Microgrids

Introduction to probabilistic forecasting

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Introduction to forecasting

Learning objectives

Through this lecture, it is aimed for the students to be able to:

- Produce **probabilistic** forecasts;
- Perform **verification** of probabilistic forecasts

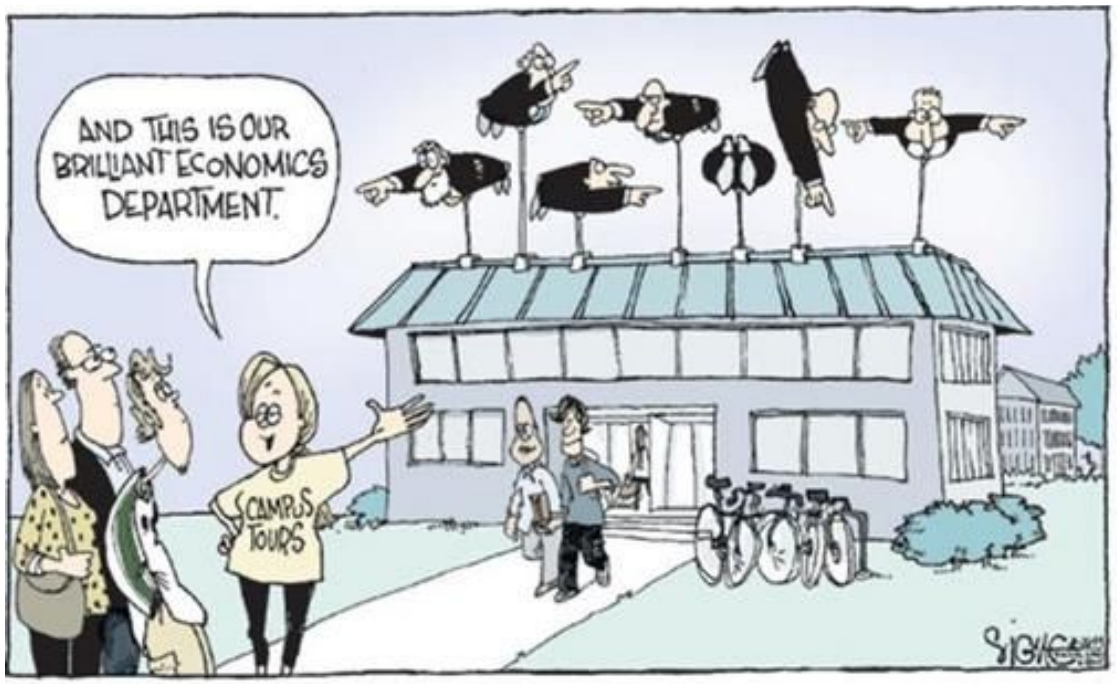
Summary

1. Reminder
2. Probabilistic forecasts
3. Verification of probabilistic forecasts

Introduction to forecasting

Reminder: forecast for decision making

Forecasting is a natural first step to ***decision-making***



Key parameters for a microgrid to forecast:

Generation: PV, Wind Power, Hydraulic Power, etc

Load: office, industrial, residential, etc

Prices: electricity, gas, (futures, day ahead, intraday, imbalances).

Introduction to forecasting

Reminder: point forecast definition

A forecast is an **estimate** for time **t + k**, conditional to information up to time t.

A **point forecast** informs of the **conditional expectation** of power generation.

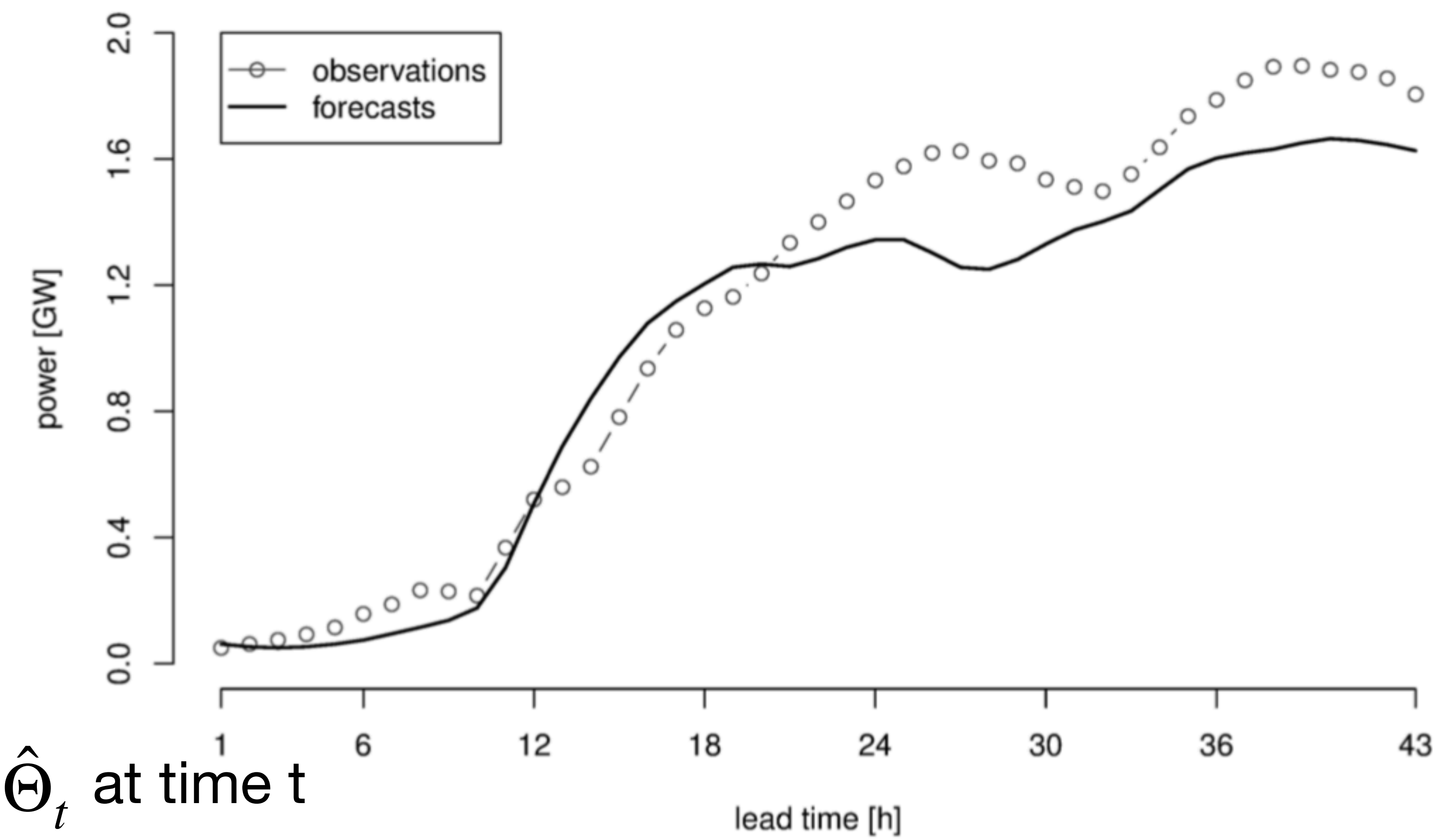
$$\hat{y}_{t+k|t} = \mathbb{E}\left[Y_{t+k|t} \,|\, g, \Omega_t, \hat{\Theta}_t\right]$$

given:

- the information set Ω;

- a model g

- its estimated parameters $\hat{\Theta}_t$ at time t



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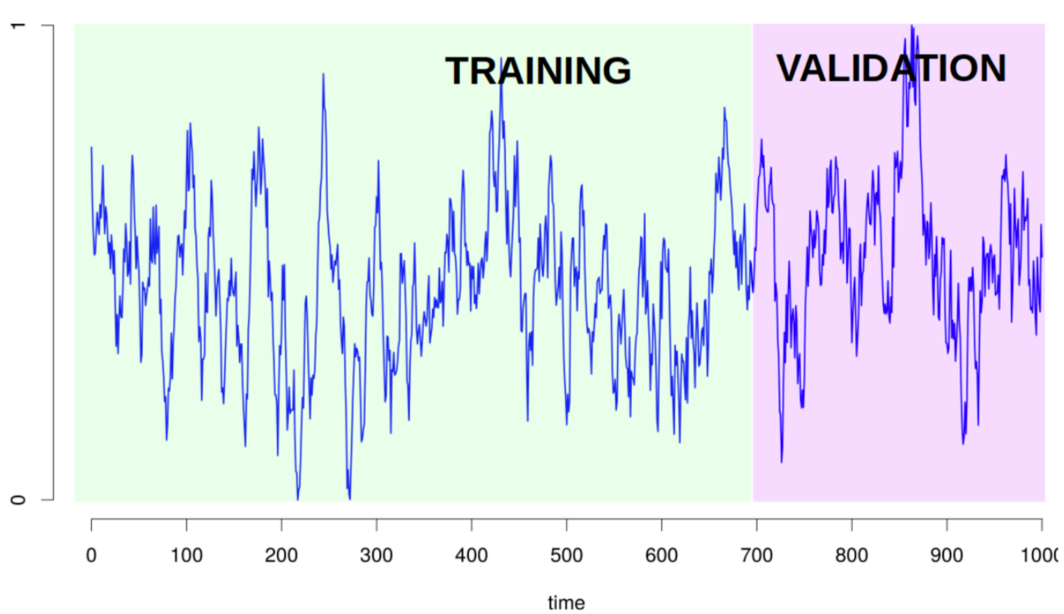
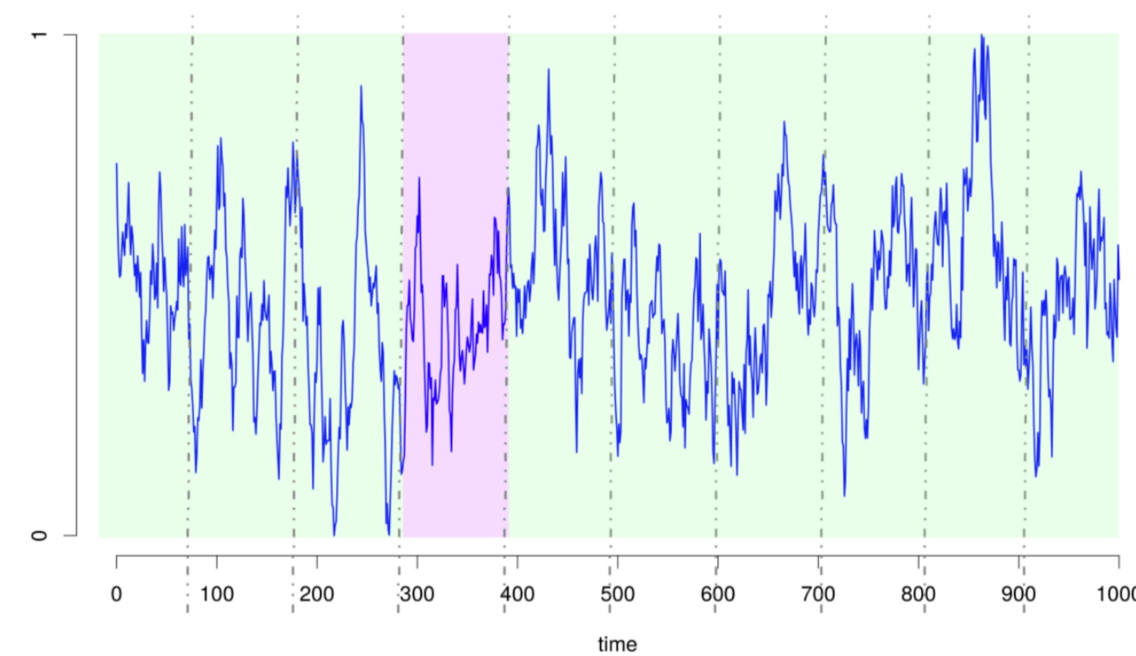
Reminder: use a strategy to assess forecasts

Several strategies to assess forecasts:

- splitting the dataset into a learning and a validation sets;

- k-cross validation: k pairs or random learning and validation sets.





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Reminder: use quantitative metrics

Bias or Nbias, for the normalized version:

$$\textbf{bias}(k) = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{t+k|t}$$

Mean Absolute Error (**MAE**) or NMAE, for the normalized version:

$$\textbf{MAE}(k) = \frac{1}{T}\sum_{t=1}^{T} |\,\epsilon_{t+k|t}\,|$$

Root Mean Squared Error (**RMSE**) or NRMSE, for the normalized version:

$$\textbf{RMSE}(k) = \left[\frac{1}{T}\sum_{t=1}^{T} \epsilon_{t+k|t}^2\right]^{1/2}$$

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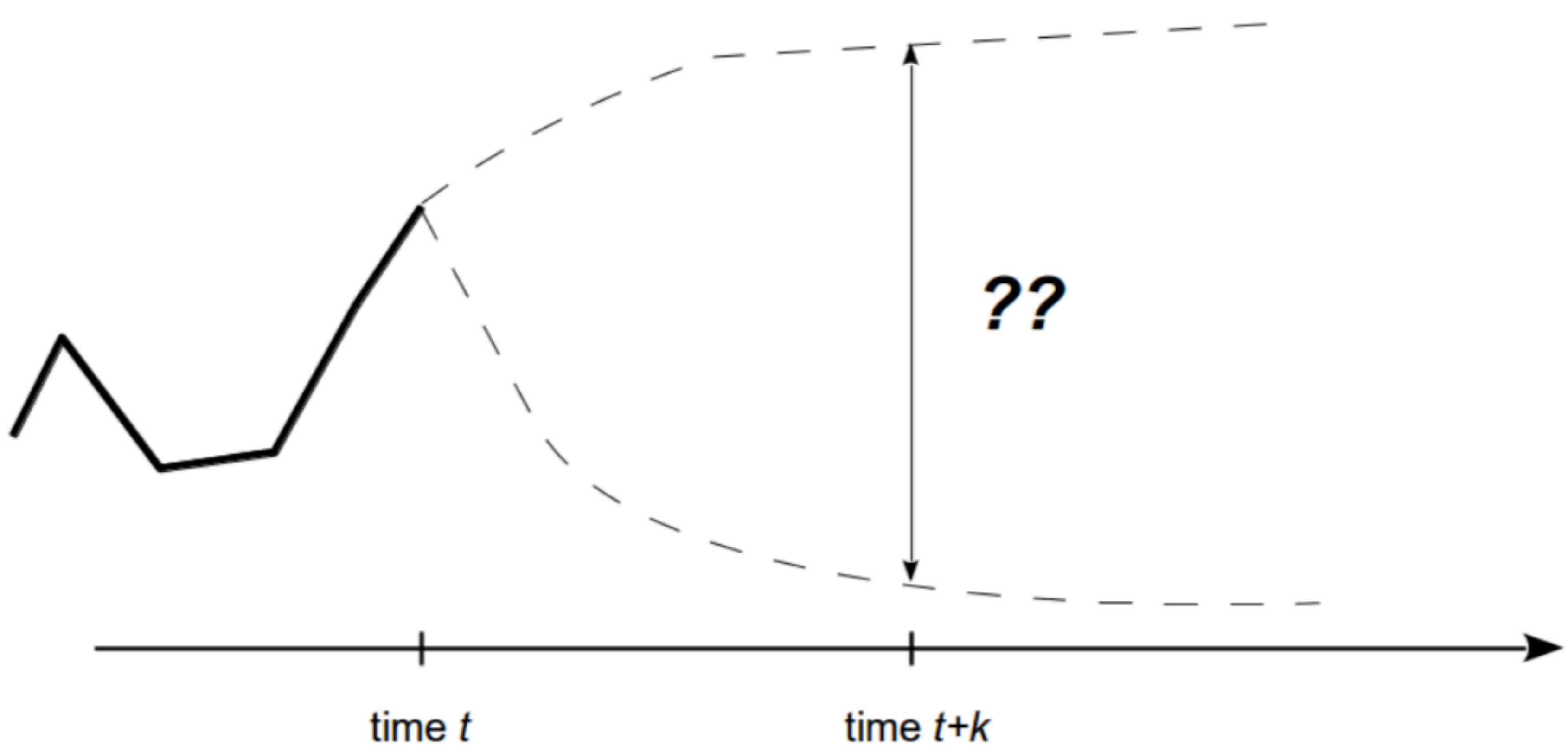
Introduction to forecasting

Probabilistic forecasting

The various types of probabilistic forecasts range, from **quantile** to **density** forecasts, **prediction** intervals, and **scenarios**.



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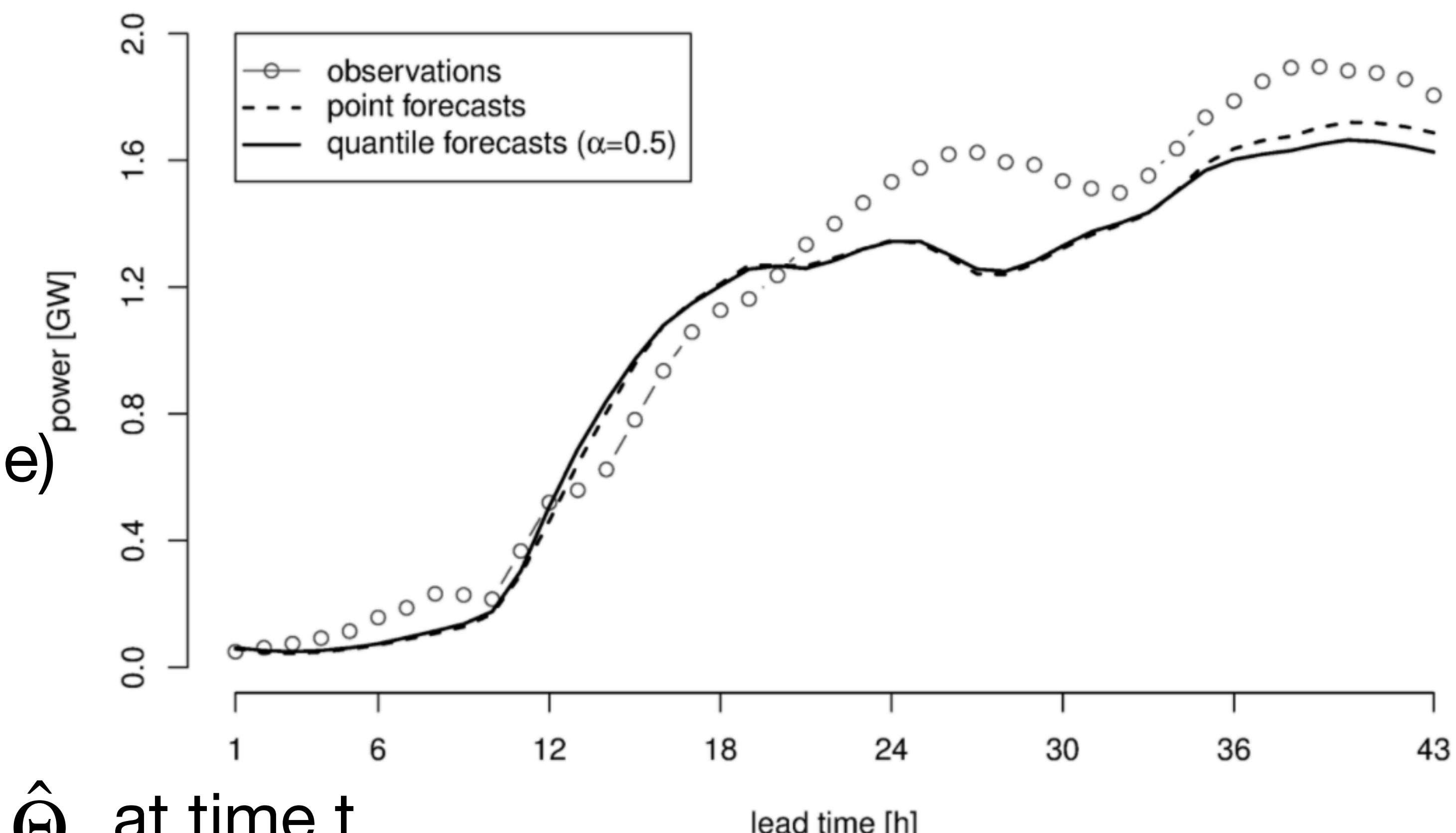
Quantile forecast definition

A **quantile** forecast is to be seen as a probabilistic **threshold** for power generation.

$$P[Y_{t+k|t} \leq \hat{y}^{(q)}_{t+k|t} \,|\, g, \Omega_t, \hat{\Theta}_t] = q$$

$$\hat{y}^{(q)}_{t+k|t} = \hat{F}^{-1}_{t+k|t}(q)$$



with:

- q the normal level (quantile)
- the information set Ω;
- a model g
- its estimated parameters $\hat{\Theta}_t$ at time t
- F the cumulative distribution function (CDF)

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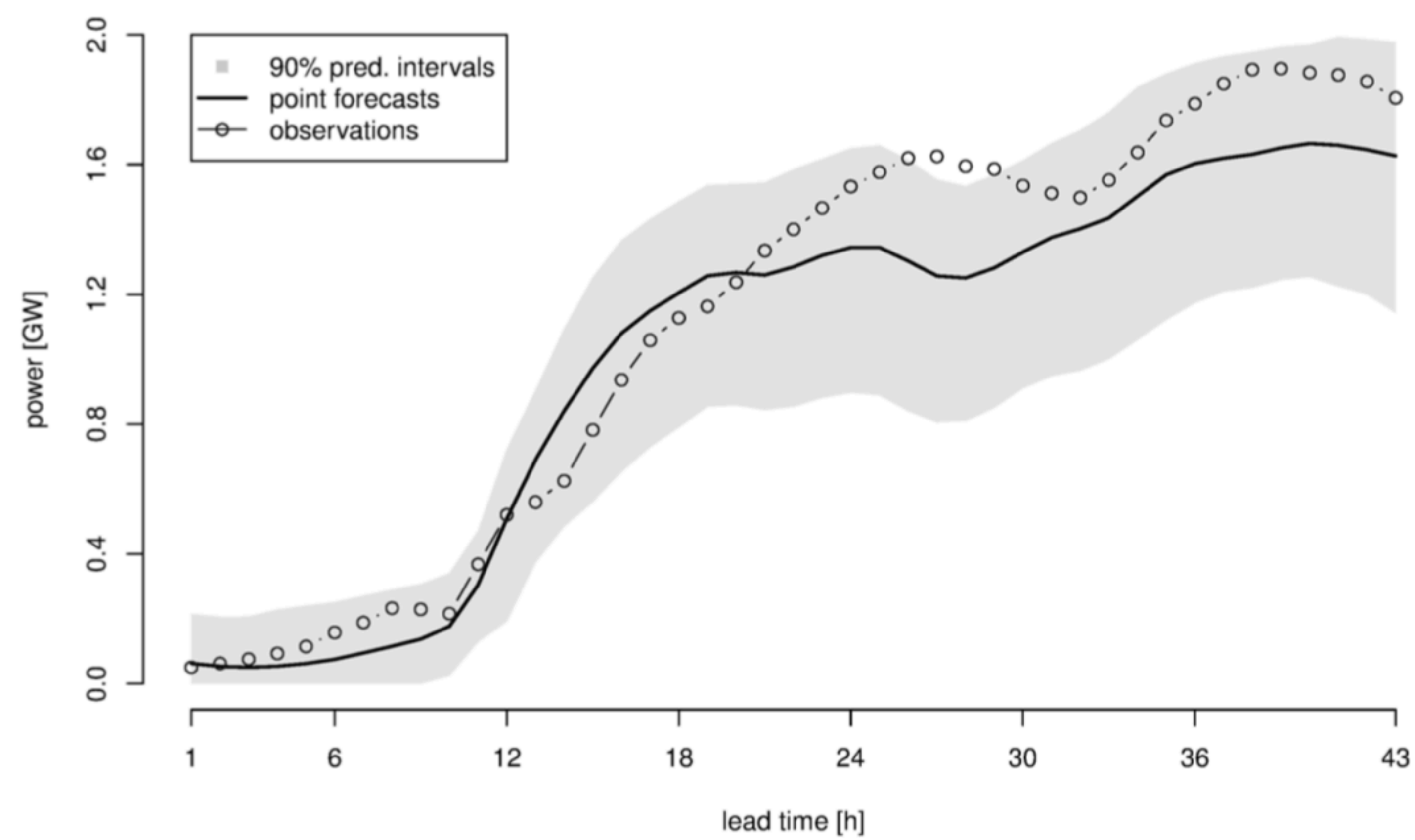
Prediction interval definition

A **prediction** interval is an **interval** within which power generation may lie, with a certain probability.

$$\hat{I}^{(\alpha)}_{t+k|t} = \left[\hat{y}^{(q=\alpha/2)}_{t+k|t}, \hat{y}^{(q=1-\alpha/2)}_{t+k|t}\right]$$

with:

- alpha the nominal coverage



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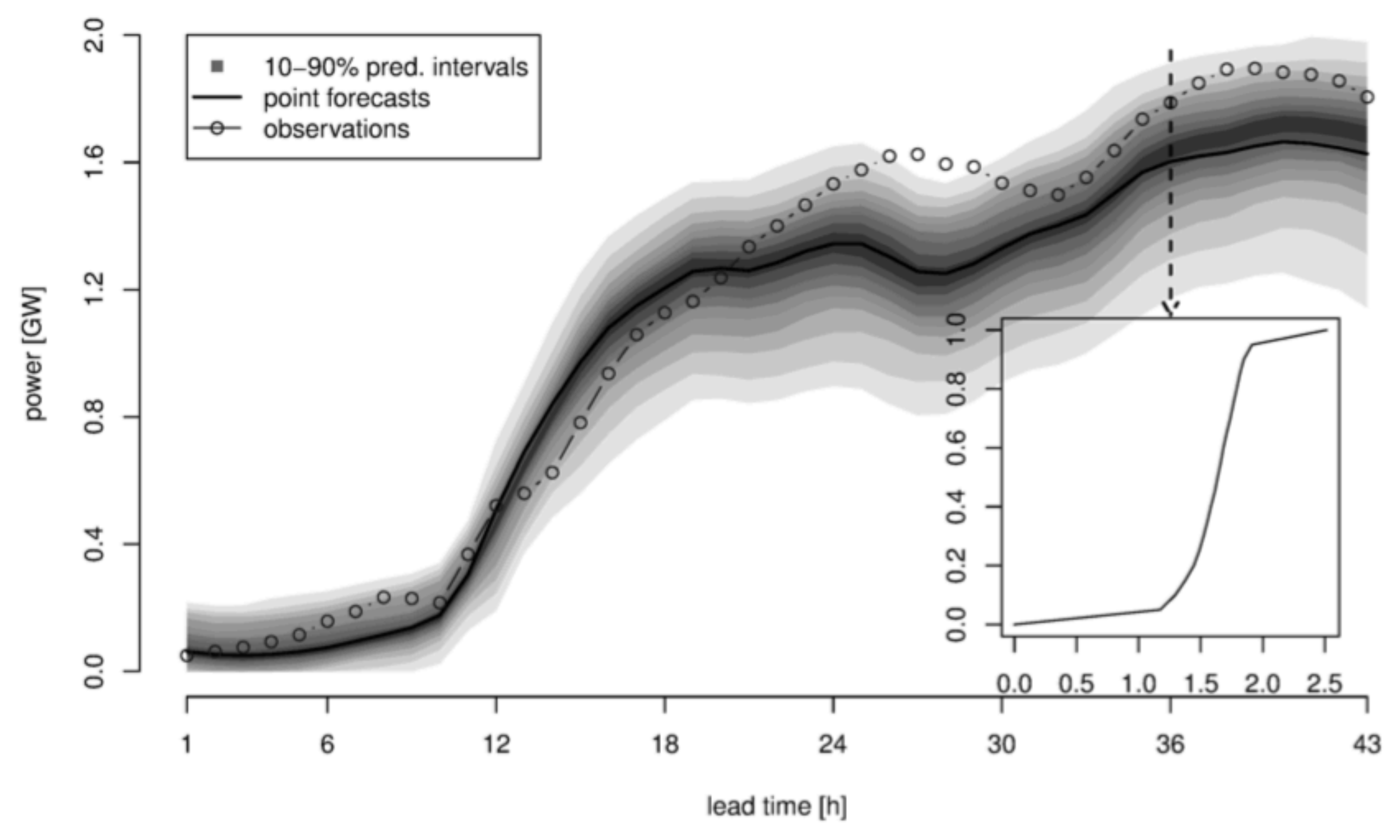
Predictive density definition

A predictive density fully describes the **probabilistic distribution** of power generation for every lead time.

$$Y_{t+k} \approx \hat{F}_{t+k|t}$$

with:

- F the cumulative distribution function for Yt+k



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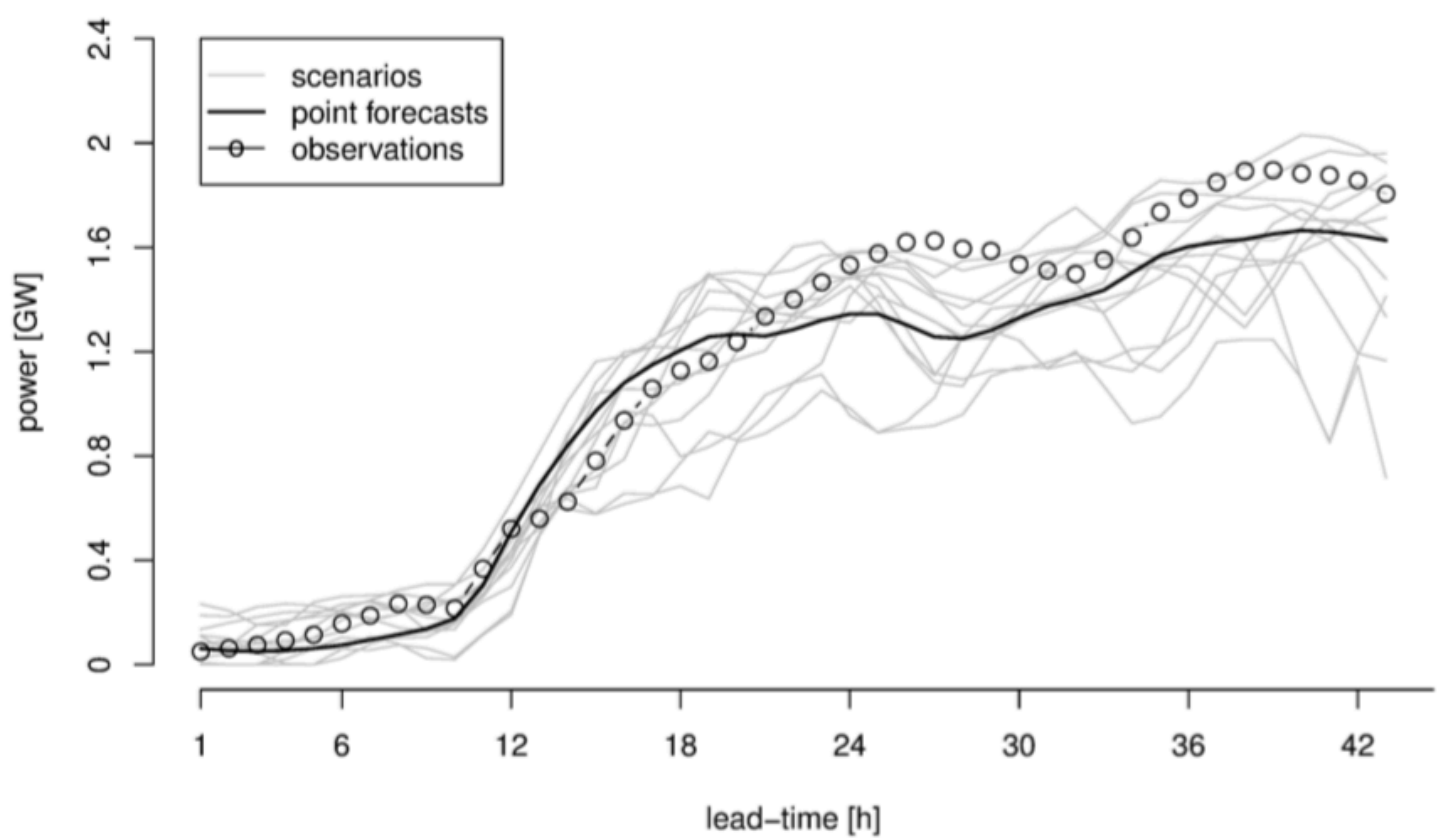
Trajectories (scenarios) definition

Trajectories are equally-likely **samples** of multivariate predictive densities for power generation (in time and/or space).

$$z_t^j \approx \hat{F}_t$$

with:

- F the multivariate predictive cdf of Yt
- z^j the j^th trajectory



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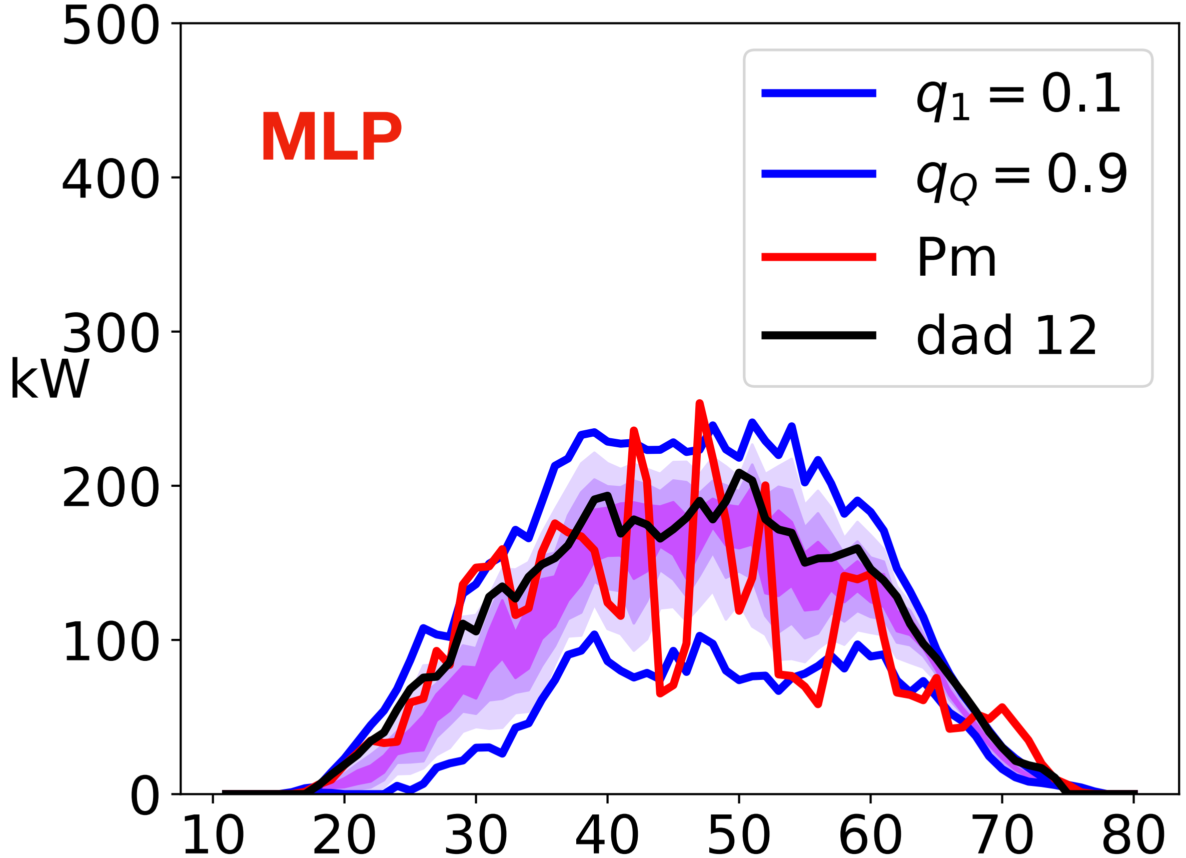
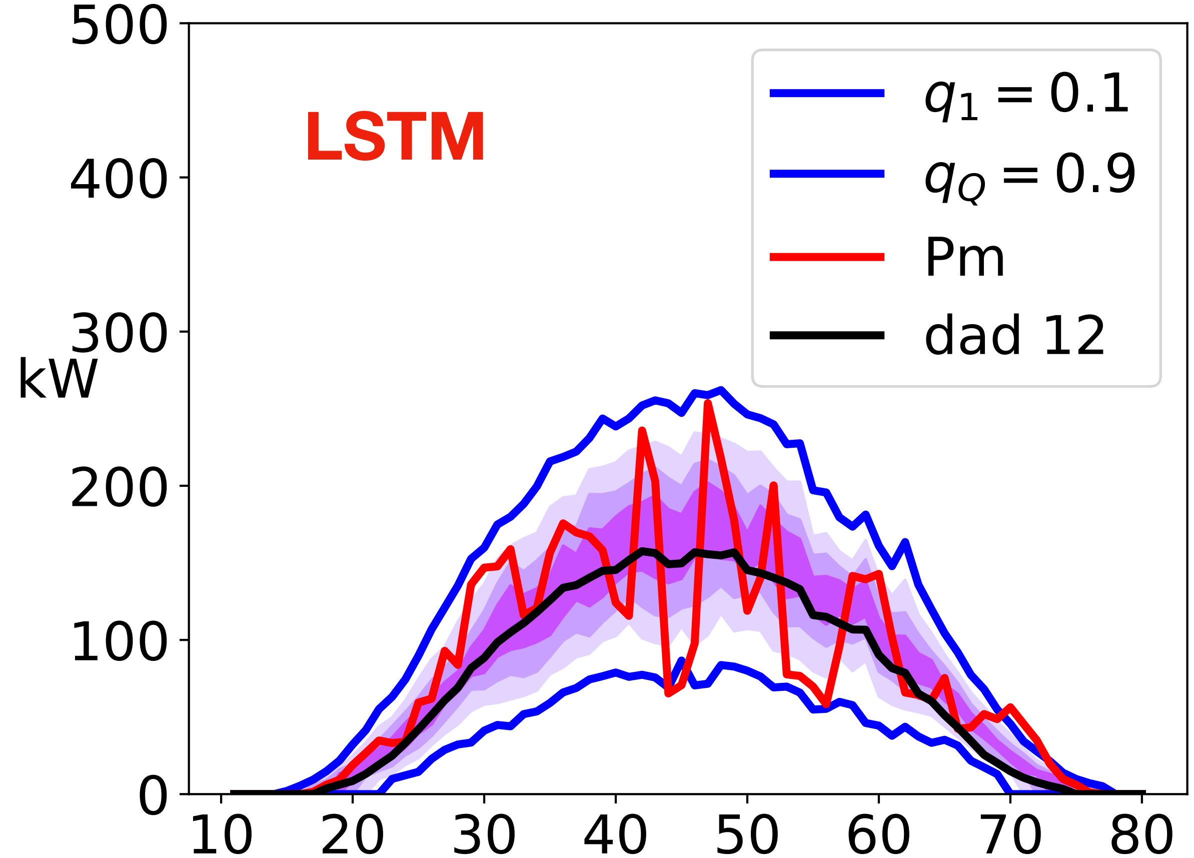
Quantile forecasts examples: PV generation





PV **quantile** forecasts computed at 12:00 for the next day along with corresponding observations (Pm in red) and point forecasts (dad 12 in black).

The model are a **feed-forward neural network** (MLP) on the left figure and a **long short term memory neural network** (LSTM) on the right figure.

Residential energy supplier

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Case study: PV parking rooftops from Liège university

PV installation of 466.4 kWp

https://www.uliege.be/cms/c_7726266/fr/2500-m-de-panneaux-photovoltaiques-bientot-en-fonction-sur-le-campus-du-sart-tilman

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Case study: PV forecasting model

The forecasting model g is a **feed-forward neural network**:

- with **one** hidden layer;
- weather forecasts of **solar** irradiation and **air** temperature as inputs;
- the output layer is composed of **96** neurons (96 time steps);
- it is implemented in **python** using Tensorflow library.

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Evaluation methodology

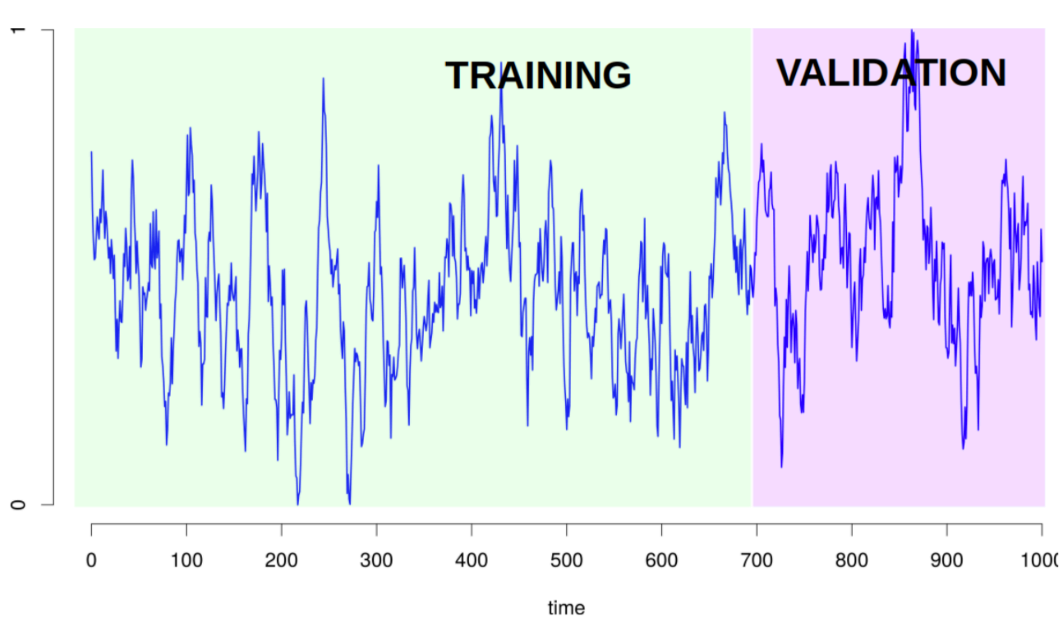
Forecasting is about being able to **predict future events**, in new situations not only explain what happen in the past.

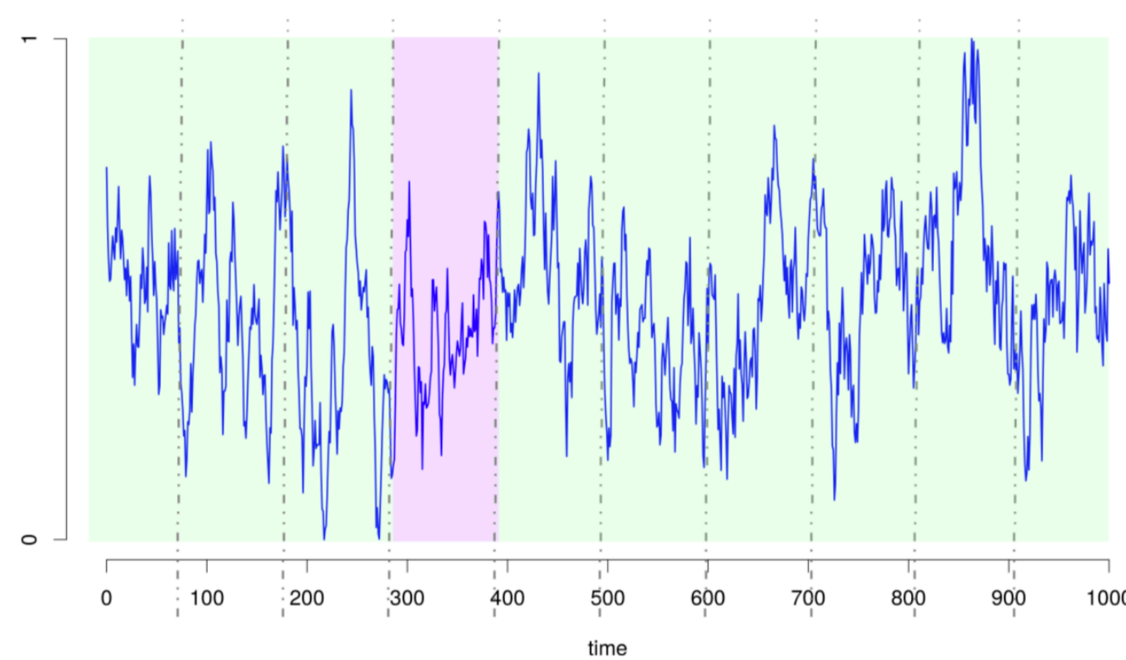
One need to verify forecasts on data that **has not been used** for the modelling!

Several strategies:

- splitting the dataset into a learning and a validation sets;

- k-cross validation: k pairs or random learning and validation sets.





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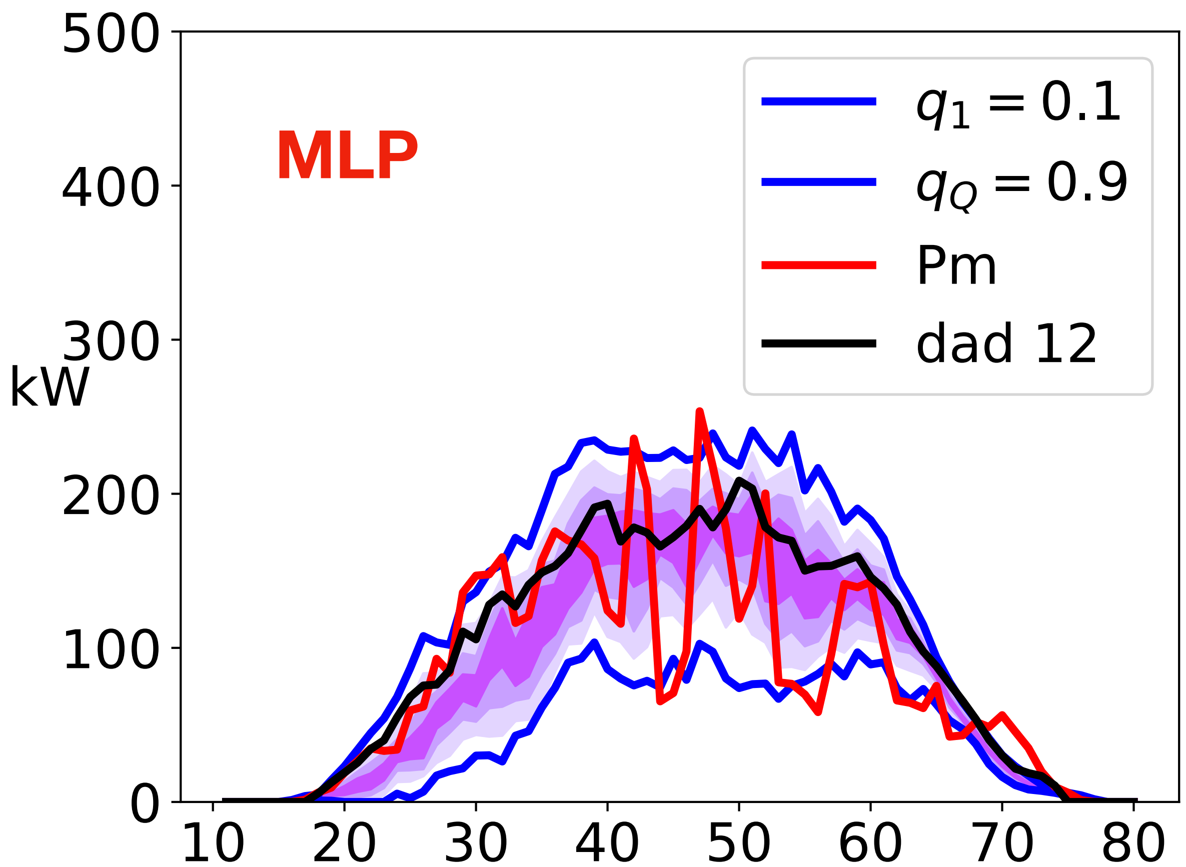
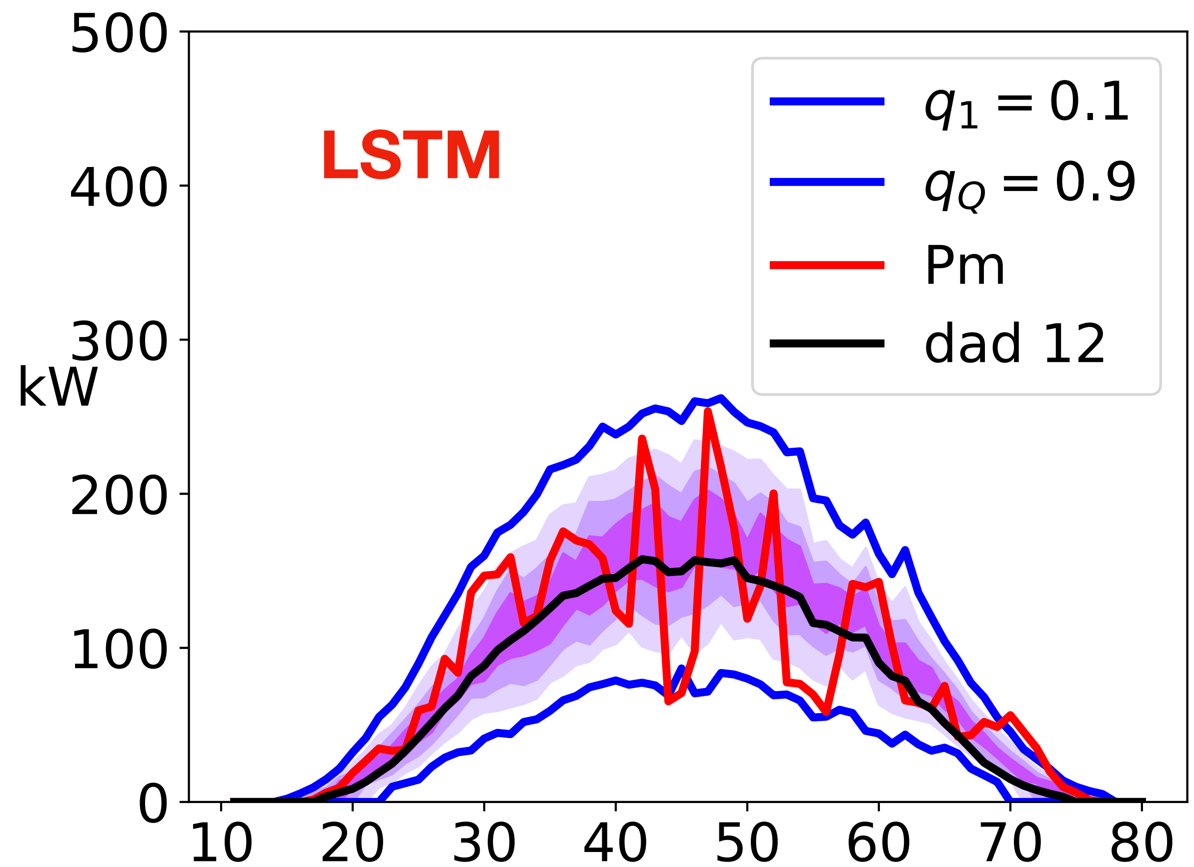
Visual inspection

Visual inspection allows you to develop **susbtantial insight** on forecast **quality**.

This comprises a **qualitative analysis** only.

What do you think of these two? Are they good or bad?





Issued on 1 August 2020 at 12:00 for 2 August 2020.

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Attribute of probabilistic forecast quality

How do you want your forecasts?

- **Reliable**? (also referred to as “probabilistic calibration”)

- **Sharp**? (i.e., informative)

- **Skilled**? (all-round performance, and of higher quality than some benchmark)

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Probabilistic calibration (reliability)

Calibration is about respecting the probabilistic contract:

- **quantile** forecast with a nominal level q = 0.5, one expect than the observations are to be less than the forecast 50% of the times;

- **prediction** interval with a nominal coverage of 90%, one expect than the observations are to be covered by this prediction 90% of the times

To do it in practice, we take a frequentist approach... we simply count!

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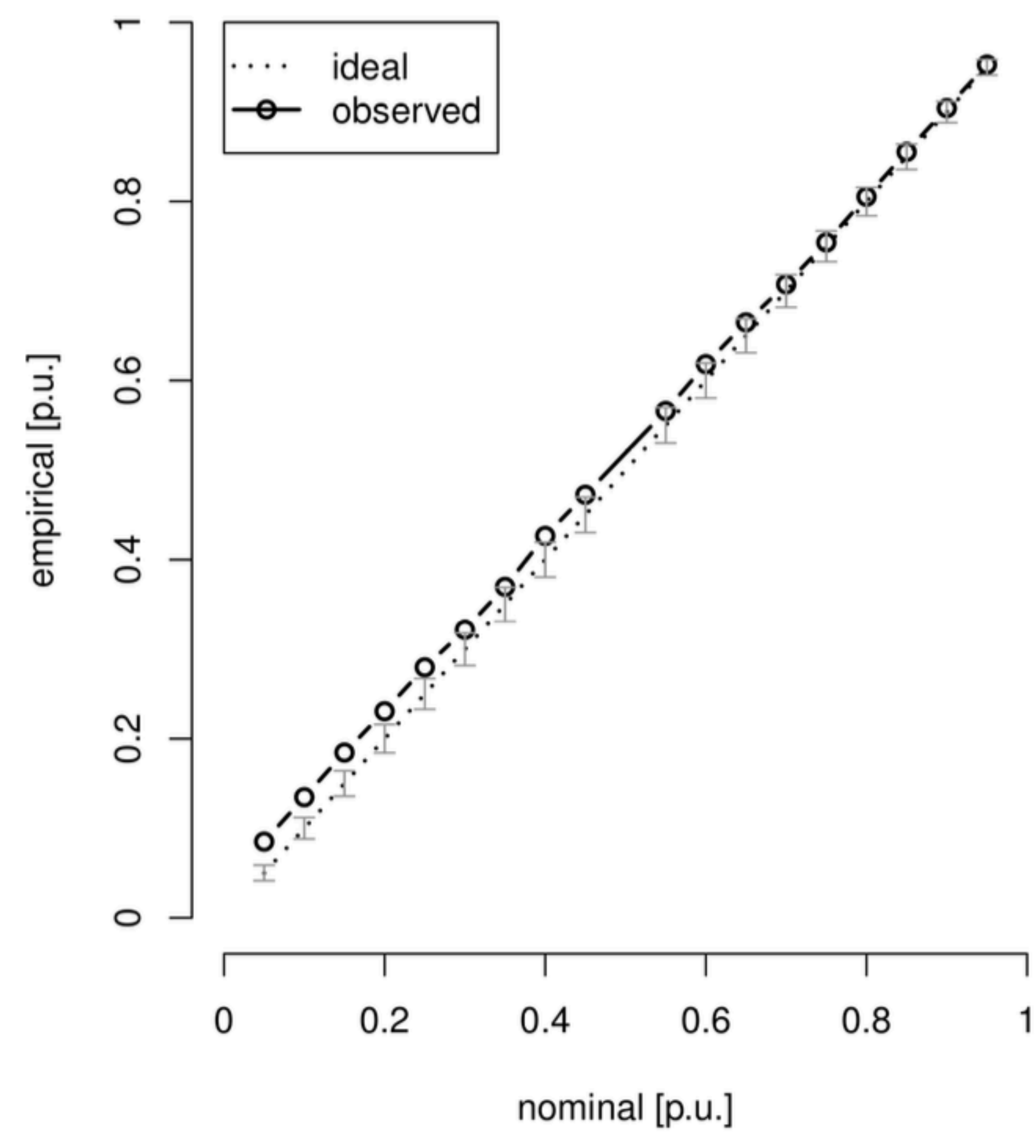
Reliability diagrams

The calibration assessment can be summarized in reliability diagrams.

Predictive densities composed by quantile forecasts with nominal levels {0.05, 0.1,…,0.45, 0.55,…,0.9, 0.95}.

Quantile forecasts are evaluated one by one, and their empirical levels are reported vs. their nominal levels

The **closest** to the **diagonal**, the better!



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Sharpness

Sharpness is about the **concentration** of probability.

A perfect probabilistic forecast gives a probability of 100% on a single value!

Consequently, a sharpness assessment boils down to **evaluating how tight the predictive densities are**...

For a given interval forecast

$$\hat{I}^{(\alpha)}_{t+k|t} = \left[\hat{y}^{(q=\alpha/2)}_{t+k|t}, \hat{y}^{(q=1-\alpha/2)}_{t+k|t}\right]$$

The width is

$$\delta^{(\alpha)}_{t,k} = \hat{y}^{(q=1-\alpha/2)}_{t+k|t} - \hat{y}^{(q=\alpha/2)}_{t+k|t}$$

Average over the validation set

$$\delta^{(\alpha)}(k) = \frac{1}{T}\sum_{t=1}^{T} \delta^{(\alpha)}_{t,k}$$

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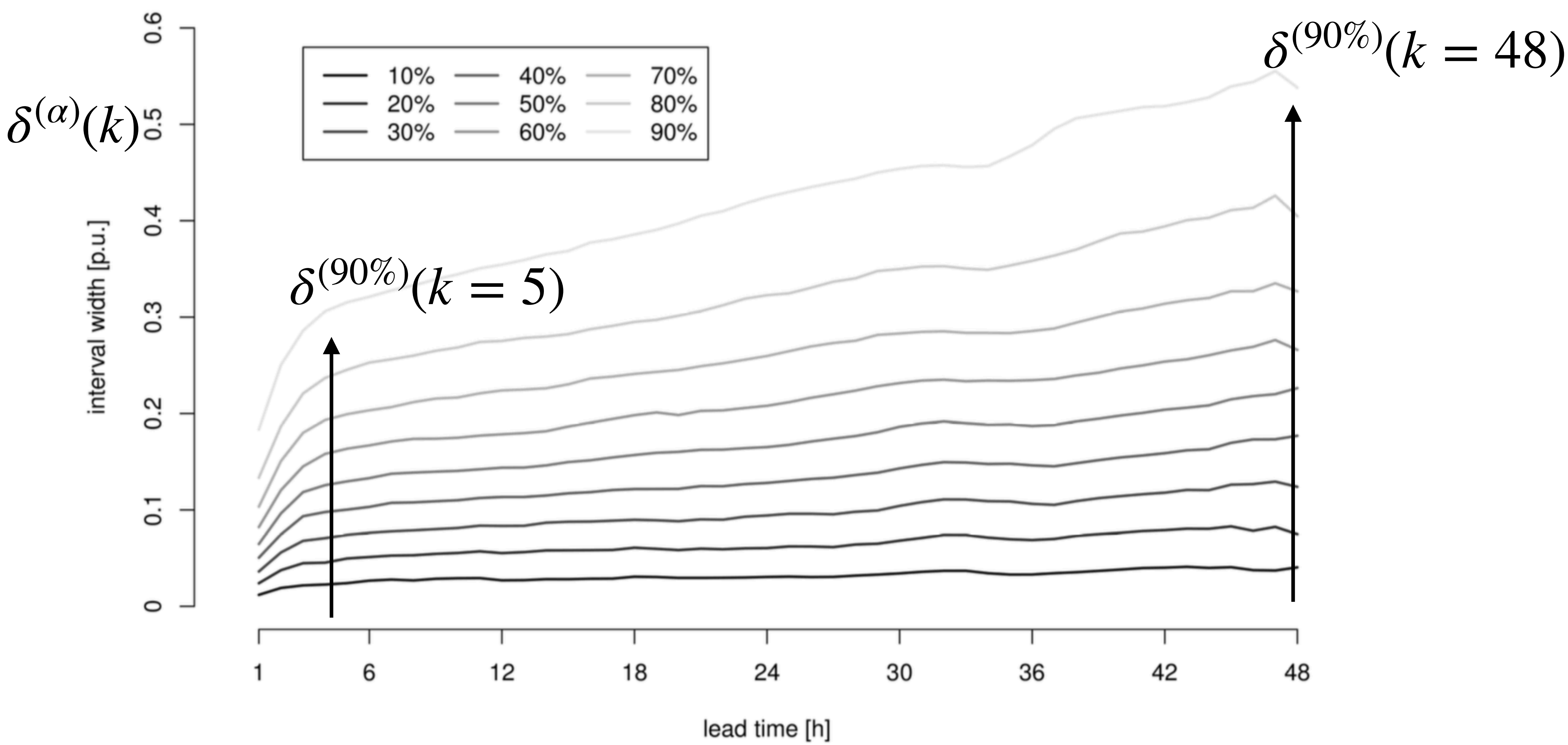
Sharpness

Predictive densities are composed by interval forecasts with nominal coverage rates = 0.1, 0.2,…, 0.9.

The interval width increases with the lead time, reflecting higher forecast uncertainty



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Overall skill assessment

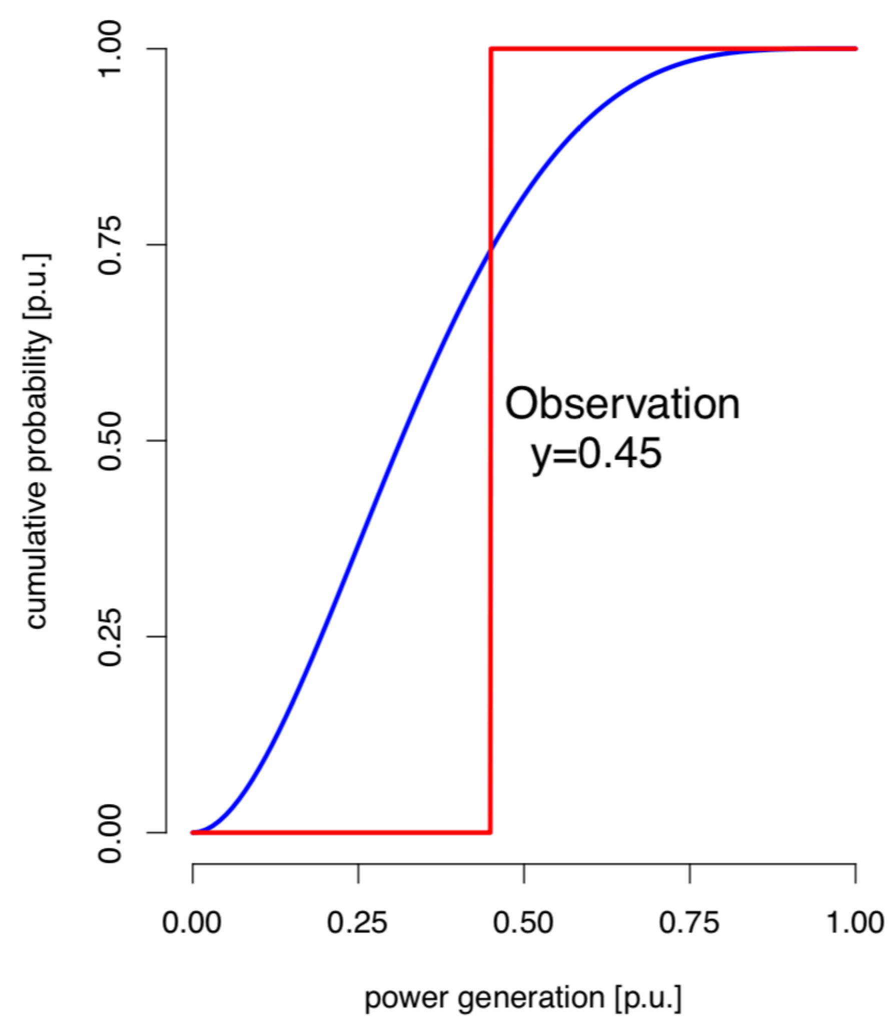
The skill of probabilistic forecasts can be assessed by scores, like MAE and RMSE for the deterministic forecasts.

The most common skill score for predictive densities is the **Continuous Ranked Probability Score (CRPS).**

$$\textbf{CRPS}_{t,k} = \int_x [\hat{F}_{t+k|t}(x) - \mathbf{1}(x \geq y_{t+k})]^2 dx$$

$$\textbf{CRPS}(k) = \frac{1}{T}\sum_{t=1}^{T} \textbf{CRPS}_{t,k}$$

CRPS and MAE (for deterministic forecasts) can be directly compared.



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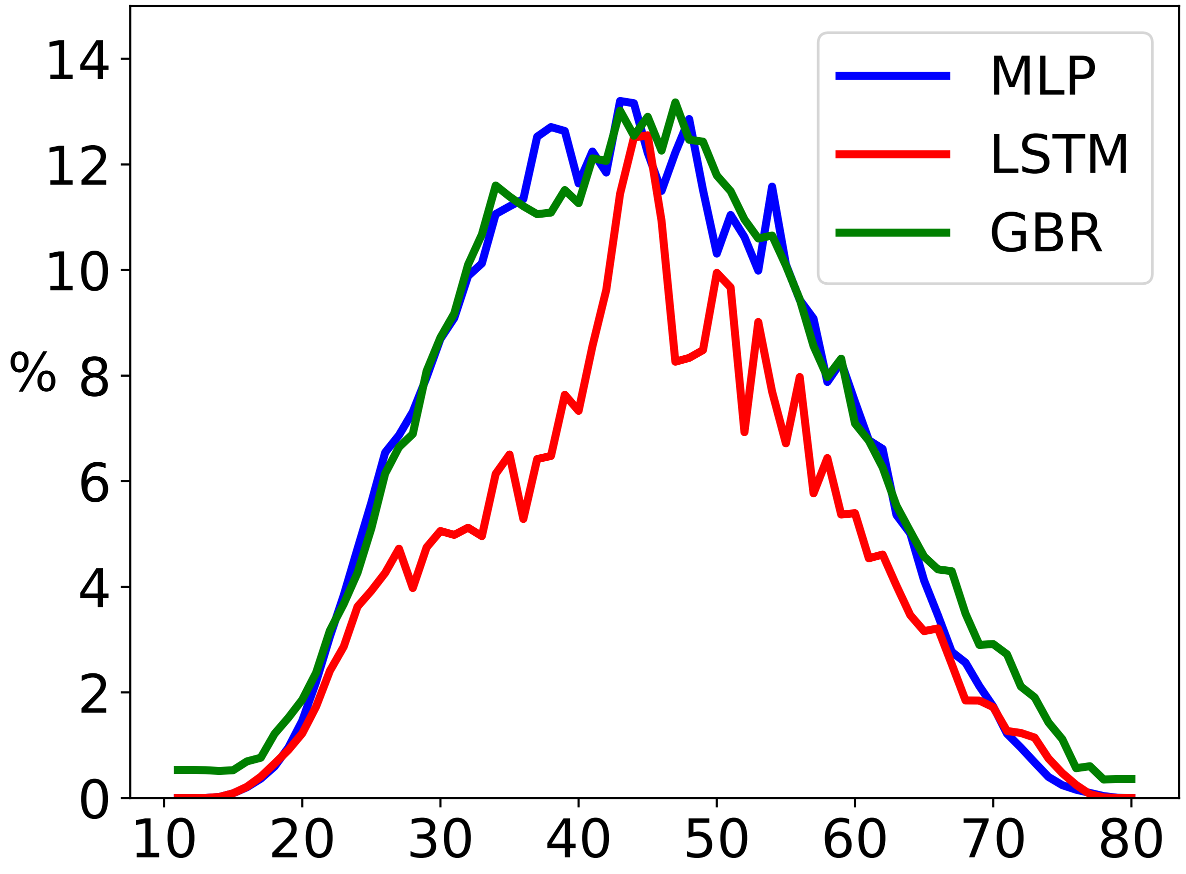
CRPS example on the case study



CRPS per lead time, from 11-cross validation, of three forecasting models for PV quantile forecasts.

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Conclusion: forecast for decision making

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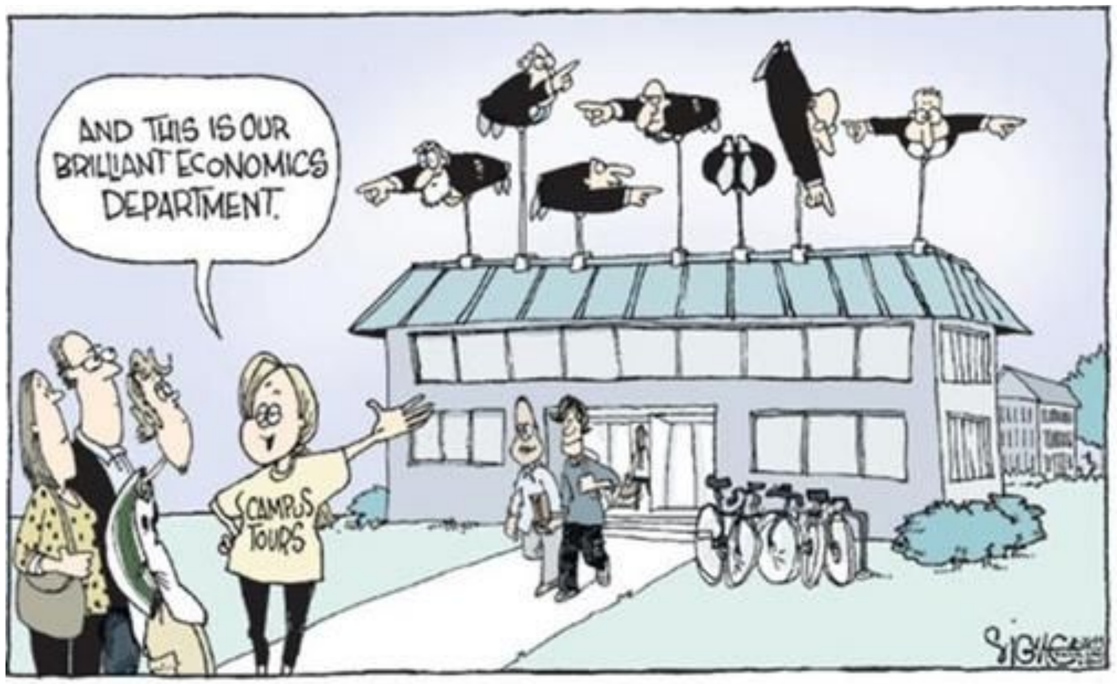

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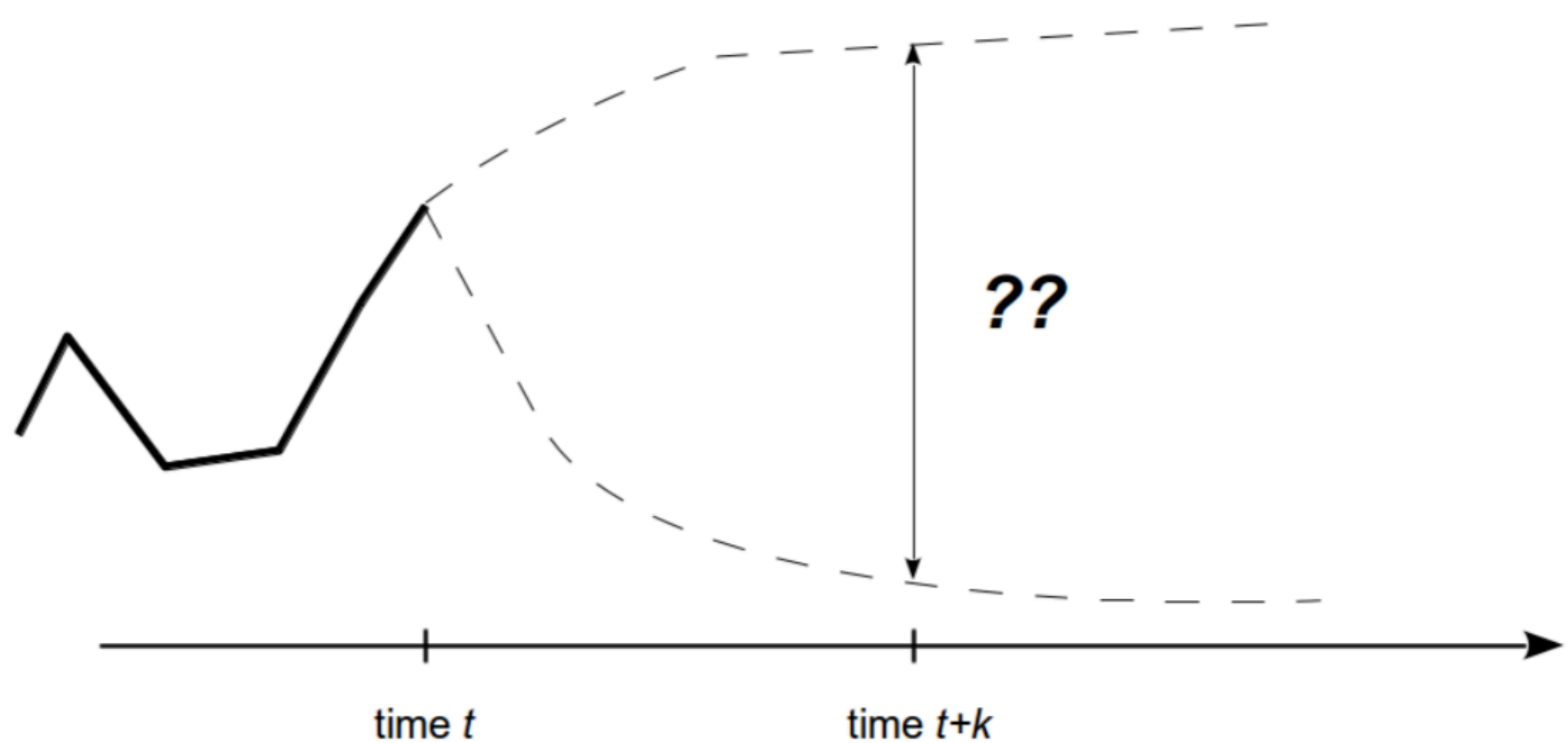

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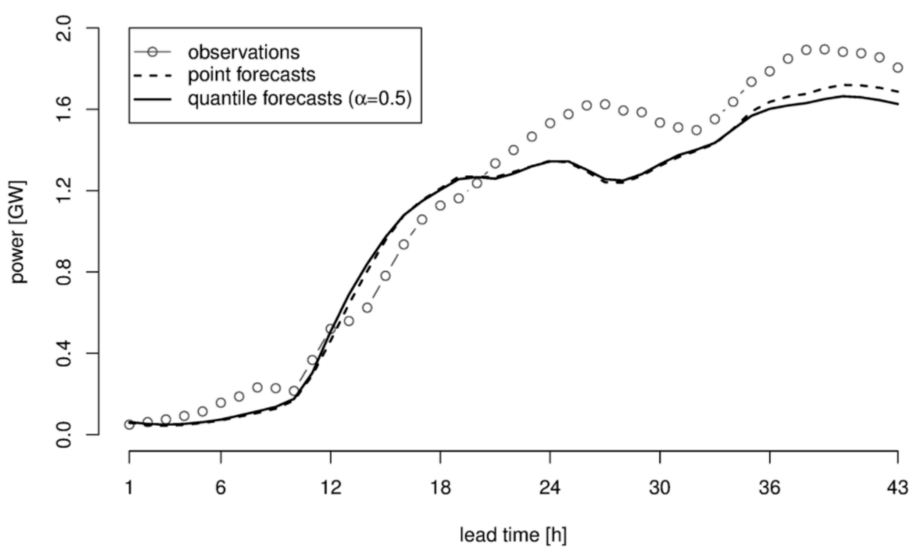

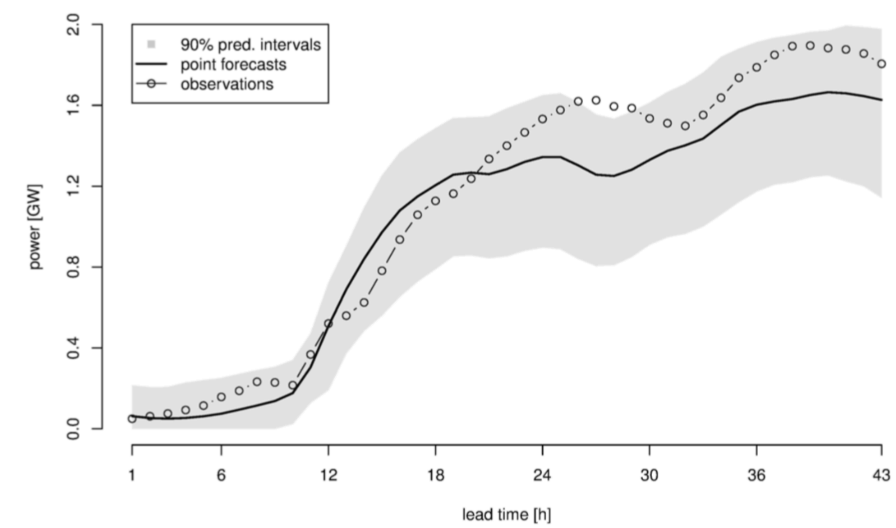

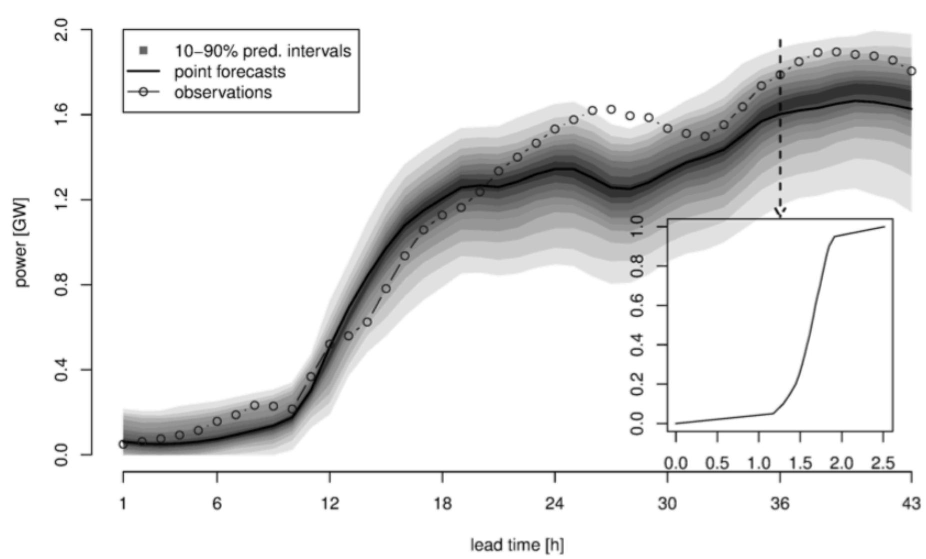

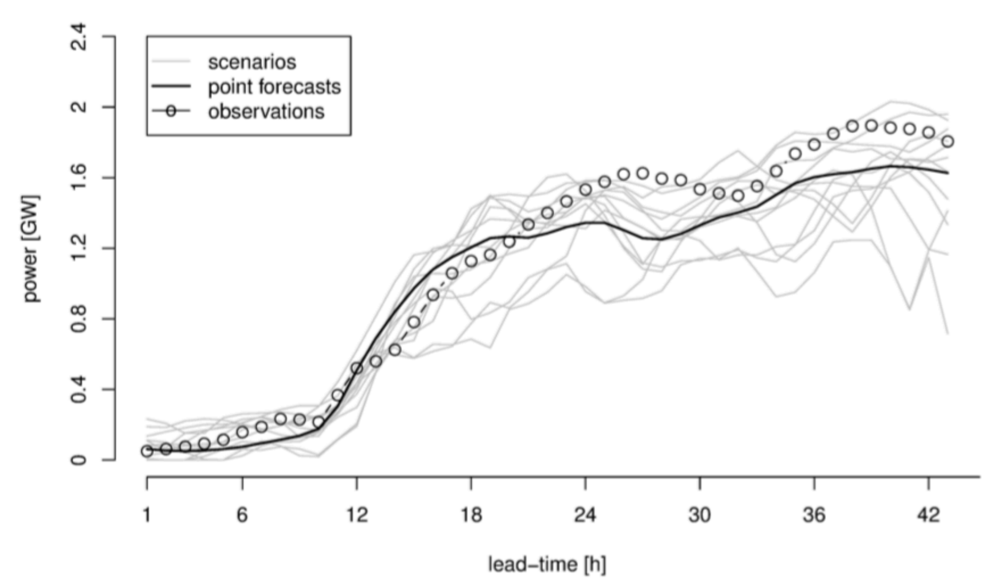

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Conclusion: attribute of probabilistic forecast quality

How do you want your forecasts?

- **Reliable**? (also referred to as “probabilistic calibration”) -> reliability diagrams

- **Sharp**? (i.e., informative) -> width

- **Skilled**? (all-round performance, and of higher quality than some benchmark) -> CRPS

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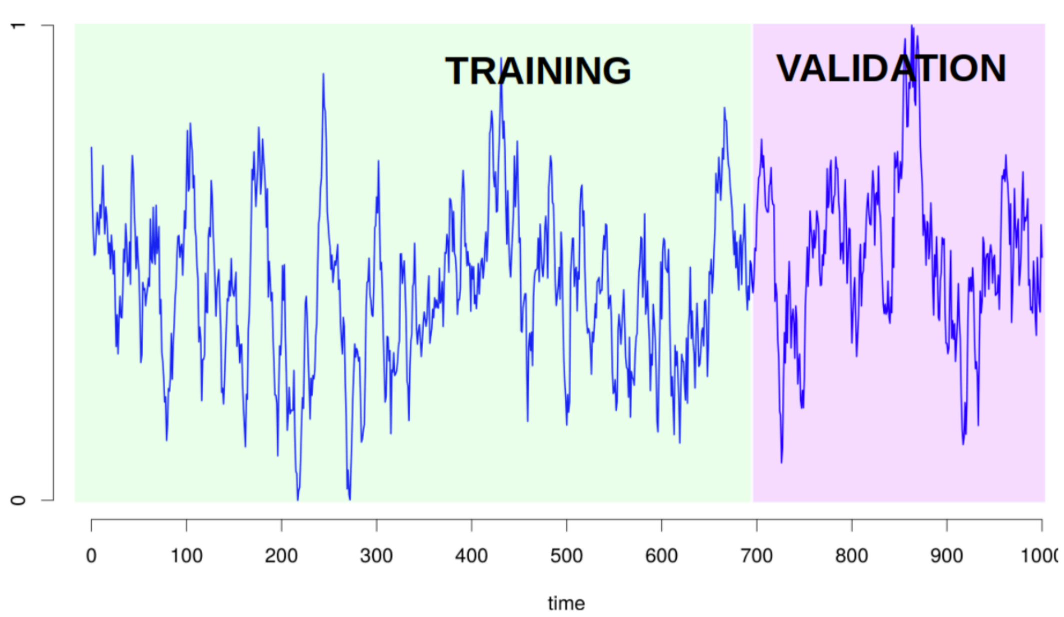

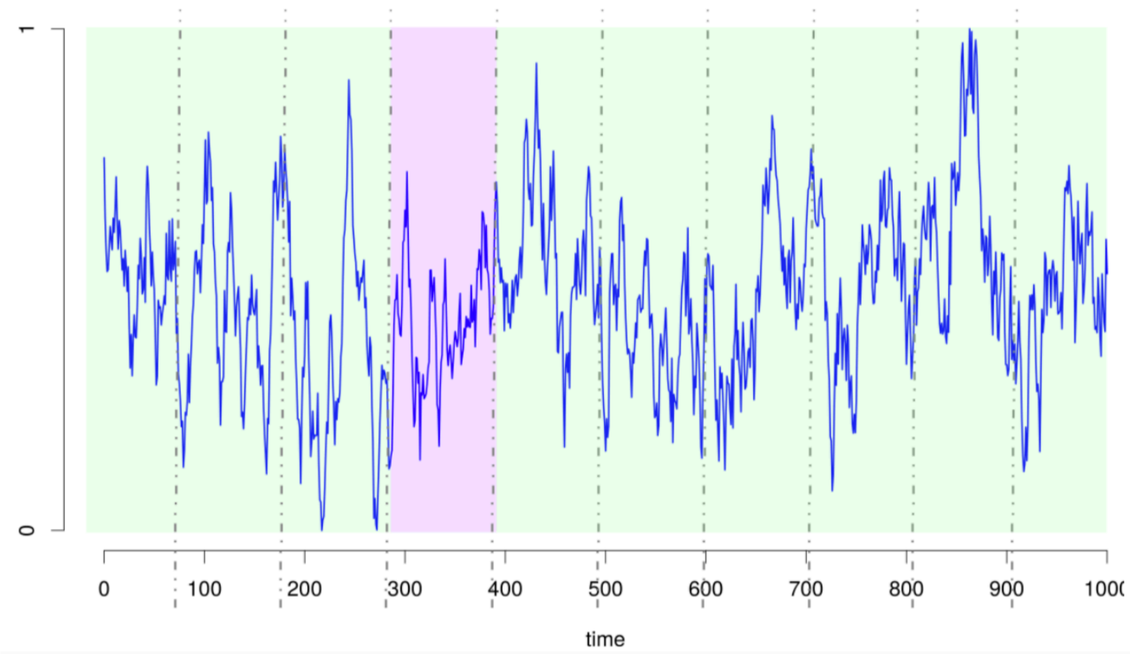

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References

Morales, Juan M., et al. Integrating renewables in electricity markets: operational problems. Vol. 205. Springer Science & Business Media, 2013.

Free online chapter: *http://pierrepinson.com/31761/Literature/reninmarkets-chap2.pdf*

Online lessons from P. Pinson:

https://energy-markets-school.dk/summer-school-2019/

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The end, to be continued …