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Irradiance prediction intervals for PV stochastic generation in microgrid applications

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ABSTRACT

The increasing interest in integrating volatile resources into microgrids implies the necessity of quantifying the uncertainty of photovoltaic (PV) production using dedicated probabilistic forecast techniques. The work presents a novel method to construct ultra-short-term and short-term prediction intervals (PIs) for solar global horizontal irradiance (GHI). The model applies the k-means algorithm to cluster observations of the clear-sky index according to the value of selected data features. At each timestep, the features are compared with the actual conditions to identify the representative cluster. The lower and upper bounds of the PI are calculated as the quantiles of the irradiance instances belonging to the selected cluster at a target confidence level. The validation is performed in 3 datasets of GHI measurements, each one of 85 days. The model is able to deliver high performance PIs for forecast horizons ranging from sub-second to intra-hour ahead without the need of additional sensing systems such as all-sky cameras.

1. Introduction

The thrust toward increasing the penetration of non-dispatchable renewable generation in the electrical grid requires to redefine conventional practices to assure reliable power system operation, see for example Lopes et al. (2007) and Olivares et al. (2014). A paradigm increasingly advocated in the recent technical literature to cope with the variability of stochastic generation is the development of robust and predictive controls. They take advantage of short-term forecasts of renewable generation in order to plan adequate counteractions to prevent, or mitigate, operational issues related to renewables power fluctuations. Examples include the dispatchability of renewables, achieving self-consumption of locally generated electricity, and the short-term redispatching of conventional generation units, see for example Xie and Ilic (2008), Zhang et al. (2013), Sossan et al. (2016) and Troy et al. (2012). The period of the redispatch control action normally depends on the availability of the reserve in a given power grid and on the performance of the forecasting tools accounting for the uncertainties. For the case of microgrids, their limited physical extension and the low granularity of the resources involve the necessity of coupling the reserves dispatch with their real-time control. In this respect, a new protocol for real-time control of microgrids has been presented in the recent literature; in this framework, the control decision is updated with a sub-second resolution (Bernstein et al., 2015; Reyes-Chamorro et al., 2015). Since photovoltaic (PV) systems represent one of the major resources in modern microgrids, the availability of irradiance forecasting is beneficial to address the aforementioned challenges at forecast horizons from sub-second up to intra-hour (Olivares et al., 2014). A further concern associated with the dense penetration of PV installations in distribution systems and microgrids is the lack of the spatial smoothing effect, resulting in large variations of the solar irradiance. As an example, Fig. 1a and b respectively show daytime global horizontal irradiance measurements (GHI, recorded at the EPFL campus by using a pyranometer) and the power consumption of a group of EPFL buildings equipped with a 95 kWp PV-roof system. As visible, GHI variations (which varies up to 85% in magnitude in less than two minutes) cause very steep fluctuations of the power production and consumption. The availability of high-quality ultra-short-term and short-term GHI forecast enables the possibility of taking preemptive control actions and mitigating the effect of its fluctuations.

In general, the choice of the forecast method is strictly related to the target forecast horizon and geographical scale. As explained in Inman et al. (2013), day-ahead regional irradiance forecasting relies on satellite observations and numerical weather predictions (NWPs). However, we here focus on local and shorter term forecasts (lower than one hour) where Artificial Intelligence (AI)

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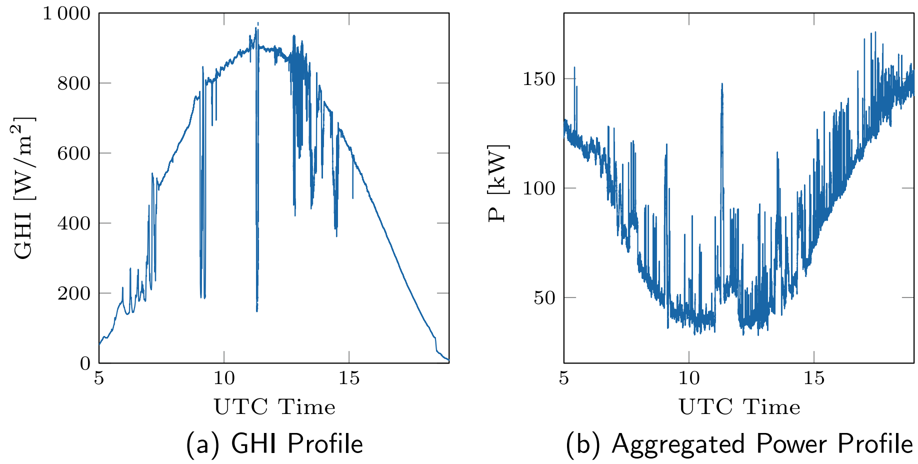

Fig. 1. GHI and aggregated power profile (load and PV production) as a function of the UTC time, registred at the EPFL campus on the 15th of May 2016.

methods are generally applied (Mellit and Kalogirou, 2008). The use of all-sky cameras is a promising solution for intra-hour forecast horizons, as introduced in Chow et al. (2011) and Calbo and Sabburg (2008). To the best of our knowledge, the only method addressing the problem of solar irradiance forecast at sub-second time scale is the one proposed in Torregrossa et al. (2015).

Two main kinds of forecast are conceived: a first kind (deterministic) considers only the point forecast while the second one (probabilistic) includes information accounting for the intrinsic uncertainty of the prediction and it is more appropriate when dealing with control and decision making in modern power systems (Bracale et al., 2013). Especially in the case of fast irradiance ramps, generally difficult to predict, PIs are necessary to define the worst-case scenario that should be considered in the control decision process.

Regarding GHI point predictions, the simplest forecast model is the persistent one, which is commonly used as a benchmark for performance evaluation. It assumes that the GHI remains constant with the forecast horizon. In general, most of the point forecast techniques are based on AI methods. A more deterministic approach consists in detecting the position of the clouds, deducing clouds motion and calculating the time when a cloud covers the sun, e.g. Chow et al. (2011) and Ghonima et al. (2012). Apart from cloud detection and motion, sky images contain more information impacting the GHI prediction: examples are the cloud cover and the type of clouds. This kind of information can be combined with machine learning methods to compute the forecast, e.g. Chu et al. (2013) and Marquez et al. (2013).

Several works address the problem of probabilistic forecast and propose PIs computation models. Probabilistic solar power forecast is proposed in Alessandrini et al. (2015) and Sperati et al. (2016) where a set of likely predictions (i.e. an ensemble) is provided using a historical set of variables and deterministic meteorological models. Authors of Alessandrini et al. (2015) use a distance criterion to retrieve similar past forecasts, under the assumptions that their errors are likely to be similar to the errors of the current forecast. These methods refer to 0–72 h forecast horizons, considering hourly power data. In Chu et al. (2015), a hybrid model is proposed, integrating Support Vector Machine (SVM), ANN and sky imaging techniques to deliver real-time PIs for direct normal irradiance (DNI) for 5, 10, 15, 20 min ahead. At each time step, the computational time is less than 5 s. Another stochastic approach in Pedro and Coimbra (2015) proposes the design of a k-nearest neighbors (KNN) algorithm. The KNN algorithm is used to predict the GHI and DNI and their uncertainty intervals, for time horizons from 5 to 30 min. More recently, Authors of Grantham et al. (2016) proposed a data-driven method to construct GHI probability densities for one hour-ahead predictions, using nonparametric bootstrap and a map of solar position. The developed method has low computational complexity, requiring 0.56 s on a personal computer. In David et al. (2016), point forecasts are generated using AutoRegressive Moving Average (ARIMA) and the associated PI is calculated using a Generalized AutoRegressive Conditional Heteroskedasticity model (GARCH), considering a prediction horizon from 10 min to 6 h. The use of recursive formulas, to update the model parameters in real-time, allows to reduce the computational complexity of the method.

Having stated this, we note that the available literature lacks of a unique forecasting tool for prediction horizons ranging from sub-second up to intra-hour and capable of operating at low levels of aggregation, where the level of volatility is higher due to the reduced spatial smoothing effect. While many methods have been proposed for intra-hour GHI forecasting and might be applied to deliver ultra-short-term predictions, there is at least the compelling need of re-assessing their performance in the light of the requirements of real-time control of local power systems. Moreover, computational complexity becomes a key concern when considering the high reporting rate of ultra-short predictions, implying that available forecasting methods with complex on-line training procedures (like ANNs, heuristic optimization-based and sky imaging) might not be suitable.

We propose a novel nonparametric method for ultra-short term forecasting of the global horizontal irradiance (GHI) to deliver predictions with a forecast horizon in the range from 500 ms to 5 min, thus suitable both in the context of real-time control of microgrids and energy management strategies. PIs computation is based on a well-known pattern recognition technique called k-means clustering (Lloyd, 1982). A training dataset is first clustered considering two empirically selected influential variables. Then, PIs are calculated by extracting the quantiles of the cluster which resembles at most the actual conditions. A clear-sky model is also introduced for the de-trending of the GHI time series. The method does not require any information from sky-imaging since it only relies on measurements of the GHI, it is computationally efficient and needs a limited training dataset. As later qualified in the paper, the real-time generation of the PIs takes, for one time instance, less than 0.5 ms. Thus, the method is applicable even when the control decision has to be taken at sub-second time scale.

The paper is organized as follows: Section 2 defines the problem and introduces the nomenclature, Section 3 explains in details the methodology adopted to deliver the PIs and discusses its computational complexity. Section 4 describes the available datasets and