Solar Production Analysis and Forecasting

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1.1. Solar Production Forecast. Why it's important?

-> Operative costs: Electricity operators (**RTE** in France, or **Red Eléctrica** in Spain) must maintain a **balance** between **generation** and **consume** each second.

- If the model fails by 500 MW at 12am, the operator has to activate a cyclic-combined central (gas) of emergency. **More expensive than programmed energy**. A good forecast could save millions in operative costs.

-> Reduction of Fines, for plant owners: One owner could say: I will produce 100 MW tomorrow at 12am. But, if it only obtains 80 MW, there is a fine to pay, due to energy deviation.

-> Solar panels in houses: A good prediction helps save money in electricity expenses…
- Help finding the best time to sell your excess of energy to the grid.
- A smart house could advise you to use more electricity at a certain hour.

1.2. Characteristics of the problem.

-> Meteo forecasting vs Solar forecasting. Meteo is a lot more complex**.** Differential equations of fluid dynamics, in supercomputers to predict pression, temperature…

-> Restricted-space regression problem. The production will never be negative, or higher than clear_sky.

-> Solar is a post-processing problem. <u>We rely on the meteo data</u>. If it fails, we fail.

-> Double cyclicality. "Loops" each day (24 h) and each year (seasons).

-> We will use **solar irradiance** variables, **meteo** variables, and **past solar productions**, to predict future solar productions (1 day).

- **Nowcasting**, complex mathematical predictions from the variables.
- **Short term forecasting** with satellite images.
- **+6h**, output from numerical data (what we are doing).

1.3. Strategy and Data.

GOAL: Predict solar production in France, 2 days in advance.

We will use **3 csv** files. From 30/01/**2022** to 31/12/**2024**. We have **1 hour per row** in every dataset.

-> **First dataset**: Past solar productions in france. (1h/row). At night -> 0's… **Target variable**.

-> Second dataset: Solar irradiance variables from a specific spot (Nouvelle-Aquitaine). These are Measures.

-> Third dataset: Weather Predictions, by hours. These represent a prediction, maybe something different happened in real life.

1.3. Strategy and Data.

$$\overset{\text{FRANCE}}{y(t+2)} = \overset{\text{(1) FRANCE}}{\underbrace{y(t)}_{\text{SOLAR PROD.}}} + \overset{\text{(2) VILLE}}{\underbrace{ax(t)}_{\text{SOLAR MEASURES}}} + \overset{\text{(3) VILLE}}{\underbrace{cz(t+2)}_{\text{WEATHER PREDICTIONS (2 days in advance)}}}$$

Predict solar production in France 2 days in advance.

-> **First dataset**: Past solar productions in france

-> Second dataset: Solar irradiance variables.

-> Third dataset: Weather predictions, by hours.

1.3. Strategy and Data.

$$\overset{\text{FRANCE}}{y(t+2)} = \overset{\text{1 FRANCE}}{\underbrace{y(t)}_{\text{SOLAR PROD.}}} + \overset{\text{2 VILLE}}{\underbrace{ax(t)}_{\text{SOLAR MEASURES}}} + \overset{\text{3 VILLE}}{\underbrace{cz(t+2)}_{\text{WEATHER PREDICTIONS (2days in advance)}}}$$

SOURCES:

-> **1º dataset**: Datagouv (République française).

-> 2º dataset: CAMS solar radiation time-series.

-> 3º dataset: Open-meteo (Weather Forecast API)

2.1. Analysis and Model. Preprocessing.

If we took a look at the Colab code…

The 3º dataset (weather prediction variables) **is first addressed.**

Then the 2º dataset (solar irradiance)**, and it's merged with the previous.**

Then the 1º dataset (solar production in France) **is treated and merged with the previous two.**

And then: **TRAINING AND TEST SPLITTING** (the test starts given a specific date)

2.1. Analysis and Model. Preprocessing.

And then: **TRAINING AND TEST SPLITTING** (the test starts given a specific date)

Also, **the 3º dataset**, with weather predictions, has been modified.

In order to provide the model “weather forecasting” for the next two days, we needed to **shift the dataset** - 2 days.

2.1. Analysis and Model. Preprocessing.

Preprocessing operations like, renaming cols, casts to datetime or numerical types, are used… At the end, a **final merge of all 3 datasets**:

```
Current nº of rows in the dataset: 25607
                    datetime  solaire_mw  toa  clear_sky_ghi  clear_sky_bhi  \
0 2022-01-30 00:00:00+00:00         0.0  0.0            0.0            0.0
1 2022-01-30 01:00:00+00:00         0.5  0.0            0.0            0.0
2 2022-01-30 02:00:00+00:00         0.0  0.0            0.0            0.0
3 2022-01-30 03:00:00+00:00         0.0  0.0            0.0            0.0
4 2022-01-30 04:00:00+00:00         0.0  0.0            0.0            0.0

   clear_sky_dhi  clear_sky_bni  ghi  bhi  dhi  ...  shortwave_radiation  \
0            0.0            0.0  0.0  0.0  0.0  ...                  0.0
1            0.0            0.0  0.0  0.0  0.0  ...                  0.0
2            0.0            0.0  0.0  0.0  0.0  ...                  0.0
3            0.0            0.0  0.0  0.0  0.0  ...                  0.0
4            0.0            0.0  0.0  0.0  0.0  ...                  0.0

  diffuse_radiation  direct_normal_irradiance  global_tilted_irradiance  \
0               0.0                       0.0                       0.0
1               0.0                       0.0                       0.0
2               0.0                       0.0                       0.0
3               0.0                       0.0                       0.0
4               0.0                       0.0                       0.0

   dew_point_2m  surface_pressure  sunshine_duration  \
0           2.7            1015.6                0.0
1           2.9            1015.4                0.0
2           2.3            1016.0                0.0
3           2.0            1016.1                0.0
4           1.7            1016.9                0.0
```

```
[5 rows x 30 columns]
```

2.2. Model Building.

To build the model, we have tried several options… obtaining the best performance with a *XGBoost* model (a model based on Random Forest, that learns based on the errors of the previous trees).

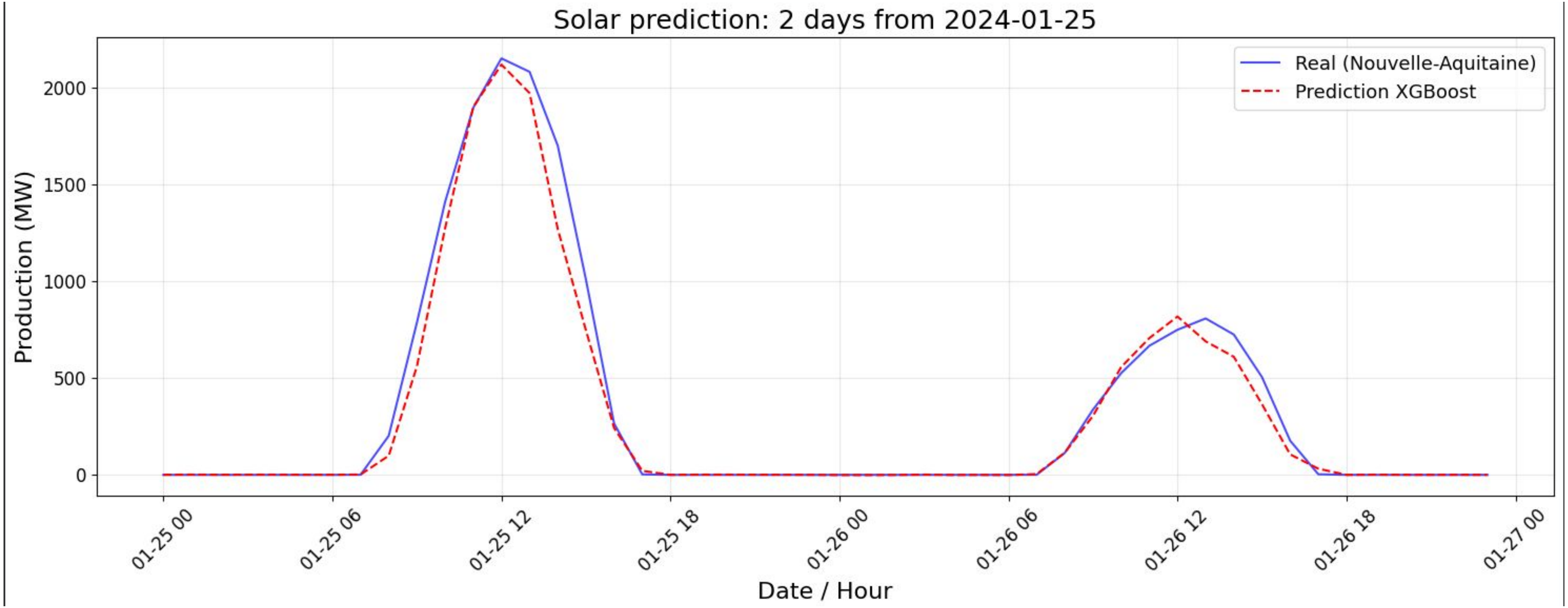
```python
# --- "ROBUST & BALANCED" CONFIGURATION, Constraints applied ---
model_xgb = xgb.XGBRegressor(
    n_estimators=1000,          # More trees but with smaller impact per tree
    learning_rate=0.03,         # Smaller steps for finer convergence
    max_depth=6,                # Lower depth to reduce overfitting/memorization
    # --- MODEL CONSTRAINTS (Regularization) ---
    colsample_bytree=0.5,       # EACH TREE can only see 50% of the features.
                                # This forces the model to learn from secondary variables!
    subsample=0.7,              # Uses only 70% of rows per iteration for diversity
    reg_alpha=10,               # Strong L1 regularization (filters out weak variables)
    reg_lambda=1,               # L2 regularization (prevents feature weights from exploding)
    # ------------------------------------------
    random_state=42
)
```

```python
model_rf = RandomForestRegress
    n_estimators=300,          #
    max_depth=20,              #
    min_samples_leaf=4,
    max_features='sqrt',
    bootstrap=True,
    random_state=42
)
```

2.3. Graphics and Results.

Real Data VS XGBoost

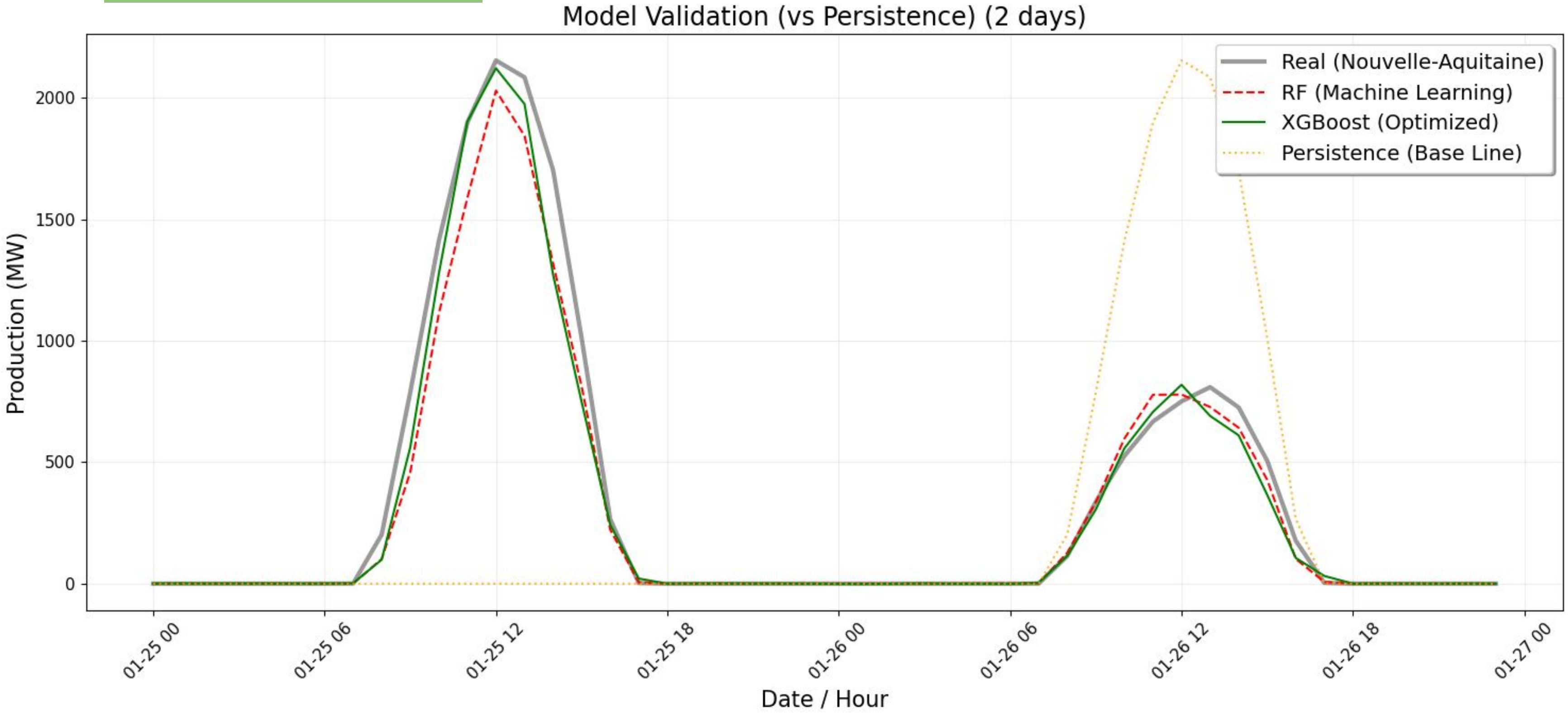
```
Metrics in the test period of (2 days):
  R2 Score: 0.9754
  MAE:      41.96 MW
  nMAE:      1.95%
```



2.3. Graphics and Results

```
Results for 2 days of test:
Metrics Random Forest   : R2=  0.9634 | MAE=   53.84 MW | nMAE=  2.50%
Metrics XGBoost         : R2=  0.9754 | MAE=   41.96 MW | nMAE=  1.95%
Metrics Persistence     : R2= -0.5913 | MAE=  383.82 MW | nMAE= 17.82%
```

Real Data VS Models



2.3. Graphics and Results

```
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Metrics Random Forest  : R2=  0.9634 | MAE=   53.84 MW | nMAE=  2.50%
Metrics XGBoost        : R2=  0.9754 | MAE=   41.96 MW | nMAE=  1.95%
Metrics Persistence    : R2= -0.5913 | MAE=  383.82 MW | nMAE= 17.82%
```

```
Mean metrics per day:
     datetime        MAE        R2  Max_Real
0  2024-01-25  56.567560  0.974536    2154.0
1  2024-01-26  27.361564  0.969380     809.0
```

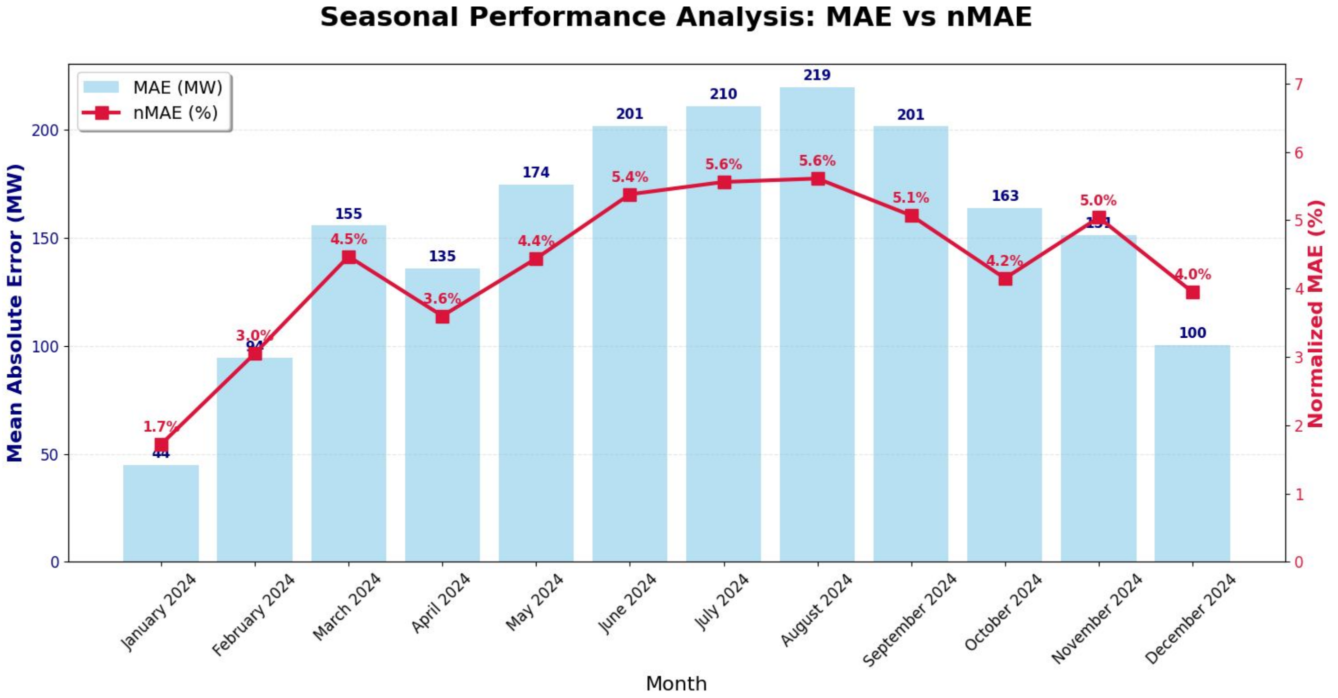
← metrics per day (separated)

```
 COMPARING PERFORMANCE BY HORIZON:
   Horizon (Days)  MAE (MW)  R2 Score  nMAE (%)
0               1     56.57    0.9745      2.63
1               7    115.97    0.8629      4.93
2              30     96.71    0.8748      3.54
```

2.3. Graphics and Results

MAE error increases as the total production increases.

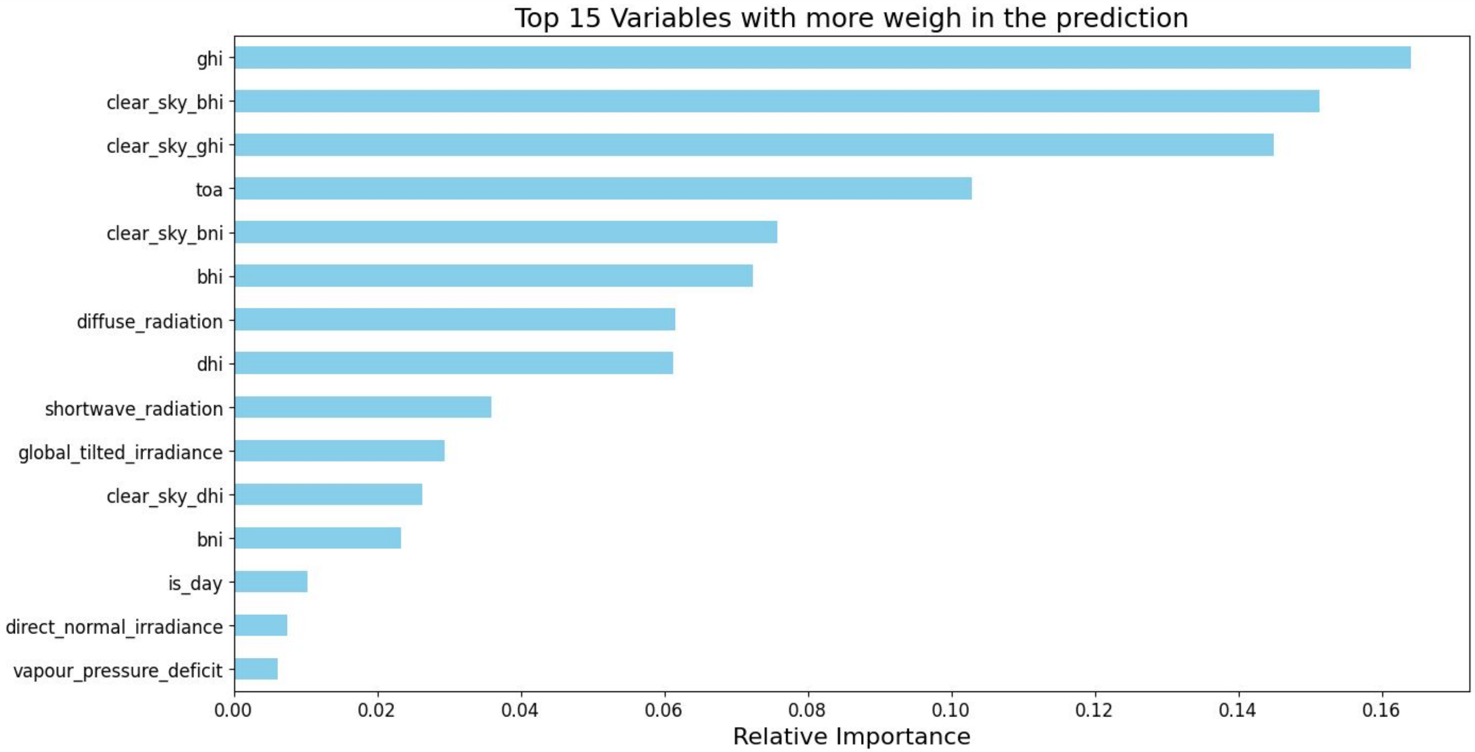
nMAE (MAE/max), gives us the real error in relationship to the amount of production (max).



2.3. Graphics and Results

RF was more balanced.

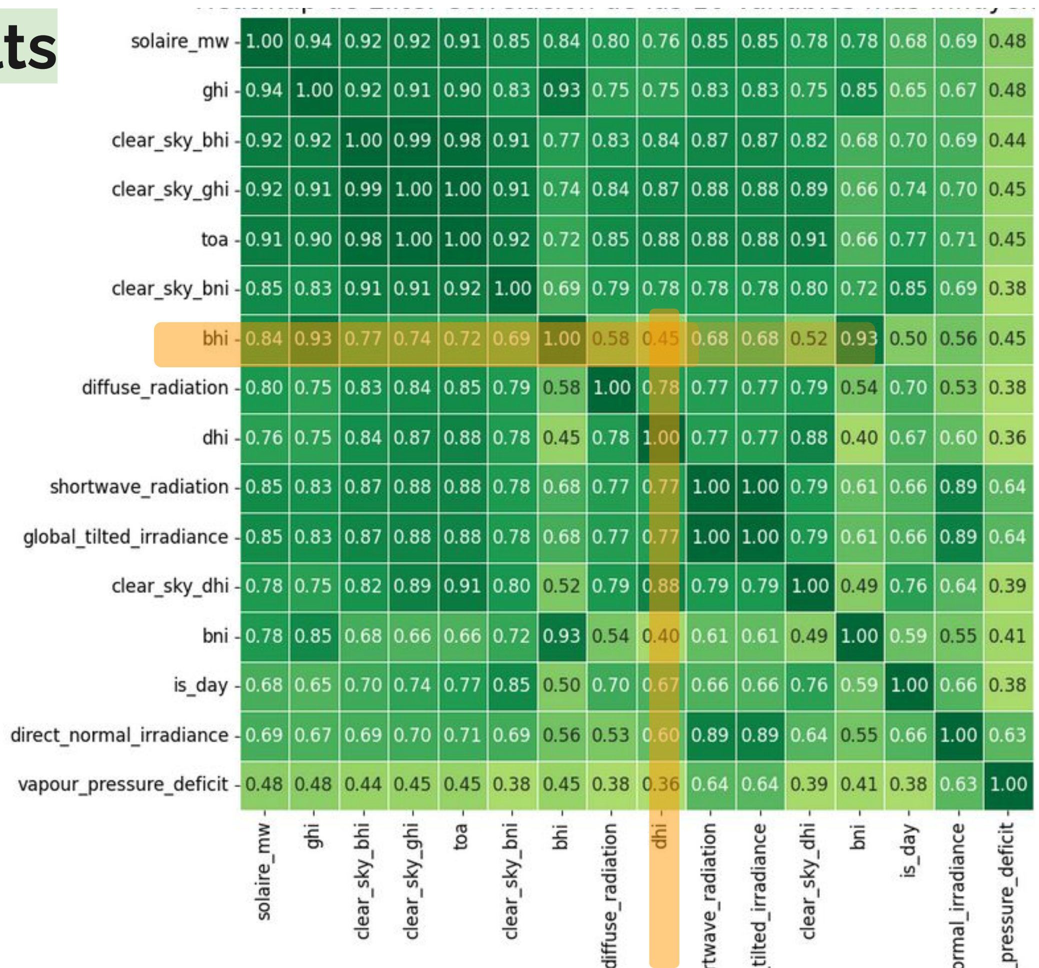
In **XGBoost, only a few variables dominated.** Not a solid model. **So, we needed to apply more regularisation.**



2.3. Graphics and Results

Heatmap of the top 15 variables

ghi clear_sky_bhi toa bhi dhi.

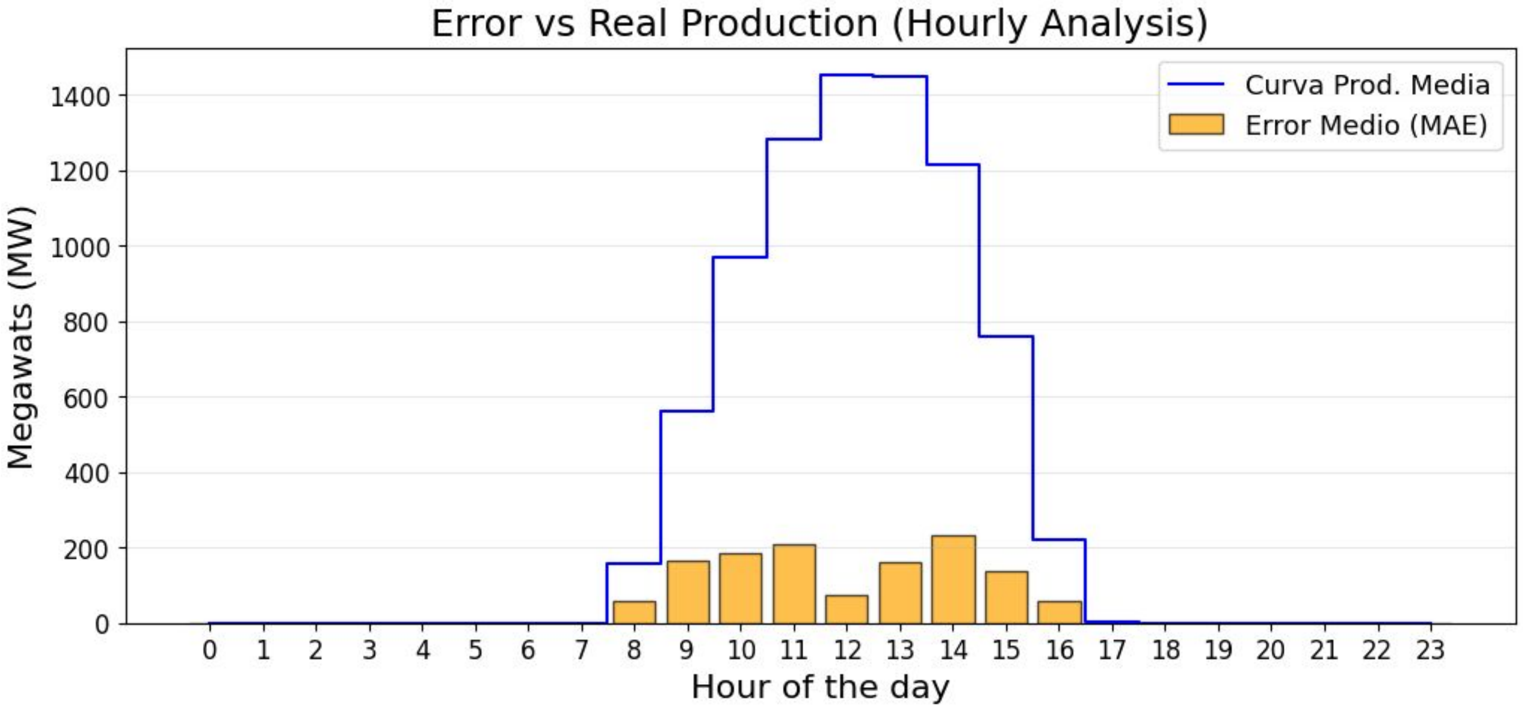


2.3. Graphics and Results

```
Metrics in the test period of (2 days):
  R2 Score: 0.9754
  MAE:      41.96 MW
  nMAE:      1.95%
```

We were obtaining good **nMAE** and **MAE** results but…
The night was a major factor.
The worst value is actually: **200MW error**

```
MAE Daylight (Only sun hours): 128.98 MW
nMAE Daylight: 5.99%
```



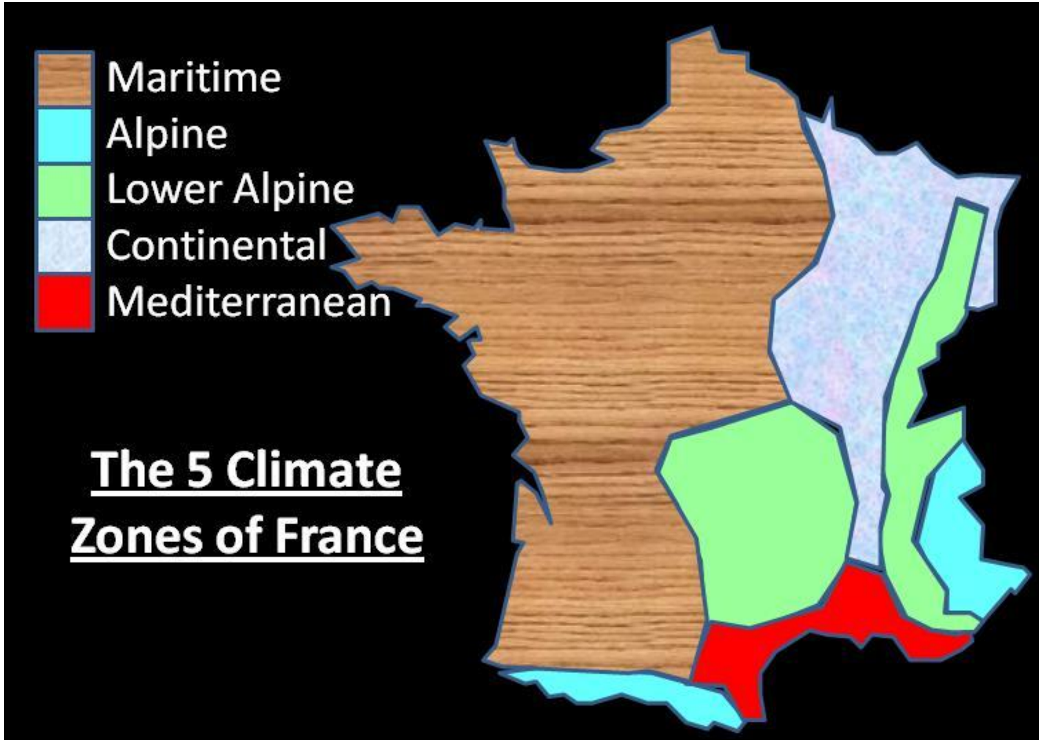
3. DIFFICULTIES & LIMITATIONS

1. **FINDING GOOD DATASETS. And stick to one plan (small size project is better than nothing)**
   a. **Limitation:** 2° and 3° datasets are only from a specific point in France.

2. **DATA LEAKAGE WHEN TESTING THE MODEL.**
   a. **Tried a lag column** for solaire_mw (1° dataset), but the model should know nothing about that!

3. **HIDDEN PROBLEMS**
   a. **Night time** made nMAE lower, and measures were inaccurate.

3. DIFFICULTIES & LIMITATIONS



4. CONCLUSION

We have provided a

```
Metrics in the test period of (2 days):
  R2 Score: 0.9754
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```

model for 2 days forecast.

→ It is not the ideal approach. However, solar production and weather variables have shown compatibilities, with the creation of a “precise” XGBoost model.

→ It is a wide range of study, and more complex models and variables are taken into account, just to predict 2-6 hours.

→ We have seen the valuable insights we can obtain from 3 datasets of solar production, solar variables and weather forecasting.

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- https://github.com/carmenabans/Solar-energy-production-forecasting-with-ML
- https://www.sciencedirect.com/science/article/abs/pii/S0038092X12001429
- Gemini AI was used for the purpose of better understanding the texts written and code of the project.