Renewable Energy Production Forecast

PROJ0016 - Big Data Project

Yann Claes, Gaspard Lambrechts and François Rozet

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University of Liège

Photovoltaic production

Tests of the provincial model

Reminder

- Output power given by

$$P = \eta I A \quad [W]$$

  with $A = area\_peak * peak\_power$
- Use production measurements from Elia to fit these 4 parameters
- Predict production using a normal distribution and irradiance forecasts

Testing procedure

- Fit the parameters on collected measures for the past 7 days
- Use this posterior model to make predictions for the current day
- Repeat for each day of 2019

Baseline models

We constructed 2 very simple baseline models:

- Predict for day $D+1$ the production measured by Elia for day D
- Predict for day $D+1$ the average production measured by Elia over the last 7 days

Error metrics

To assess the posterior and baseline models, we use the MSE and RMSE.

We also compute these metrics for our prior model and for the predictions made by Elia.

Eventually, we average these measures over all conducted tests.

Results

	MSE	RMSE
Prior model	682.451	23.617
Posterior model	469.842	19.398
Baseline 1	2361.555	40.390
Baseline 2	2003.102	39.617
Elia's forecast	423.539	17.891

Table 1: Mean of the MSE and RMSE (MW) for 2019.

Conclusions

- The posterior model seems to perform better than the baseline and prior models
- Elia's forecast is better but we reach, on average, reasonable results
- These results are obtained using irradiance measurements, not irradiance forecasts

Introducing forecasts

Collecting forecast measures

Forecast measures have been collected from April 2nd and cover up to 7 days from the current day

Introducing forecasts in the model

- Similar comparison procedure
- No access to past irradiance forecasts
- Fit on past irradiance measurements
- Predict using irradiance forecasts

Testing the model on forecasts

A first test has been conducted for a period of 10 days, starting the predictions from April 3rd.

Results

	MSE	RMSE
Prior model	2797.307	50.281
Posterior model	1385.751	32.594
Baseline 1	1294.487	24.136
Baseline 2	1039.525	27.152
Elia's forecast	292.916	15.219

Table 2: Mean of the MSE and RMSE (MW) for 10 days.

Conclusions

- Posterior model performs better than our prior model
- Baseline models both outperform our posterior model

Conclusions

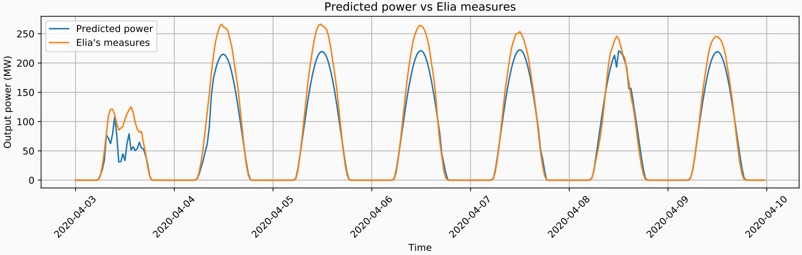


Figure 1: Comparison between Elia's measurements and the prior model (using irradiance measurements).

Conclusions

- Measurements made by Elia over this period are all very similar
- Baseline models use past data *as is*
- Forecasts are sometimes unreliable

Conclusions

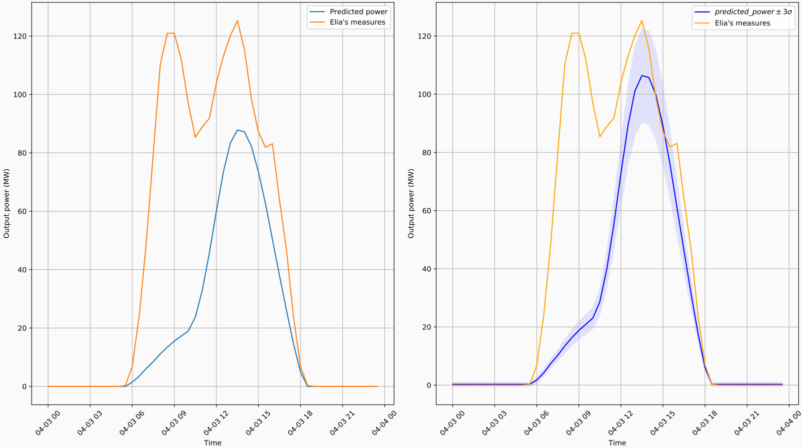


Figure 2: Comparison between the naive predictive model and the posterior predictive model (April 3rd).

Conclusions

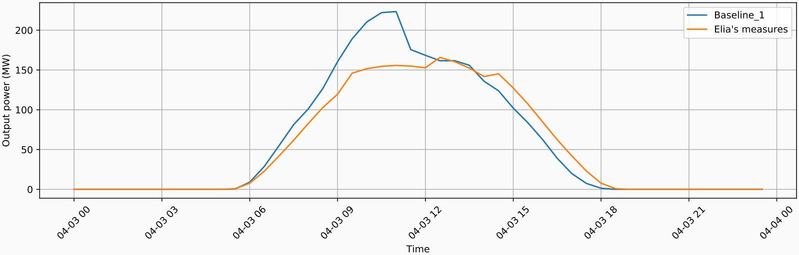


Figure 3: Comparison between the first baseline ($D - 1$) and Elia's measures (April 3rd).

Conclusions

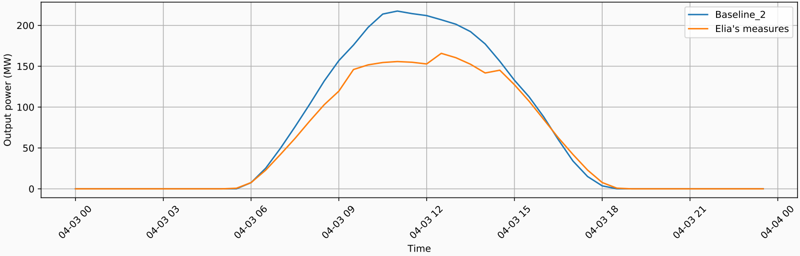


Figure 4: Comparison between the second baseline (average) and Elia's measures (April 3rd).

Combining panel enumeration and solar model

Outputs of the panel enumerator

We managed to get, as outputs:

- The coordinates of each panel installation
- The area of each installation
- The surface azimuth of each installation

Predicting at the city scale

We have managed to process all satellite images for the city of Liège and estimated the output production for the same period as the previous section.

Predicting at the city scale

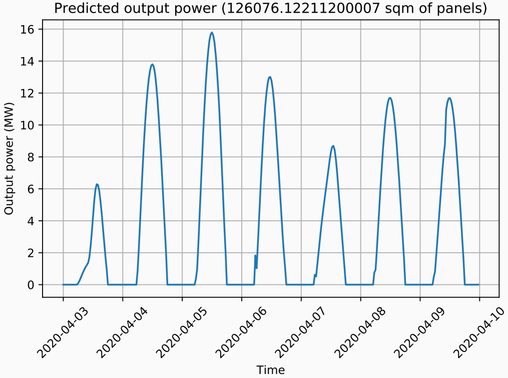


Figure 5: Predicted production in the city of Liège (using irradiance forecasts).

Predicting at the city scale

- Production curves will mainly depend on the irradiance forecasts' curve
- Order of magnitude will depend on the estimated surface of panels

For the city of Liège, we cannot draw conclusions from Elia since they measure provincial production.

Next objectives

Next objectives

- Conduct the abovedefined tests on a larger period of April, using irradiance forecasts
- Try and get reliable estimates of the panel installations in the province of Liège, to compare with Elia's measurements

Photovoltaic panels enumeration

Reminder

Two objectives :

1. Apply our model to our initial problem, *i.e.* the enumeration of photovoltaic panels in the province of Liège.
2. Evaluate more precisely the precision of our model (U-Net) using the average precision metric.

WalOnMap

WalOnMap [1] images are organized under the Web Map Tiles Service standard [2].

We used the `owslib` package to request the tiles (the images) one by one.

To save space and ease the following computations, the produced masks were saved as polygons unde the VGG Image Annotator [3] format.

VGG Image Annotator

Enumeration

We ran into two major issues before succeeding to apply the model.

- WalOnMap images are much more blurry than the one of California. Therefore, we added further data augmentation transformations like blurring, smoothing and sharpening.
- The scales of the two datasets are dissimilar. One pixel in Wallonia is 0.14 m and one pixel in California is 0.30 m. We decided to upscale the Californian images by a factor of two.

Enumeration

If most panels were detected, a lot of shadows and dark roofs were also.

To evaluate the actual performances of the model, we annotated by hand (using VIA) more than 600 images.

Enumeration

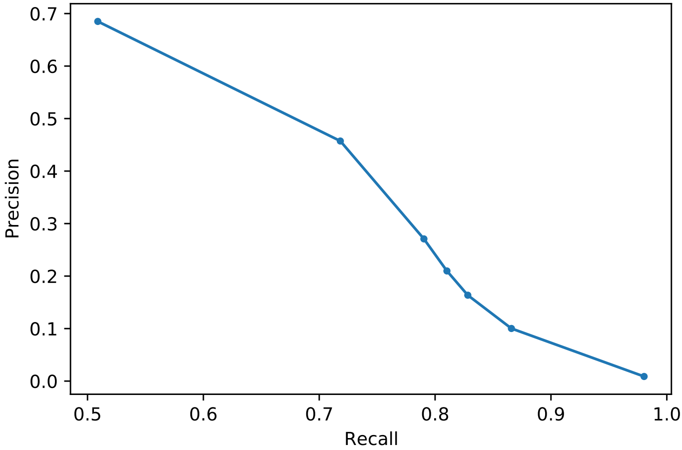


Figure 6: Precision-Recall curve of U-Net before fine tuning.

Enumeration - Fine tuning

We fine tuned our model for 20 more epochs on a subset of our hand-annotated images.

Enumeration - Fine tuning

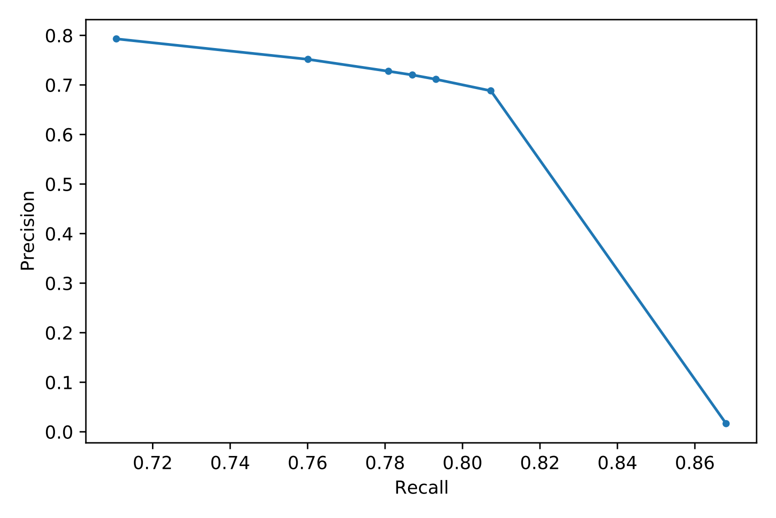


Figure 7: Precision-Recall curve of U-Net after fine tuning.

Quick demonstration

Enumeration - Binding

There was still to bind our enumeration model with the photovoltaic production model.

Since we stored polygons (cf. VIA format) and the tiles are geo-referenced, it was not too hard to compute the localization and area of each installation we had detected.

The azimuth is deduced from the minimal area bounding rectangle of the polygon.

Average precision

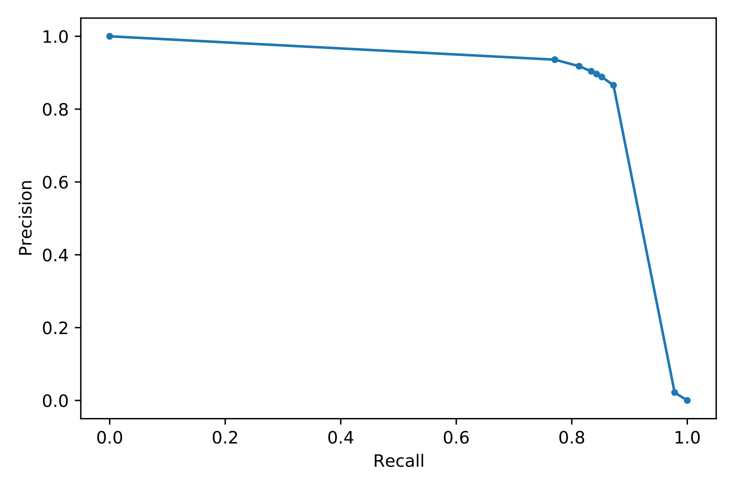


Figure 8: Precision-Recall curve of U-Net on the Californian validation set.

Average precision

The average precision is 88.6 %.

Wind power production

Addition of new variables

The first idea was to add the following variables:

- Total power monitored by Elia
- Yearly total installed power in Wallonia
- One day before power measurements

Addition of new variables

Protocol 2	Method	MAE[1]	sMAE[1]	MQL10[1]	MQL90[1]
With the new variables	Extra Trees	28.27	4.43%	53.42	56.33
	Gradient Boosting	30.98	4.27%	51.23	55.21
Without the new variables	Extra Trees	28.13	4.03%	46.63	50.32
	Gradient Boosting	31.11	4.46%	48.32	47.91

[1] MW

Multilayer Perceptron

A new type of supervised learning has been tested: the MLP.

Method	MAE[1]	sMAE[1]
MLP with new variables	30.98	4.27%
Gradient Boosting with new variables	30.98	4.27%
Gradient Boosting without new variables	31.11	4.46%

[1] MW

Conclusion

- Adding new temporal variable has not helped
- All considered supervised learning method seemed to cap at a threshold around 30 MW in terms of MAE.

However,

- The set of variable that explains the output can be made more refined

New learning set

- Weather measurements only
- At every 68 known wind farms of Wallonia (data from 2018-2019)
- Each weather measurement is 7-dimensional (wind speed, wind gust, wind bearing, humidity, temperature, air density, pressure
- In total, 476 weather variables
- Around two years of yearly measurements, resulting in 18 000 samples.

New learning set

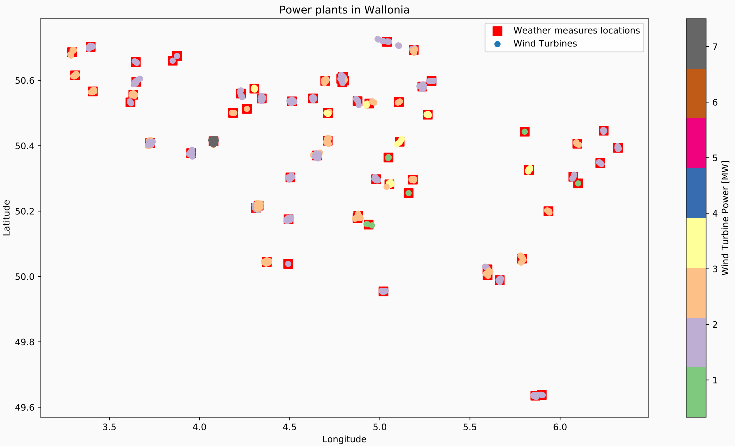


Figure 9: Wind turbines and weather measurements

Results on validation set

Method	MAE[1]	sMAE[1]	MQL10[1]	MSL90[1]
Gradient Boosting 15	31.11	4.46%	48.32	47.91
Gradient Boosting 68	28.46	3.92%	51.19	49.33

[1] MW

Results on test set

The test set is composed of day-ahead numerical weather prediction (DANWP) instead of weather measurements. Only 9.5 days have been collected for now.

Model	Validation MAE [MW]	Test MAE [MW]
15-measurements	31.1	45.42
68-measurements	28.46	40.72

Results on test set

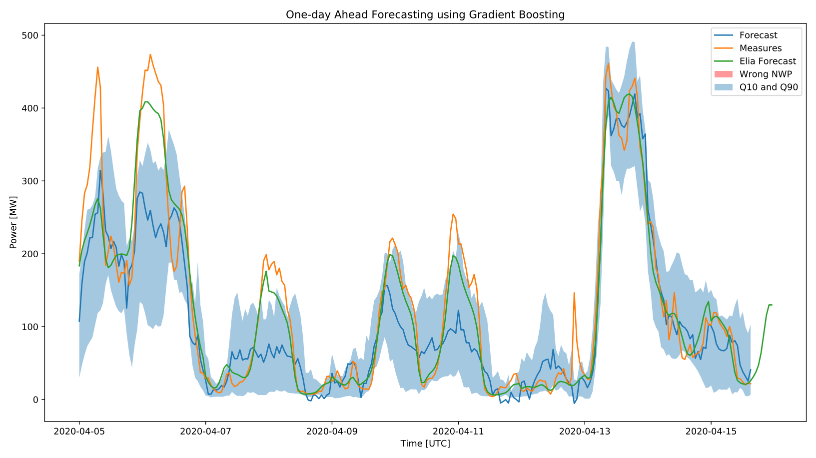


Figure 10: 15-measurements Gradient Boosting

Results on test set

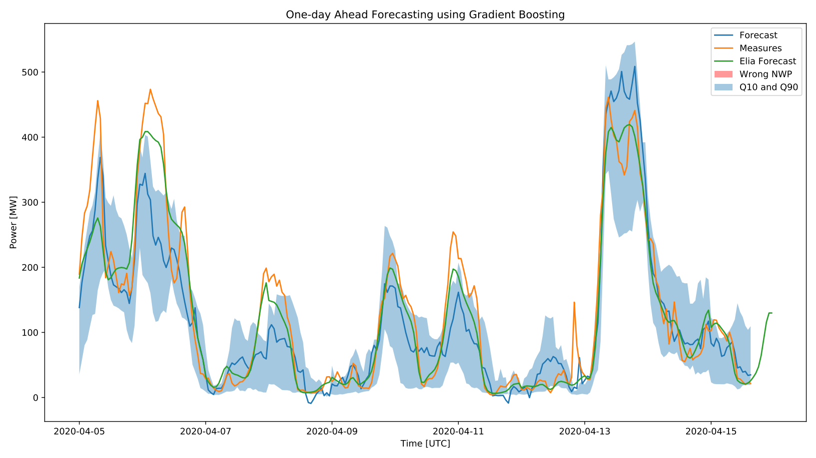


Figure 11: 68-measurements Gradient Boosting

Features importances

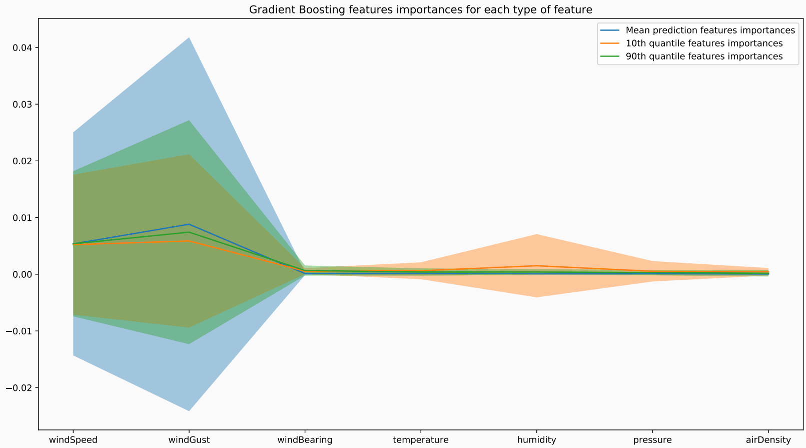
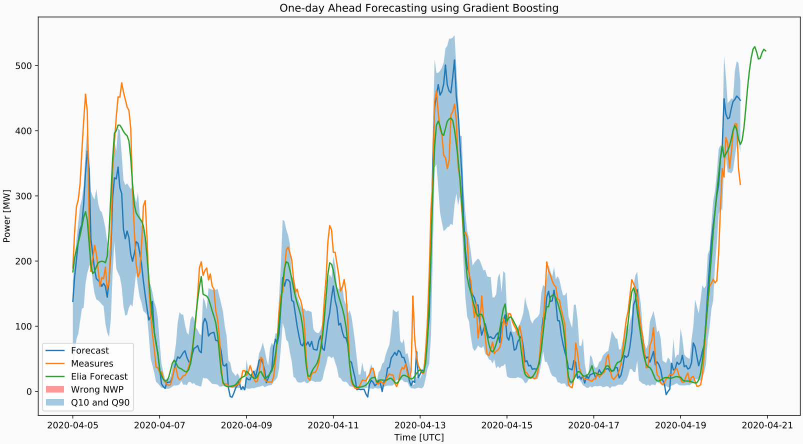


Figure 12: Features Importance

Results on test set on 13.5 days

The MAE was 40.72 MW on the 9.5-days test set, and is 36.89 MW on the 13.5-days test set.



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