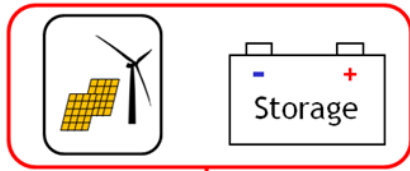




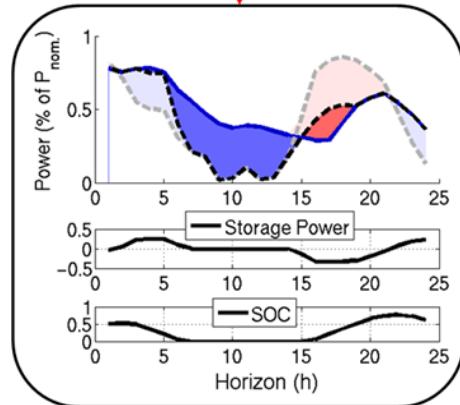
Probabilistic photovoltaic forecasting  
combining heterogeneous sources of  
input data for multiple time-frames

**Thomas Carriere**, Christophe Vernay, Sebastien Pitaval,  
François-Pascal Neirac, George Kariniotakis

- Operational requirements for PV power forecasting:



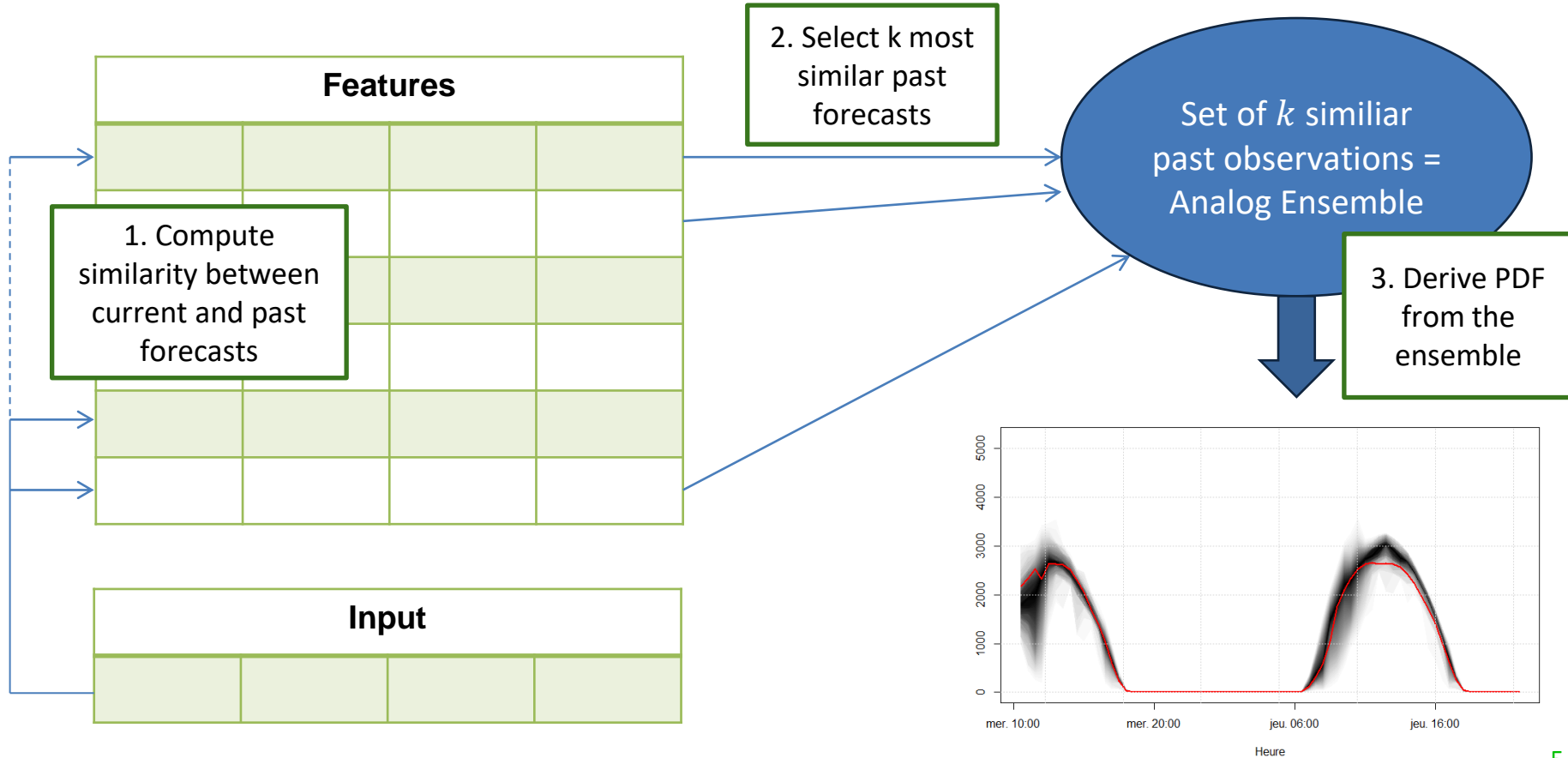
Market Participation



- Provide both short- and long-term accurate forecasts
- Provide forecasts with small resolutions
- Probabilistic forecasts for decision under uncertainty
- As fast as possible

- Many PV power forecasting models satisfy some of these requirements.
- In this work we propose a **single model** to meet all these objectives at once.
- This effectively simplifies the usage of PV power forecasts in several decision-making processes

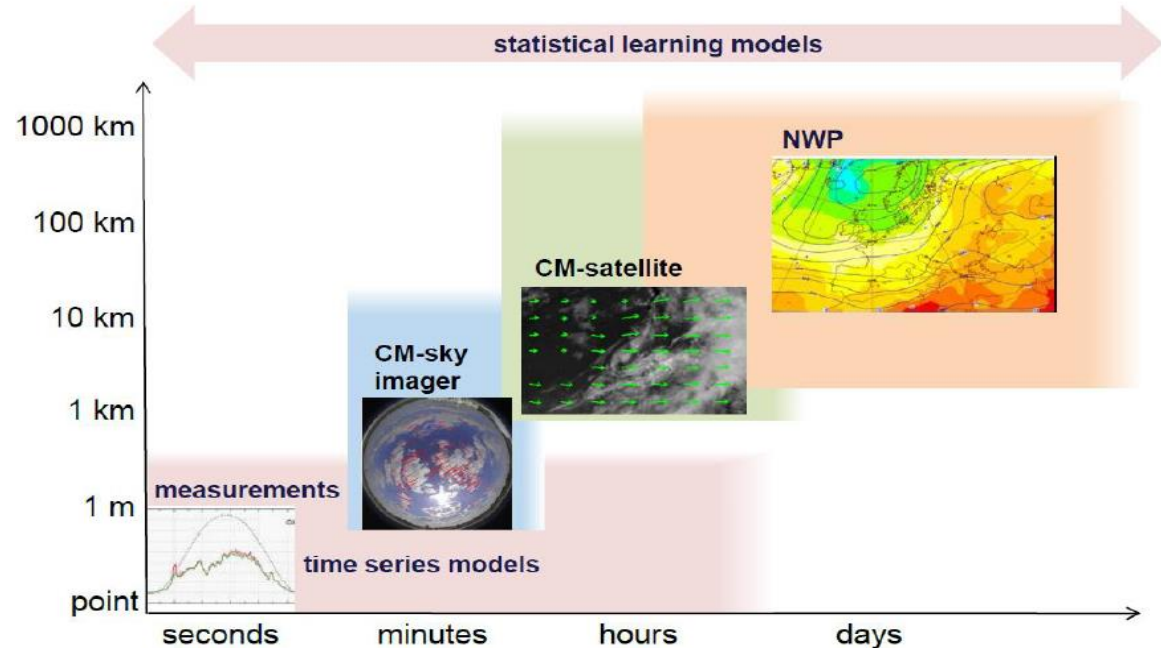
- Solution based on the Analog Ensemble (AnEn) method [Alessandrini2015]:
  - Provide both short-term and long-term accurate forecasts
  - Provide forecasts with small resolutions
  - Probabilistic forecasts for decision under uncertainty
  - As fast as possible



- To achieve short-term forecasts:

Use of different data sources:

- Measurements for very short-term
- Satellite data for short-term



- Standard AnEn model:

$$\|F_t, A_t\| = \sum_{i=1}^{N_v} \frac{w_i}{\sigma_{f_i}} \sqrt{\sum_{j=-k}^k (F_{i,t-j} - A_{i,t-j})^2}$$

- The weights  $w_i$  are optimized on a training set (“wrapper”)
  - We propose a “filter” approach to compute the weights directly from the history without an optimization loop

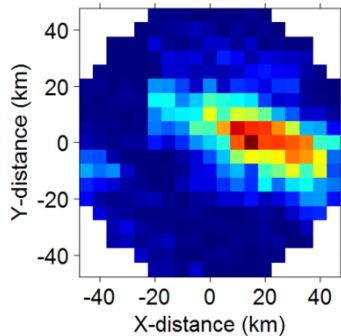
- When  $h$  is the forecast horizon:

$$\|F_t, A_t^h\| = \sum_{i=1}^{N_v} w_i^h \sqrt{\sum_{j=-k}^k (F_{i,t-j} - A_{i,t-j}^h)^2}$$

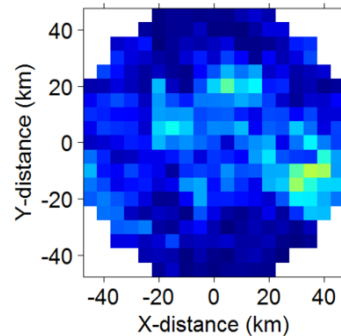
- The weights  $w_i^h$  are dependent on the forecast horizon.
  - Compute the weight of each feature based on its Mutual Information (MI) with the measurements
  - Normalize the weight so that the sum of all the weights coming from a same data source is not higher than a set limit.



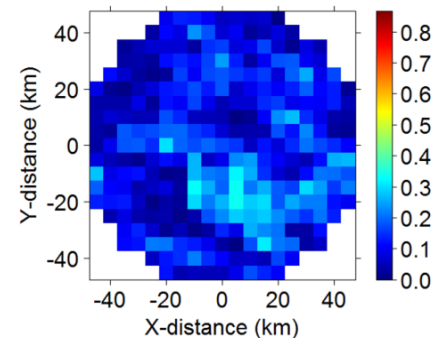
- Satellite data: Estimation of GHI time series for each pixel from geostationary satellite images following [Blanc2011]
  - Very large number of redundant features
  - Selection of representative pixels based on MI with the measurements



T + 30 minutes



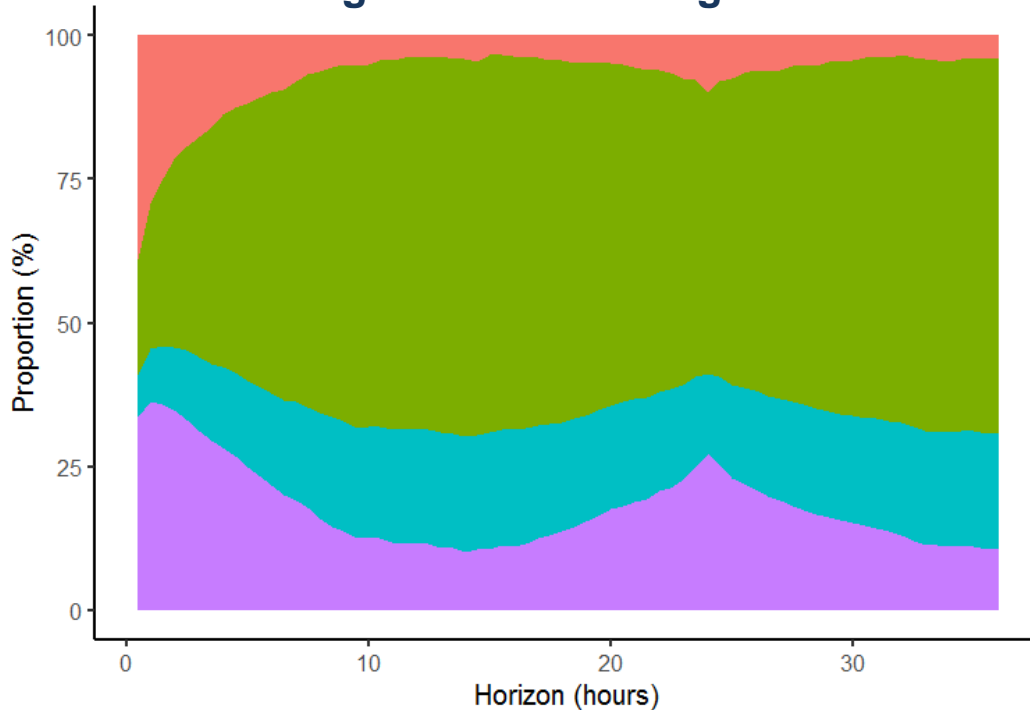
T + 90 minutes



T + 250 minutes

# Methodology

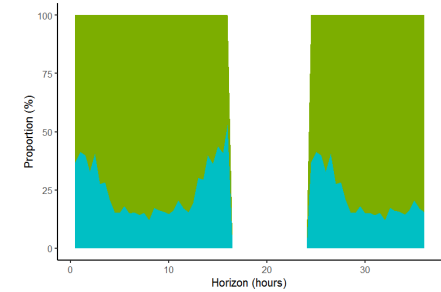
### Average over all starting times



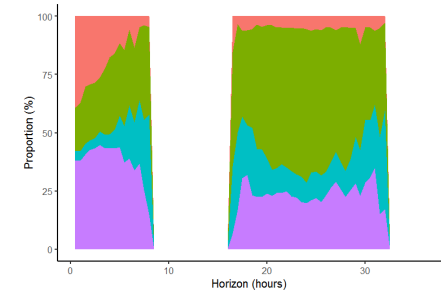
Features

- Measures
- NWP
- CLS
- Satellite

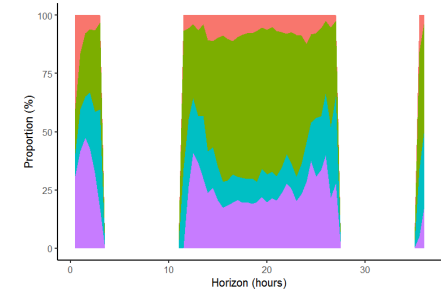
3 AM



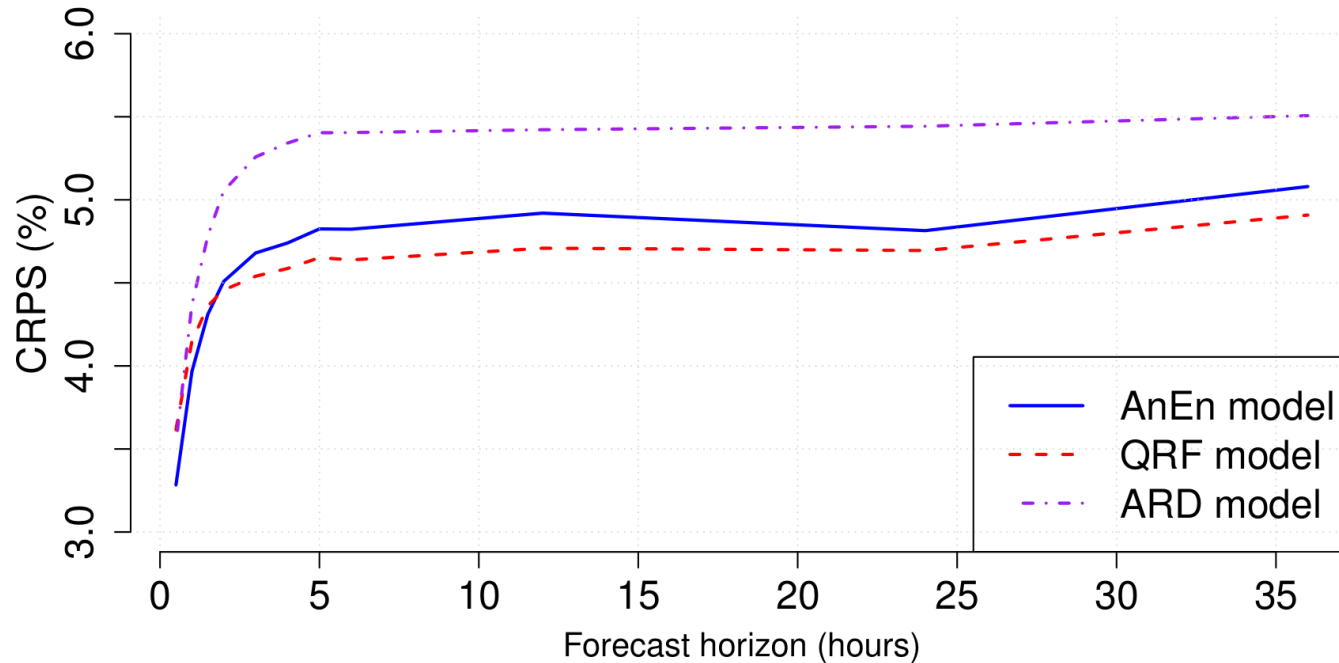
12 AM



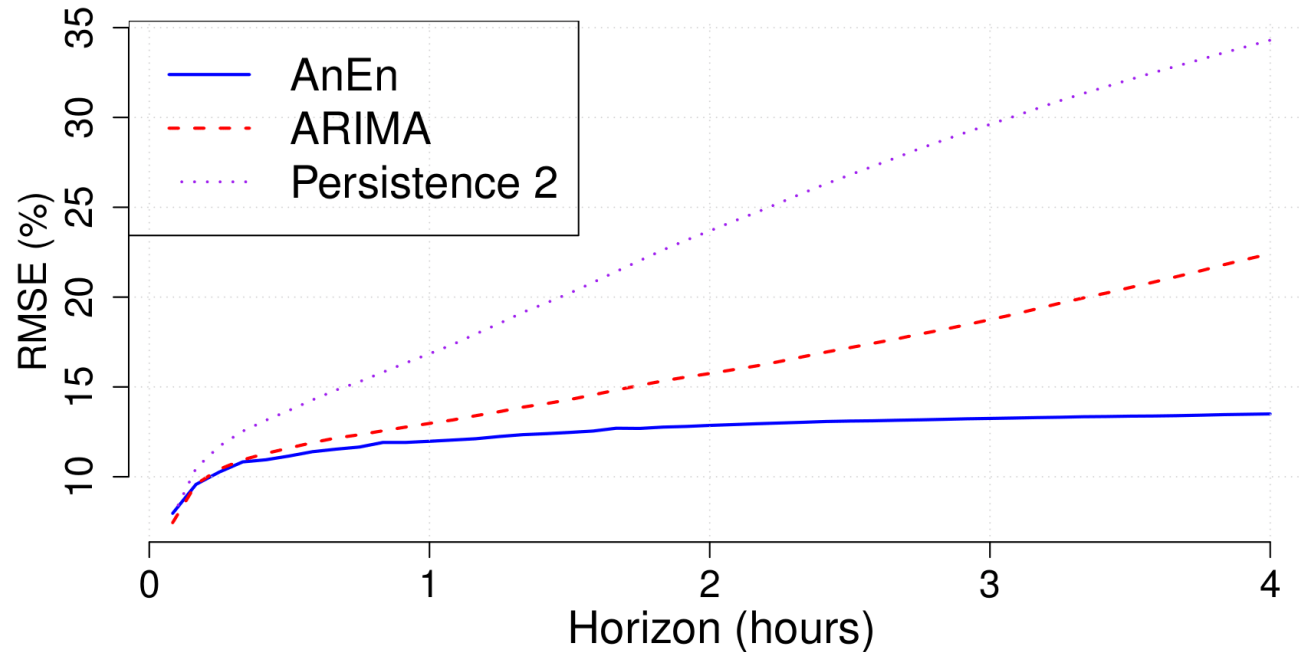
17 PM



- Forecast performance for day-ahead 30-minute forecasts:



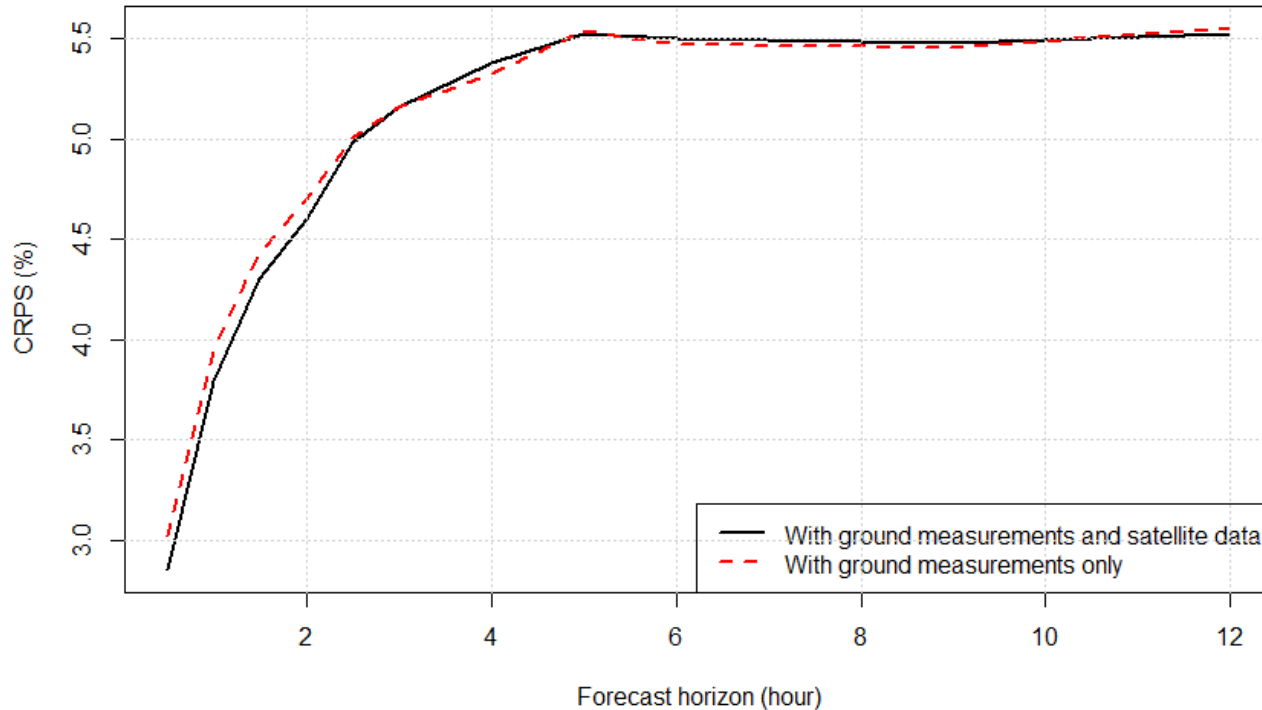
- Forecast performance for intra-day 5-minute forecasts:



## COMPUTATION TIME REQUIRED FOR PROVIDING THE FORECASTS FOR ONE GIVEN HORIZON, IN SECONDS

	30-minute resolution		5-minute resolution	
	Training	Forecasting	Training	Forecasting
AnEn	-	1.87	-	8.77
Persistence 1	-	5e-3	-	6e-3
Persistence 2	-	5e-3	-	6e-3
ARIMA	9.2e-2	2.5e-7	10e-2	3.7e-3
QRF	4.26	1.3e-2	68.0	4e-2
ARD	10.75	10e-3	154	1e-3

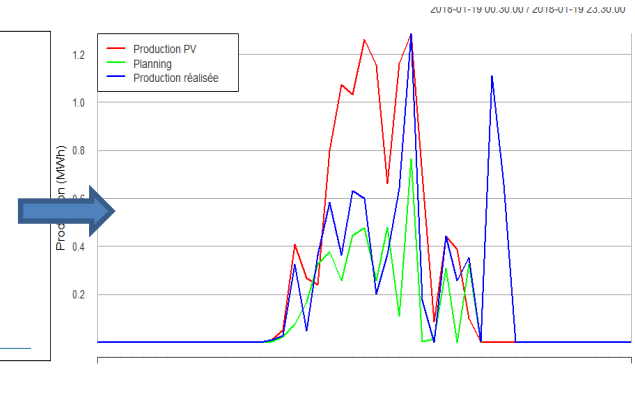
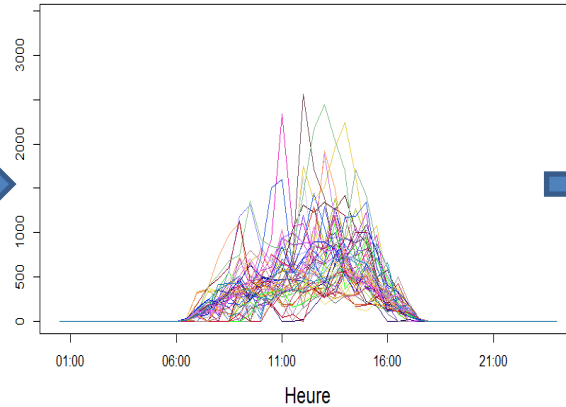
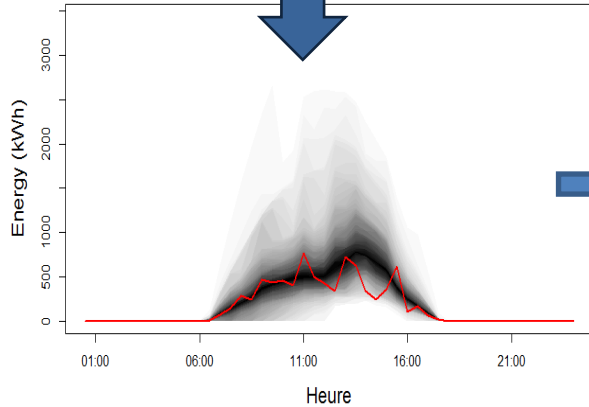
- Added value from satellite data:



# Conclusions and perspectives



- Forecast for an aggregation of 13 plants, 92 MW
- Stochastic control of the aggregation participating in electricity markets with storage



- A single forecasting model that can quickly provide accurate forecast for temporal resolutions from 5-minute to 1-hour, and horizon from 5 minutes to 3 hours
- Added value from satellite data is still limited:
  - Correct residual weights for measurements at the 24-hour horizon
  - Add a Convolutional Neural Network to extract relevant features from satellite pictures
- Integrate all-sky imagers to further improve short-term forecasts
- T. Carriere, C. Vernay, S. Pitaval, F.P. Neirac, G. Kariniotakis, *A Novel Approach for Probabilistic Photovoltaic Power Forecasting Covering Multiple Time Frames*, Under revision for IEEE Transactions on Smart Grid, Preprint available at <https://hal.archives-ouvertes.fr/hal-02043353>