Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

REEL Demo – Romande Energie ELectric network in local balance Demonstrator

Deliverable: 4c Tools for multi time horizon PV point forecasting and prediction intervals

Demo site: Aigle

Developed by
Dr. Enrica Scolari, Dr. Fabrizio Sossan and Prof. Dr. Mario Paolone
Distributed Electrical Systems Laboratory, EPFL

[Lausanne, 29.04.2020]

NOTE: This work has been carried out in the framework of the Doctoral thesis of Dr. Enrica Scolari entitled "Modelling and Forecasting of Photovoltaic Generation for Microgrid Applications: from Theory to Validation" under the supervision of Prof. Dr. Mario Paolone at the Distributed Electrical Systems Laboratory of the EPFL. The report presents parts of this Thesis related to this deliverable. The full Thesis is accessible at this URL:
https://infoscience.epfl.ch/record/263659/files/EPFL_TH9039.pdf

1. Description of deliverable and goal

1.1. Executive summary

Abstract

The massive integration of stochastic renewable generation in modern power systems requires decentralized control schemes that cope with the uncertainties of the distributed energy resources (DERs). Among the DERs, small-scale photovoltaic (PV) systems are expected to represent most of the future power generation capacity. Therefore, solar resource assessment and the associated forecasting at various time scales are of fundamental importance for power systems operators.

The activity here summarized focuses on developing forecasting methods based on the integrated use of time series, all-sky camera images and generation models of PV systems, considering short-term temporal horizons (below one hour) and fine spatial resolution (single site installations). We aim to improve the efficiency of forecasting methods developed by the DESL through prediction of clouds movement and associated cover of the sun disk. For this, we developed and validated different machine-learning techniques relying on the integrated use of Global Horizonal Irradiance (GHI) time series, all-sky image processing and cloud motion identification. Furthermore, a methodology to estimate the irradiance from all-sky images is proposed, investigating the possibility of using all-sky cameras as irradiance sensors.

1.2. Research question

The research question that this activity aims to respond is the following: how the stochastic behavior of a PV plant can be quantified by predictive control frameworks specifically designed for the real-time control of microgrids or active distribution networks ?

1.3. Novelty of the proposed solutions compared to the state-of-art

Given of the major role that stochastic resources (i.e., PV and wind) play in the modern and future electrical infrastructure, the predictive assessment of PV power production variability, and the associated uncertainty, in a probabilistic way is essential [1]. Since the solar irradiance is highly dependent on the cloud coverage, image-based solar cloud

forecast has been largely studied by the recent literature, [2, 3]. Even more, the use of all-sky cameras for irradiance estimation has recently come to prominence. Compared to pyranometers, all-sky images provide additional information, like the cloud map and movement. Compared to satellite images, the all-sky camera can deliver local high-frequency images. Recently, Authors of [4] estimate both the Direct Normal Irradiance (DNI), and the diffuse horizontal irradiance (DHI) using information from a camera system with a charge-coupled device (CCD) sensor.
We have developed a new machine-learning method to forecast the prediction intervals of the GHI for different time horizons. The method relies on the integrated use of GHI time-series and all-sky camera images. As a side result, we have proposed a method to estimate the GHI from images delivered by an all-sky camera.
The method extracts first a number of features from historical all-sky images and from a clear-sky model. Then, it performs a feature selection to determine the most relevant features by applying principal component analysis (PCA), [5].

1.4. Description

The undertaken research steps are the following.

Quantification of the uncertainty associated with solar volatility.
We focused on forecast horizons that are meaningful in microgrids control applications (i.e. from sub-second up to minutes). A simple method to deliver prediction intervals (PIs) for the GHI is proposed and its performance assessed. The proposed technique extracts information from a limited training set: data are clustered off-line by using the *k*-means algorithm and the quantiles of the obtained clusters are then used for PIs computation. The process to compute the PIs is performed in two ways (a) Method A: we cluster the original clear-sky index time-series; and (b) Method B: we cluster the differentiated clear-sky index time-series: to verify if differencing leads to better prediction performance. The method does not rely on any specific point forecast technique and does not need any information from sky imaging. We show that two the proposed algorithm outperforms the benchmark case with simple quantiles extractions and the benchmark case considering the ARIMA (Auto Regressive Integral Moving Average) model Gaussian distribution of the point forecast error (an example of analysis is shown in Table 1).

Table 1 PI coverage probability (PICP) - the PI normalized averaged width (PINAW) and overage width-based Criterion (CWC) [%] for a time horizon of 1 min and a probabilistic coverage of 95%.

	Season		
Method	Summer	Autumn	Winter
Method A	90.1-10.2-25.2	90.8-4.81-11.4	88.8-8.87-23.4
Quantiles A	94.7-56.7- 112	93.1-29.5-61.9	95.8-34.7-34.7
Method B	96.9-10.5-10.5	97.5-3.26-3.26	97.8-9.1-9.1
Quantiles B	89.7-13.8-34.8	90.6-6.1-14.6	91.7-6.73-15.3
ARIMA+GAUSS	93.4-19.2-40.3	94.0-8.13-16.5	95.6-10.6-10.6

Furthermore, performance is shown to be in line, or improve, those available in the literature for various forecast horizons and using a shorter and limited training set. The method is applied to the original and differentiated clear-sky index time-series. Results show that the benefit coming from the time-series differentiation decreases while increasing the forecast horizon (an example of this analysis is reported in Figure 1).

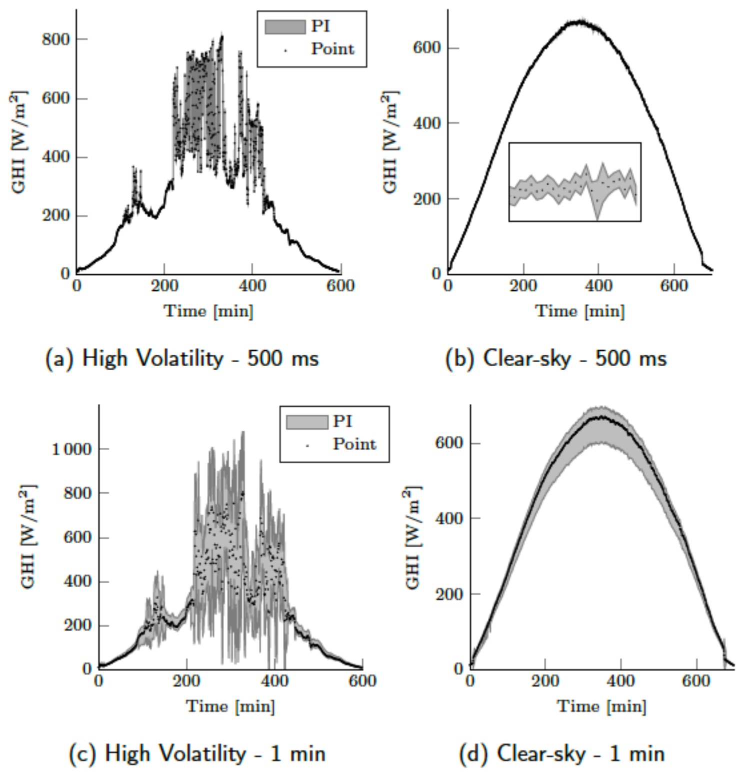

Figure 1 PIs and realizations are shown for different forecast horizons considering daylight hours, probabilistic coverage of 99% and Method B is applied. Two days with different weather conditions are selected from the Winter period.

It is shown that the proposed method is able to adapt the widths of the PIs in order to guarantee the target coverage.

<u>Prediction of the local cloud cover in the sun disk</u>.

Several cloud segmentation and motion methods were analyzed. Regarding binary cloud segmentation, a new method based on the intensity-to-blue ratio is proposed and proved to outperform available methods based on different color channels (e.g, the red-blue ratio) and supervised segmentation models. A preliminary analysis on different cloud motion algorithms has shown that the optical flow is the most promising method. Furthermore, we have shown that the information on the local cloud cover can be used to improve a machine learning based method to deliver GHI PIs, besides the sole use of past irradiance measurements proposed in the previous chapter (an example of such analysis is show in Figure 2).

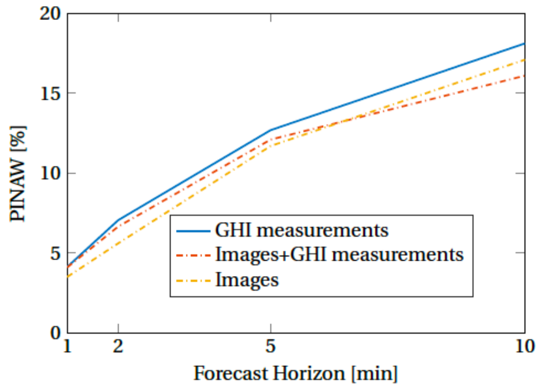

Figure 2 PINAW of the GHI prediction for different forecast horizons.

Since the main drawback of the proposed toolchain is that the prediction method is still dependent on the pyranometer, we evaluate the possibility of using the sky-camera as a GHI sensor itself. With this aim, a machine learning-based method to estimate the GHI using images from an all-sky camera is proposed. At first, a large set of features is extracted from the images, and then feature selection is performed using principal component analysis (PCA). The subset of selected features is then used as input to train an artificial neural network (ANN), considering the clear-sky index as a target. Furthermore, SEVIRI thermal channels are used alone and in combination with features from the camera as input to the same procedure (PCA and ANN), to evaluate if this information can improve the GHI estimation. Performance evaluation is presented using pyranometer measurements, collected in the same location of the camera, as ground truth. The analysis considers for different periods of the year and three different time resolutions (i.e., 1, 5, and 15 min). The GHI estimations are benchmarked against the Heliosat-2, a well-established method to estimate the GHI from satellites (e.g. Meteosat in Europe). Results show that the all-sky camera-based GHI estimations proposed in this work outperform the Heliosat-2, with a RMSE relative improvement of 20-45%. In particular, this happens when fast irradiance dynamics are present (e.g. during partly-cloudy conditions), due to the fact that satellites-based models lack the spatial and temporal resolution needed to capture localized fluctuations (Table 2).

Table 2 GHI estimations comparison for selected days at 1 min.

	Cloud-free		Partly-cloudy	
	ASI	H-2	ASI	H-2
puRMSE [%]	6.7	6.8	12.7	17.5
nRMSE [%]	13.3	13.6	34.9	47.9
MAE [W/m^2]	43.3	46.0	82.8	103
MBE [W/m^2]	3.7	5.0	22.0	6.1
CC	0.97	0.97	0.89	0.80

Results also suggest that the additional information from satellites thermal channels are not improving the estimation. The method has been extended to the case of GHI point forecast, showing an improvement with respect to a simple persistent method for forecast horizons higher than 1 min. Future work will evaluate how to integrate the information from the two best performing methods (ASIs-based and H-2), for example by distinguishing between clear-sky and partly-cloudy conditions beforehand.

1.5. Regulatory and legal barriers for implementation

There is not any regulatory or legal barrier associated to the implementation of the proposed method per se.

2. Achievement of deliverable:

2.1. Date

December 2019

2.2. Demonstration of the deliverable

This deliverable has been achieved through the development of tools for multi-time horizon PV forecasting and prediction intervals estimation and their validation through deployment and testing into an industrial hardware platform.

3. Impact

The tools developed and validated in the frame of this activity feed in FURIES' activities related to the grid control, notably those associated with Demand Site Management (subtask 1.2) and operation of a BESS for grid control (subtask 1.4). Indeed, the PV and power generation forecasting will be considered for the DSM and feeder dispatching at the Rolle and Aigle sites respectively of the REeL demo.

4. Publications

4.1. References

[1] F. L. Lewis and F. Lewis, Optimal estimation: with an introduction to stochastic control theory. Wiley New York et al., 1986.

[2] C.W. Chow, B. Urquhart,M. Lave, A. Dominguez, J. Kleissl, J. Shields, and B.Washom, "Intra-hour forecasting with a total sky imager at the {UC} san diego solar energy testbed," Solar Energy, vol. 85, no.

11, pp. 2881 – 2893, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0038092X11002982
[3] S. R. West, D. Rowe, S. Sayeef, and A. Berry, "Short-term irradiance forecasting using skycams: Motivation and development," Solar Energy, vol. 110, pp. 188 – 207, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/ S0038092X14004150
[4] B. Kurtz and J. Kleissl, "Measuring diffuse, direct, and global irradiance using a sky imager," Solar Energy, vol. 141, no. Supplement C, pp. 311 – 322, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0038092X16305722
[5] S.Wold, K. Esbensen, and P. Geladi, "Principal component analysis," Chemometrics and intelligent laboratory systems, vol. 2, no. 1-3, pp. 37–52, 1987.

4.2. Related publication from authors

- E. Scolari, F. Sossan, M. Haure-Touz´e, M. Paolone, Local estimation of the global horizontal irradiance using an all-sky camera (Solar Energy, 2018).
- E. Scolari, F. Sossan, and M. Paolone, Experimental Comparison of Maximum Power Estimators for a Single Unit Photovoltaic Plant (35th EU PVSEC Conference, Brussels 2018).
- E. Namor, F. Sossan, E. Scolari, R. Cherkaoui, M. Paolone, Experimental Assessment of the Prediction Performance of Dynamic Equivalent Circuit Models of Grid-connected Battery Energy Storage Systems (IEEE PES ISGT Europe, Sarajevo, October 21-25, 2018).
- R. Gupta, F. Sossan, E. Scolari, E. Namor, L. Fabietti, C. Jones, M. Paolone, An ADMM-based Coordination and Control Strategy for PV and Storage to Dispatch Stochastic Pro-sumers: Theory and Experimental Validation (PSCC XX Power Systems Computation Conference, Dublin 2018).
- E. Scolari, L. Reyes-Chamorro, F. Sossan, M. Paolone, A Comprehensive Assessment of the Short-Term Uncertainty of Grid-Connected PV Systems (IEEE Transaction on Sustainable Energy, 2018).
- L. Reyes-Chamorro, A. Bernstein, N. J. Bouman, E. Scolari, A. Kettner, B. Cathiard, J.-Y. Le Boudec and M. Paolone, Explicit Real-Time Control of Power Flows in Microgrids (IEEE Transaction on Industrial Informatics, 2018).
- E. Scolari, F. Sossan, M. Paolone, Photovoltaic Model-Based Solar Irradiance Estimators: Performance Comparison and Application to Maximum Power Forecasting (IEEE Transaction on Sustainable Energy, 2017).
- L.Magnone, F. Sossan, E.Scolari, M. Paolone, A Heuristic Cloud Motion Detection Algorithm Based on All-Sky Images to Support Solar Irradiance Forecast (44th IEEE PVSC Photovoltaic Specialists Conference, Washington DC, 2017).
- E. Scolari, F. Sossan, M. Paolone, A Model-Based Filtering Strategy to Reconstruct the Maximum Power Generation of Curtailed Photovoltaic Installations: application to forecasting (IEEE PES PowerTech Conference, Manchester 2017).
- E. Scolari, F. Sossan, and M. Paolone, Irradiance prediction intervals for PV stochastic generation in microgrid applications (Solar Energy, 2016).