et al. (2009a) and by Marquez and Coimbra (2011): they assumed a normal distribution in forecast errors for simplicity, and gave confidence intervals as multiples of the standard deviation associated with a given confidence level (e.g. 2σ for 95.4% confidence, 3σ for 99.7% confidence). They calculated σ, and therefore confidence intervals, as a function of sky conditions and solar position (or time of day), since these parameters strongly influence forecast accuracy (see 5.3). Bacher et al. (2009) proposed confidence intervals for PV forecasts using quantile regression. Similarly to Lorenz et al. (2009a) and Marquez and Coimbra (2011), they specified confidence intervals as a function of forecast horizon and "normalized solar power", their PV equivalent of sky condition. Mathiesen, Brown and Kleissl (2012) calculated quantile regime-based confidence intervals for coastal California based on geostropic wind speed and direction to infer the likelihood of marine layer clouds. In principle, confidence intervals could also be obtained via ensemble forecasts, which are commonly used for example to forecast probabilities of precipitation. However, this approach has not yet been explored for solar forecasting.

5.2 *Benchmarking of forecasts*

Since forecast accuracy depends strongly on the location and time period used for evaluation and on other factors, it is difficult to evaluate the quality of a forecast from accuracy metrics alone. More insight can be gained by comparing the accuracies of different forecasts against a common set of test data.

For instance, some simple forecast methods can serve as benchmarks against which to evaluate forecasts. One very simple, commonly used reference is the persistence forecast, which basically assumes that "things stay the same", which in the solar case implies projecting past values of the clear sky or clearness index into the future (see e.g. Beyer et al., 2009). Other common reference forecasts include those based on climate normals and simple autoregressive methods (Beyer et al., 2009). Whatever the choice of reference model, forecasts can be compared simply by comparing their accuracy metrics, or else 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 improvement in the chosen metric with respect to the reference model (numerator) to this same improvement in the case of a perfect forecast with no errors (denominator). To illustrate, Bacher et al. (2009) reported an improvement in RMSE by 36% with respect to persistence, which corresponds to an RMSE skill score with respect to persistence of 0.36.

Benchmarking can also be used to identify conditions under which forecasts perform relatively well, or poorly. For instance, 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, Lorenz et al. (2011a) have used comparisons to persistence to flag problems with PV forecasts in Germany during the winter, and to develop improved algorithms to deal with snow.

Finally, comparisons can also be applied to various forecast models to set benchmarks for accuracies that can be expected by the best current models in a given region, and to spur innovation and forecast improvement. Such benchmarking exercises have been performed for instance in the US (Perez, 2011), in Canada and in four European countries (Lorenz et al., 2009b). The best results for day-ahead forecasting have so far been obtained from post-processing of global NWP models, which have outperformed forecasts based on mesoscale NWP models. The performance of global NWP models also seems less dependent on the region of evaluation (Lorenz et al., 2009b). This is also suggested by Mathiesen and Kleissl (2011), who noted bias patterns for the ECMWF model in the US similar to those reported for Germany. The benchmarking exercises also highlight that solar forecast accuracy depends on the region of evaluation: for instance, RMSEs ranged from about 20% to 35% in Spain, reaching 40% to 60% in Central Europe (Lorenz et al., 2009b).

5.3 *Factors that influence forecast accuracy*

Introduction

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 affected by uncertainties related to the different modelling steps that are needed to make energy forecasts out of irradiation forecasts. The maximum achievable accuracy is determined mainly by the following factors:

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

Local climate and weather conditions

As stated in (Beyer et al., 2009) and (Lorenz et al., 2009), the accuracy of solar and PV forecasts depends mostly on climate type and weather conditions. It was shown in (Beyer et al., 2009) as part of a study performed with 26 ground measurement stations in Spain during one year (2005) that forecast accuracy is highly influenced by regional climate. In that study, forecast accuracy measures (both RMSE and bias) were shown to be much poorer for installations in the northern region of Spain as compared to the central and southern regions of Spain. Also (Lorenz et al., 2009) found that for central European stations, the relative Root Mean Square Error (RMSE) ranges from 40% to 60% compared with values of 20% to 35% for Spanish stations. Another study focusing on Switzerland (Müller and Remund, 2010) concluded that the forecast error (RMSE) was lower in places with sunnier weather conditions.

Among the factors that can explain this regional dependence are the dependence on weather situation (clouds that are commonly represented by the clear sky index "k_T^*"), the sun elevation angle and the local terrain conditions. As shown in Figure 9, there is a direct relationship between the sky conditions and the accuracy of the forecasts (Beyer et al., 2009): Clear skies are relatively easier to forecast (lower percent RMSE) than partly cloudy and overcast weather conditions. Figure 9 also shows that the forecast accuracy decreases as the solar elevation angle decreases. The solar elevation angle distribution not only causes a regional dependency of the forecast accuracy, but also a seasonal dependency as found in (Beyer et al., 2009) and (Lorenz et al., 2009) as well as daily one (Müller and Remund, 2010), compromising the forecasting as the solar elevation decreases.

Finally, concerning the local terrain conditions, it has been shown in (Pelland et al., 2011) that forecasting accuracy of a single site is highly affected due to micro-climatic effects, especially in mountainous regions.

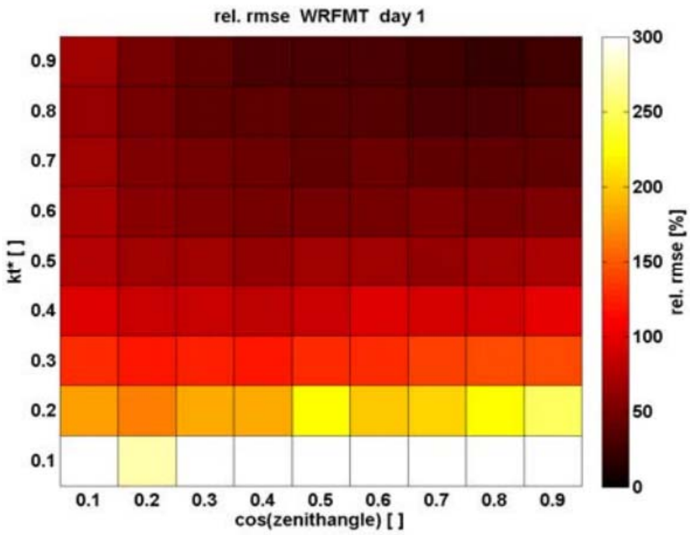

Figure 9 RMSE as a function of the cosine of the solar zenith angle and the predicted clear sky index (Beyer et al., 2009). The solar elevation angle increases from left to right.

Single-site or regional forecast

Besides single-site forecasting, forecasting of the aggregated regional PV production is often demanded. As in the case of wind forecasting, Lorenz et al. (2009) show that solar and PV forecast accuracy improves significantly as the size of the geographic area under consideration increases, with a reduction in root mean square error (RMSE) of about 64% for a forecast over an area the size of Germany as compared to a point forecast. This is due primarily to decreasing correlations between forecast errors from two locations as their separation increases, leading to (partial) cancellations between the errors at individual sites. This effect was modelled in detail by Focken et al. (2002) in the case of wind: They showed that both the size of the geographic area and the number of stations or systems considered contributed to error reduction, with the reduction from an increased number of stations saturating beyond a certain threshold for a given geographic area.

Forecast horizon

As discussed in section 3, the most adequate forecasting technique depends on the forecast horizon required: Numerical Weather Prediction models (NWP) perform best for horizons of 1 or 2 days ahead, whereas statistical models based on local ground measurements, possibly combined with satellite or sky imager data of cloud movements, are more adequate for short-horizons of less than 6 hours ((Hammer et al., 1999) and (Lorenz et al., 2009)). Accuracies typically decrease with increasing forecast horizon, with a steeper decrease for methods such as persistence forecasting based solely on past data.

Accuracy measures

As discussed in Sections 5.1 and 5.2, different users are interested in different measures of forecast accuracy and the strategies used to optimize forecast accuracy will vary depending on which accuracy measures are selected for optimization. When stating forecast accuracy, it is important to specify not only which metric is used (RMSE, MAE or other), but also to clarify whether this value has been calculated over complete 24 hour periods or only taking into account daylight hours. When normalizing the accuracy value, especially for PV forecasts, it should be specified whether it is normalized by the mean produced power during the considered period or the rated power of the PV system(s).

6. Solar forecast survey results

Important criteria for the evaluation of forecast systems were determined and brought together in the questionnaire "Use of solar and PV forecasts for enhanced PV integration". It was distributed in August 2011 to about 30 experts in order to collect different case studies.

The questionnaire included a total of 34 questions grouped in 7 blocks:

1. model names
2. temporal range
3. post processing schemes (e.g. MOS)
4. additional parameters (e.g. global radiation on inclined planes, PV production)
5. spatial information and aggregation
6. forecast evaluation
7. uncertainty and references

It was aiming at shortest (0 – 6 h) as well as short time (6 – 72 h) and at statistical as well as deterministic forecasts.

Up to now 15 organizations have filled in the questionnaire. The organizations are from the private and public sectors (universities and meteorological offices) and are based in North America, Europe and Japan. Table 2 gives an overview of the 15 answers.

Table 2 Overview of survey results.

Organi-sation form	Source	Type	Global model	Mesoscale model	Reso-lution [km]	Area	Maximum time horizon [d]
Science	DLR (DE)	NWP	ECMWF	-	25	Point	2
Science	CanmetENERGY(CAN)	NWP / P	GEM	-	15	Point	2
Met. office	JWA (JP)	Cloud motion*	-	-	1	Point	0.25
Met. office	MeteoSwiss (CHE)	NWP	ECMWF	Cosmo***	2 / 7	Point	1 / 3
University Private	Univ. Oldenburg / Meteocontrol (DE)	NWP / P	ECMWF	-	25	Point/ Regional	3
University	Univ. Jaen (ES)	NWP	ECM/GFS	WRF	3	Point	3
University	DTU IMM (DK)	NWP	ECMWF	Hirlam	-	Point	2
University	AIST / Waseda (JP)	NWP / P	JMA-GSM	NHM	5	Point	1.5
University	Univ. GIFU (JP)	NWP	JMA-GSM	MM5	2	Point	2
University	UCSD (USA)	Cloud motion**	-	-	<0.1	Point	<0.1
Private	3E (BE)	NWP / P	ECMWF	-	-	Point	6
Private	Bluesky Wetteranalyse (A)	NWP / P	GFS	Cosmo	-	Point	3
Private	Irsolav (ES)	NWP / P	GFS	-	-	Point	3
Private	Meteotest (CH)	NWP	GFS	WRF	10	Point	2.5
Private	Weather Analytics (USA)	NWP / P	GFS	-	1	Point	6

NWP = numerical weather prediction model, P = post processing, * = satellite images, ** = Sky imager
*** Cosmo 2 km for 0 – 24 h, Cosmo 7 km for 0 – 72 h forecasts.

The results of the questionnaire show only a part of the models used worldwide. Especially in Germany, many commercial models are run as regional power prediction is needed for the grid integration of PV due to the higher penetration level. As a rule of thumb, regional PV forecasts appear to be needed when yearly energy production of PV reaches a level of 1 – 2% of yearly energy demand.

Most of the models described deal with the time frame of 6 – 72 hours ahead and include numerical weather prediction models (NWP). No purely statistical model is included.

The underlying global NWP models ECMWF (www.ecmwf.org) and GFS (http://www.emc.ncep.noaa.gov/GFS/) are those that are used most often (almost 50 % each). It can be noted that GFS is mostly used by private companies, as ECMWF is too expensive to use for small private companies (although the accuracy of the radiation parameters of ECMWF is higher as will be shown later). Most groups using NWP are using either a limited area forecast model and/or statistical post-processing.

In Table 3 the internet links for the mesoscale models and the solar radiation models used are listed.

Table 3 Internet links of the mesoscale and solar radiation models

Type	Name	Link
Mesoscale / solar	Cosmo	http://www.cosmo-model.org
Mesoscale	Hirlam	http://hirlam.org
Mesoscale	MM5	http://www.mmm.ucar.edu/mm5/
Mesoscale	NHM	http://www.mri-jma.go.jp/Project/mrinpd/INDEXE.htm
Mesoscale	WRF	http://www.wrf-model.org
Solar	Univ. Oldenburg / Meteocontrol (DE)	http://www.meteocontrol.de/energy-weather-services/prognosedienstleistungen/solarstromprognose/
Solar	UCSD (USA)	http://solar.ucsd.edu
Solar	Univ. Jaen (ES)	http://matras.ujaen.es
Solar	Univ. GIFU (JP)	http://net.cive.gifu-u.ac.jp
Solar	3E (BE)	http://www.3E.eu
Solar	Bluesky Wetteranalyse (A)	http://www.blueskywetter.com
Solar	Irsolav (ES)	www.irsolav.com
Solar	Meteotest (CH)	http://www.meteotest.ch/en/footernavi/energy_economy/energy_forecasts/
Solar	Weather Analytics (USA)	http://www.weatheranalytics.com

Post-processing is done either by simple de-biasing and smoothing of several surrounding pixels, by Kalman filters or by more complex neural networks (mostly by groups in Spain and Japan). Standard model output statistics (MOS) like multiple linear regressions are not used in the included examples. About 50% of the models also include additional parameters like PV production, and not only global radiation on a horizontal plane.

Two models are made for very short term forecasting. One model made by University of California San Diego (UCSD) is based on a sky imager and delivers data up to 20 minutes ahead (see Section 3.2.1). The other model coming from the Japan Weather Association (JWA) is based on cloud motion vectors and delivers results up to 6 hours ahead. This type of model is also run for example by the

State University of New York and the University of Oldenburg (Lorenz et al., 2004), but those organisations did not fill in the questionnaire for this type of model.

14 of 15 models were used for point forecasts and only one also for a regional forecast. The regional forecast is made with help of a regionalisation or upscaling model based on online PV measurements (Lorenz et al., 2011).

Information about accuracy was given for 13 of the 15 models. As expected, the results are difficult to compare, as the validations were made at different locations with different time steps. Nevertheless, we try to show an overview in Table 4 in order to give an indication of the scale of uncertainties. Whenever possible, we compare the root mean square error (RMSE, see 5.1) in relation to persistence by giving a ratio (in %) of forecast RMSE to persistence RMSE. To enhance the quality of the comparison we have entered also the results of the benchmarking within the IEA SHC Task 36 (Lorenz et al., 2009) as well as the publication of Pelland et al. (2011).

Table 4 Uncertainty information for the given models.
(If not marked, the uncertainties are taken from the questionnaire).

Source	Location	Time step and forecast time	Uncertainty % of persistence (= 100% - skill score)	Uncertainty RMSE (relative or absolute)
DLR (DE)	Southern Spain	1 h, day 1		DNI: 50 – 64% RMSE
CanmetENERGY (CAN)	Canada, USA	1 h, day 1 – 2	57%[1]	
JWA (JP)	Japan	30 Min, 1h.		140 W/m²
MeteoSwiss (CH)	Switzerland	-	-	-
Univ. Oldenburg / Meteocontrol (DE)	Switzerland Southern Spain Canada, Spain	1 h, day 1	65%[2] 61% [2] 57% [2]	42 % RMSE 21 % RMSE
Univ. Jaen (ES)	Southern Spain	1 h, day 1	72% [2]	
DTU IMM (DK)	Denmark		68% [2]	
AIST / Waseda (JP)	Japan	1 h, day 1		100 W/m²
Univ. GIFU (JP)	Gifu	1 h		64% RMSE
UCSD (USA)	San Diego, 4 days	30 sec. 5 min.	50% 75%	
3E (BE)	Benelux	1h, day 1		GHI: 100 W/m², 44% Power: 47%
Bluesky Wetteranalyse (A)	Switzerland	1 h, day 1	65%[2]	
Irsolav (ES)	Spain	1 h, day 1		18 – 35% RMSE
Meteotest (CH)	Switzerland	1 h, day 1	72% [23]	41% -50% RMSE
Weather Analytics (USA)	-	-	-	

For a forecast time horizon of 24 – 48 h the RMSE is in the range of 57 – 72% of persistence RMSE. The results are dependent on the site. The cloudier the region, the higher the uncertainty. The best results for day-ahead forecasts are achieved with the GEM and ECMWF models in combination with post-processing, while the highest values of uncertainty are reached by GFS based WRF. The use of mesoscale models does not seem to enhance the quality. Post-processing (mainly spatial averaging

[1] Pelland et al., 2011
[2] Lorenz et al., 2009
[3] Müller and Remund, 2010

and bias corrections) can lower the uncertainties (relatively) by 15 – 25% (Pelland et al., 2011, Müller and Remund, 2010).

The spatial resolution is in the range of 2 – 25 km. The influence of resolution on the quality of the results is not apparent (as it is for other meteorological parameters). This is also supported by the experience that spatial smoothing of model output leads to lower uncertainty (see Section 3.2.2). The reason for this is the fact that the exact positions of clouds cannot be calculated for more than 6 hours ahead due to chaotic behaviour of the system.

Conclusion

Solar and photovoltaic forecasting is a dynamic research and development area, with new models and findings emerging rapidly. The overview of the current state of the art in this field presented in this report is therefore bound to gradually become outdated – and the authors welcome this! In particular, solar and photovoltaic forecasts have only recently been introduced into electricity system operation, for instance in Germany and Spain. Dialogue between system operators and the research community will help ensure that appropriate accuracy metrics are targeted and become the focus of forecast improvement efforts. Probabilistic or ensemble forecasting for instance could form the basis of probabilistic unit commitment or other novel approaches to system operation adapted to a strong presence of variable renewables on the grid. Forecasting rapid solar ramp rates is also garnering attention among electricity system operators and has not yet received significant attention from the research community. Likewise, the advent of the smart grid with predictive control of buildings and electricity loads will place its own requirements on solar and PV forecasting and help spur new developments.

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