



## Review of solar irradiance forecasting methods and a proposition for small-scale insular grids



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### ABSTRACT

Integration of solar energy into the electricity network is becoming essential because of its continually increasing growth in usage. An efficient use of the fluctuating energy output of photovoltaic (PV) systems requires reliable forecast information. In fact, this integration can offer a better quality of service if the solar irradiance variation can be predicted with great accuracy.

This paper presents an in-depth review of the current methods used to forecast solar irradiance in order to facilitate selection of the appropriate forecast method according to needs. The study starts with a presentation of statistical approaches and techniques based on cloud images. Next numerical weather prediction or NWP models are detailed before discussing hybrid models. Finally, we give indications for future solar irradiance forecasting approaches dedicated to the management of small-scale insular grids.

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## 1. Introduction

The contribution of photovoltaic systems (PV system) power production to the electric power supply is constantly increasing. Utility companies and transmission system operators have to deal with the fluctuating input from PV system energy sources. This is a new challenge compared with power production from conventional power plants that can be adjusted to the expected load profiles. An efficient use of the fluctuating energy output of PV systems requires reliable forecast information.

Note that the reliable forecasting of the expected solar resource is but one aspect of the broad question of solar resource assessment that ranges from, for example the work of Perez et al. [1] on variability to Lucia [2] on the link between the entropy generation maximum principle and the exergy analysis of engineering and natural systems. In this paper, we focus solely on the, once again, broad field of forecasting, broad both in approaches taken, and the time scales covered.

Load patterns forecasted for the next 2 days provide the basis for scheduling of power plants and planning transactions in the electricity market in order to balance the supply and demand of energy and to assure reliable grid operation [3]. These forecasts are used by utility companies, transmission system operators, energy service providers, energy traders, and independent power producers in their scheduling, dispatching and regulation of power.

In particular, insular territories experience an unstable electricity network and use expensive means in order to provide the power for the peak demand periods. Their grids are generally not interconnected with any continent and all the electricity must be produced inside the territory. The power of grid connected PV plants increases fast and can interfere with network stability. An efficient forecasting method will help the grid operators to better manage the electrical balance between demand and power generation. Kostylev and Pavlovski [4] identify three forecasting horizons (intra-hour, intra-day and day ahead) related to the grid operator activities (ramping events, variability related to operations, unit commitment, transmission scheduling, day ahead markets, hedging, planning and asset optimization).

Forecasting of global horizontal irradiance (GHI) is the first and most essential step in most PV power prediction systems. GHI forecasting approaches may be categorized according to the input data used which also determine the forecast horizon.

- Statistical models based on online irradiance measurements are applied for the very short term timescale from 5 min up to 6 h (see Reikard [5]). Examples of direct time series models are autoregressive (AR) and autoregressive moving average (ARMA) models. Furthermore, artificial neural networks (ANNs) may be applied to derive irradiance forecasts.
- For short-term irradiance forecasting, information on the temporal development of clouds, which largely determine surface solar irradiance, may be used as a basis.
  - Forecasts based on cloud motion vectors from satellite images (Lorenz et al. [6]) show good performance for the temporal range from 30 min up to 6 h.
  - For the subhour range, cloud information from ground-based sky images may be used to derive irradiance forecasts with much higher spatial and temporal resolution compared with the satellite-based forecasts.
- For longer forecast horizons, from about 4 to 6 h onward, forecasts based on numerical weather prediction (NWP) models typically outperform the satellite-based forecasts (see Perez et al. [1], Heinemann et al. [7]).
- There are also combined approaches that integrate different kinds of input data to derive an optimized forecast depending on the forecast horizon.

Solar irradiance forecasts was assessed in terms of root mean square error (RMSE) and mean bias error (MBE or bias) which are defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (x_{pred,i} - x_{obs,i})^2} \quad (1)$$

$$MBE = \frac{1}{n} \cdot \sum_{i=1}^n (x_{pred,i} - x_{obs,i}) \quad (2)$$

where  $x_{pred,i}$  and  $x_{obs,i}$  represent the  $i$ th valid forecast and observation pair, respectively and  $n$  is the number of evaluated data pairs. These metrics are not formulated in the same way in all the papers we reviewed. David et al. [8] illustrated several formulas wrongly called RMSE or MBE.

Many solar irradiance forecasting models have been developed. These models can be divided into two main groups: statistical models and NWP models. Statistical models are based upon the analysis of historical data. They include time series models, satellite data based models, sky images based models, ANN models, wavelet

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