Benchmarking different approaches to convert surface solar irradiance into PV power production: a case study with an operational forecast system for a roof-top PV farm

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Background and objective

- Forecasting PV power production few hours ahead optimizes the decisions of micro-grid energy management system by maximizing its PV self-consumption
- Most of PV power forecast methods, using cloud cover observations from geostationary satellite images, requires a conversion from global horizontal irradiance (GHI) to PV power (P_{PV}). Physical models use precise knowledge of PV panels characteristics. They provide instant values of P_{PV} from GHI, air temperature (T_{air}) and wind speed (WS) forecast. Machine learning approaches use historical data without requiring PV plant information. It can learn specific local features that physical model ignore (recurrent shadowing, PV material ageing etc.)
- This work assess the performance of a physical model and machine learning methods against power measurements of a rooftop farm operational since July 2020.

A smart building demonstrator

The start-up incubator of *Institut Polytechnique de Paris* is a building in partial self-consumption equipped with:

- 17 kW_p of PV capacity, 30.5 kWh of battery storage
- 53 PV panels distributed in 6 distinct technologies (PERC, half-cells, Mono-Si, bifacial etc.). 2 different tilt angles (20° and 30°)

The SIRTA observatory

Located at 500m of the smart building, the SIRTA observatory holds a hundred of meteorological instruments including:

- Pyranometers and photometers of radiation observation international networks (BSRN, AERONET …)
- Any other observation useful for PV power modeling (temperature, wind speed, albedo, PV panel testbench …)

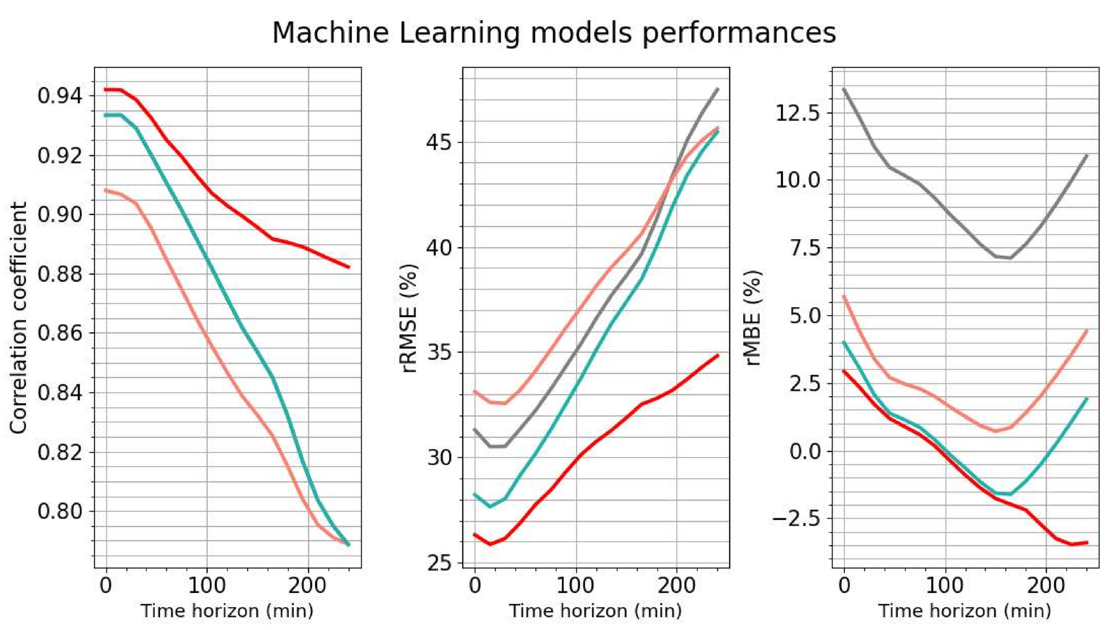
More information at https://sirta.ipsl.fr/ or scan

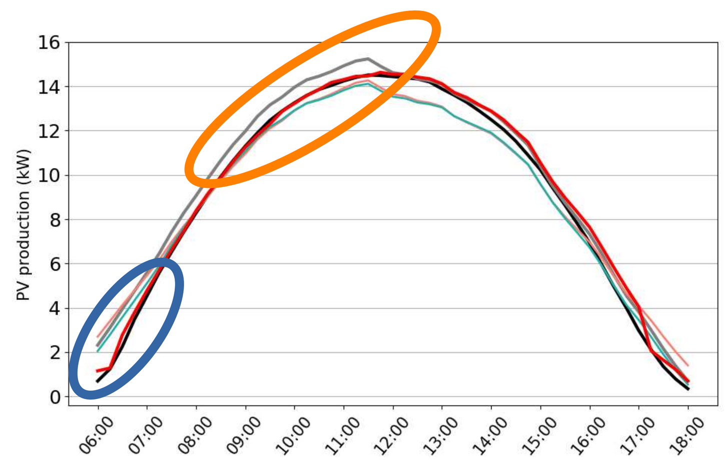
Machine learning methods

We set up methods requiring historical records of GHI and P_{PV} rather than PV panel characteristics.

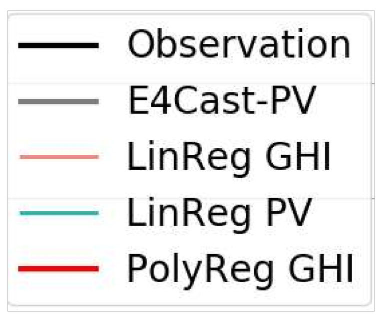
Following a benchmark performed by [6], we tested these following methods:

- LinReg GHI: $P_t = a_t * GHI_{t=0} + b_t$ (where a_t,b_t are regression coefficients for time horizon t)
- LinReg PV: $P_t = a_t * E4P_{t=0} + b_t$ (E4P is the output of E4Cast-PV method)
- PolyReg GHI : $P_t = f(GHI_{t=0}, GHI_{t=-30min}, T_{air t}, WS_t, SZA_t, SAA_t,$ *satellite image cloud index features)* *f* is a 3rd degree polynomial function, SZA and SAA solar zenith and azimuth angles)
- Kernel Ridge Regression (KRR) (tested but not shown here)
- Multi-Layer Perceptron – Artificial Neural Network (MLP-ANN) (tested but not shown here)



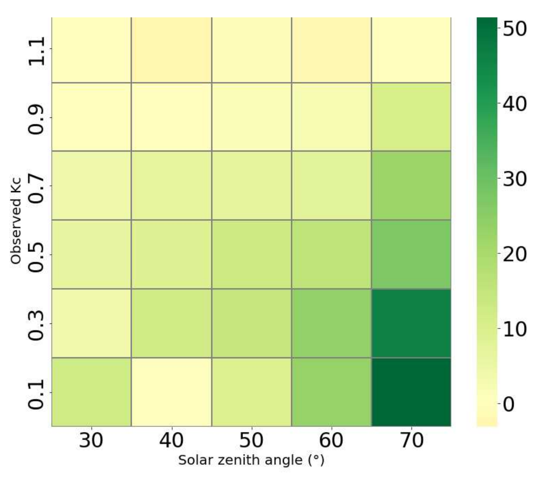


Polynomial regression using GHI shows the best performance. On 2021-04-23, it ***cancels the morning bias*** *and* ***corrects the overestimation***



Dataset train: October 2020 to June 2022 excepted July, October 2021 and January, April 2021. These last months are used as validation dataset. A linear regression converting GHI to PV is less accurate than E4Cast-PV. PolyReg_GHI model shows the best performance. The use of external parameters provide a significant improvement.

This heatmap presents the relative RMSE (%) reduction provided by PolyReg_GHI. Errors are statically more reduced in cases with cloudy situations and low sun elevation accuracy.

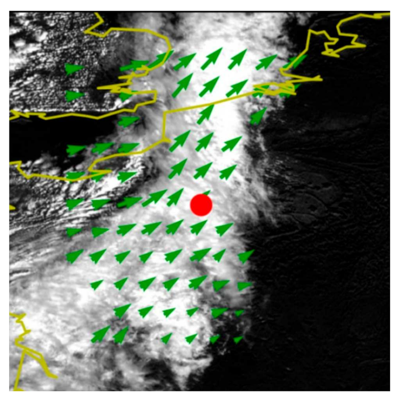


Satellite-based forecast method

An operational chain forecast GHI every 15 min using images from Meteosat satellite using cloud motion vector computation (see details in [1]).

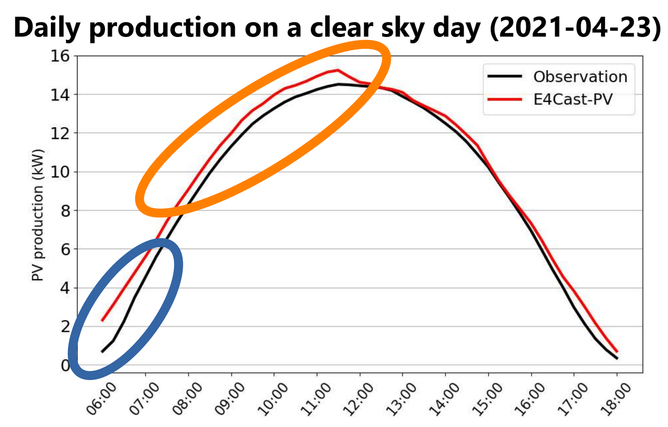
GHI is currently converted into PV power with a physical model called E4Cast-PV using:

- GHI split into direct and diffuse radiance [2]
- Plane-of-array irradiance modeling [3]
- Back PV cell temperature modeling using [4]
- PVWatts power model [5]



Cloud motion vectors applied on a Meteosat-11 image. The extrapolation of the cloud cover enables to forecast the GHI over a target point (from [1]).

E4Cast-PV assess PV power from satellite-derived GHI at t = 0min in time horizon



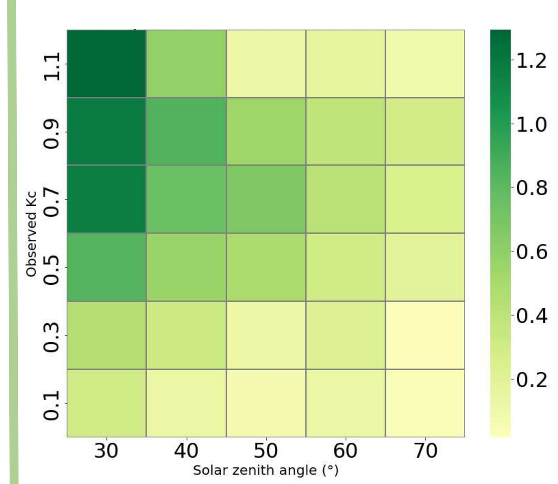
E4Cast-PV is a physical model assuming that PV panels characteristics are well known and requiring only GHI and air temperature as instant values. ***Trees shadowing in the morning is ignored*** *and PV power is* ***overestimate until 13:00 UTC.***

Application of a Kalman filter

To study the operational case where no historical data are available, we assess the performance of E4Cast-PV method corrected by a Kalman filter (KF) following the implementation published by [7].

KF has been applied on forecast performed from October 2020 to June 2022 for E4Cast-PV. Time horizon at 0 min shows a significant decrease of relative mean bias error. KF has no positive impact on machine learning methods

This heatmap presents the abolute MBE (kW) reduction provided by Kalman filter on E4Cast-PV. KF reduces the error for clear sky cases with high solar positions.



Model	Corr. Coef.	rRMSE (%)	rMBE (%)
E4Cast-PV	**0.93**	**31.0**	**13.3**
E4Cast-PV + KF	**0.92**	**30.2**	**5.1**
LinReg_GHI	0.91	33.2	6.8
LinReg_GHI + KF	0.90	35.1	5.4
LinReg_PV	0.93	28.1	4.5
LinReg_PV + KF	0.90	34.0	-5.4
PolyReg_GHI	0.95	25.2	3.1
PolyReg_GHI + KF	0.92	31.7	1.3

Conclusion and perspectives

- Following a recent state-of-the-art, we performed a benchmark of methods converting GHI into PV power
- Results showed clearly the performance of the polynomial regression using external variables. Kalman filter reduces strongly the bias of the physical model, without positive impact on machine learning methods.
- Advanced methods with long training (KRR, MLP-ANN) did not provide significant improvements.
- Further studies will investigate the influence of on-hand predictors.

Bibliography and acknowledgement

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