SHORT-TERM FORECAST OF DISTRIBUTED PV WITH ALL-SKY IMAGER

Caroline DEFOREIT
STEADYSUN – France
caroline.deforeit@steady-sun.com

Aurélie FERRAGE
ERDF – France
aurelie.ferrage@erdf.fr

Alain ABELLO
STEADYSUN – France
alain.abello@steady-sun.com

ABSTRACT

This paper presents the results of an experimentation of short-term distributed solar PV production forecast using an all-sky camera. It is focused on a demonstration project in and around Lyon, France, which covers more than 300 PV plants. In this paper, we will see the results of day-ahead forecasts and short-term forecasts (less than 30 minutes). Short-term forecasts are made using all-sky imagers installed near the PV plants. The paper analysed how production data impact day ahead forecast and how distance between the cameras and the PV plants influence short-term forecast results. We'll then conclude on the efficiency of these forecasts for distributed PV.

INTRODUCTION

In order to integrate solar energy more effectively into the electricity grid, ERDF (France's main electricity DSO) is leading with Steadysun a full-scale operation in Lyon and its suburbs. This projects aims to establish a very accurate forecasting system for decentralized photovoltaic production using numerical weather prediction and **real-time images taken by several cameras.**

DEMONSTRATION PROJECT

Description

The experiment covers more than 300 PV plants in and around Lyon, France. The solar plants (mainly rooftop installations) are between 2 and 200 kWc.
Data from each Solar PV plants are gathered and send using the new Linky Smart Meter. These data are then aggregated and integrated into the forecasting model, substantially increasing the accuracy of the forecasts by running self-learning algorithm.

The forecasts are made for several time horizons:
- For the next days, with an update every 6 hours or 12 hours
- During the day for the next half hour, with an update every minute

For this last time horizon, two fish-eye cameras provide non-stop 360-degree images of the sky. Steadysun software analyzes cloud movement and uses these information to predict fluctuations in PV production for the next half hour.

Forecasts are generated at three spatial scales:

- At PV plant level (only for the biggest ones)
- At LV (low-voltage) network level, with a group of several plants spread over an area of several square kilometers
- For the entire HV (high-voltage) network, with an aggregated sampling of several plants spread over several dozen square kilometers

This multi-scale approach is crucial for ERDF to optimize its grid management at each scale (LV or HV) while integrating as much renewable energy production as possible.

Image 1: sky-imager

Forecasts for aggregated plant

Main forecasts are processed for an aggregation of plants (i.e. LV network): it consist in forecasting the production of a sum of plants located in a same area. In that case, precise information (GPS coordinate, peak power, tilt/azimuth of modules plan, etc.) for each plant are not known or provided. The forecast algorithm uses mean or estimated values for the equivalent aggregated plant.

Production data can be available for some individual plants, but most of the time, for confidentiality and privacy reasons, they are only available at an aggregated level. In the frame of this project, these data could not be transferred to a third party (i.e. forecast service provider). A self-learning algorithm uses data regarding solar PV production to improve the model of the plant and compensate statistical errors.

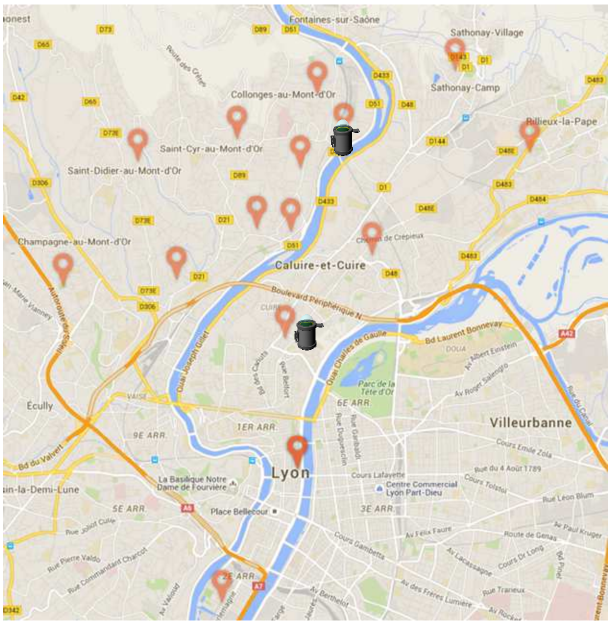

Figure 1: map with aggregated plants and cameras

DAY-AHEAD FORECASTS RESULTS

Production forecast for the next days is based on the processing of meteorological forecasts. Usually it requires access once a day to the current production data of the supervised plant in order to run self-learning algorithm and increase accuracy.
In the case of aggregated plants, production data had varying qualities. From one day to another, the number of plants for which the productions were actually measured and added may vary.

The following table summarizes the accuracy obtained over a year for 1 and 2 days ahead forecast:

	nMAE D+1	nMAE D+2
AG1	5.90	6.50
AG2	6.94	7.82
AG3	6.18	6.75
AG4	6.57	7.23
AG5	6.01	6.63
AG6	5.69	6.18
AG7	5.62	6.27
AG-all	6.08	6.69
Sum of AG	5.52	6.16

- AG1 to AG7 are 7 aggregated plants, each of them being the sum of 5 to 50 PV plants.
- AG-all is the aggregation of all the PV plants (~ 300). In that case, the software has only access to the global production.
- “sum of AG” corresponds to a forecast obtained by the sum of the 7 forecasts of AG1 to AG7.
- Mean Absolute Error are computed based on the average power over 30 minutes intervals, night time periods are not included, value normalized by peak power.

From one aggregated plant to another, nMAE reaches 5.62% to 6.94% for D+1.
These differences could be due to:
- The quality of data production which may vary, and then be misused by the self-learning software
- The lack of representativeness of the “average” characteristics. As we used physical models, the value of tilt and azimuth for plane of modules is quite important.

D+1 nMAE is 8% to 11% smaller than D+2. It is clearly linked to the increased accuracy of Numerical Weather Prediction at smaller time horizon.

nMAE for “Sum of AG” is 8%-9% smaller than AG-All. It means that in order to increase the accuracy it is better to forecast each area (i.e. aggregated plant) and sum these forecasts, rather than directly generate a forecast for the whole area.
The reason is that in the former case we have access to production data for each zone and not only that of the overall aggregate. In this case it is 7 times more information. Self-learning algorithms are applied to each of the 7 aggregate which increase the quality of the solar PV production model.

INTRADAY FORECASTS RESULTS

Short term forecast

Two fisheye cameras have been installed in the Lyon region and are taking hemispherical images every minute. These images are sent to a server. The software uses them in real-time to detect if there is clouds, how much solar energy they let through, and their evolution over time. In a second step, the electrical production is predicted for all the aggregated plants. Finally, these forecasts are sent to ERDF.

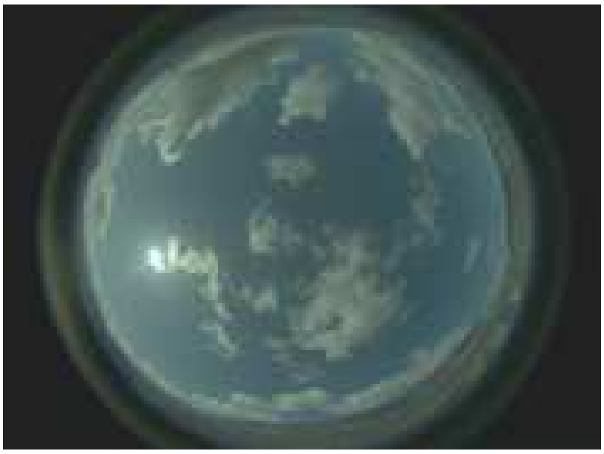

Image 2: Image from the sky-imager

The forecasts include information on the level of uncertainty using probabilistic percentiles from 10% to 90%. These confidence intervals allow a proper assessment of the possible short term evolutions.

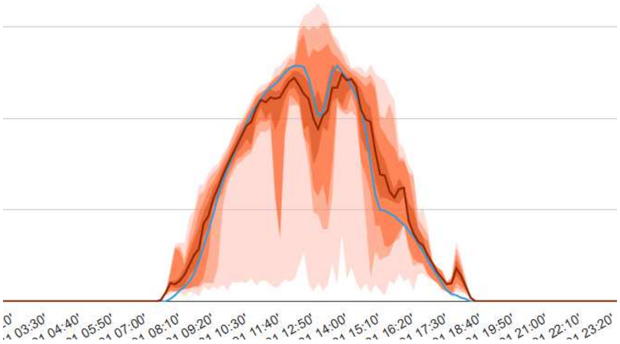

Figure 2: Actual (blue) vs Forecast (red/orange for percentiles) – 5 minutes ahead

The position of the camera is important. It's important to avoid having a section of the sky masked by nearby buildings. Figure 3 show illustrate this point: in December for one of the two cameras, in the morning of December, the sun was hidden by a building. The Figure shows the predictions obtained on two consecutive days. When the sun is no longer visible, the algorithm considers that a cloud is present, and anticipates a drop of production.

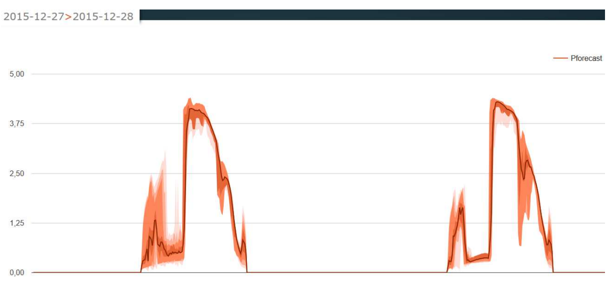

Figure 3: forecasts with drop when sun masked by nearby building

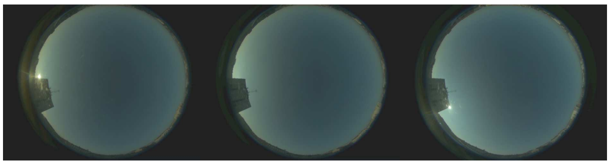

Image 3: Images taken in the morning

Covered area

One of the questions addressed by this project is the size of the area covered by a camera.
Figure 4 shows the evolution of the nMAE according to the distance between the center of the aggregate and the camera. Not surprisingly, the best (lowest NMAE) are obtained for an aggregate centred on the camera (all of its plants are located within 1 km). With aggregate at 2 km, the nMAE is 3 times higher. Then the loss of accuracy is still relatively limited. The most distant aggregates are located at about 5 km.

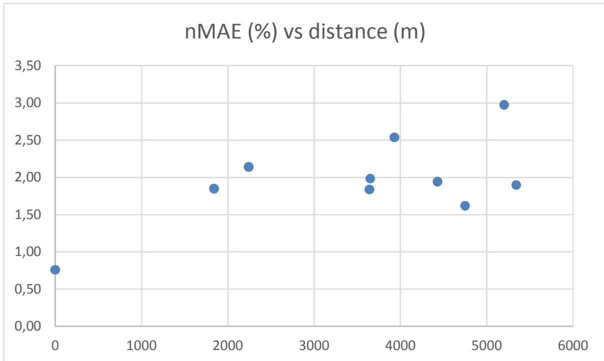

Figure 4: nMAE with distance from the camera

Figures 5 and 6 show on the same day, forecast for local aggregated plant and another one located at 5 km.The main difference is that the confidence interval is larger for the furthest.

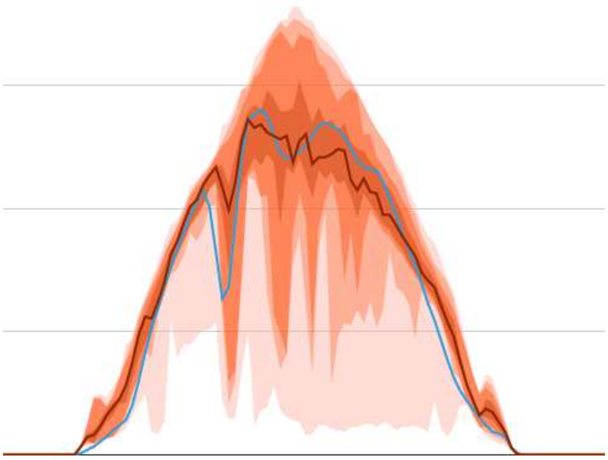

Figure 5: Forecast for aggregated plant centered on camera

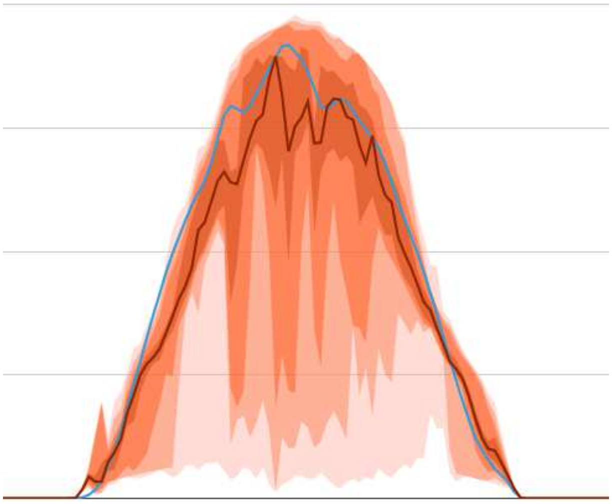

Figure 6: Forecast for aggregated plant located at 5 km from camera

Figures 7 and 8 show the forecasts obtained for the same plant but from the images of each of the 2 cameras. One is north of the plant, the other south.
The forecasts for the morning are different, mainly for uncertainty aspect (confidence intervals are not the same). There is also a drop at 1 PM anticipated by one camera, but not by the other one.
On the other hand, for the afternoon both forecasts are similar, with very low uncertainty.

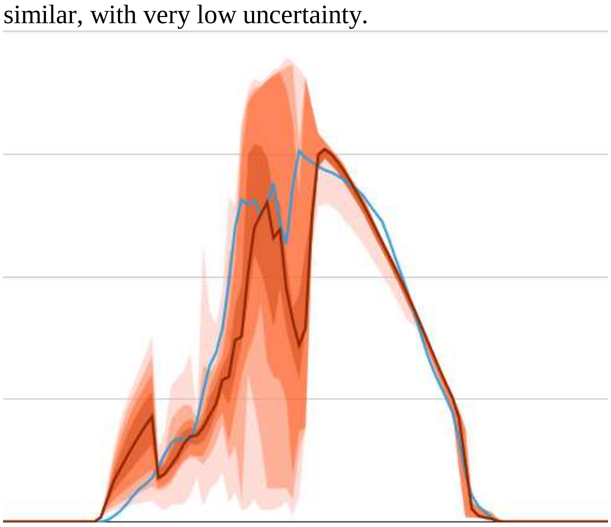

Figure 7: Forecast for aggregated plant located at 2 km south from camera

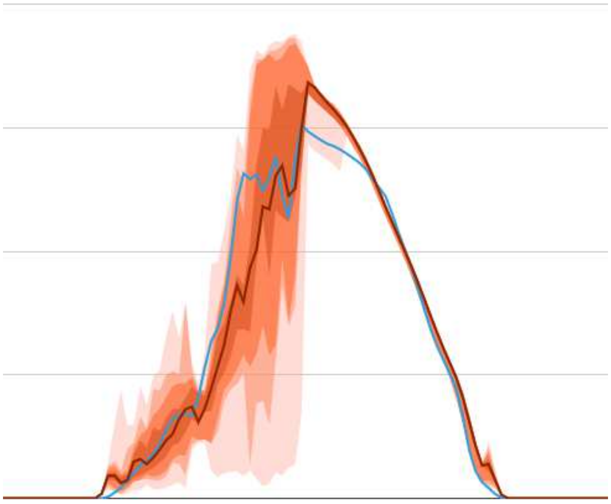

Figure 8: Forecast for aggregated plant located at 2 km north from camera

At this stage, images from two cameras are used separately, so the software generates two different forecasts for the same aggregated plant. The next step will be to use both images to better understand the position and movement of clouds and provide a more accurate prediction.

CONCLUSION

Through GreenLys, the first full-scale Smart Grid demonstration project in France, ERDF (France's main distribution grid operator) and start-up STEADYSUN are experimenting new advanced solution to facilitate the integration of solar PV on the electricity grid. The most novel approach currently being tested entails installing two "cloud cameras" monitoring the sky in order to provide citywide PV production forecasts for the next half hour.
Having such accurate information updated in real time — a technological revolution — will facilitate the integration of renewables into the grid. ERDF will be better able to manage production peaks distributed across the grid to anticipate any issues before they arise.