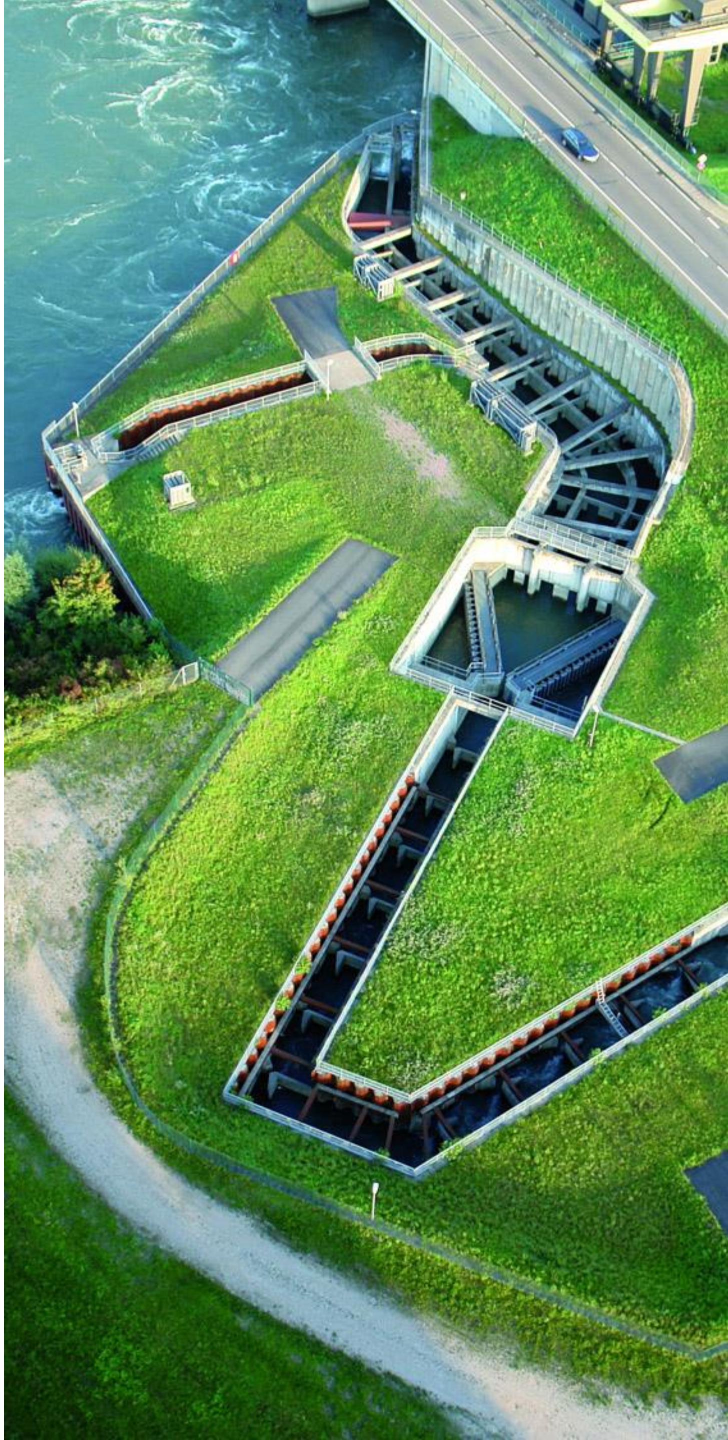
EDF R&D

Détection d'anomalies dans des series temporelles : une approche non paramétrique

Christian Derquenne



Séminaire de statistique appliquée du CNAM – 28 janvier 2022

Plan

Context and goal

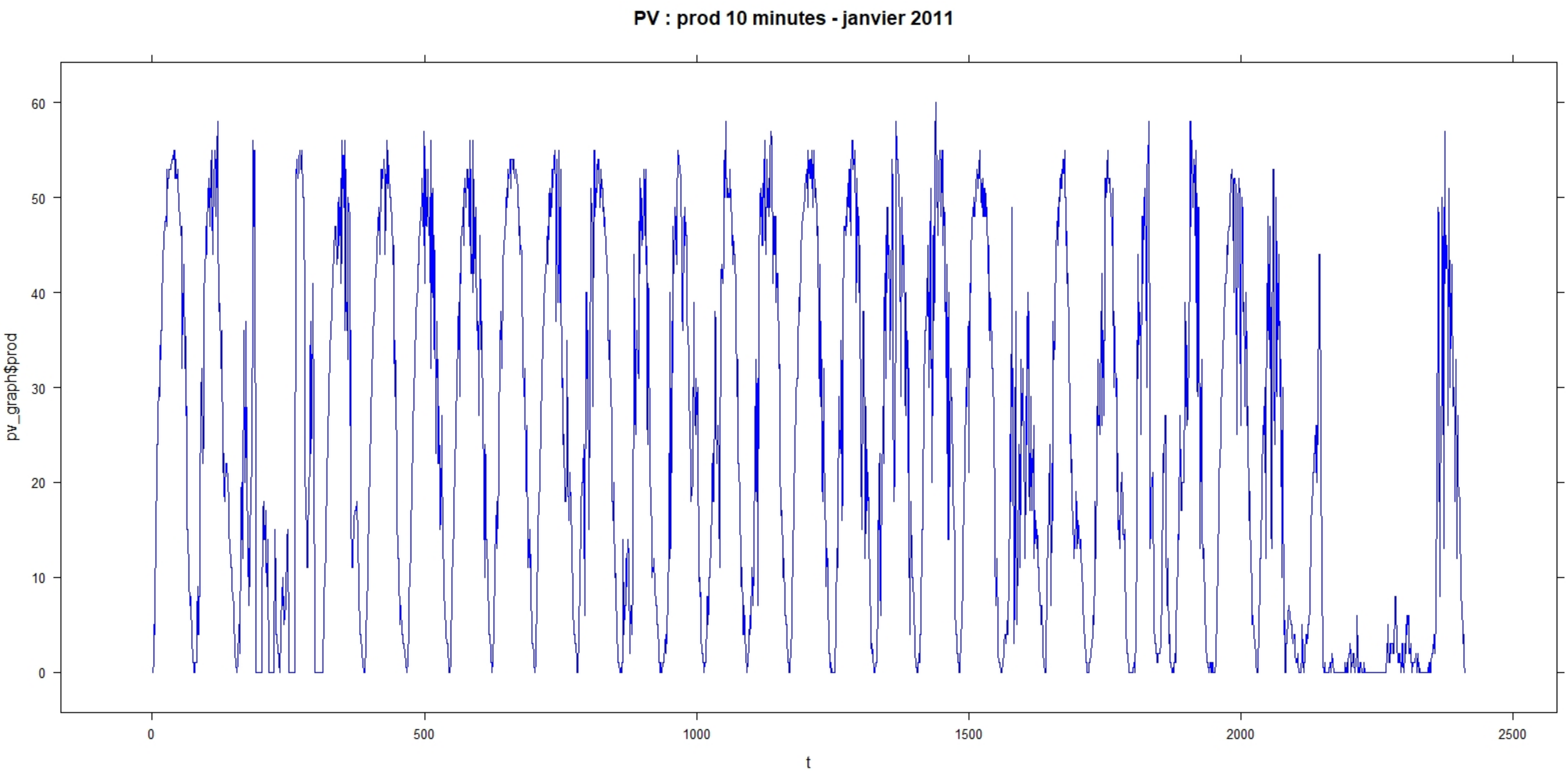
A non parametric approach for anomalies detection

Application of approach on PV data

Contributions, applications and further researches

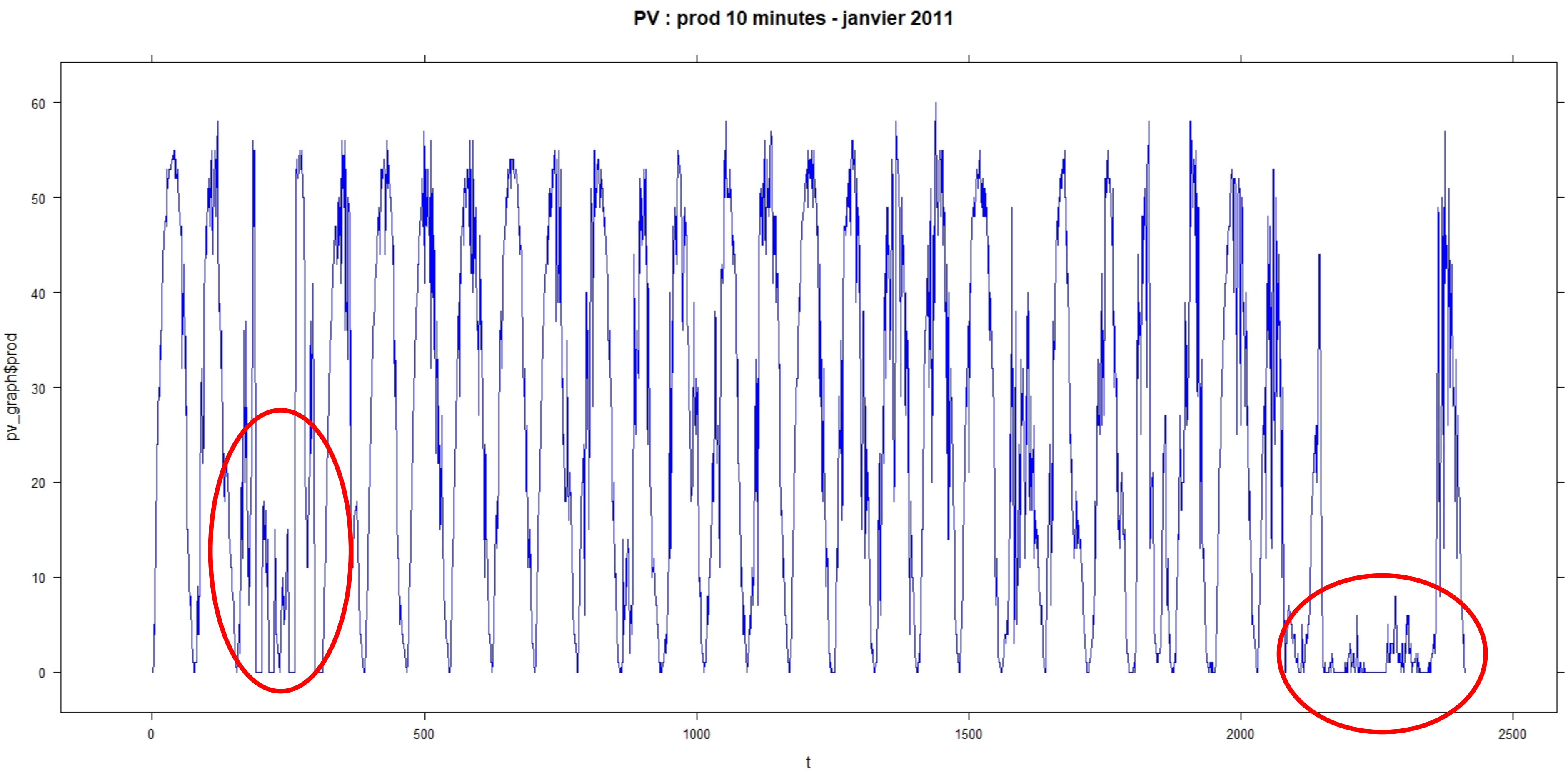
Context and goal

Photovoltaic data (PV stations)



Context and goal

Photovoltaic data : *anomalies detection*



Context and goal

Applications

- ✓ **Using these data in energy management for production or consumption forcasting**
- ✓ **Problem :** quality of results can be affected in presence of outliers, anomalies, breaks, …
- ✓ **Solutions :** detecting anomalies, breaks before modelling; robust model approaches

Some definitions

- ✓ **Breaks detection** = Search for changes in behavior (which may be long) in average, in variance, both, in distribution …
  - ➢ **Offline *vs* online**
- ✓ **Anomalies detection** = Search for sudden changes in behavior (of medium or short duration): peaks, troughs, …
  - ➢ **Offline *vs* online**

Context and goal

Anomalies detection : *some approaches*

✓ **Rather non-parametric approaches**

- using robust statistics based on ranks [Friend et al., 2007]
- forcasting models based on LSTM (Long-Short Term Memory) joint to Deep Learning [Maya et al., 2019]
- detection of anomalies on aggregated times series [Derquenne, 2015]
- tests non paramétriques conjoints à une approche bayesienne (modèle Bernoulli Detector) pour séries temporelles univariées et multivariées [Harlé, 2006]
- utilisation de réseaux bayesiens (graphes de dépendance entre signaux) [Harlé, 2006]

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Anomalies detection approach

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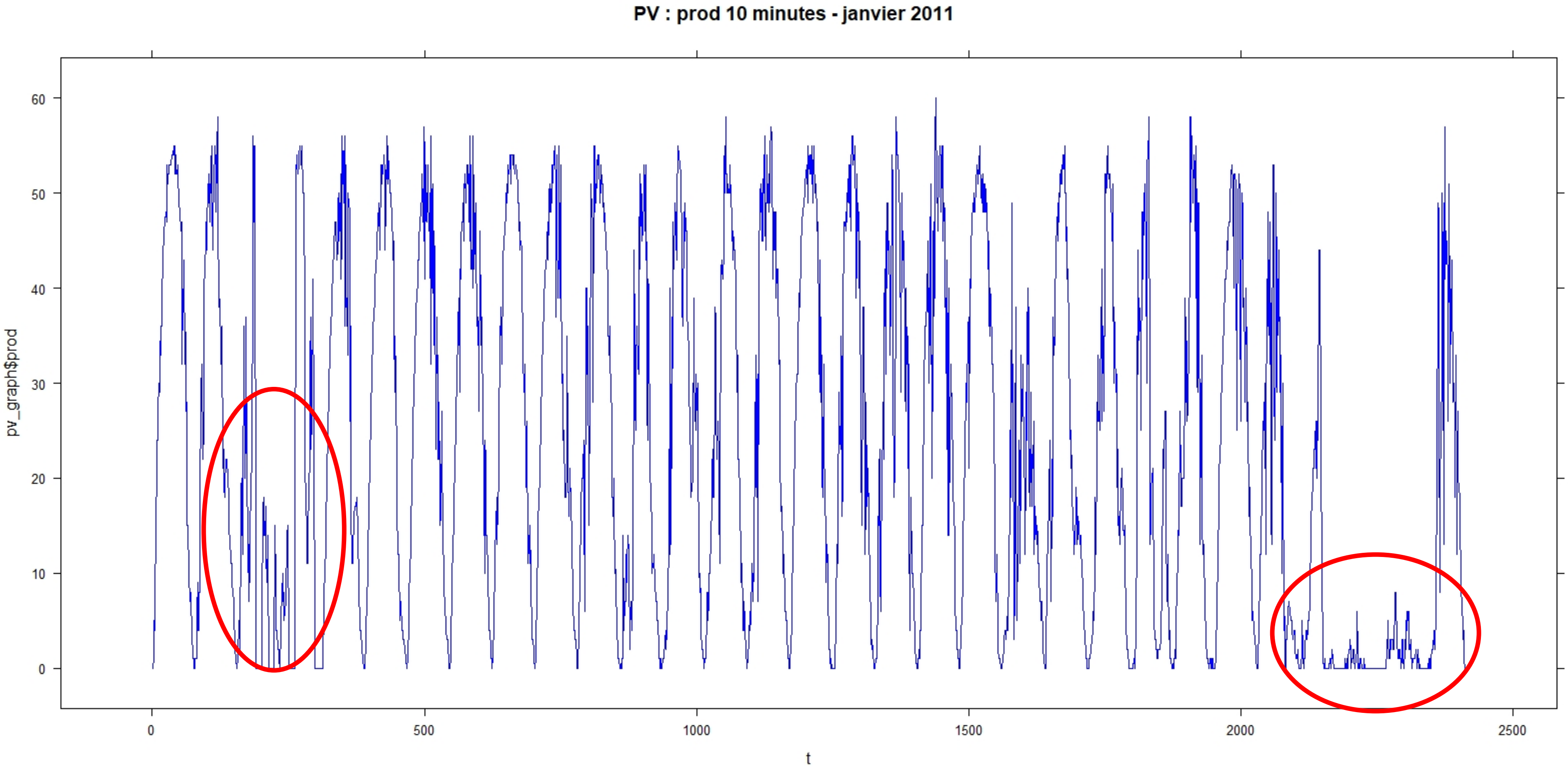
Overall principle of approach

- ✓ **Splitting of time series**
- ✓ **Categorization of time series**
- ✓ **Aggregation of data** (for instance : 10 min → 1 hour)
- ✓ **Building of aggregating marginal distributions of the categories**
- ✓ **Building of the statistic of test**
- ✓ **Building of empirical distribution empirique of test**
- ✓ **p-value calculation**

Anomalies detection approach

The approach step by step (1)

✓ **The data**



Anomalies detection approach

The approach step by step (2)

Let's $Y_{t,(t=1,T)}$ be a seasonal regular time series

→ For instance, Y_t is a PV production extracted by 10 minutes

→ T = number of observed data by 10 minutes

✓ **Splitting of time series in *M* categories**

→ allows to reason of comparable quantities (for ex, by month)

$$I_0 = 0 \qquad I_1 = \left[0\,;\max_t Y_t / M\right]$$

$$I_m = \left[(m-1)\times\max_t Y_t / M; m\max_t Y_t / M\right]$$

...

$$I_M = \left[(M-1)\times\max_t Y_t / M;\max_t Y_t\right]$$

...

where m is the number of the category

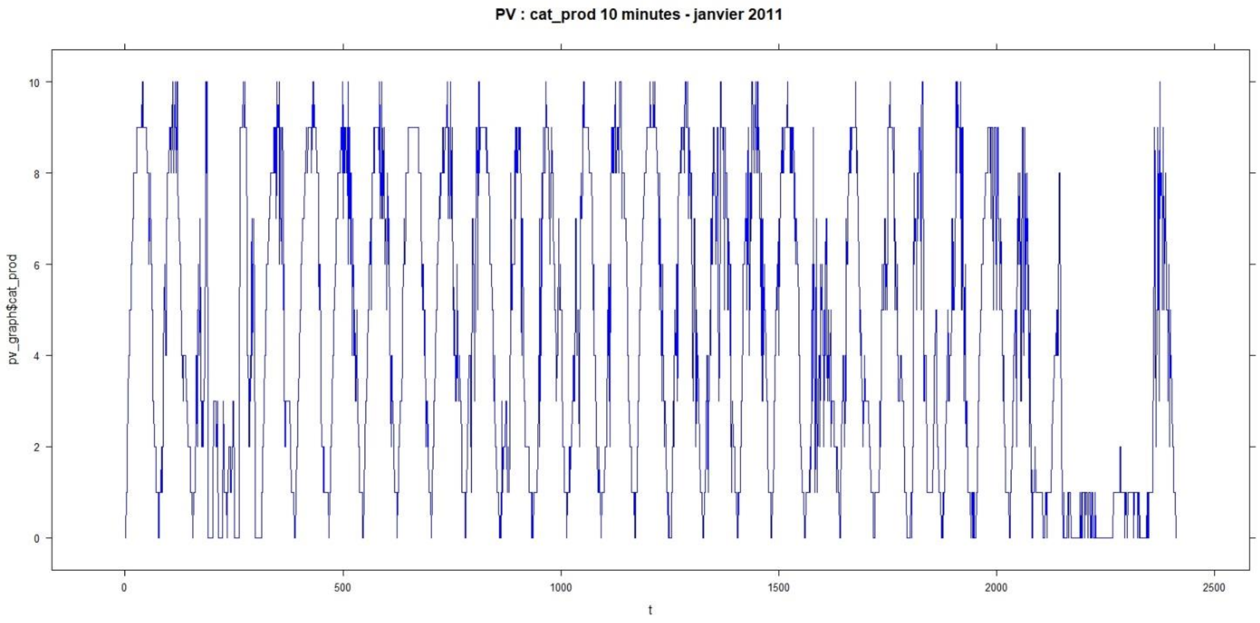
Anomalies detection approach

The approach step by step (3)

Categorisation of the time series

→ comes from of previous splitting and allows to reason on ordinal categorical values

$$b_t = m \times 1_{[Y_t \in I_m]} \quad \text{where } m \text{ is the number of category}$$



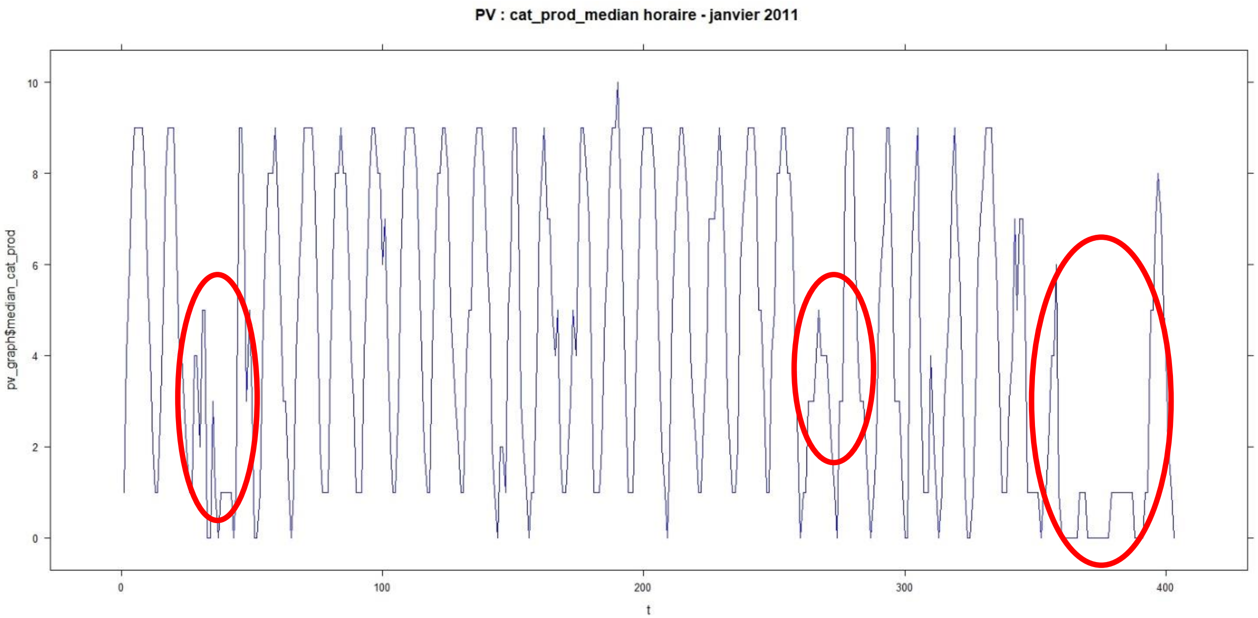
Anomalies detection approach

The approach step by step (4)

Aggregation of data

→ allows to summarize, if necessary, categorical data (10 min to 1 hour)

$$b_{j,h} = \operatorname*{\mathbf{med}}_{t \in (j,h)} b_t \quad \text{where } h \text{ and } j \text{ are respectively : hour } h \text{ of day } j$$



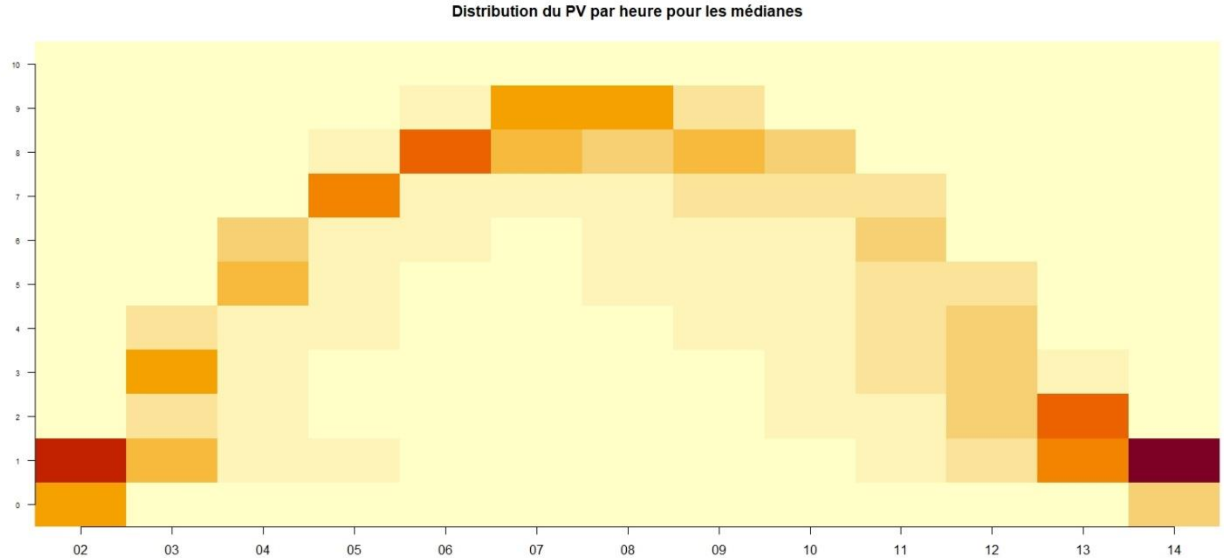
Anomalies detection approach

The approach step by step (5)

Hourly marginal distributions of the categories

→ allows to obtain observed proportions of the categories for each hour

$$f_m(h) = N_m(h) \Big/ \sum_{l=0}^{M} N_l(h) \qquad \text{where} \qquad N_m(h) = \sum_{j=1}^{n_h} 1_{[b_{j,h}=m]}$$



and n_h is the number of days for the study period for the hour h

Anomalies detection approach

The approach step by step (6)

Building of the statistics of test

→ allows to provide the structure of anomalies

$$S_j^{(moy)} = \frac{1}{card(\Omega)} \sum_{h\in\Omega} \sum_{m=0}^{M} 1_{[b_{j,h}=m]} f_m(h) \quad \text{where } j \text{ is the number of day}$$

$$S_j^{(med)} = \underset{h}{\mathbf{med}} \sum_{m=0}^{M} 1_{[b_{j,h}=m]} f_m(h) \qquad S_j^{(LMS)} = \underset{h}{\mathbf{lms}} \sum_{m=0}^{M} 1_{[b_{j,h}=m]} f_m(h)$$

For a day j and an hour h :

$$S_{j,h} = \sum_{m=0}^{M} 1_{[b_{j,h}=m]} f_m(h)$$

Interpretation : The lower the value of the statistic for an observation $S_{j,h}$ the lower its frequency of occurrence, the more likely it is to be an "anomaly"

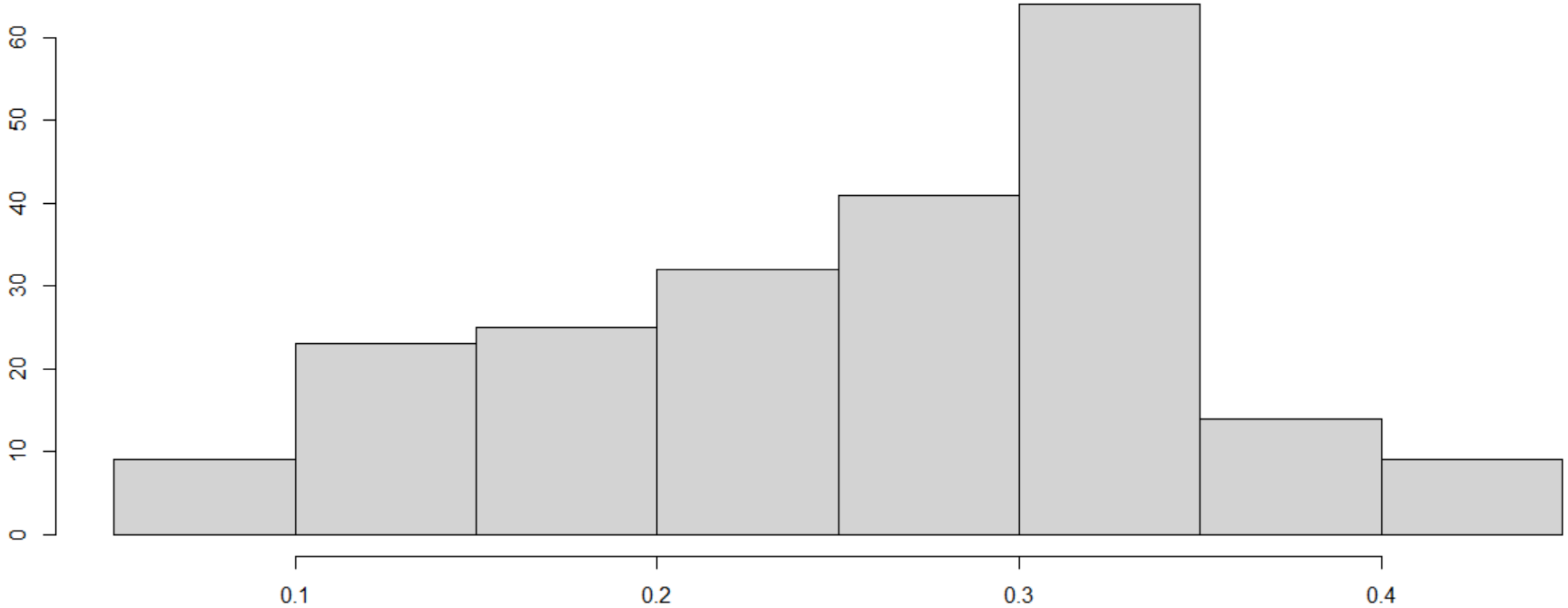
Anomalies detection approach

The approach step by step (7)

Building of empirical distribution of test

→ allows to take into account all the values observed for each day (global) or each hour (individual)

$$F_h(S_{j,h}) = \Pr\lfloor D_h < S_{j,h} \rfloor$$ is the empirique cumulative distribution fonction D_h for $S_{j,h}$



Anomalies detection approach

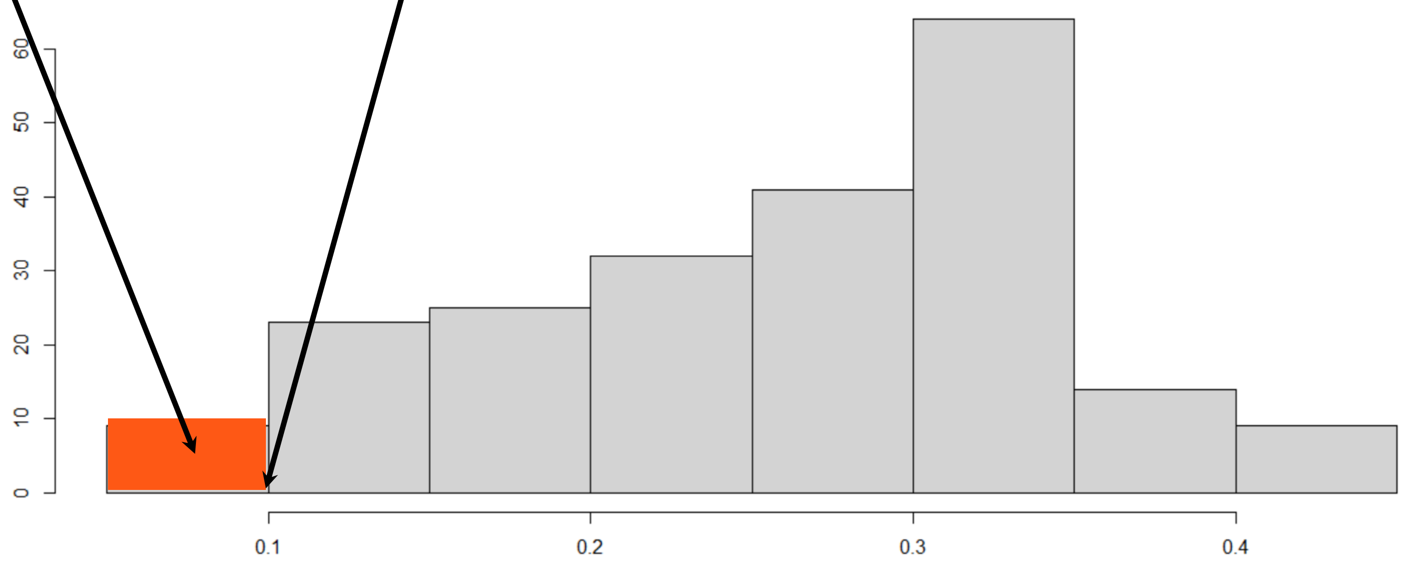
The approach step by step (8)

p-value calculation

→ building under null hypothesis (absence of anomaly) and coming from MC simulations

$\mathrm{H}_0 : Y_t$ is not an anomaly vs $\mathrm{H}_1 : Y_t$ is an anomaly

$$p-val = \Pr\left[D_h < s_{j,h}^{(obs)}\right]$$



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Application of approach on PV data

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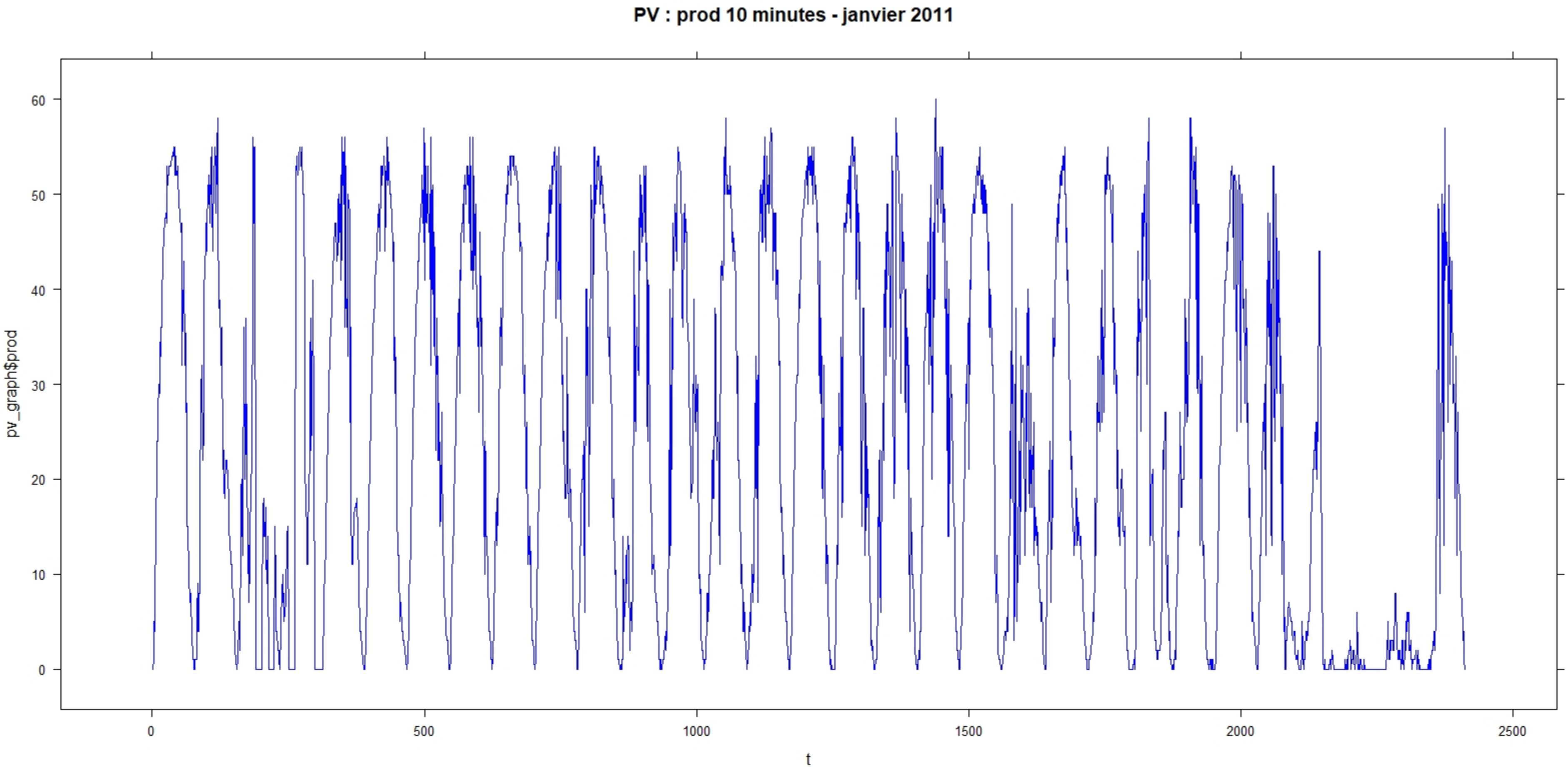
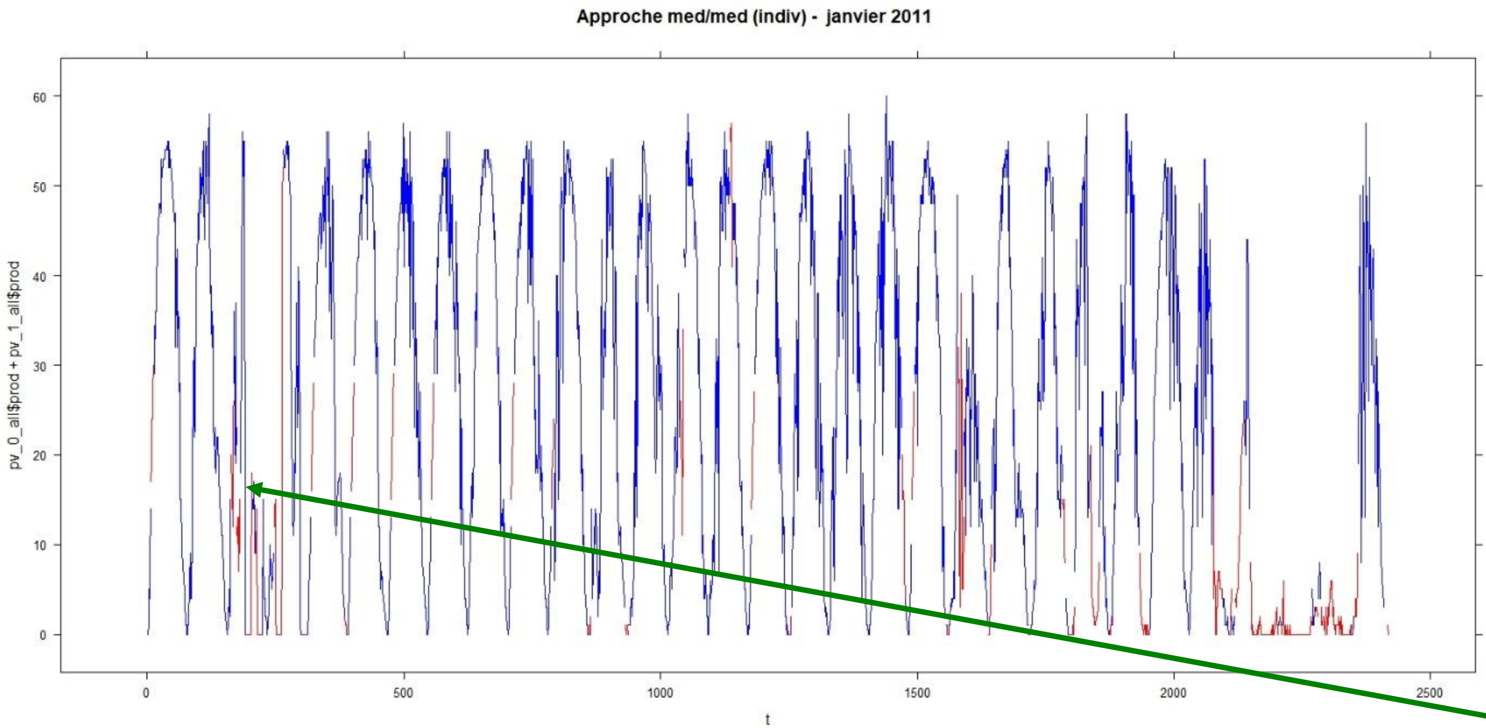
Photovoltaic data (PV stations)



Application of approach on PV data

Photovoltaic data (PV stations)

Are there abnormal hourly PV productions on January 3, 2011 ?

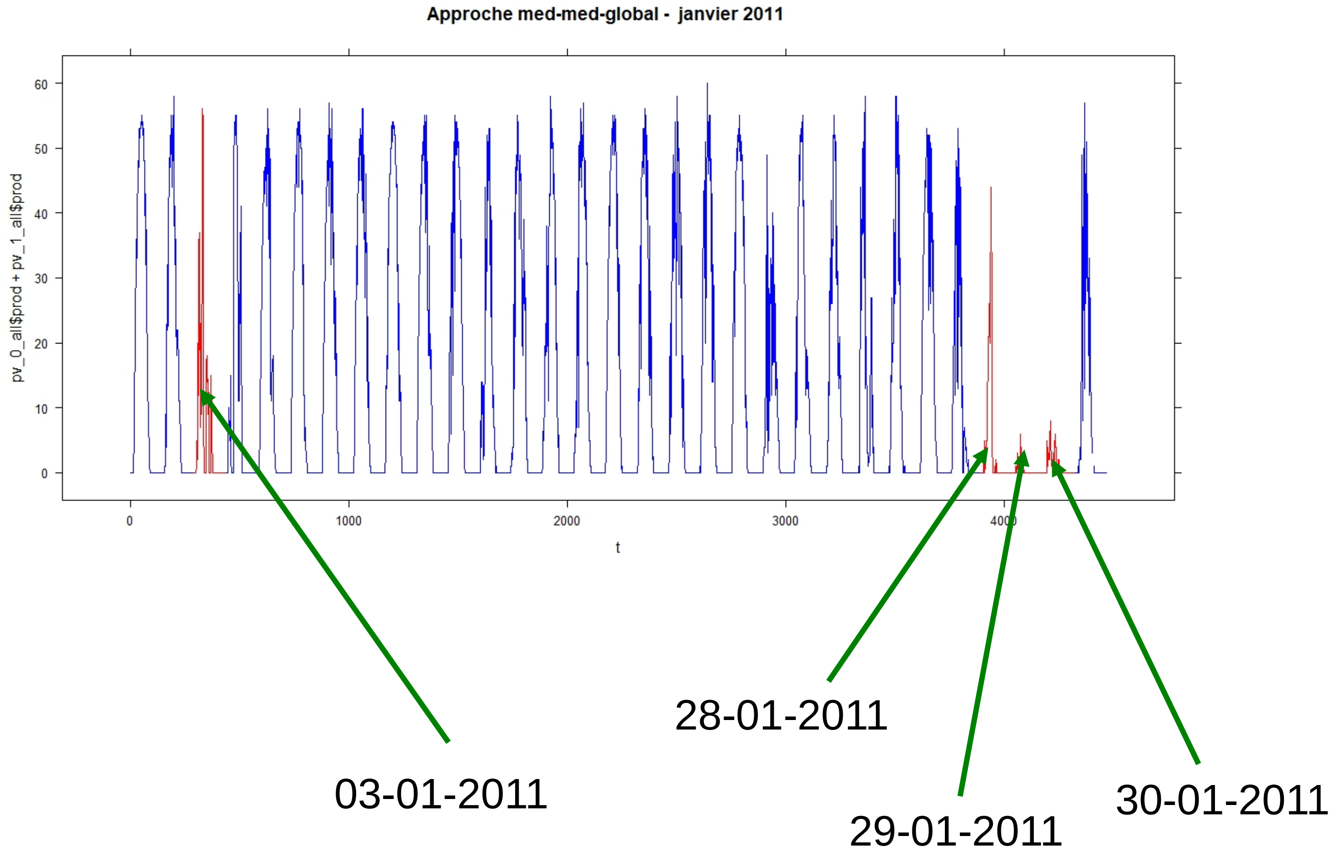


For instance, $s_{j,13}^{(obs)} = 0.0092$ then p-value $= 0.045$ (3-01-2011 – 13:00)

Application of approach on PV data

Photovoltaic data (PV stations)

Overall, is the PV production for that same day abnormal ?



Days	*p*-values
03-01-2011	0,0391
28-01-2011	0,0018
29-01-2011	0,0001
30-01-2011	0,0018

Application of approach on PV data

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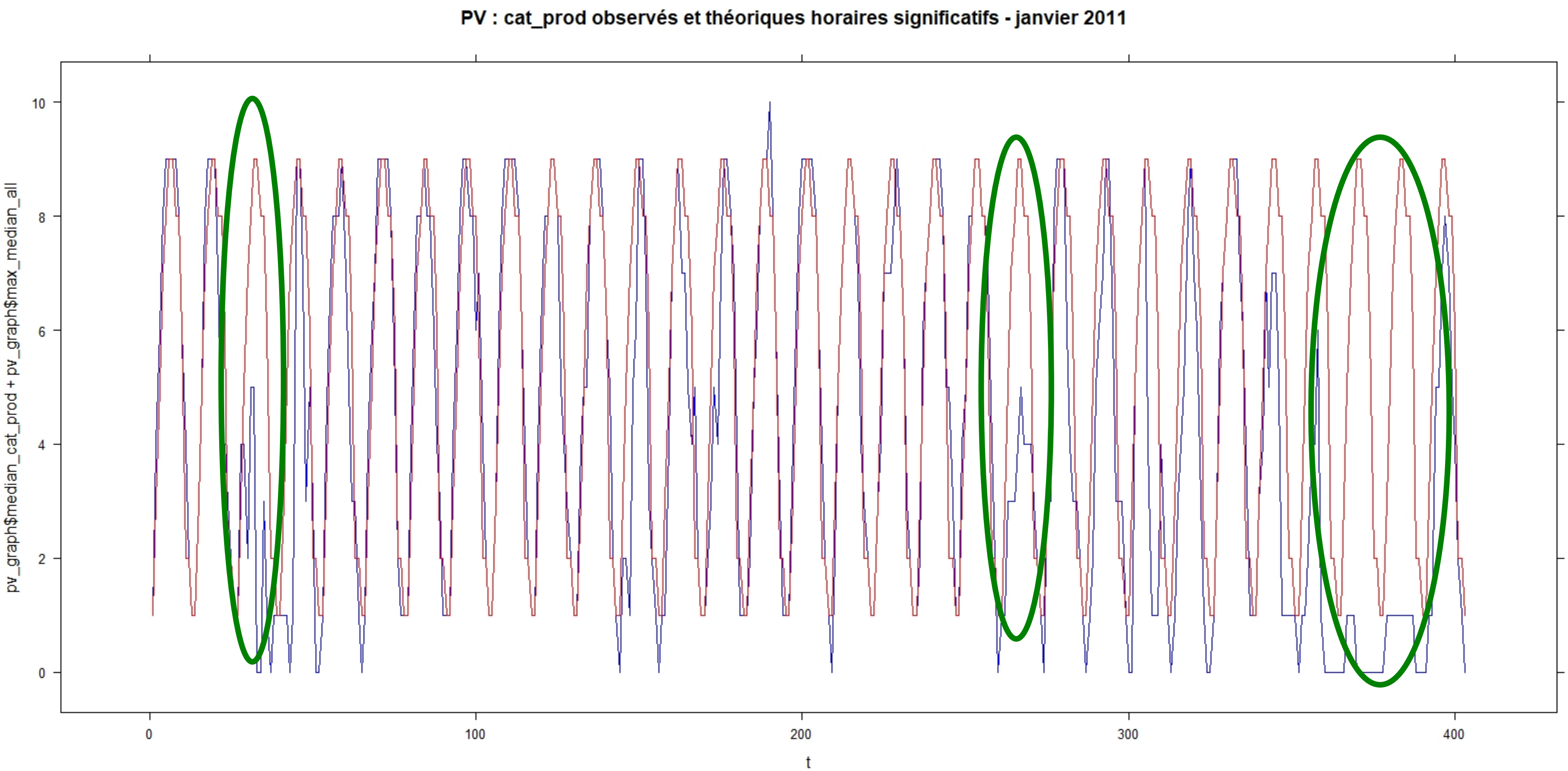
Photovoltaic data (PV stations)



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Application of approach on PV data

$\boxed{\text{Contributions, applications and further researches}}$

Contributions, applications, further research

Approach for regular (or almost regular) time series

Applications : forcasting of PV production, temperature (response or predictor), electric consumption (response), detecting cardiac desease on ECG, …

Comparing to other approaches of anomalies detection

To extend this approach for online strategies

Bibliography

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