Available online at www.sciencedirect.com

ScienceDirect

Solar Energy 124 (2016) 57–67

SOLAR ENERGY

www.elsevier.com/locate/solener

Model-free computation of ultra-short-term prediction intervals of solar irradiance

D. Torregrossa *, J.-Y. Le Boudec, M. Paolone

Swiss Federal Institute of Technology in Lausanne, Switzerland

Received 2 September 2015; received in revised form 16 November 2015; accepted 17 November 2015
Available online 12 December 2015

Communicated by: Associate Editor Mario A Medina

Abstract

We propose an ultra-short-term dynamic interval predictor (DIP) of solar irradiance. Our DIP relies on experimentally observed correlations between the derivative of the solar irradiance and the forecast error in the next time-step. The main originalities of this DIP are (i) its independence from the method used for the point forecast of solar irradiance, (ii) its independence from the error distribution of the point-forecast method. We compare the DIP with the most common prediction interval methods. By using significant data set covering several months of experimental observations, we have observed higher accuracy and lower width of the prediction intervals of the proposed DIP.

Keywords: Forecast; Ultra short-term; Solar irradiance; Prediction intervals

1. Introduction

Today's trend of vast connections of distributed generation in low- and medium-voltage power networks accounts for quality-of-supply of electrical distribution grids in a way that, in several countries, operational constraints are already attained. Additionally, it is necessary that their active contribution be quantified in real-time and, eventually, controlled. In this respect, one of the main concerns of distribution network operators refers to the definition of optimal control-schemes in which the high volatility of renewable-energy resources (RERs) can be accounted for. The choice of the forecast time window is extremely important and it is highly correlated to the design of real-time control of RERs in order to provide grid primary-ancillary services (e.g., Song et al., 2013; Vrakopoulou et al., 2013; Heniche et al., 2013). Several control strategies have been proposed (database model in Song et al. (2013), stochastic optimization in Vrakopoulou et al. (2013), multiagents in Heniche et al. (2013)) to define dedicated real-time energy-management systems and, in some cases, the concept of real-time control is associated with time dynamics below 1 s (Heniche et al., 2013).

More specifically, the authors of Bernstein et al. (2015), Reyes Chamorro et al. (2015) recently proposed a solution to the challenging problem of controlling a distribution network in real-time by using explicit power setpoints. In this framework the resources can advertise their current internal needs and power availability by simple messages in order to enable a grid controller to maintain the state of the system within secure limits. The framework, called *Commelec*, is designed to be robust (i.e., it avoids the problems inherently posed by software controllers) and scalable (i.e., it easily adapts to grids of any size and complexity). It is based on software agents, that are responsible for

* Corresponding author. Tel.: +41 787209227; fax: +41 (0) 21 693 46 62.
E-mail address: dimitri.torregrossa@epfl.ch (D. Torregrossa).

http://dx.doi.org/10.1016/j.solener.2015.11.017
0038-092X/

resources/subsystems (Resource Agents) or entire grids (Grid Agents) and they communicate using a simple yet powerful protocol with a refresh rate of around 100 ms. A detailed description of the proposed framework is given in Section 2.

In this context, the real-time control can be considerably improved if the Grid Agents are able to bound the uncertainty of power injections, due to stochastic sources, at a horizon of one or a few control cycles (fraction of a second). For systems with photovoltaic (PV) panels, it is worth observing that the solar irradiance has an extreme volatility in time scales below a second.[1] It is thus interesting to find ultra-short-term forecast bounds for the solar irradiance of PV panels, and such is our goal in this paper.

The available literature on prediction intervals for PV energy-conversion systems is characterized by the following four main limitations (Singh et al., 2013; Kardakos et al., 2013; Trapero et al., 2014; Lorenz et al., 2009; Marquez and Coimbra, 2011; Bacher et al., 2009; Segura and Vercher, 2001): (i) absence of methods proposing prediction intervals targeting the time scale of seconds or sub-seconds; (ii) absence of methods proposing prediction intervals able to track the highly-dynamic volatility of the solar irradiance; (iii) absence of methods able to account for distributions of the point-forecast errors other than Gaussian; (iv) strong dependency of the prediction interval with the specific method used for the point forecast computation. To the best of our knowledge, the only works that are independent of the point-forecast method are (Wan et al., 2014; Pinson and Tastu, 2014). Machine-learning methods capable of quantifying uncertainty bounds of point forecasts are presented in Wan et al. (2014), Pinson and Tastu (2014).

In this paper we propose a model-free prediction interval of the solar irradiance. The method, henceforth called the dynamic interval predictor (DIP), is able to estimate the magnitude of the prediction intervals by assessing the correlations between the measurements of the derivative of solar irradiance and the point-forecast error in the next forecasting time-step.

With respect to the above-listed drawbacks of traditional prediction intervals, the DIP exhibits the following characteristics: (i) the prediction intervals are computed within a time scale ranging from 250 ms up to 750 ms; (ii) it does not depend directly on the method used for the point forecast; (iii) it is able to track high dynamics of the solar irradiance and (iv) it is capable of self-improving its performances during its use because it is able to correct the magnitude of the prediction intervals for future computations.

The paper is structured as follows. The Commelec framework, for which the proposed DPI has been deployed, is described in Section 2. A brief summary of the different existing methods for prediction intervals is reported in Section 3. In order to highlight the need of ultra-short-term forecast, experimental evidences of sub-second solar dynamics are illustrated in Section 4. In the same section, by using experimental data, the existing correlations between the derivative of solar irradiance and the point-forecast error in the next forecasting time-step have been analyzed. The proposed DIP is described in detail in Section 5. The robustness of the DIP, and its comparison with the other commonly used prediction intervals methods, are illustrated in Section 6. In particular, since the available literature on point forecast computation contains a considerable amount of works based on heuristic technique (Mellit and Pavan, 2010; Mellit and Kalogirou, 2008; Sfetsos and Coonick, 2000; Behrang et al., 2010), Section 6 also assesses the performances of the proposed DPI coupled with an ANFIS (adaptive neuro-fuzzy inference system) point forecast model. The main findings of the work and its applicability are summarized in Section 7.

2. The Commelec control framework

In the Commelec framework, a software agent is associated with a resource (henceforth called “Resource Agent”, RA), or an entire system, including a grid and/or a number of devices (henceforth called “Grid Agent”, GA). There is a well-defined relationship between the agents, which follows from the tree structure of the distribution networks. An example of agents relationship is shown in Fig. 1 where GA is in charge of controlling RAs $A_1, \ldots, A_N$, who are responsible for subsystems $S_1, \ldots, S_N$.

Each Resource Agent advertises its internal state to its Grid Agent using the following three elements. (1) The *PQ profile A* is the region in the (P,Q) plane (for active and reactive power) that the subsystem under the control of this Resource Agent can deploy. (2) The *virtual cost C* is a function, that defined for every (P,Q) in the *PQ* profile, returns a number $C(P,Q)$ interpreted as the willingness of this subsystem to apply a requested power setpoint (P,Q). It is virtual in the sense that it is not directly related to a monetary value. (3) The *belief function BF* returns the set of all possible (actual) setpoints so that this subsytem *might* in reality implement, when instructed to implement a target setpoint. This accounts for the uncertainty in a subsystem operation. In particular, highly controllable subsystems are expected to have ideal beliefs, namely

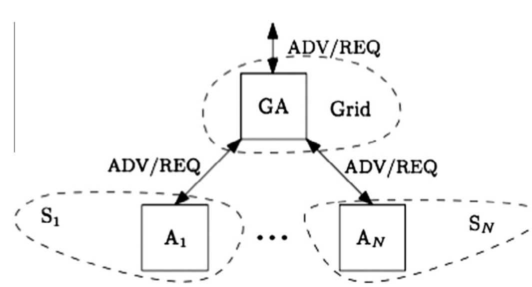

Fig. 1. A general scheme for showing Commelec agents interactions.

[1] An experimental quantification of the sub-second PV volatility is given in Section 3.