Microgrids

Introduction to forecasting

Jonathan Dumas
jdumas@uliege.be

Introduction to forecasting

Learning objectives

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

- Understand the context of **forecasting** with application to renewable energy;
- Produce **deterministic** forecasts;
- Perform **verification** of deterministic forecasts

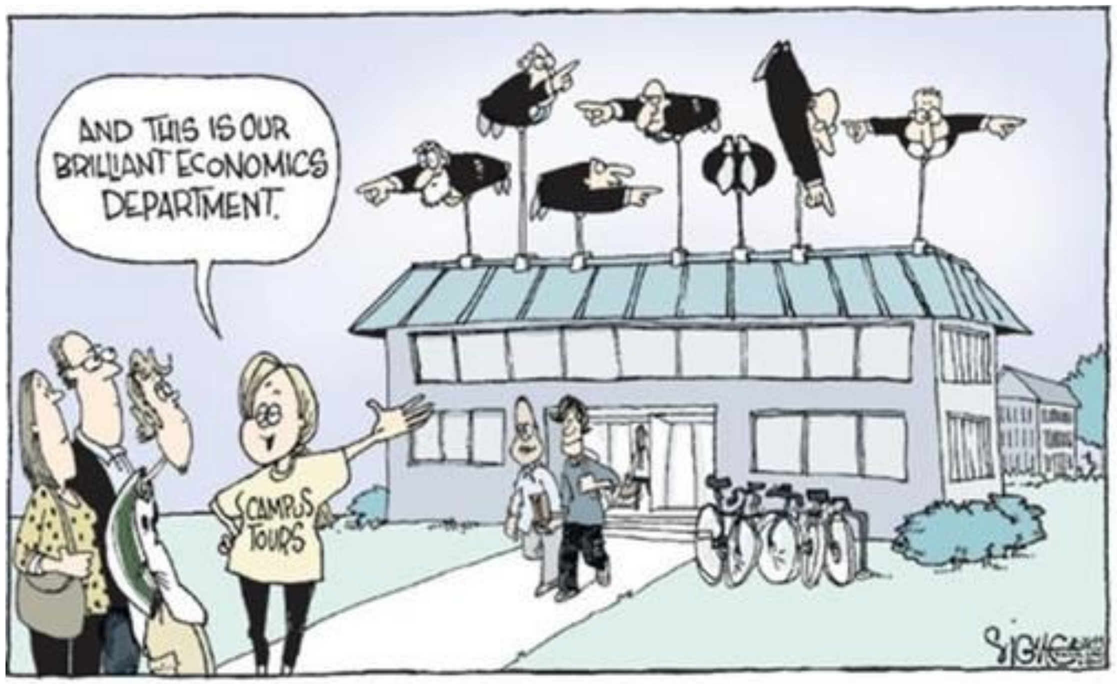
Summary

1. Forecasting context
2. Sources of errors
3. Deterministic forecasts
4. Verification of deterministic forecasts

Introduction to forecasting

Context: why forecasting ?

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



Believing we know what will happen:

- helps making decisions but mainly;
- **makes us more confident** about it!

Key areas:

- **energy**, finance, economics;
- weather and climate, etc.

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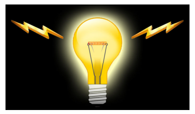
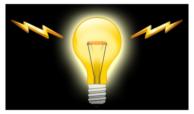
Energy sector: what to forecast ?

Energy producers

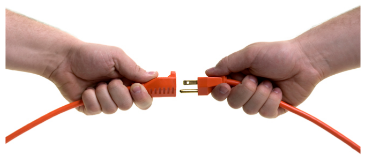


TSO / DSO



Residential consumers (small)

Energy suppliers



Industrial consumers (large)

Market operators: EEX, EPEXSPOT

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Energy sector: what to forecast ?

Different **needs** for each participant !

- the **electric load** (energy suppliers, TSO & DSO);
- day-ahead **prices** (energy suppliers, energy markets, etc);
- **imbalance** volumes and prices (energy suppliers, TSO a DSO);
- potential **congestion** on inter-connectors (TSO & DSO);
- **generation** from renewable energy sources (producers, TSO & DSO);
- Etc

Nearly all these quantities are driven by **weather** and **climate**!

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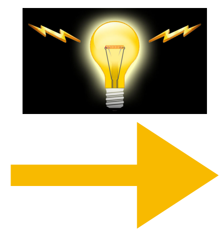
Energy sector: what to forecast ?

Energy producers

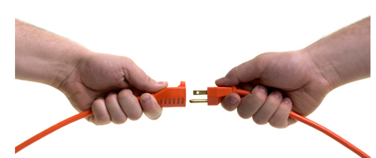
Optimize benefit from generation



TSO / DSO

Balance the grid.

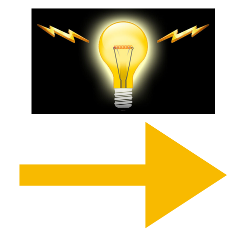
Energy suppliers



Optimize benefit by selling energy.

Market operators: EEX, EPEXSPOT

Optimize transactions.



Residential consumers (small)

Industrial consumers (large)

Optimize consumption.

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Renewable energy forecasts in decision-making

Forecast information is widely used as **input** to several decision-making problems:

- definition of **reserve** requirements (i.e., backup capacity for the system operator);
- **unit commitment** and **economic dispatch** (i.e., least costs usage of all available units);
- coordination of renewables with **storage;**
- design of optimal **trading strategies;**
- electricity **market-clearing;**
- optimal **maintenance planning** (especially for offshore wind farms).

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Renewable energy forecasts in decision-making

Inputs to these decision-making methods are:

- **deterministic** forecasts;

- probabilistic forecasts as **quantiles** and **intervals; -> next lesson**

- probabilistic forecasts in the form of **trajectories** (/scenarios);

- **risk indices** (broad audience applications).

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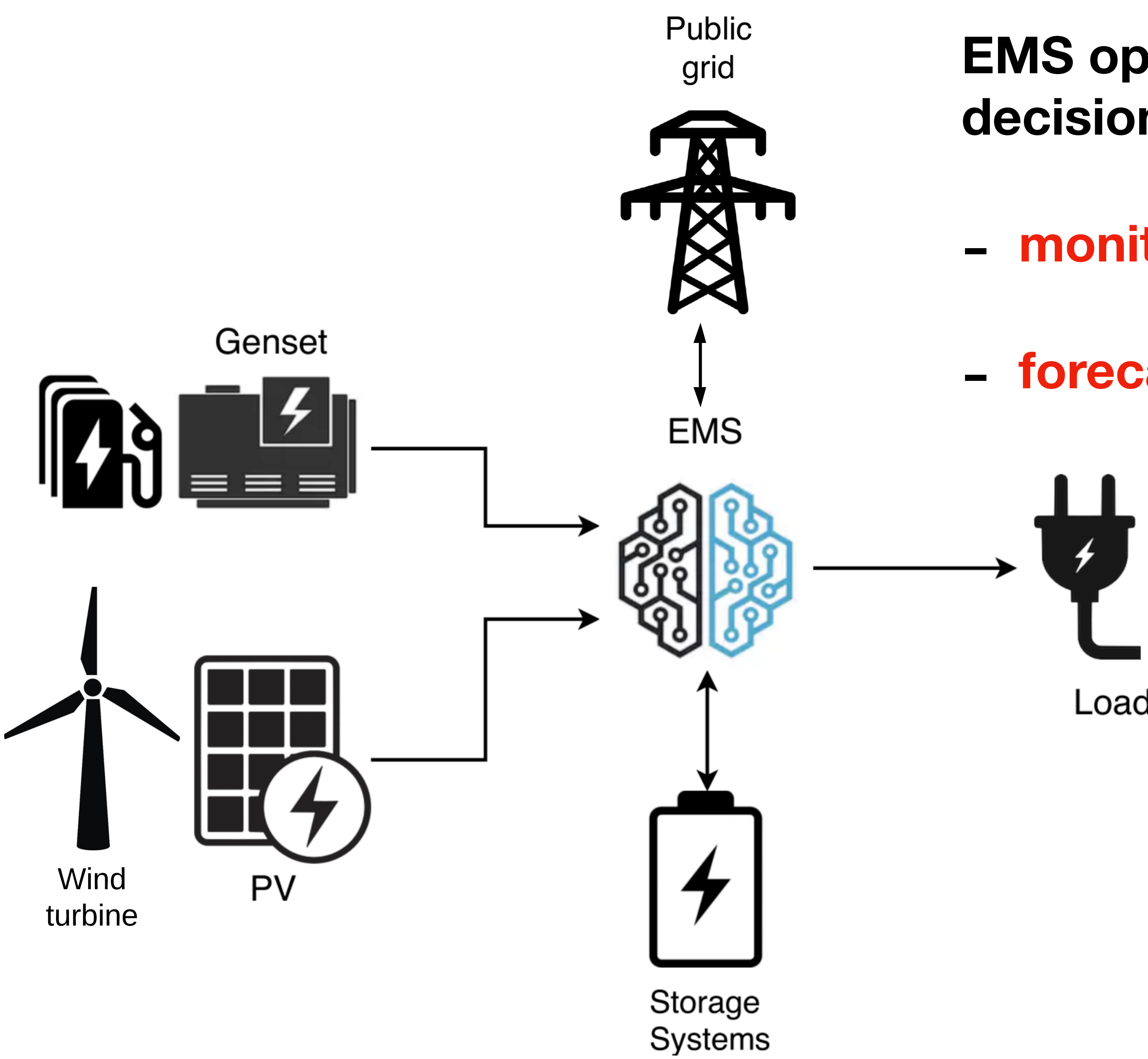
Microgrid reminder



EMS optimizes the decisions based on:

- **monitoring**
- **forecasting**

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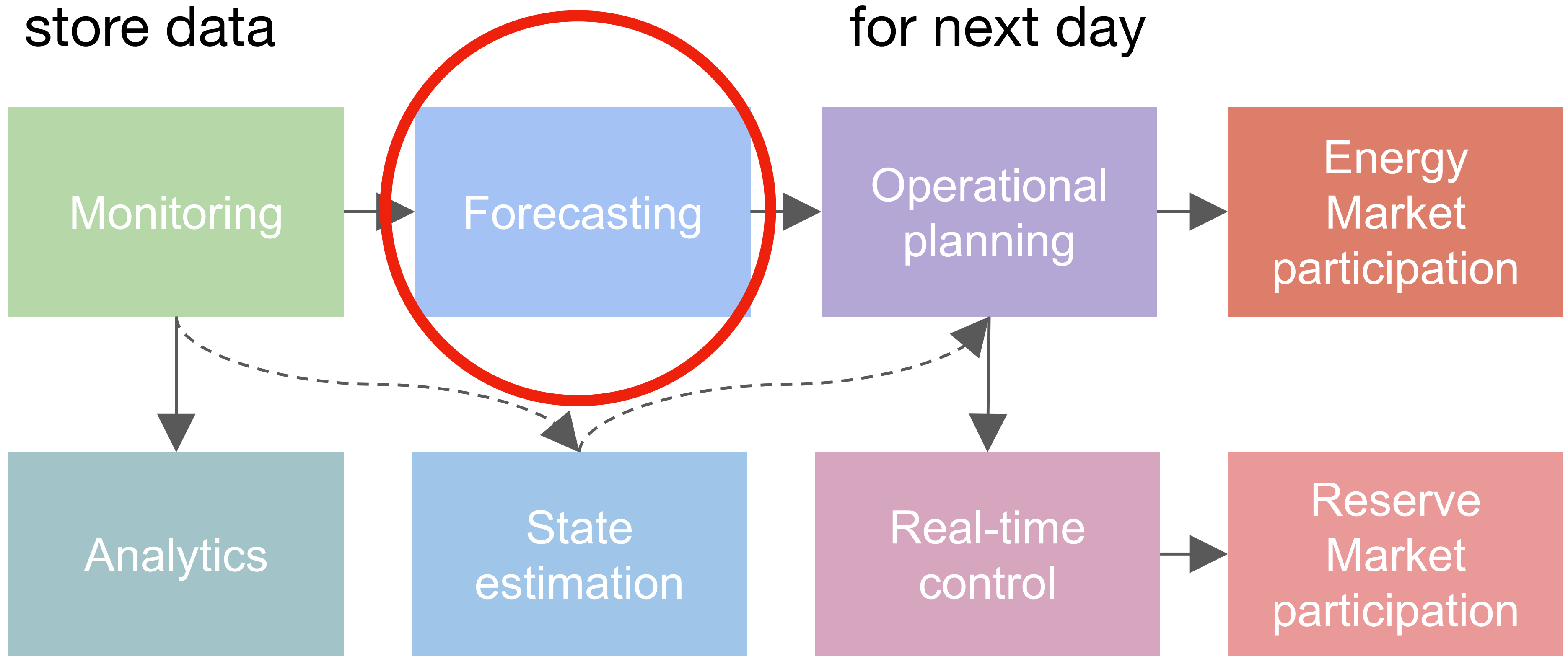
EMS reminder

Pull and store data

Consumption & generation

Take decisions for next day



Present data, decisions and results

Calibrate models using data

Take decisions for next seconds

Arrows indicate a dependency between functional modules, not a flow of information!

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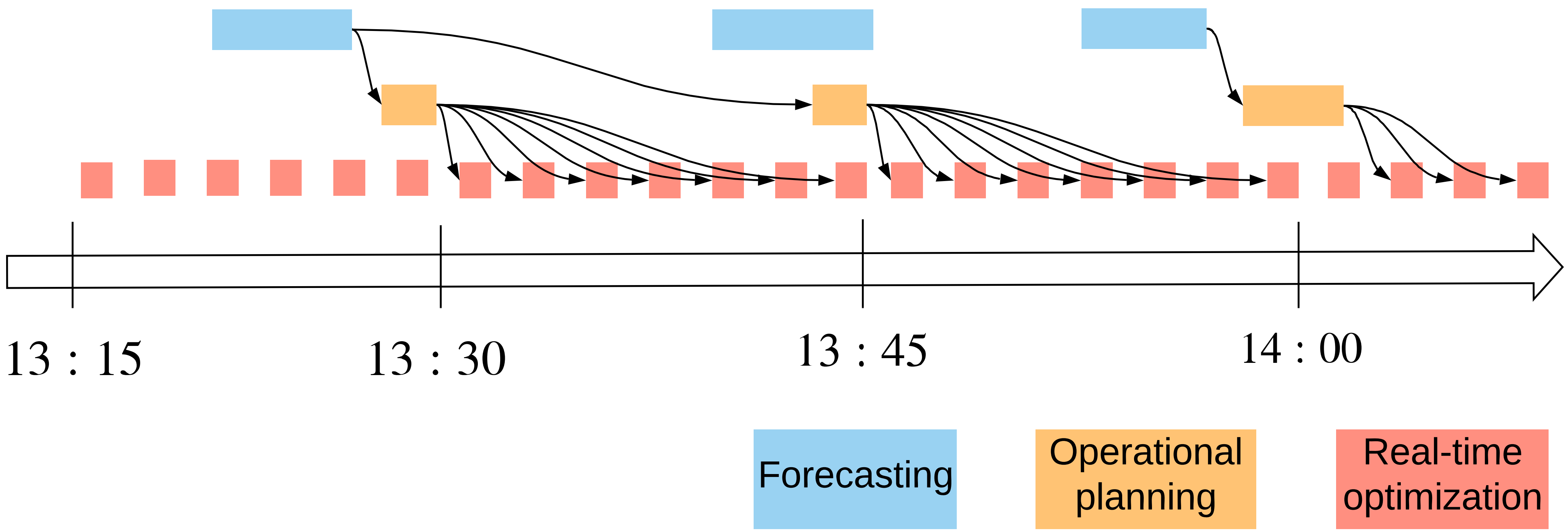
EMS time line



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Microgrid key parameters to forecast

Generation: PV, Wind Power, Hydraulic Power, etc

Load: office, industrial, residential, etc

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

Residential energy supplier

Summary

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Introduction to forecasting

Contribution to forecast uncertainty/error

To generate renewable energy forecasts in electricity markets, necessary inputs include:

- recent power generation **measurements**;

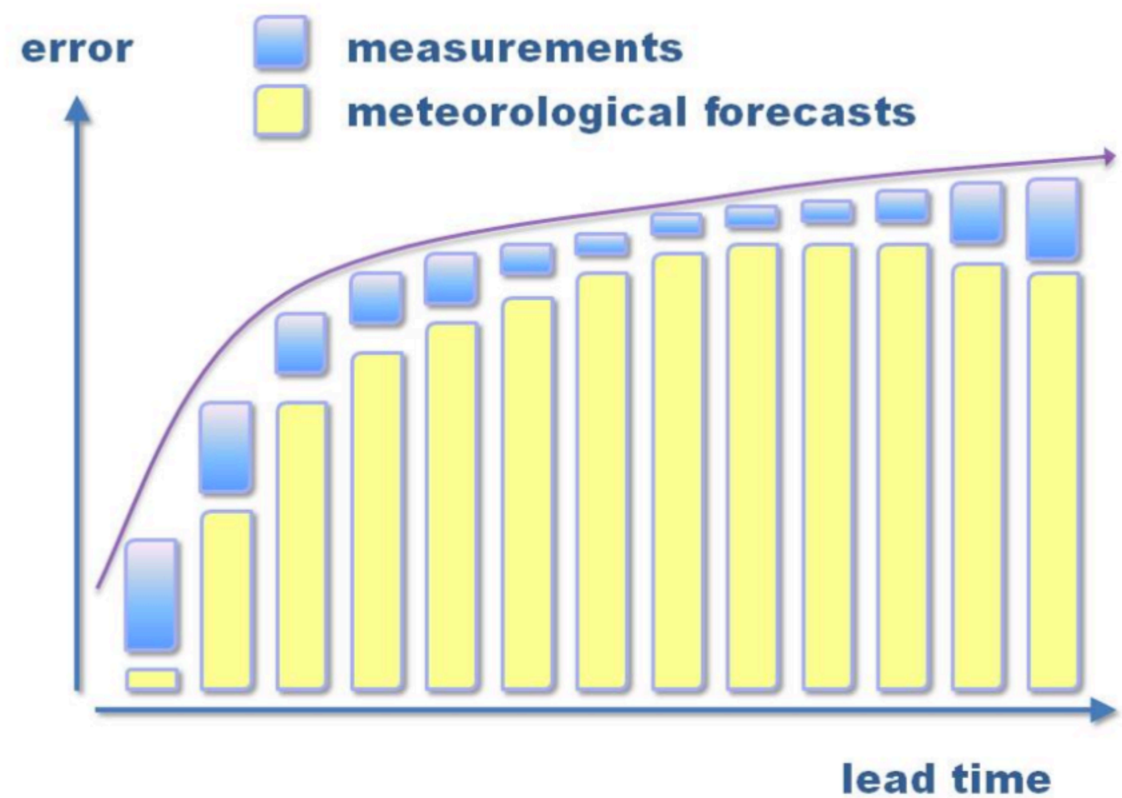
- **weather** forecasts for the coming period;

- possibly **extra info** (off-site measurements, radar images, etc.).

Their importance varies as a function of the **lead time** of interest:

- short-term (0-6 hours): you definitely need **measurements;**

- early medium-range (6-96 hours): **weather** forecasts are a must have!



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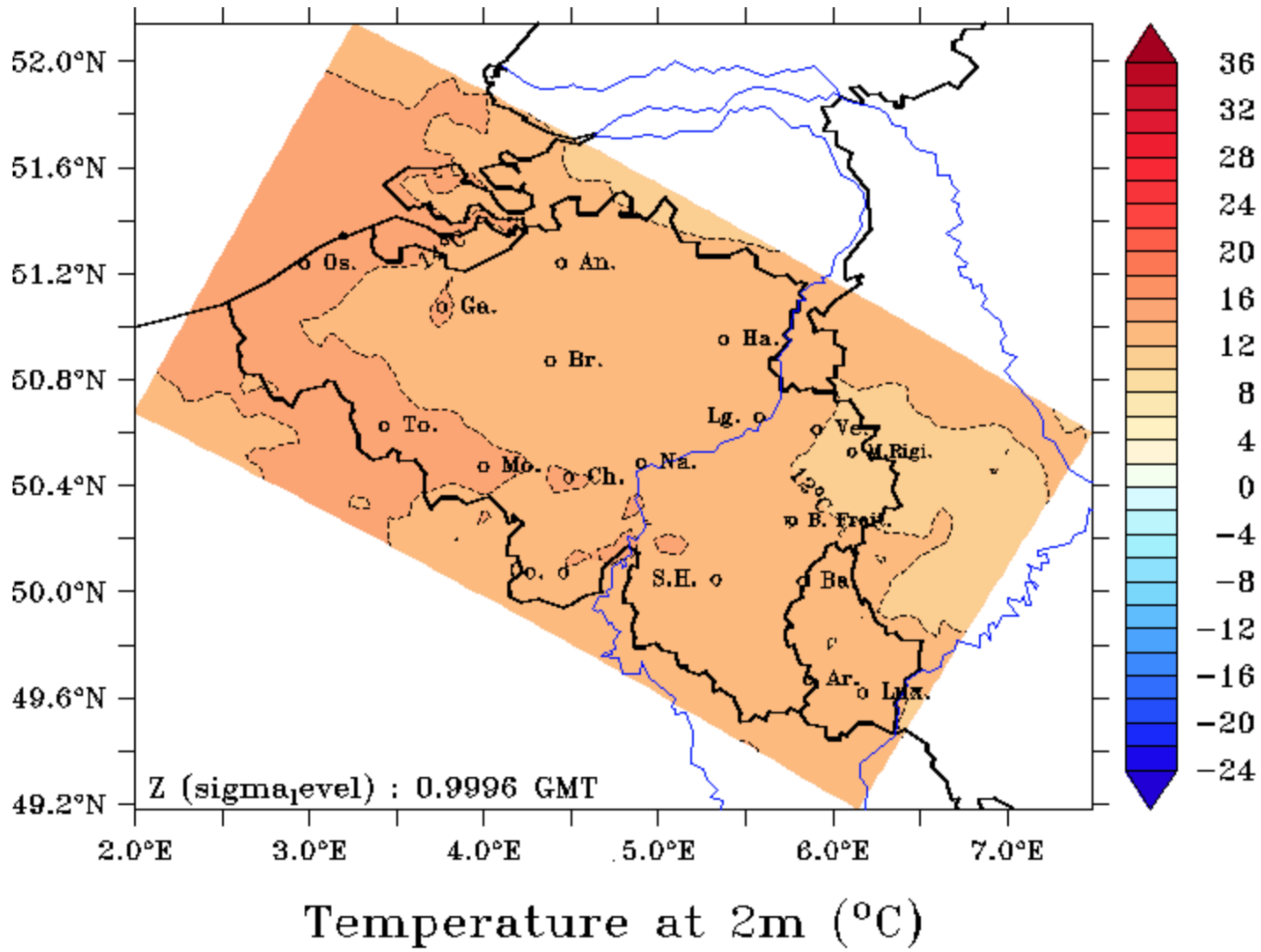
Weather forecasts



http://climato.be/cms/index.php?climato=fr_previsions-meteo

X. Fettweis, J. Box, C. Agosta, C. Amory, C. Kittel, C. Lang, D. van As, H. Machguth, and H. Gallée, "Reconstructions of the 1900–2015 greenland ice sheet surface mass balance using the regional climate MAR model," Cryosphere (The), vol. 11, pp. 1015–1033, 2017.

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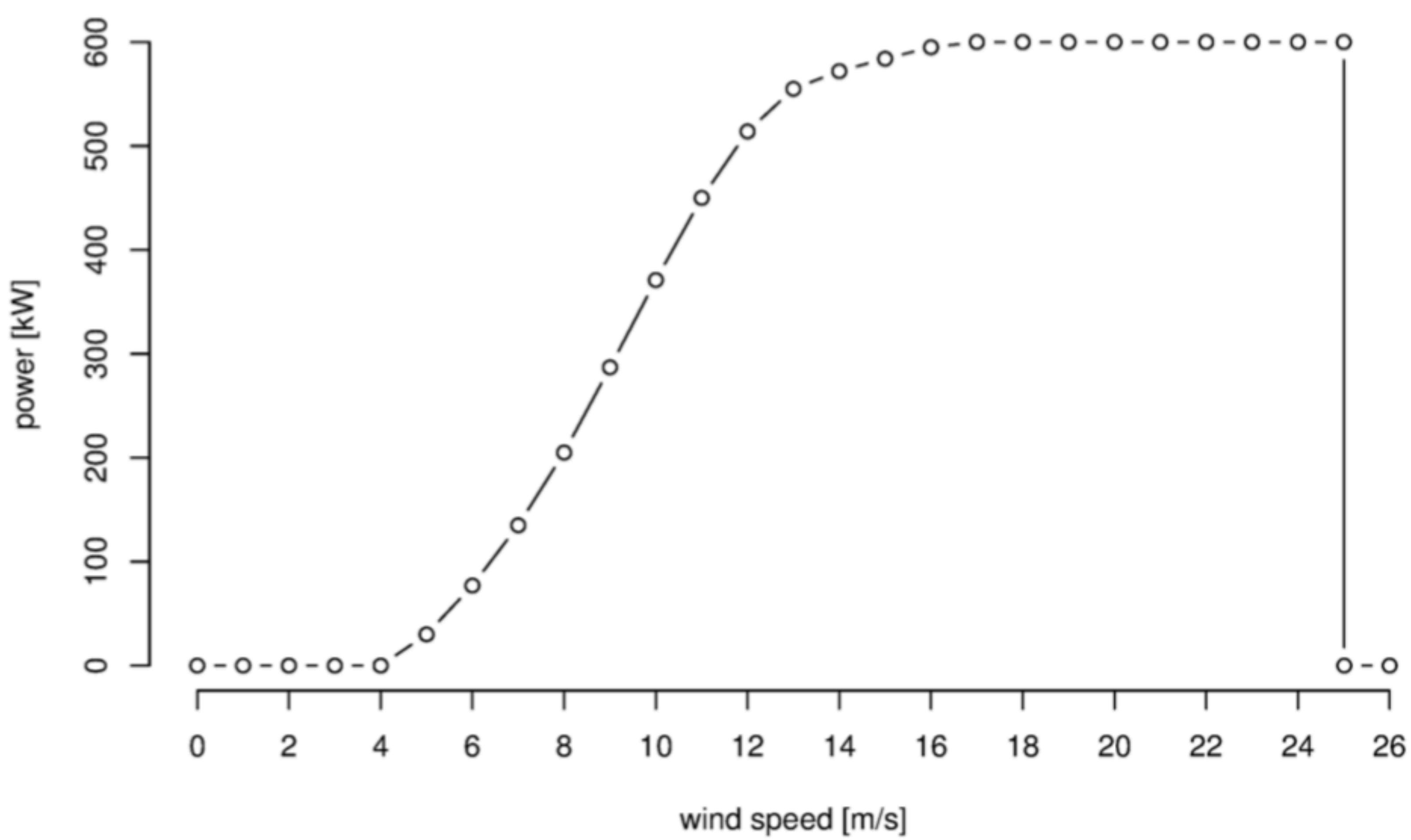
A wind power curve

A large part of the prediction error **directly** comes from prediction of **weather** variables.

This uncertainty in the meteorological forecast is then **amplified** or **dampened** by the power curve (model).

Power curve of the Vestas V44 turbine (600 kW)



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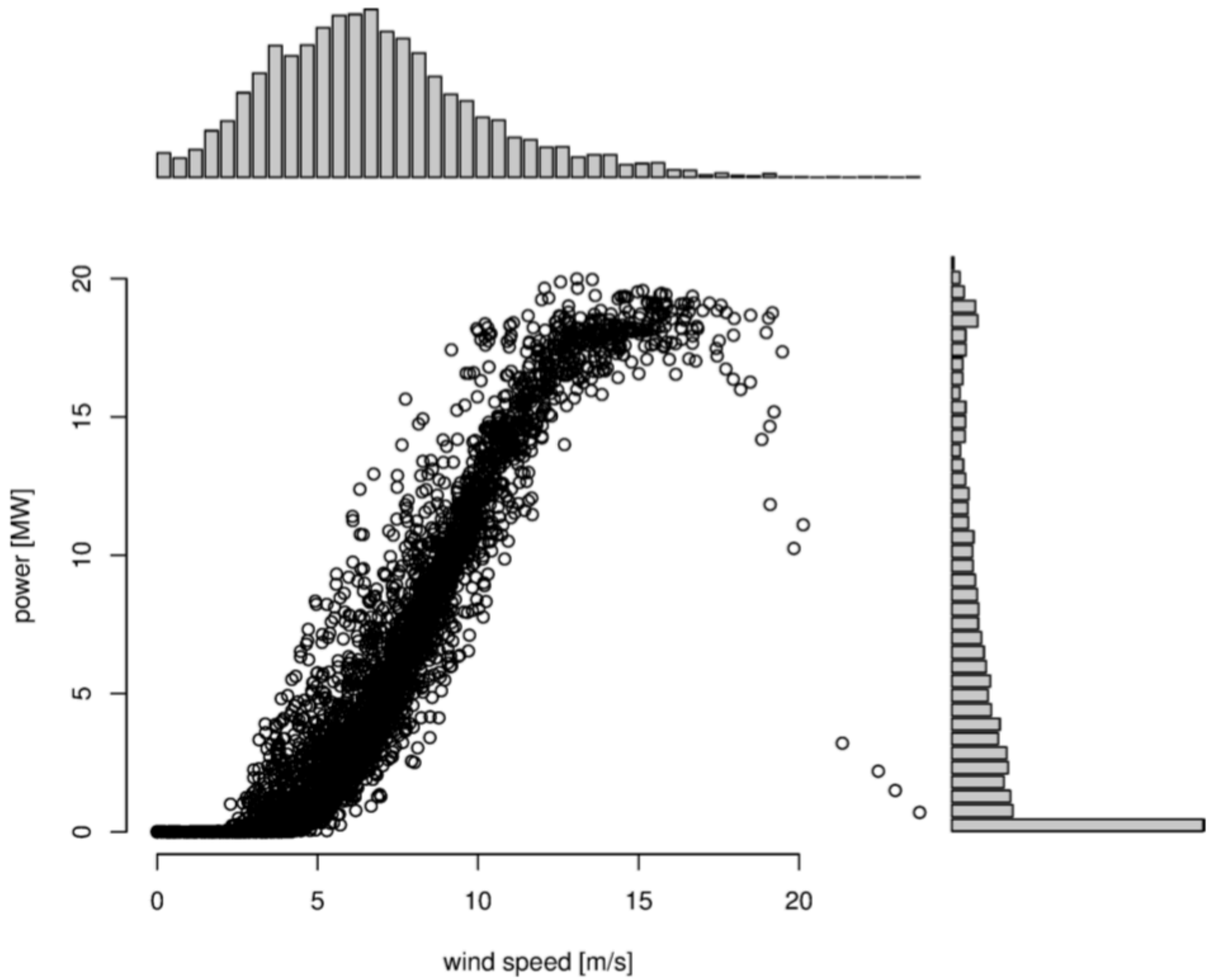
The actual wind power curve

The actual power curve looks different!



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Introduction to forecasting

Forecast setup

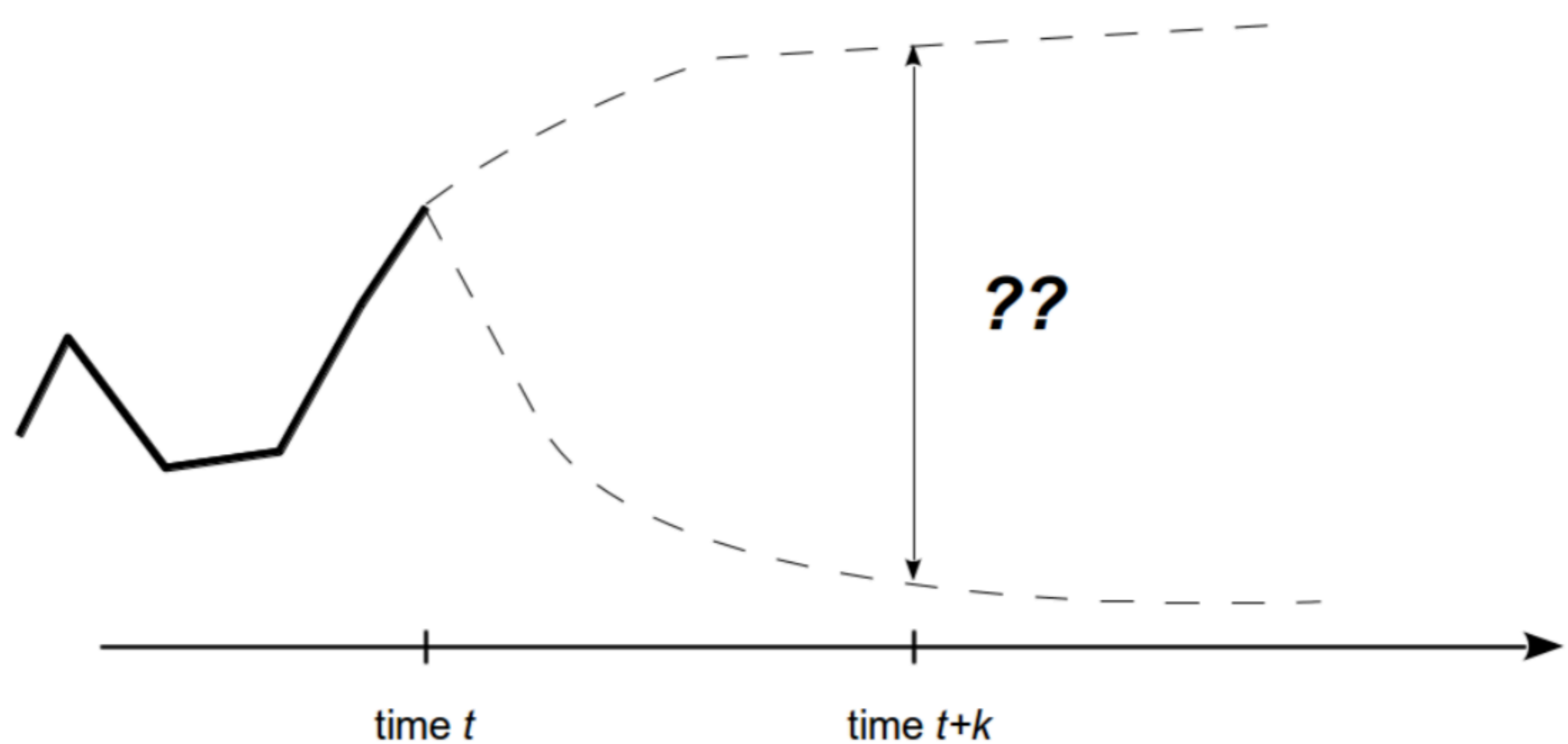
The practical setup:

- we are at time **t** (e.g., at 11am, placing offers in the market);

- interested in what will happen at time **t + k** (any market time unit of tomorrow, e.g., 12-13);

- **k** is referred to as the **lead time**;

- Yt+k : the **random variable** "power generation at time t + k".



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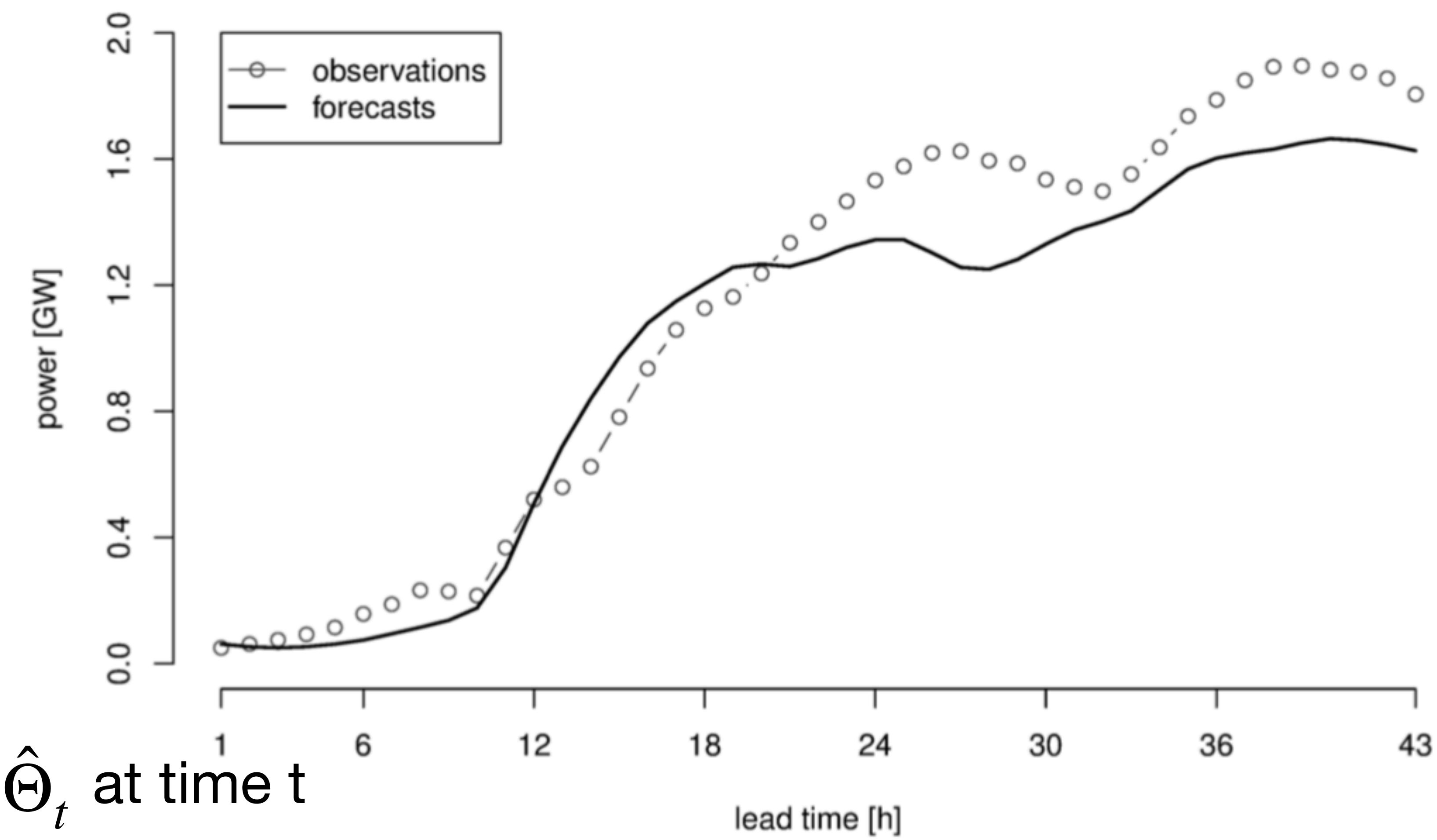
Deterministic forecast definition

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

Introduction to forecasting

Forecasting model

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

given:

- the information set Ω;
- a **model** g
- its estimated parameters $\hat{\Theta}_t$ at time t

g:

- **machine learning** models: neural networks, gradient boosting, etc;
- **parametric** model; $p^{PV} = aI + bI^2 + cIT$
- **statistical** model: ARIMA, etc.

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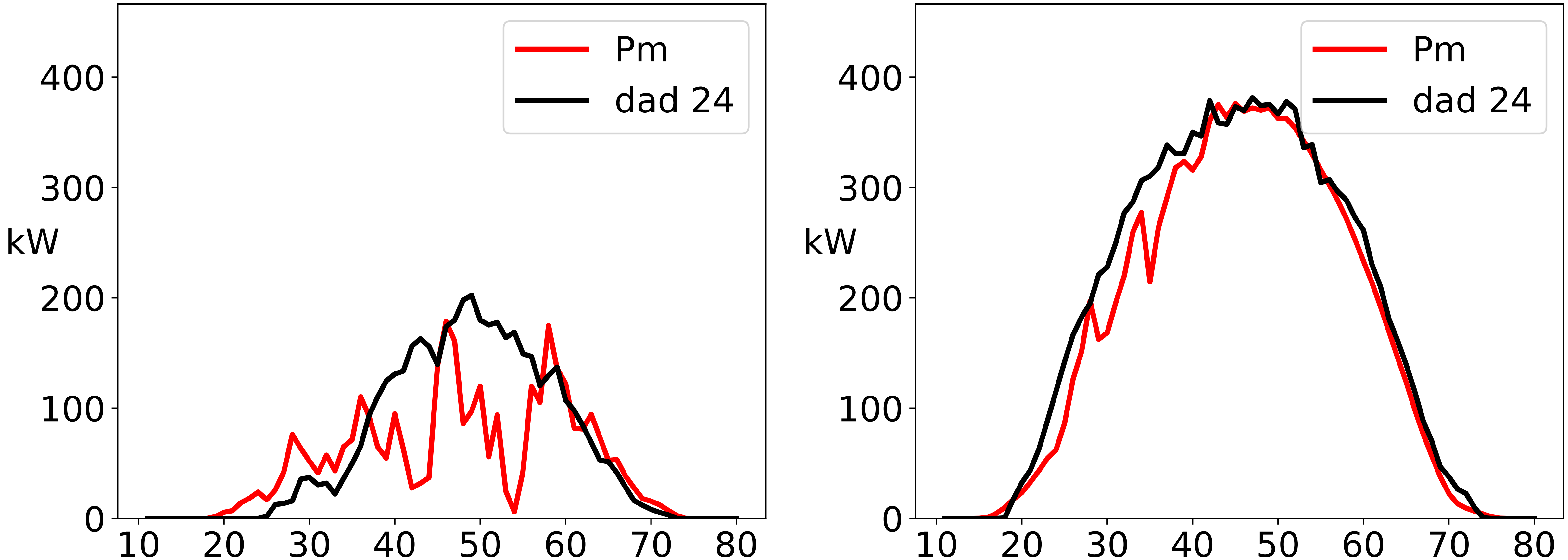
Point forecasts examples: PV generation



PV point forecasts (dad 24) computed at 12:00 for the next day along with corresponding observations (Pm in red) by using a neural network.

Introduction to forecasting

Forecasting classification into 2 dimensions

1. Time dimension

- **Forecasting horizon**

  VST (minutes to day), ST (day to week), MT (week to year) and LT (years)

- **Forecasting resolution**

  minutes, hours, days, years …

2. Spacial dimension

- **Spatial forecasting horizon**

  residentials, microgrids, industries, cities, distribution grid, states, transportation grid …

- **Spatial resolution**

  W, kW, MW, GW

Dumas, J., & Cornélusse, B. (2019). Classification of load forecasting studies by forecasting problem to select load forecasting techniques and methodologies. https://arxiv.org/abs/1901.05052

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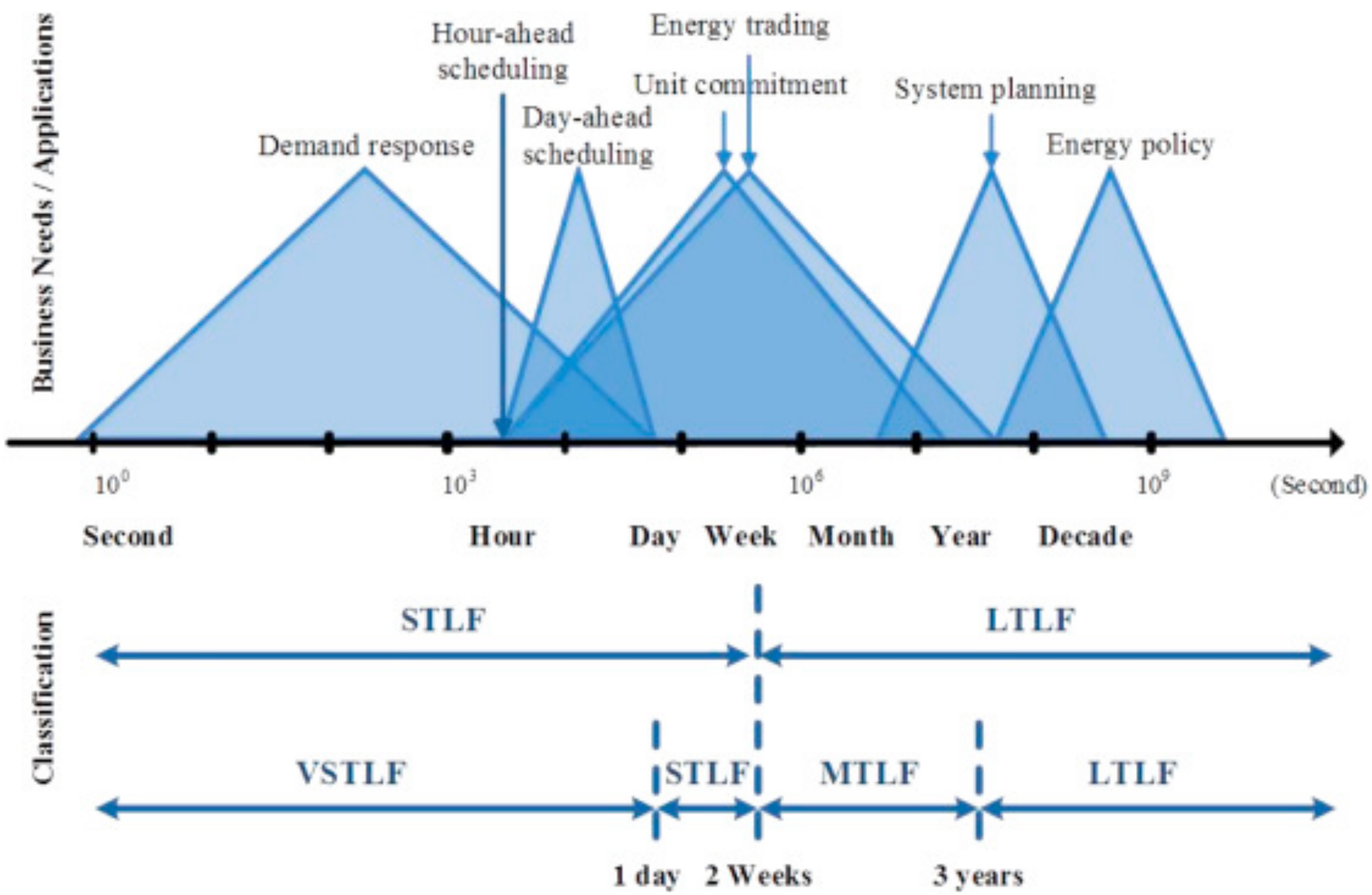
Classification over the time dimension



Tao Hong. Short Term Electric Load Forecasting. PhD thesis, 2010.

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Forecasting predictors

Weather variables

WARNING Depend on the forecasting problem !!!!

- Time series: temperature, solar irradiation, wind speed, rainfall … -> ST/VST
- Mean/standard deviation: temperature, solar irradiation … -> MT/LT

Calendar variables

- days, hours of the days, special day … -> VST/ST
- trend, years, months -> MT/LT

Historic values

- t-15min, t-1h, t-24h, t-7d, mean(t-1d) … -> VST/ST
- Mean/standard deviation: t-1week, t-1month … -> MT/LT

Cross effects

- temperature * calendar variables …
- lagged load * temperature

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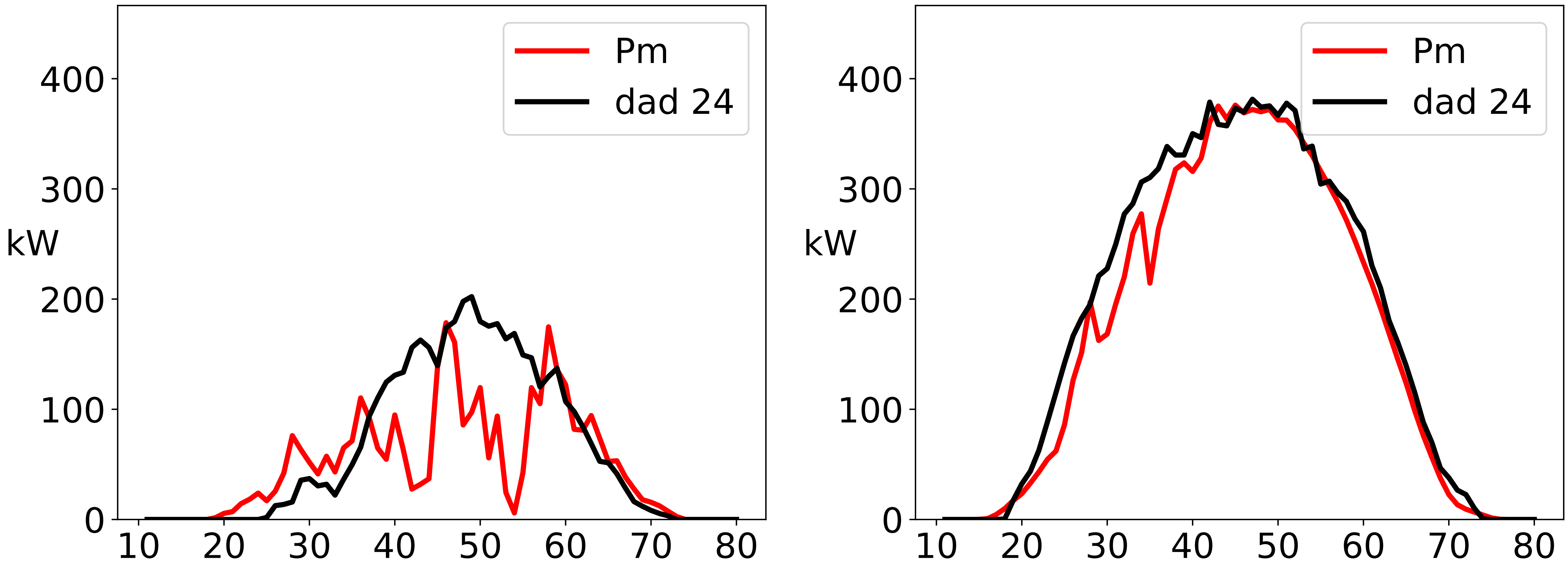
Point forecasts examples



Predictors = weather forecasts of **solar** irradiation and air **temperature**.

The predictors are thee inputs of a neural network.

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.

Introduction to forecasting

Evaluation methodology

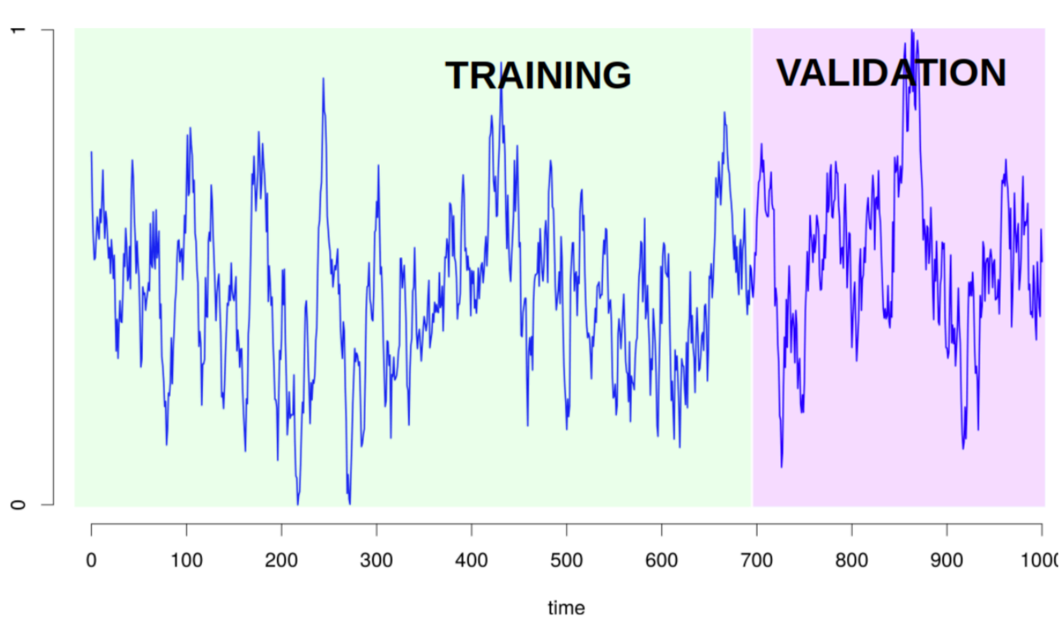
Forecasting is about being able to p**redict future events**, in new situations not only explain what happen in the past.

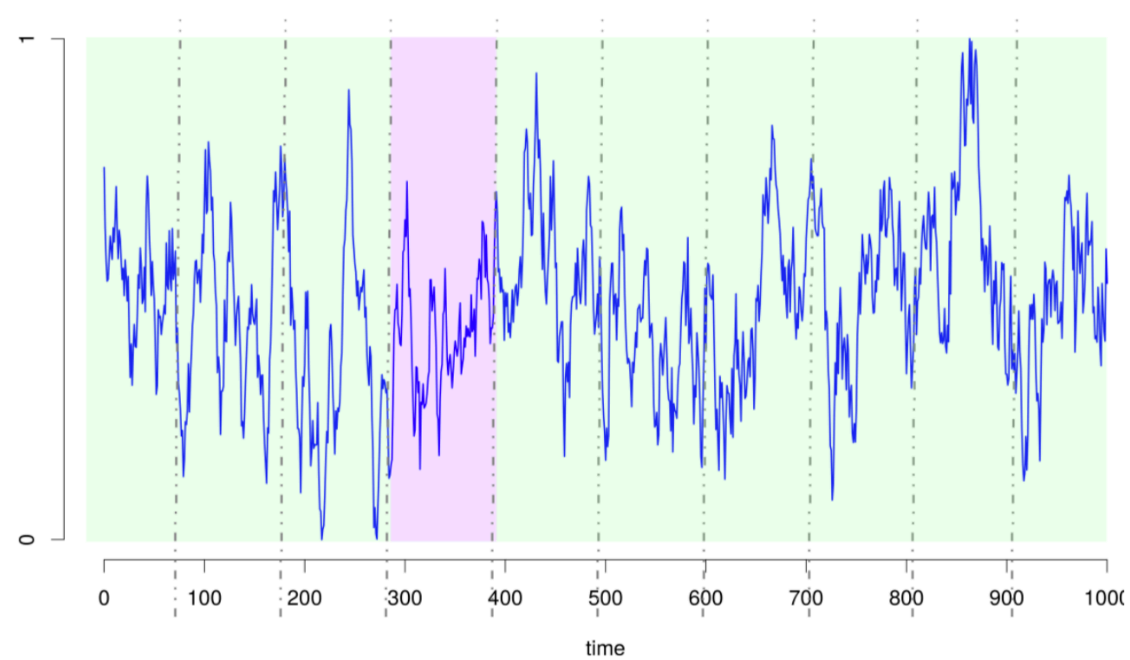
One need to verify forecasts on data that **has not been used** for the modelling!

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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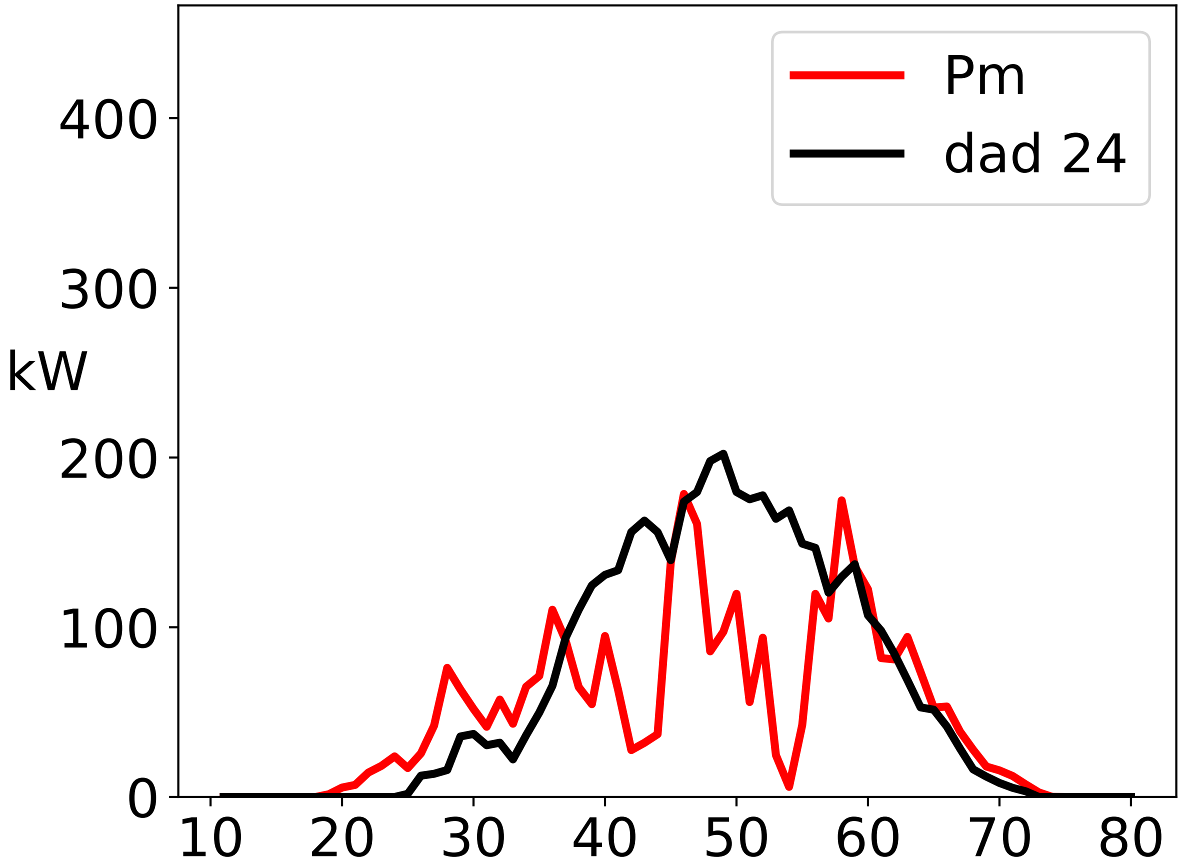
Visual inspection

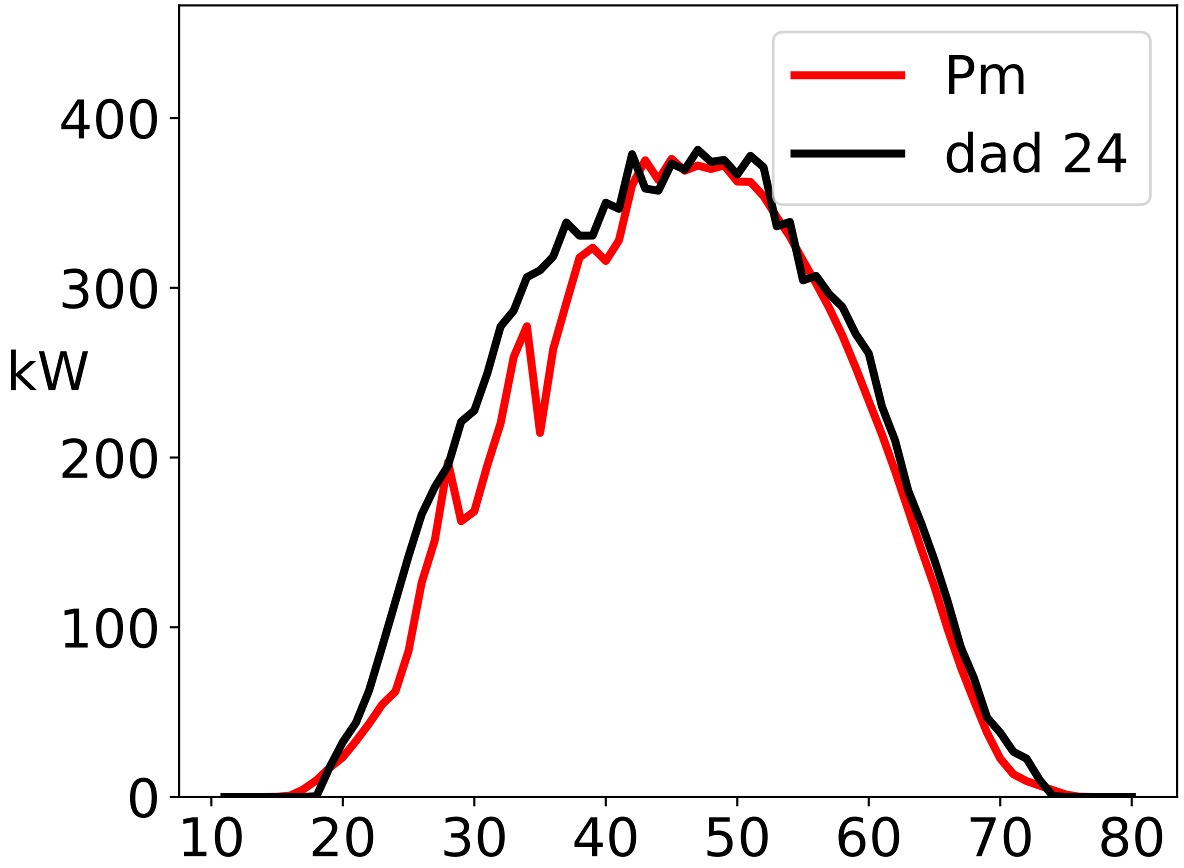
Visual inspection allows you to develop **susbtantial insight** on forecast **quality**.

This comprises a **qualitative analysis** only.

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



Issued on 3 April 2020 at 12:00 for 4 April 2020.



Issued on 4 May 2020 at 12:00 for 5 May 2020.

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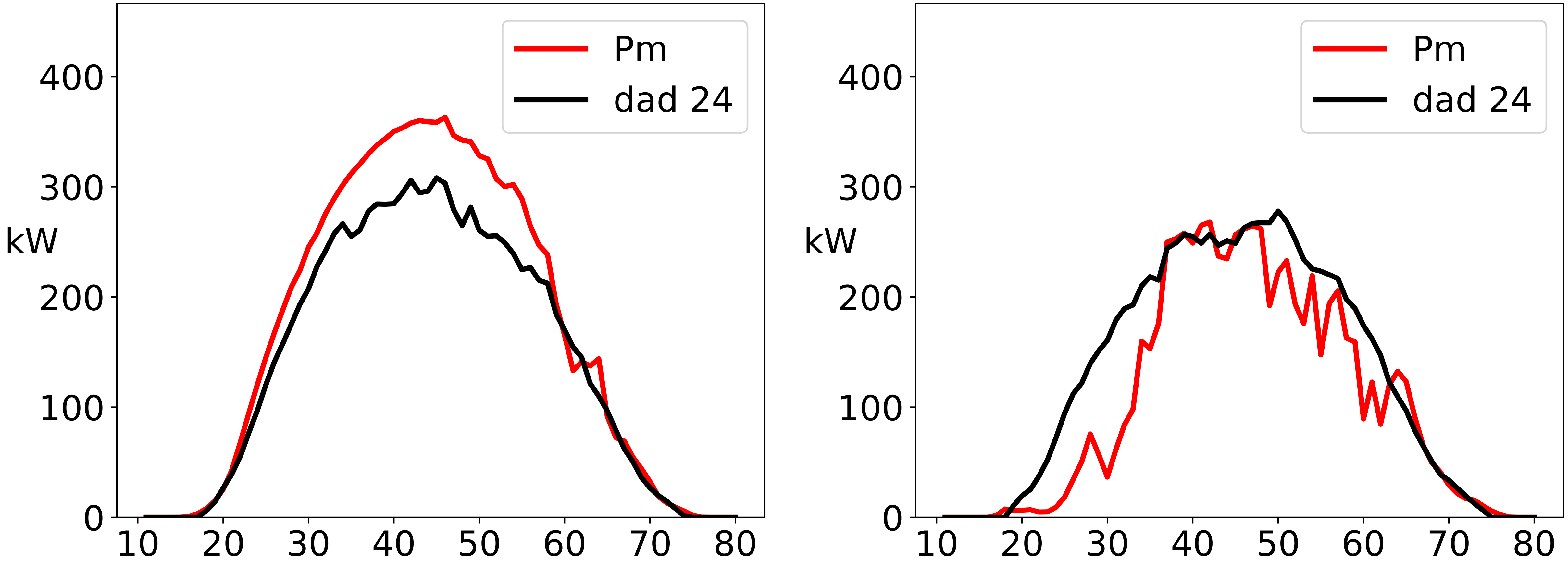
Amplitude and phase errors

The errors are most often **driven by weather forecasts** errors.

Typical errors are **amplitude** errors (left below) and **phase** errors (right below).



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Quantitative metrics

Qualitative analysis ought to be complemented by a **quantitative** analysis.

The forecast error is defined by

$$\epsilon_{t+k|t} = y_{t+k|t} - \hat{y}_{t+k|t}$$

It can be normalized

$$\epsilon_{t+k|t} = \frac{y_{t+k|t} - \hat{y}_{t+k|t}}{P_n}$$

with Pn the nominal capacity.

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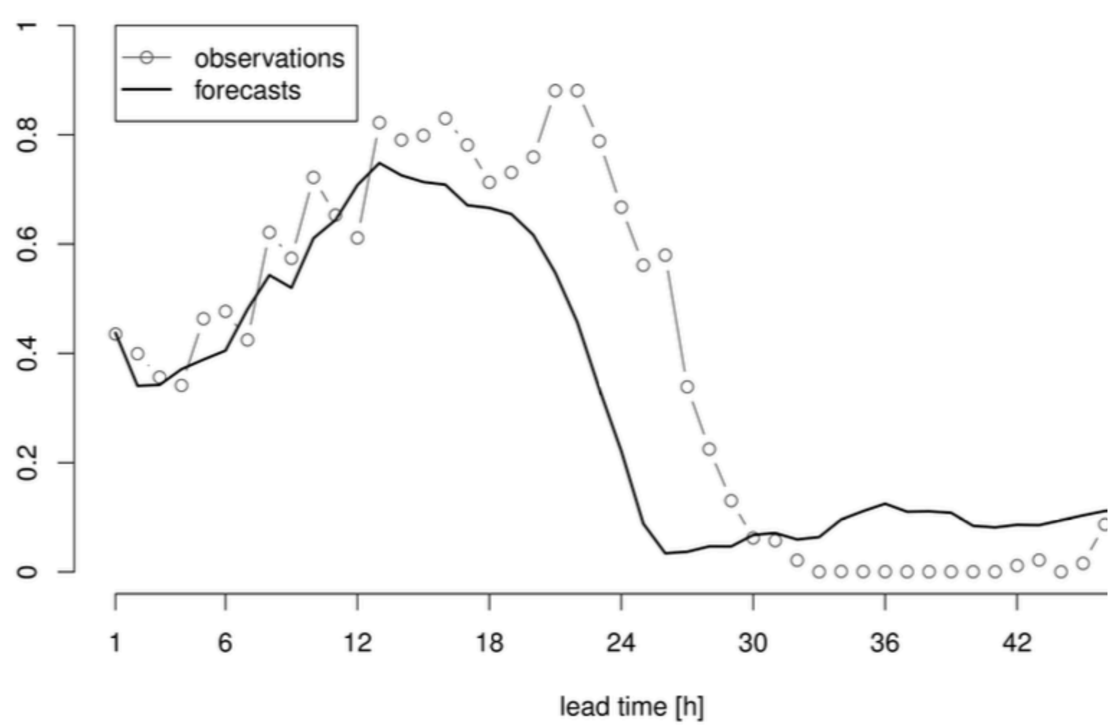
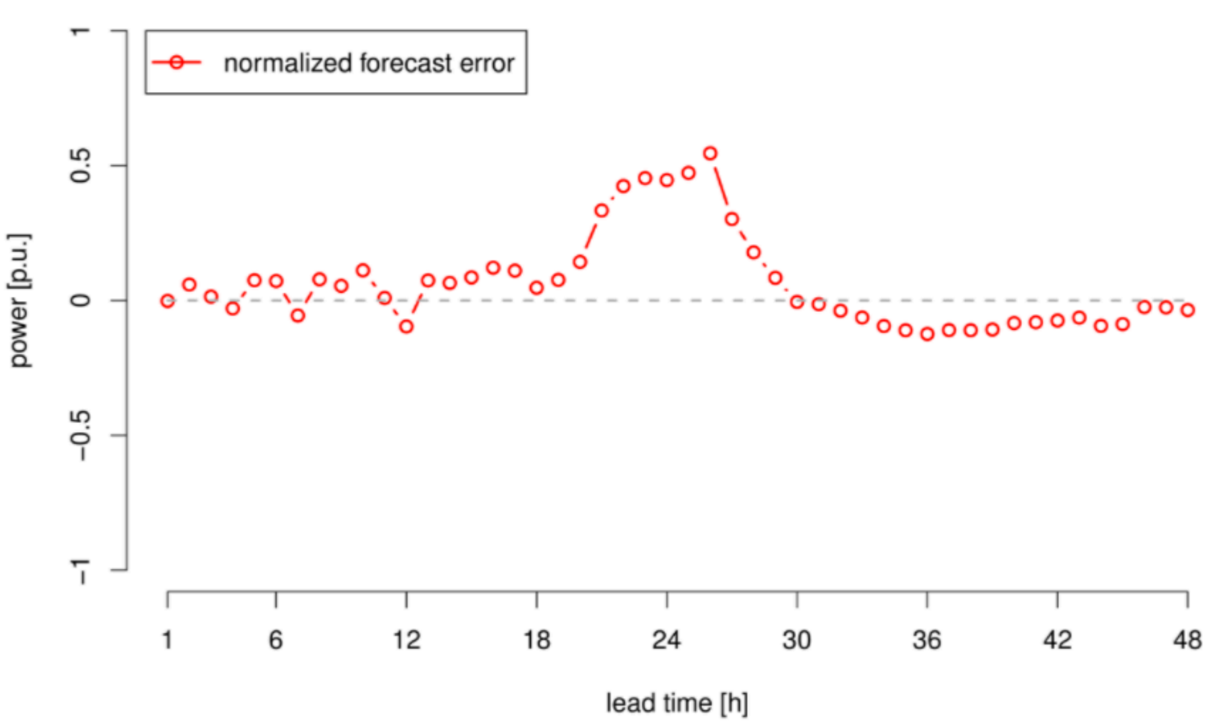
Quantitative metrics

Example on a wind farm with the normalized error.





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Quantitative metrics

Scores are to be used to **summarize** aspects of forecast **accuracy**.

The most common scores include, as function of the lead time k:

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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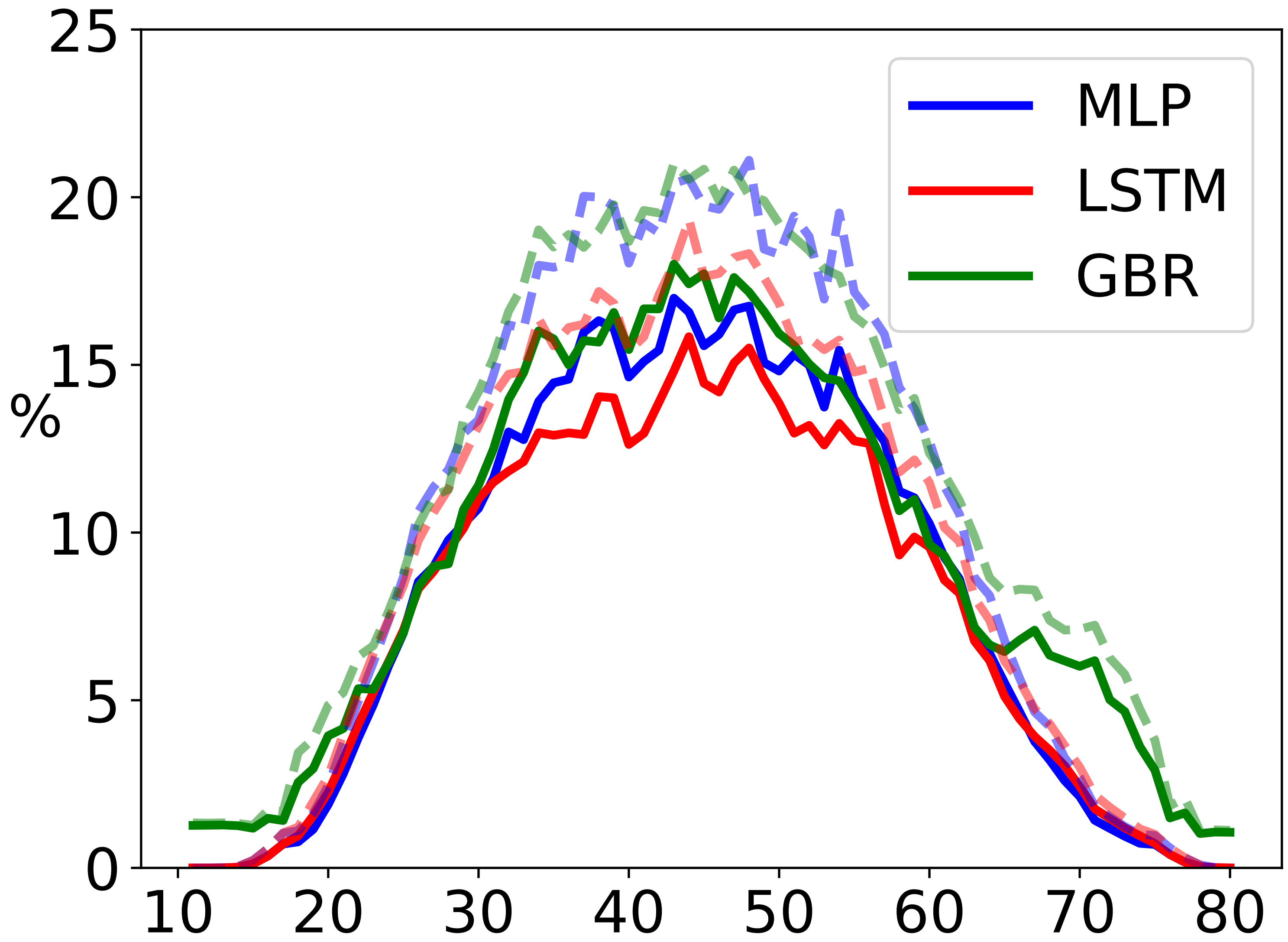
Example on the case study



NMAE (plain) and **NRMSE** (dashed) for three forecasting models from **11-cross validation**.

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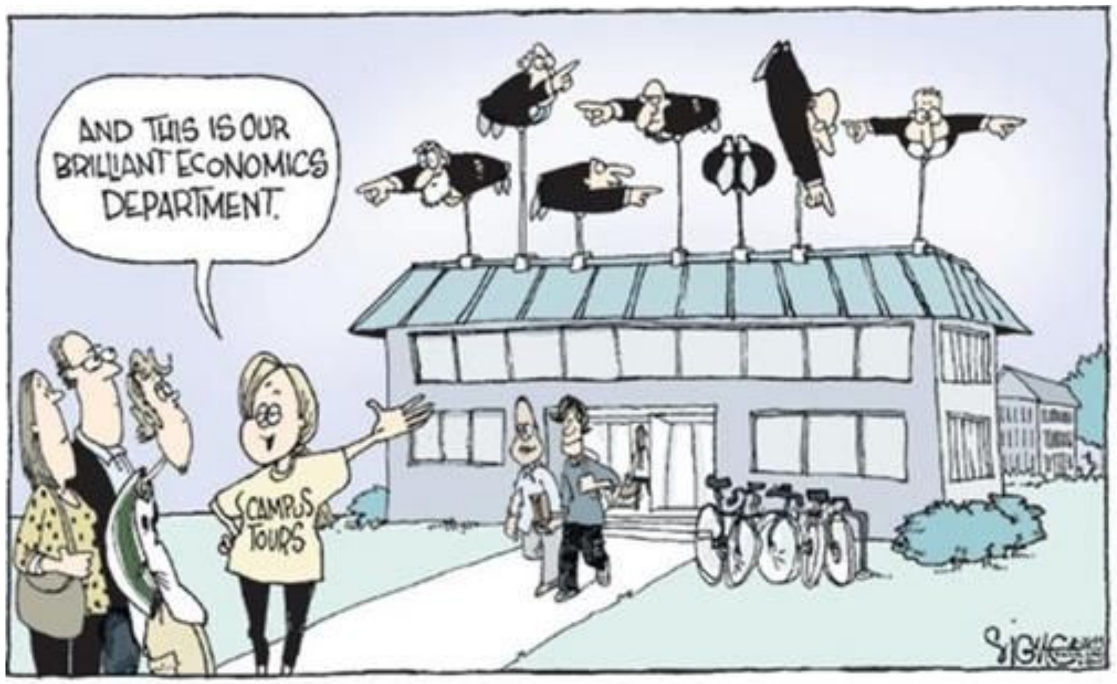
Conclusion: forecast for decision making

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

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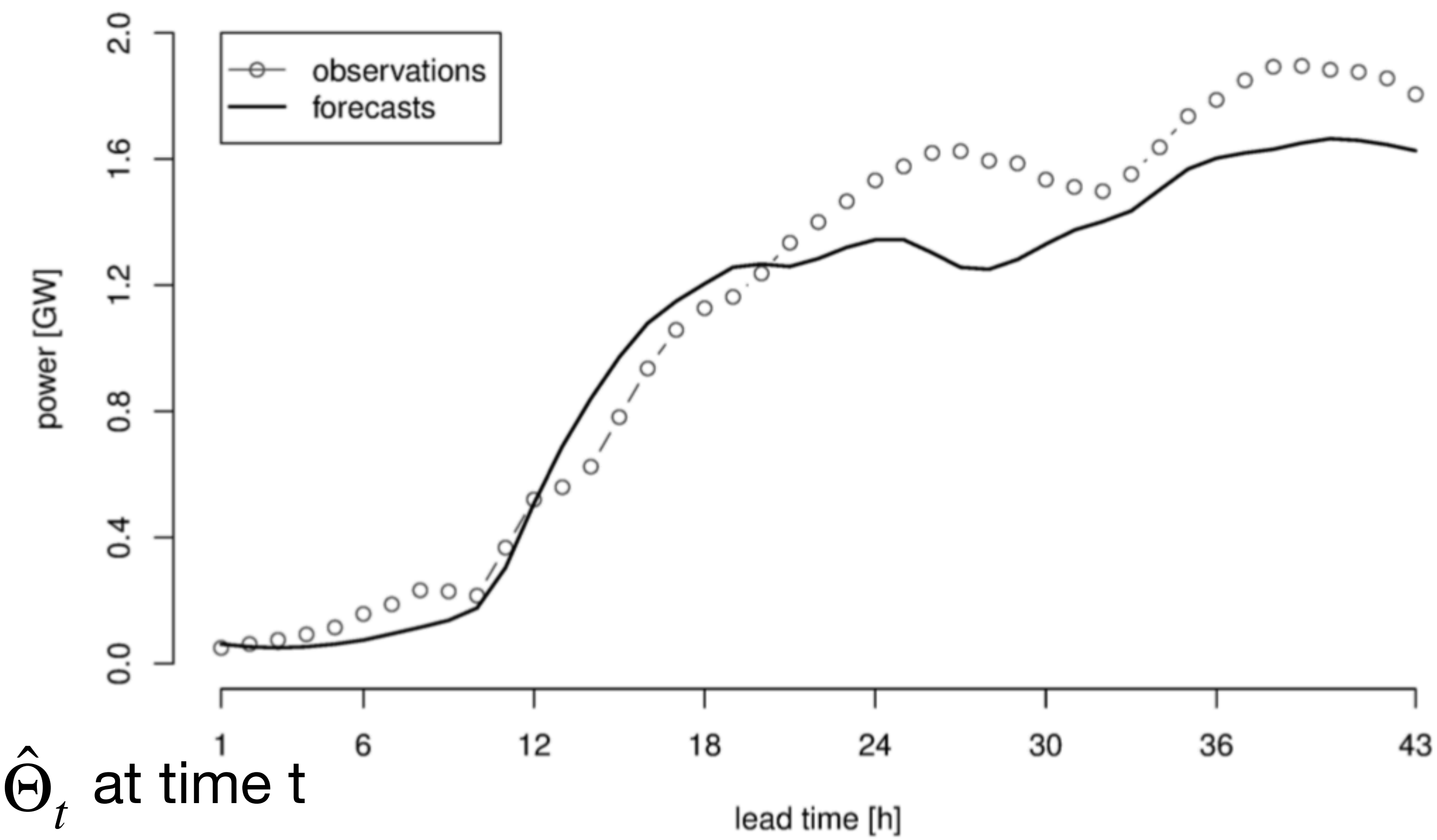

given:

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Conclusion: use a strategy to assess forecasts

Several strategies to assess forecasts:

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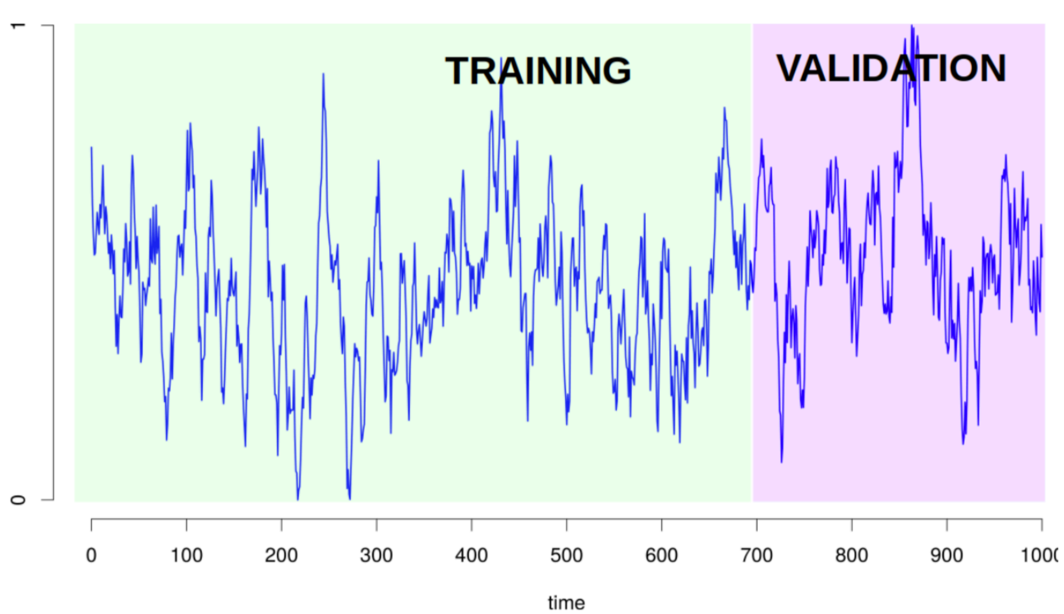

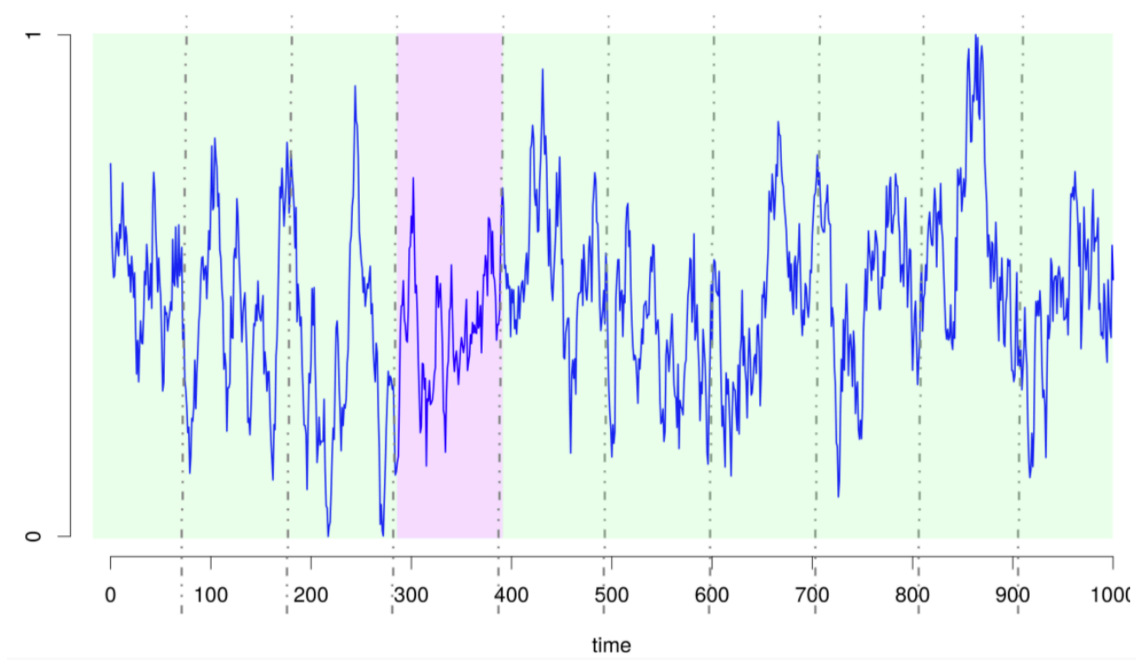

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Conclusion: use quantitative metrics

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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/

http://pierrepinson.com/index.php/teaching/

The end, to be continued …