Microgrids

Lecture 1:introduction to forecasting

LIÈGE université

Jonathan Dumas
jdumas@uliege.be

Introduction to forecasting

Lecture 1 - sources

- Renewables in Electricity Markets online lectures (open-access): modules 8, 9, and 10. https://pierrepinson.com/index.php/teaching/

- The DTU CEE Summer School 2019 “Data-Driven Analytics and Optimization for Energy Systems”: Statistical and Machine Learning for Forecasting lecture https://energy-markets-school.dk/summer-school-2019/

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

- Dumas, Jonathan. "Weather-based forecasting of energy generation, consumption and price for electrical microgrids management." https://arxiv.org/abs/2107.01034.

Introduction to forecasting

Quiz

Could you define «forecasting »?

Introduction to forecasting

Quiz

Based on the information available in the present, judging/estimating what **is likely to happen in the future**.

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

Introduction to forecasting

Summary

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

Introduction to forecasting

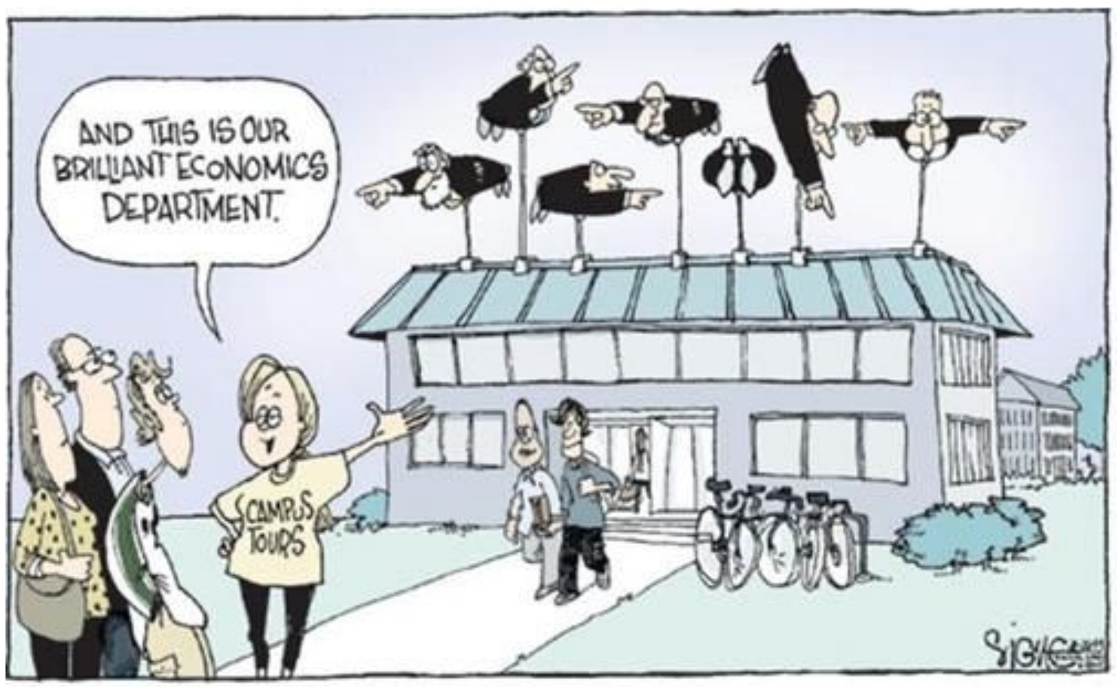
Quiz

Why do we use forecasts?

Introduction to forecasting

Context: why forecasting?

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



Believing we know what will happen:

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

Key areas:

- **energy**, finance, economics;
- weather and climate, …

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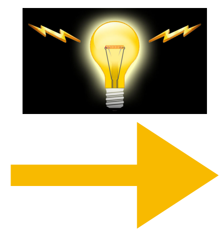
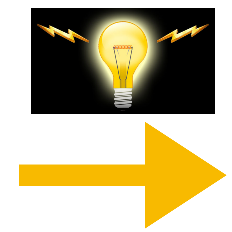
Reminder: the energy key players

Energy producers

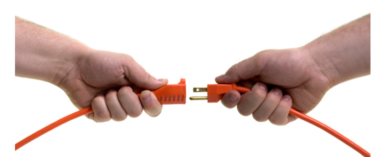


TSO / DSO



Residential consumers (small)

Energy suppliers



Industrial consumers (large)

Market operators: EEX, EPEXSPOT

Introduction to forecasting

Quiz

What are the key variables to forecast in the energy sector?

Introduction to forecasting

Energy sector: what to forecast?

Different **needs** for each participant!

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

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

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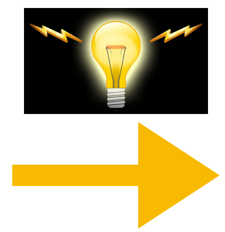
Energy sector: what to forecast?

Energy producers

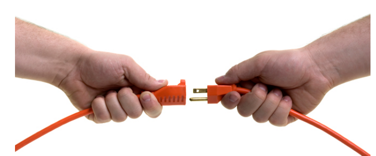
Optimize benefit from generation



TSO / DSO

Balance the grid.

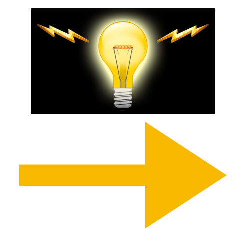
Energy suppliers



Optimize benefit by selling energy.

Market operators: EEX, EPEXSPOT

Optimize transactions.



Residential consumers (small)

Industrial consumers (large)

Optimize consumption.

Introduction to forecasting

Quiz

Do you know decision-making problems in the energy sector?

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Renewable energy forecasts in decision-making

Forecasts are used as **input** to numerous 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).

Introduction to forecasting

Quiz

Do you know the different types of forecasts?

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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).

Introduction to forecasting

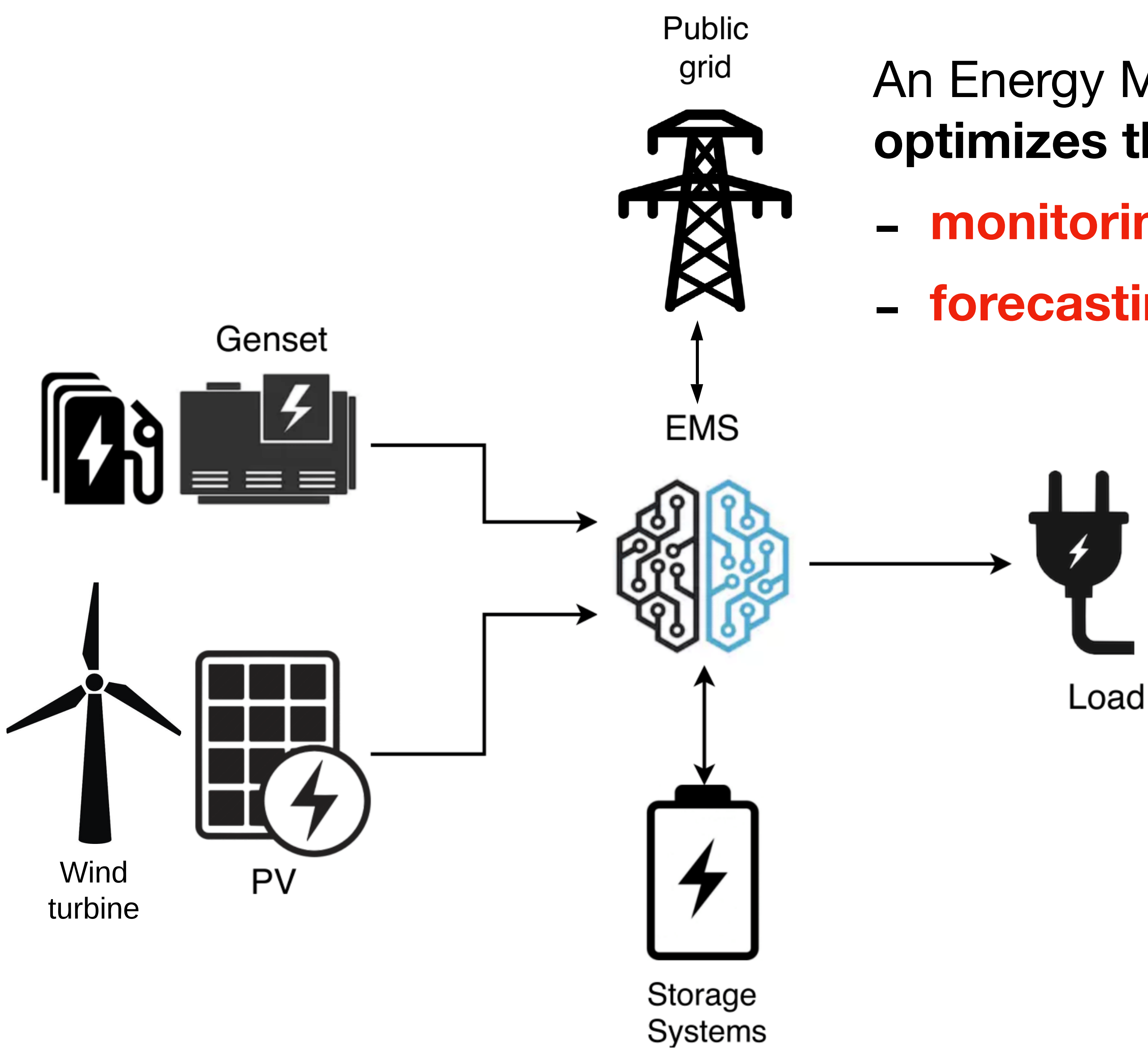
Quiz

What is a microgrid?

What is an energy management system?

Introduction to forecasting

Microgrid reminder



An Energy Management System (**EMS) optimizes the decisions** based on:

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

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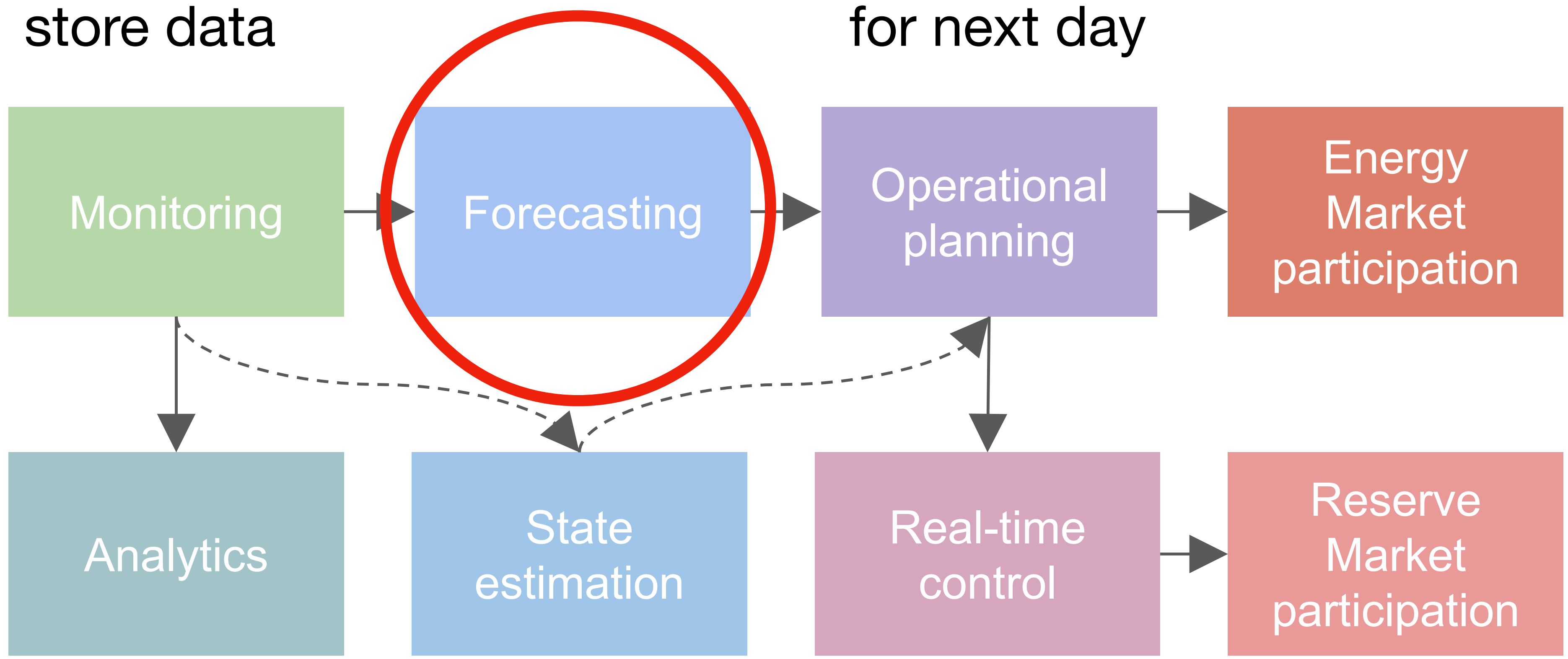
EMS reminder

Consumption & generation

Pull and store data

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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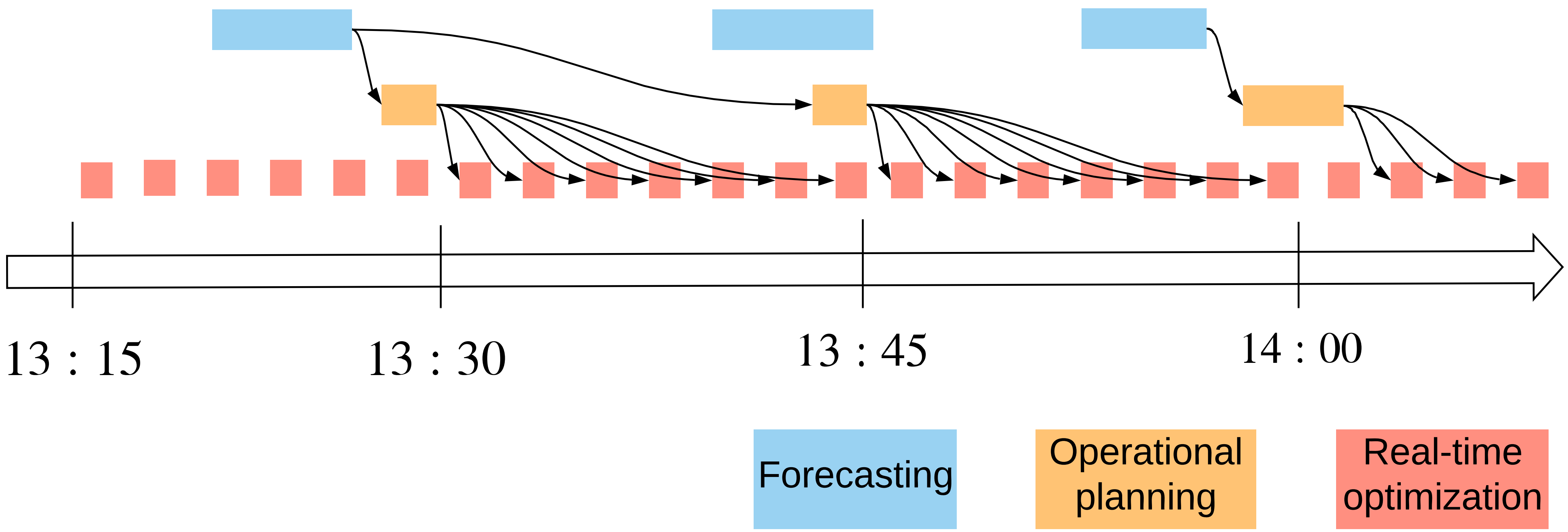
EMS time line



Introduction to forecasting

Quiz

What could be the key microgrid variables to forecast?

Introduction to forecasting

Microgrid key parameters to forecast

Generation: PV, Wind Power, Hydraulic Power, …

Load: office, industrial, residential, …

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

Introduction to forecasting

Summary

1. Forecasting context
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Introduction to forecasting

Quiz

Any idea about a way to classify forecasts?

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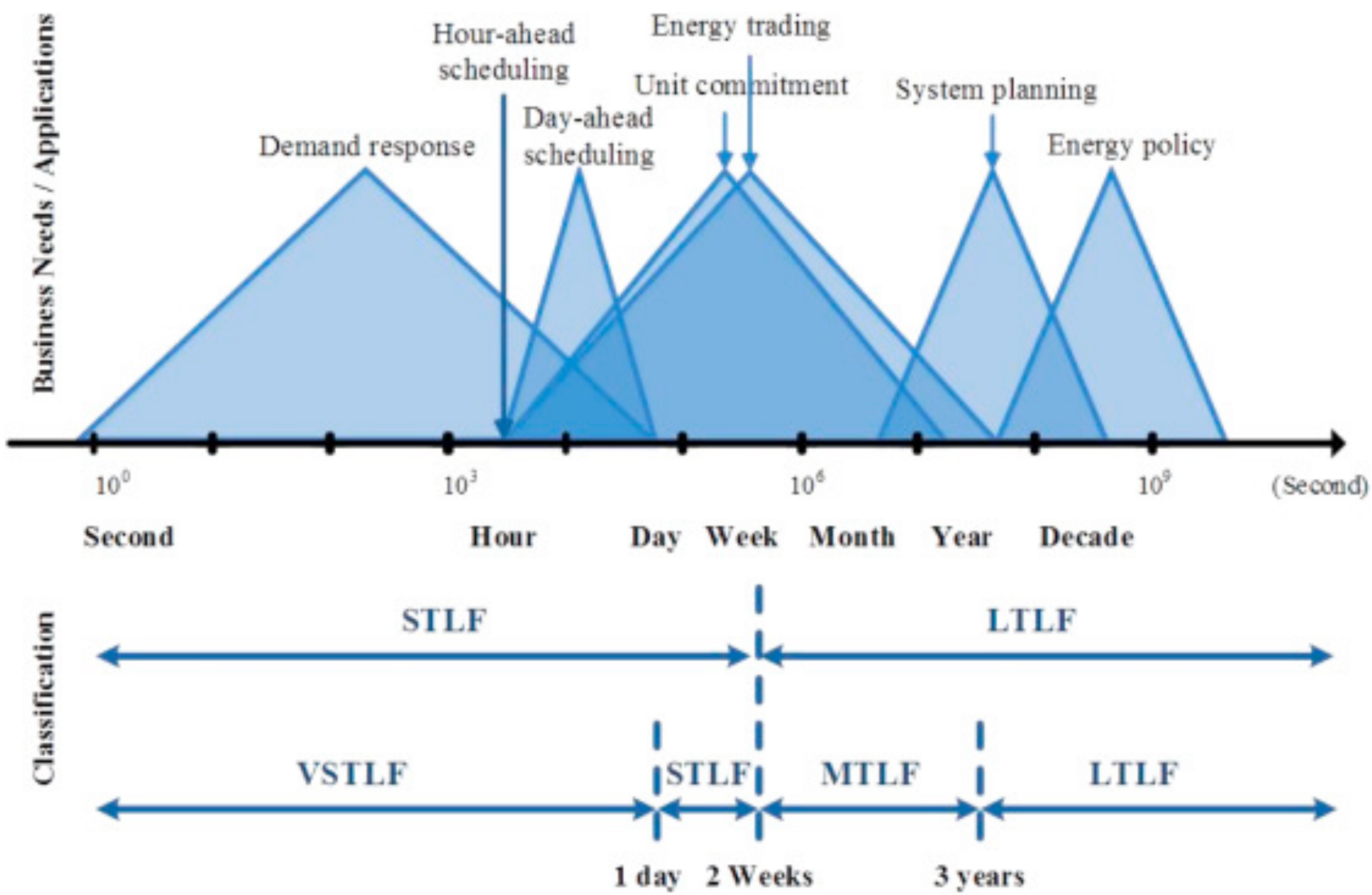
Classification over the time dimension



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

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Forecasting classification into 2 dimensions

1. **Time** dimension

- **Forecasting horizon**

  VST (minutes to a day), ST (day to a week), MT (weeks to a 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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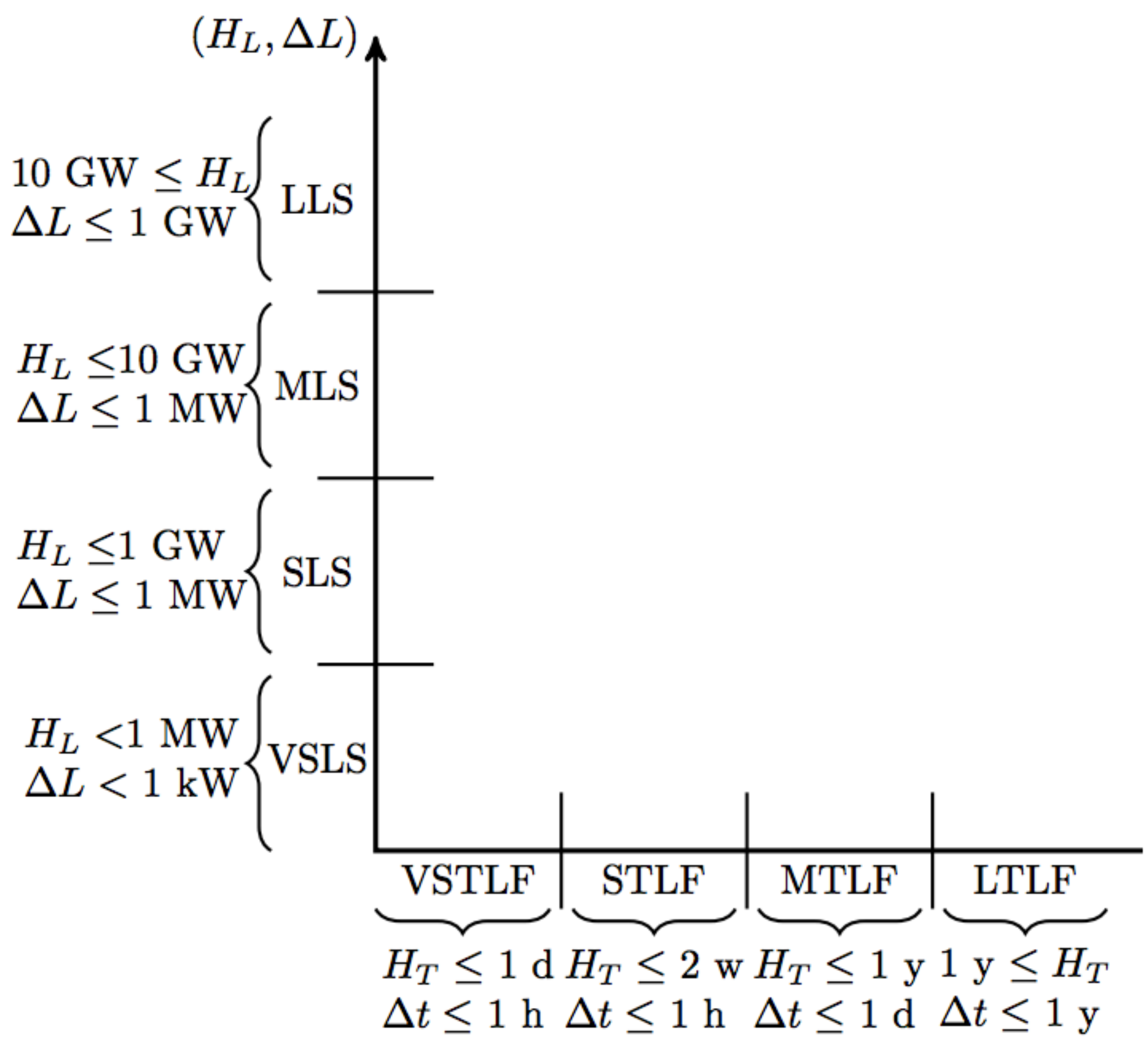
Forecasting classification into 2 dimensions



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*](https://arxiv.org/abs/1901.05052)

Introduction to forecasting

Quiz

What kind of data to use as inputs of forecasting models?

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Forecasting predictors

Weather variables **WARNING: it depends 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

Residential energy supplier

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Introduction to forecasting

Forecast setup

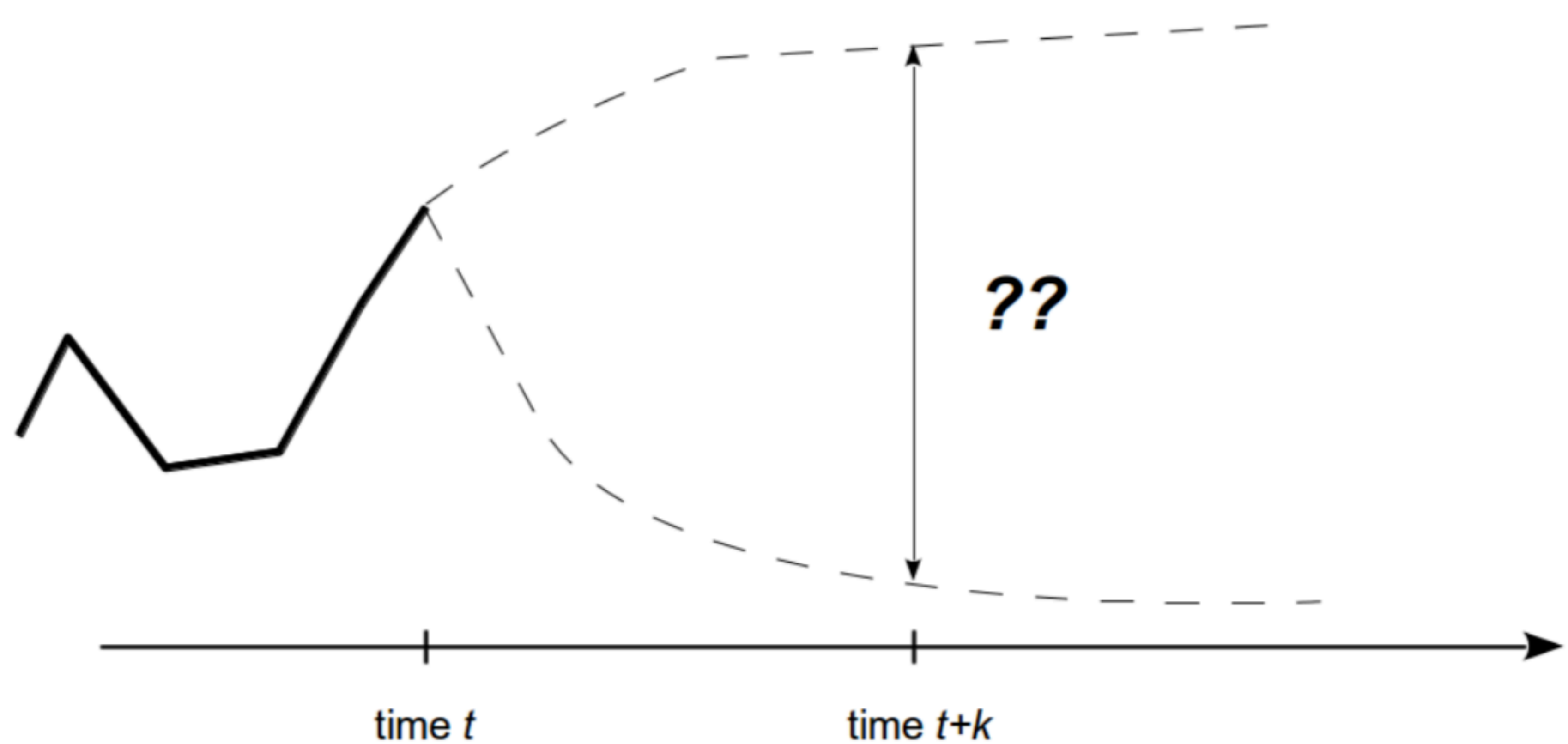
The experimental setup:

- 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".



Introduction to forecasting

Quiz

What could be a « *deterministic* » forecast?

Introduction to forecasting

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.

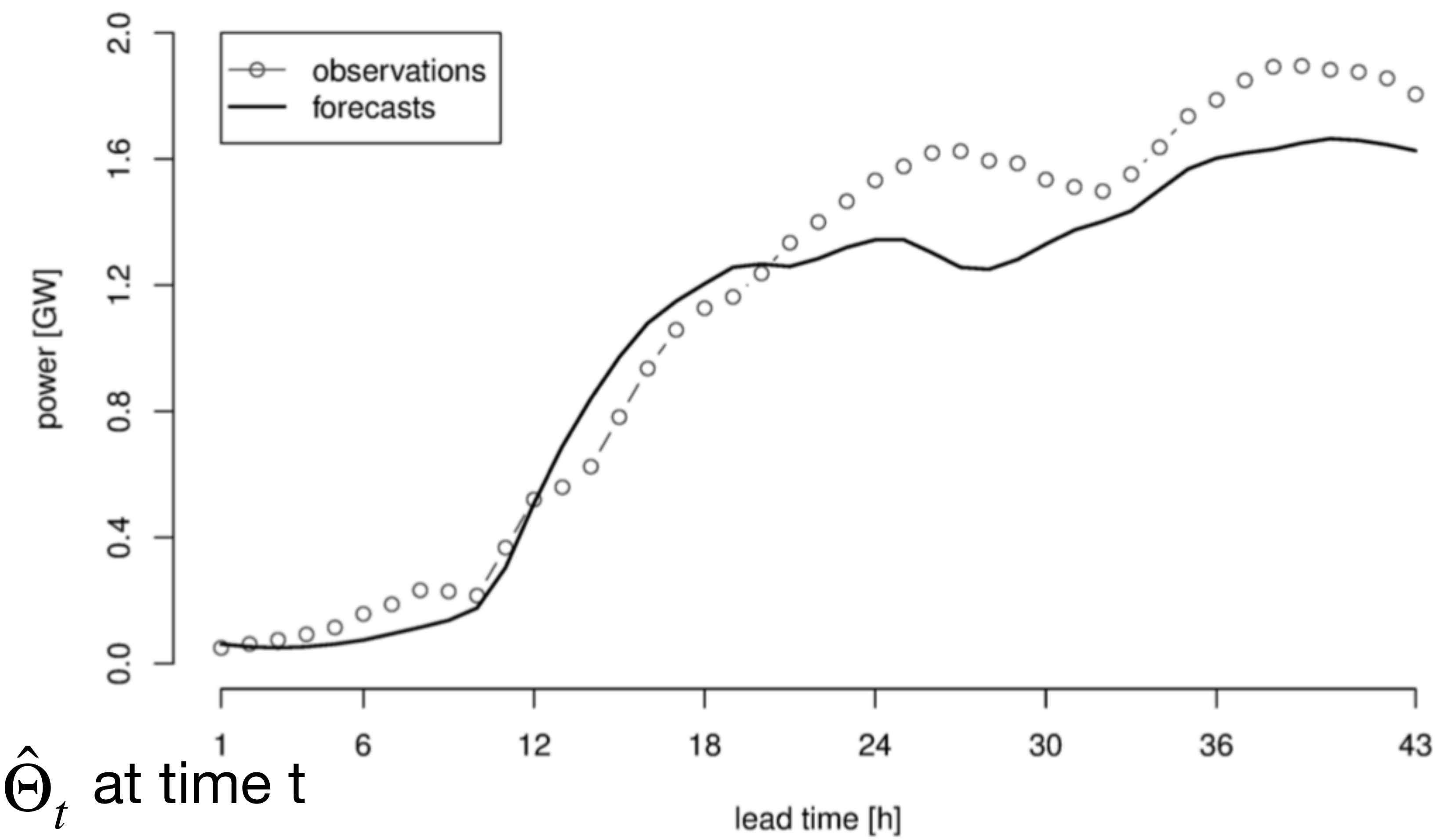
$$\hat{y}_{t+k|t} = \mathbb{E}\left[Y_{t+k|t} \,|\, g, \Omega_t, \hat{\Theta}_t\right]$$

given:

- the information set Ω;

- a model g

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



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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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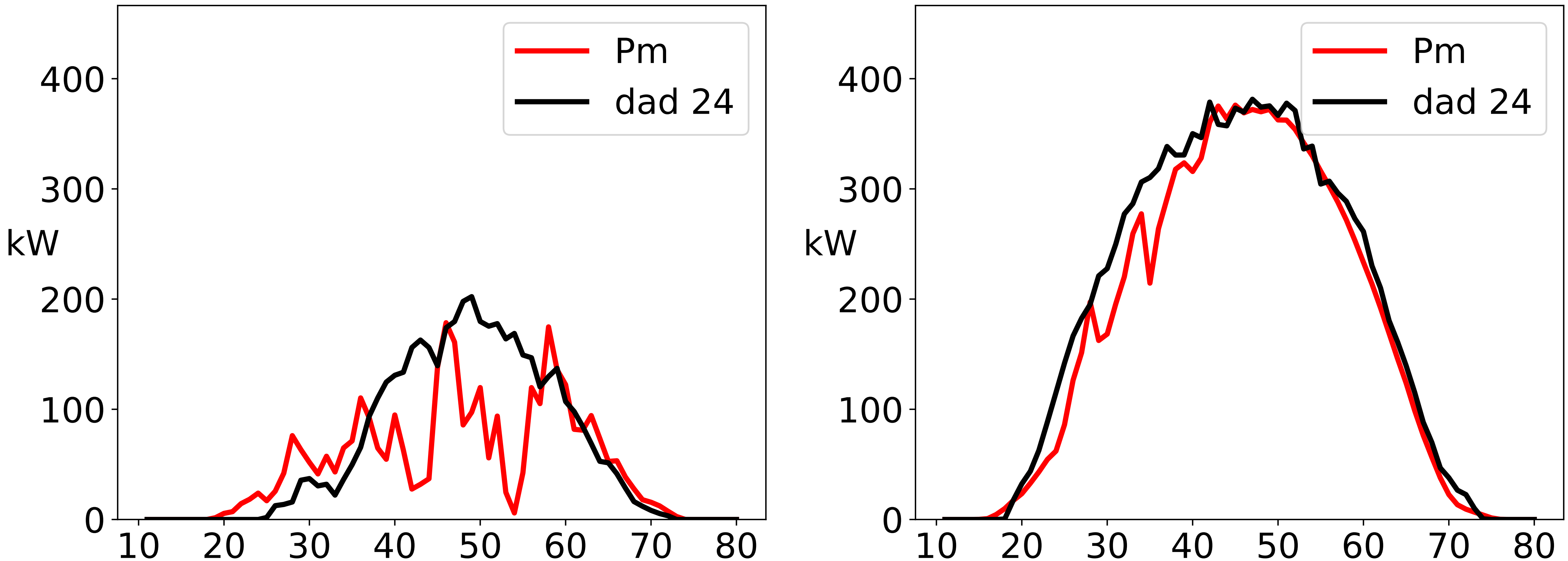
Point forecasts examples: PV generation

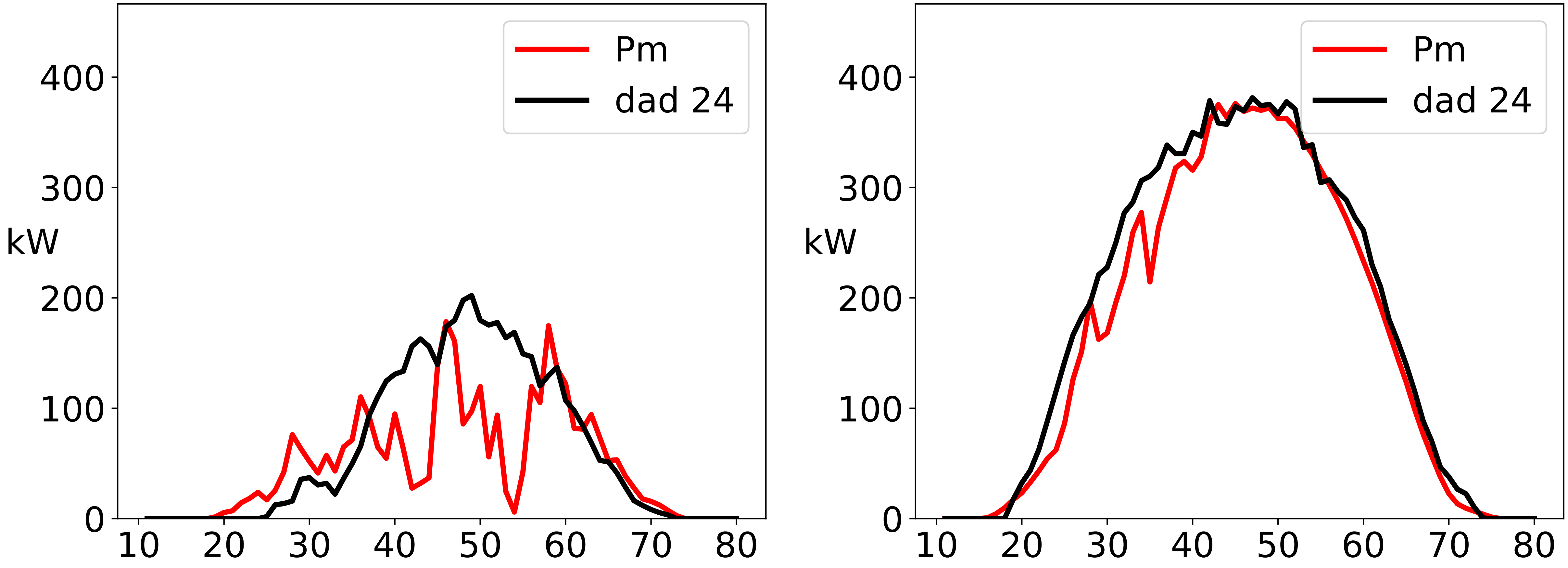


PV point forecasts (dad 24) are computed using a **neural network** at noon for the next day, and the corresponding observations are in red (Pm).

J. Dumas, C. Cointe, X. Fettweis and B. Cornélusse, "Deep learning-based multi-output quantile forecasting of PV generation," 2021 IEEE Madrid PowerTech, 2021, pp. 1-6, doi: 10.1109/PowerTech46648.2021.9494976. https://arxiv.org/abs/2106.01271

Introduction to forecasting

Point forecasts examples



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

The predictors are the inputs of a neural network.

Residential energy supplier

Summary

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Introduction to forecasting

Quiz

Depending on the forecasting horizon, what could be the origins of the forecasting errors?

What is the main forecasting error driver between weather forecasts and recent observations?

Introduction to forecasting

Contribution to forecast uncertainty/error

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

- recent power generation **measurements**;

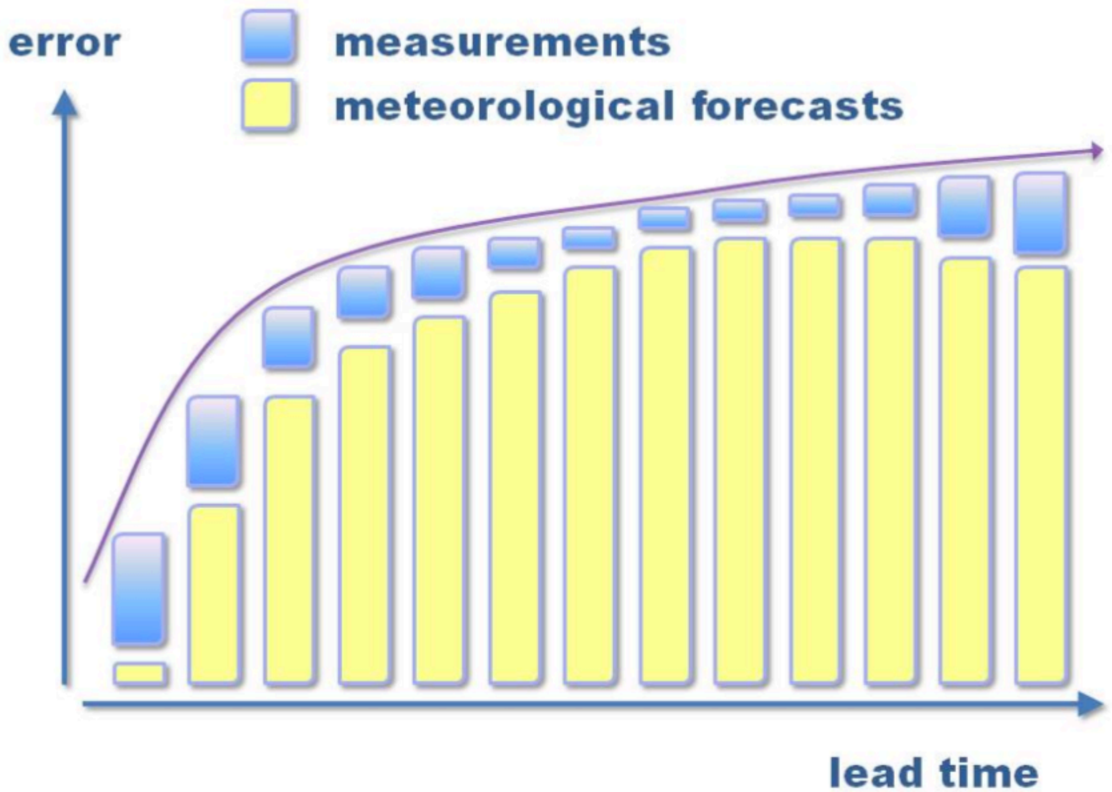
- **weather** forecasts for the coming period;

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

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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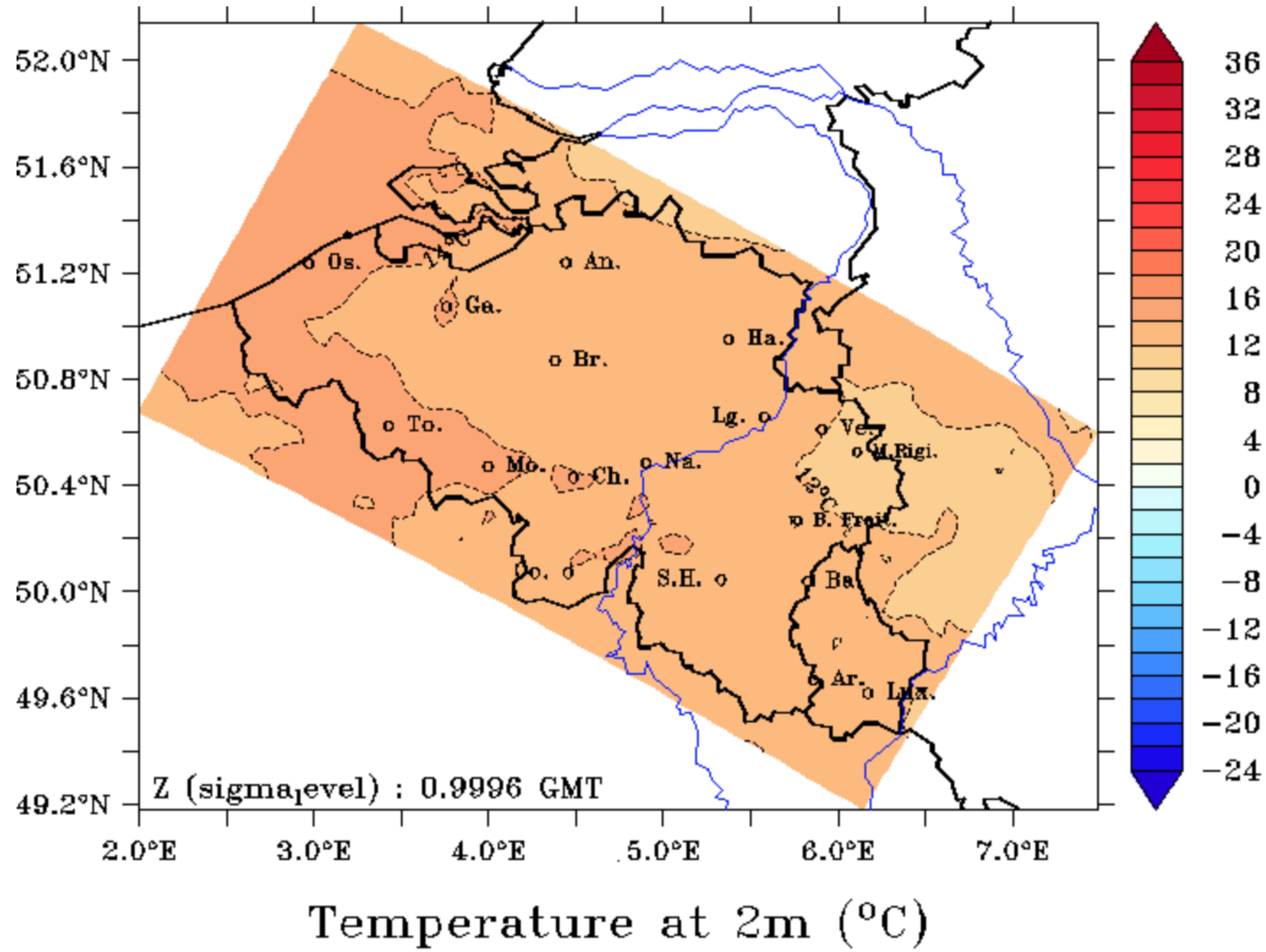
Weather forecasts: the regional climate model (MAR) from Liège university



https://www.climato.uliege.be/cms/c_5635501/fr/belgique

Reference: *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.*

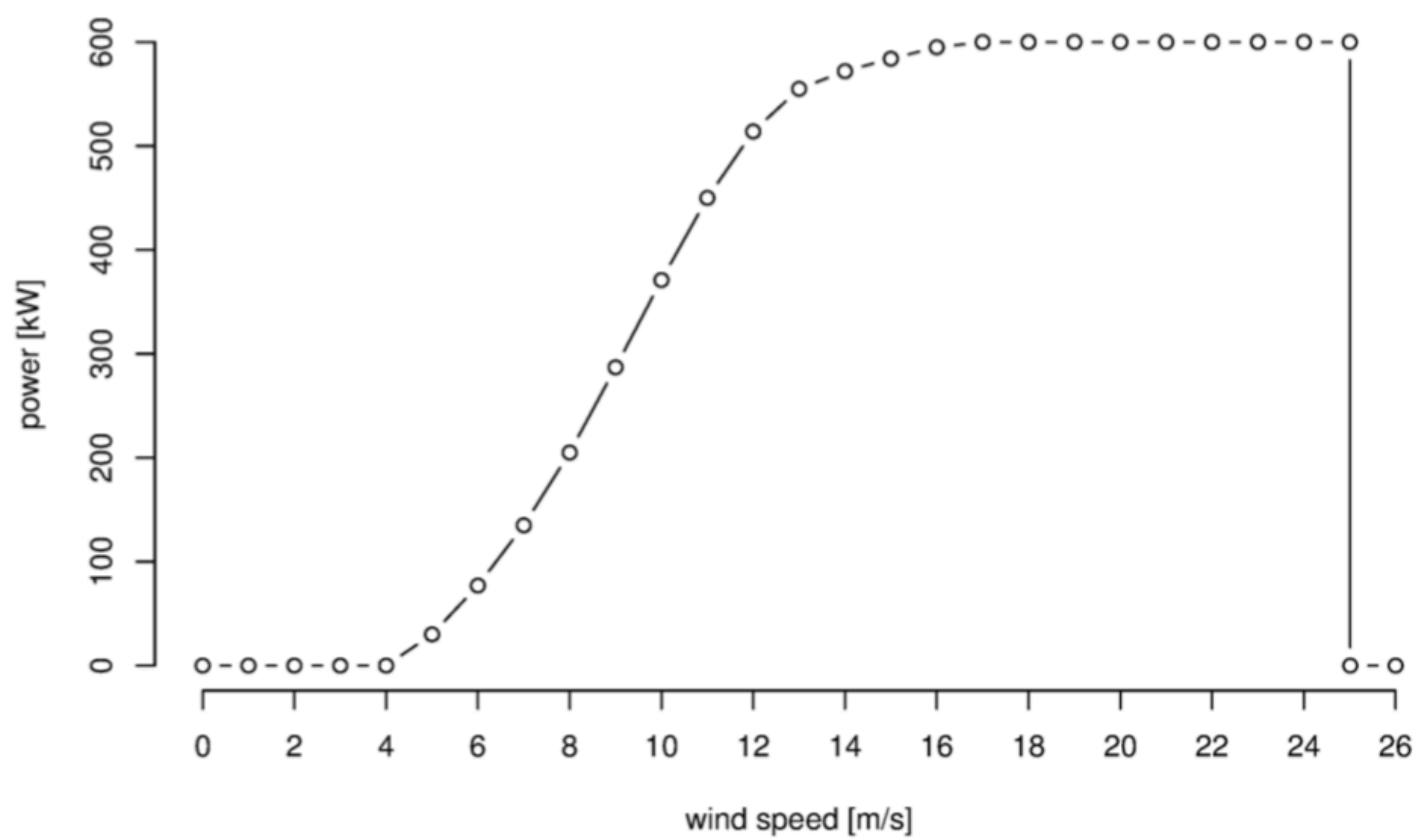
Introduction to forecasting

A wind power curve

A large part of the prediction error **directly** comes from the 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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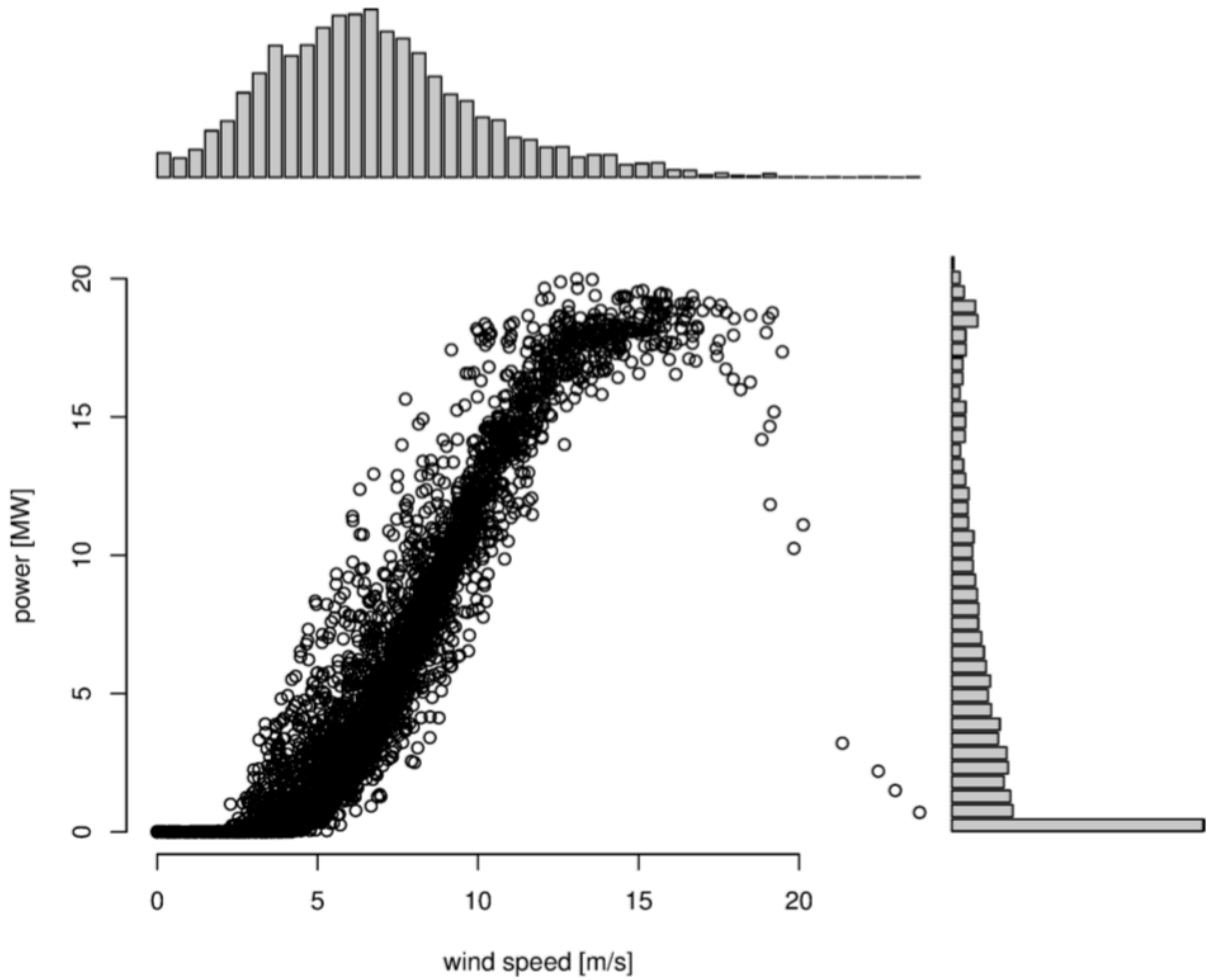
The actual wind power curve

The actual power curve looks different!



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Introduction to forecasting

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

J. Dumas, C. Cointe, X. Fettweis and B. Cornélusse, "Deep learning-based multi-output quantile forecasting of PV generation," 2021 IEEE Madrid PowerTech, 2021, pp. 1-6, doi: 10.1109/PowerTech46648.2021.9494976. https://arxiv.org/abs/2106.01271

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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 the TensorFlow library.

TensorFlow reference: Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Rafal Jozefowicz, Yangqing Jia, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Mike Schuster, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org.

Introduction to forecasting

Evaluation methodology

Forecasting is about **predicting future events in new situations**, not only explaining what happened in the past.

One need to verify forecasts on data that **are not used** for the modeling!

Introduction to forecasting

Quiz

Any idea about a strategy to evaluate the forecasts?

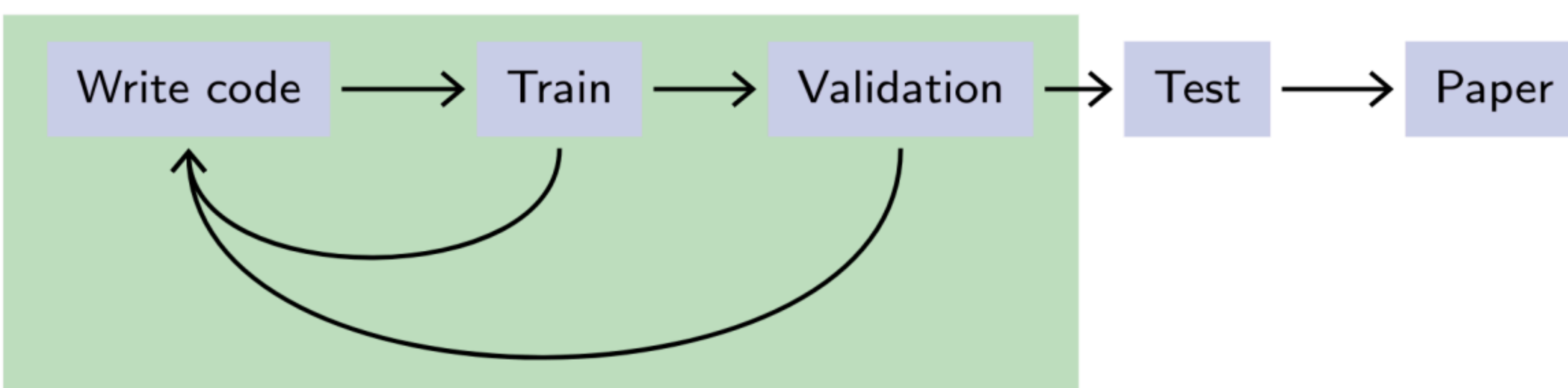
Introduction to forecasting

Evaluation methodology: training, validation, and testing sets

Forecasting is about **predicting future events in new situations**, not only explaining what happened in the past.

One need to verify forecasts on data that **are not used** for the modeling!

A good practice in machine learning is to use a dedicated part of the dataset as an independent testing set that is not used to train the models but only to estimate the generalization error. Ideally, the dataset **is divided randomly into three parts**.



Proper evaluation protocols. Credits: Francois Fleuret, EE559 Deep Learning, EPFL
https://fleuret.org/dlc/

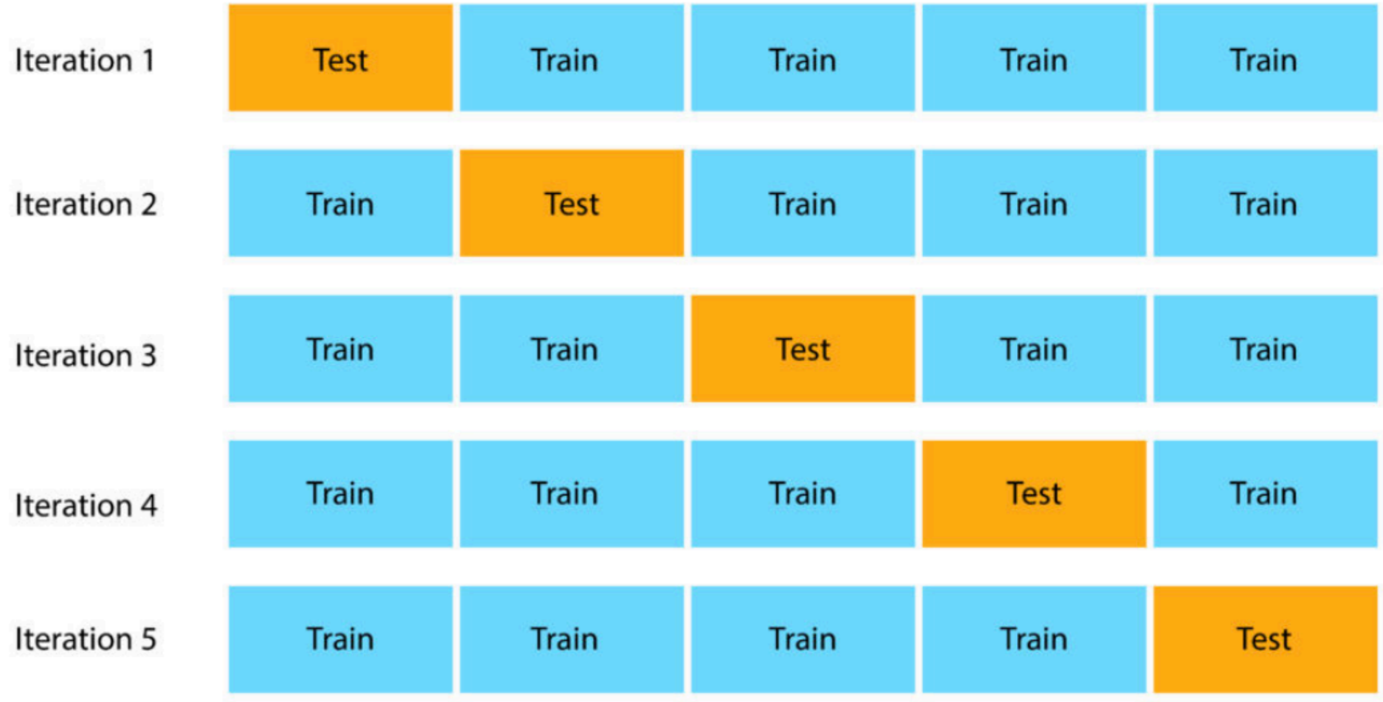
Introduction to forecasting

Evaluation methodology: k-cross fold validation

It consists of **dividing the dataset into k-folds**. Then, the model is trained on k−1 folds, and **one fold is left out to evaluate the testing error**.

In total, the model is trained k times with k pairs of learning and testing sets. The generalization error is estimated by averaging the k errors computed on k testing sets.

Note: the hyper-parameters optimization is already done.



Introduction to forecasting

Quiz

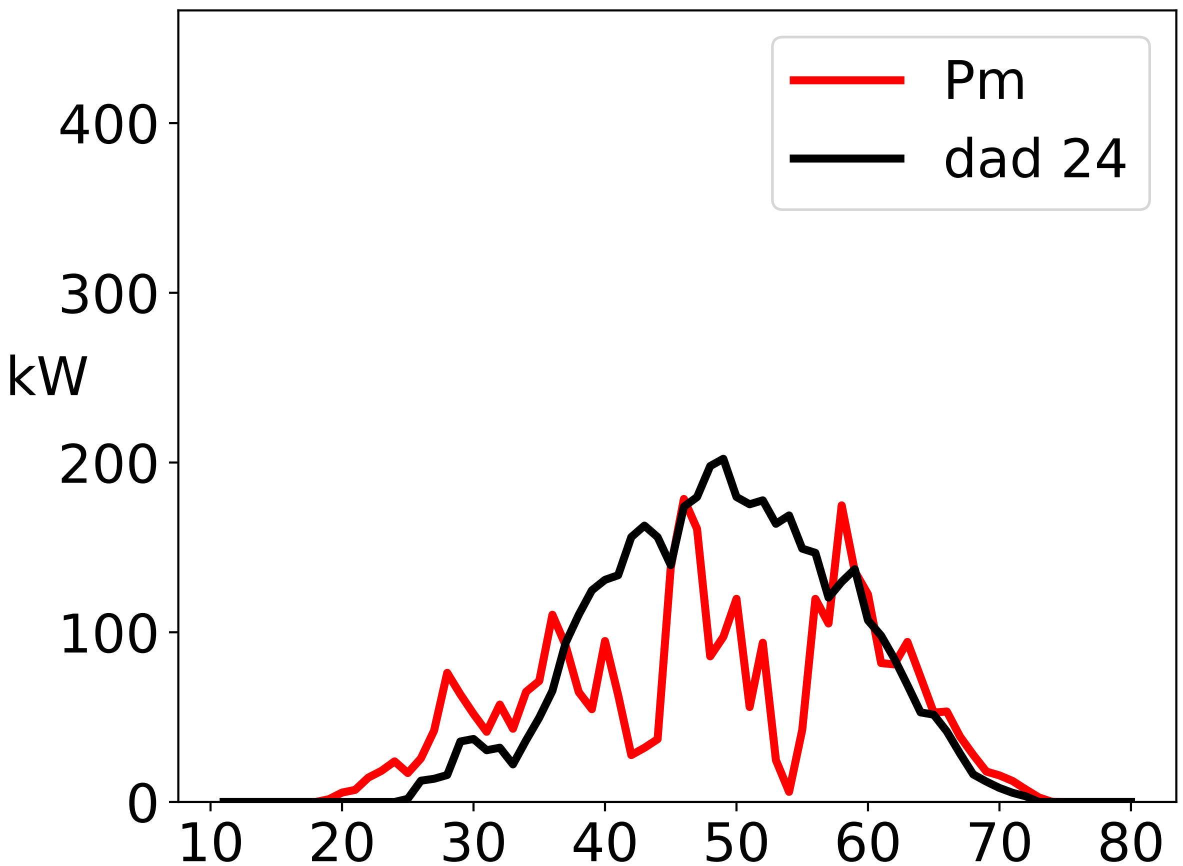
Once the strategy is set, how to evaluate qualitatively the forecasts?

Introduction to forecasting

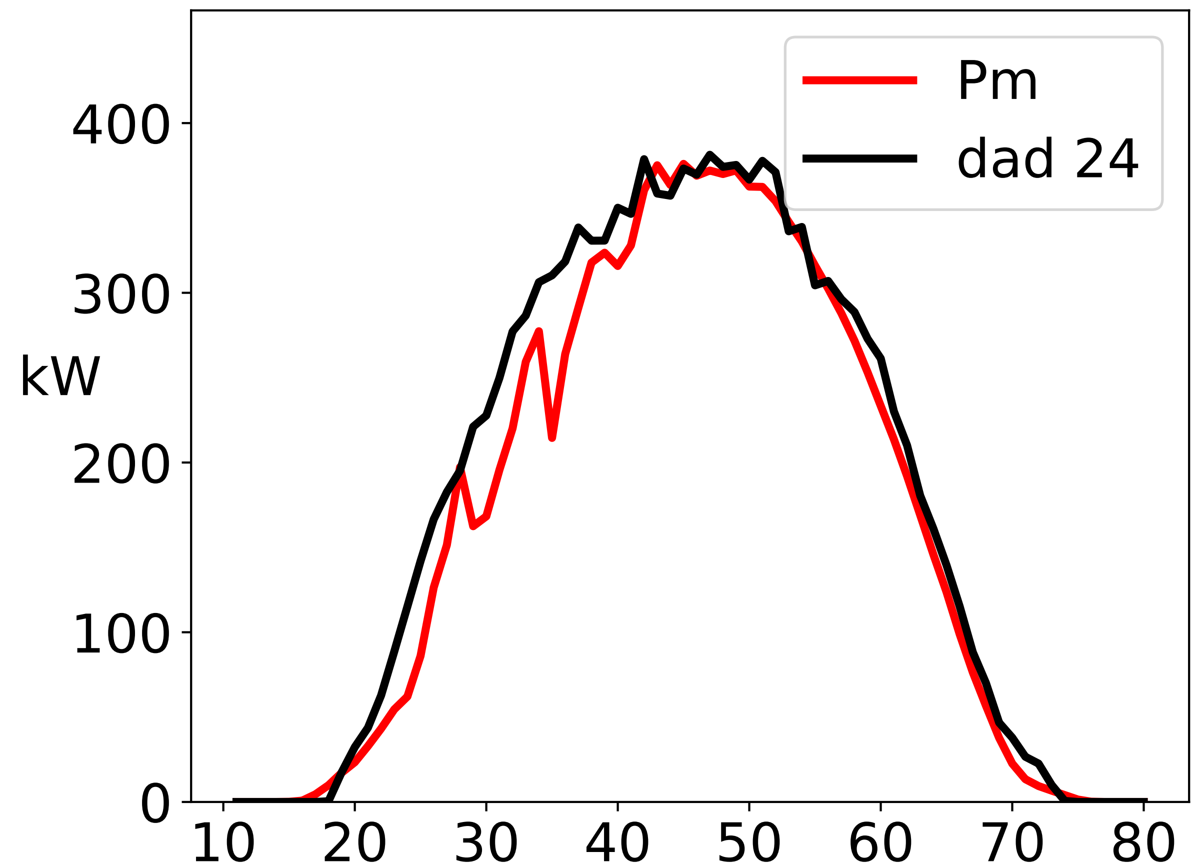
Visual inspection

Visual inspection allows substantial **insight into forecast quality** development, and it 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.



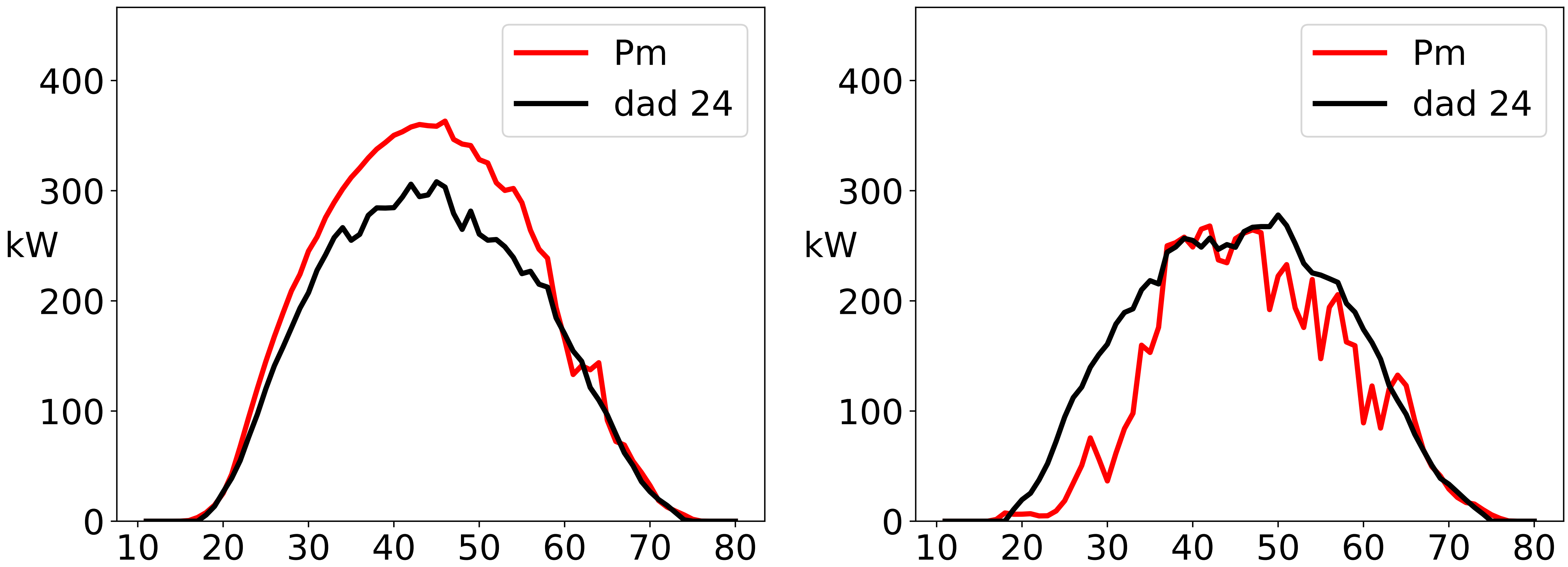
Issued on 4 May 2020 at 12:00 for 5 May 2020.

Introduction to forecasting

Amplitude and phase errors

Weather forecasts errors most often drive the forecasting errors.

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



Introduction to forecasting

Quantitative metrics: forecast error definition

Qualitative analysis ought to be complemented by **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**

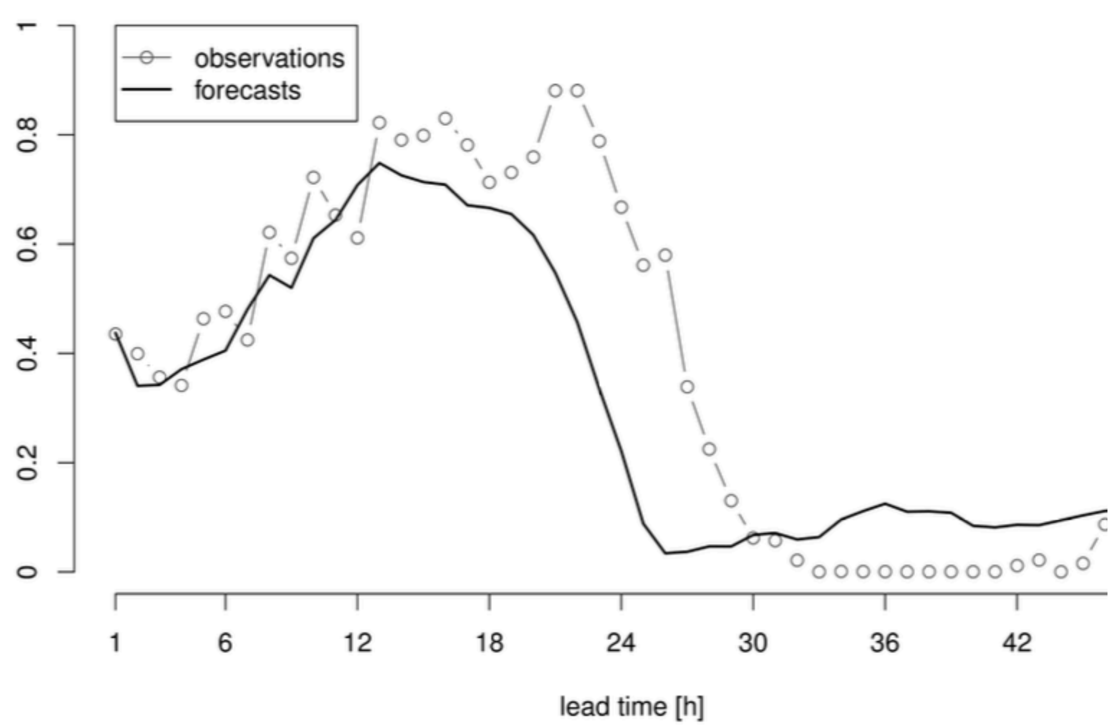
$$\epsilon_{t+k|t} = \frac{y_{t+k|t} - \hat{y}_{t+k|t}}{P_n}$$

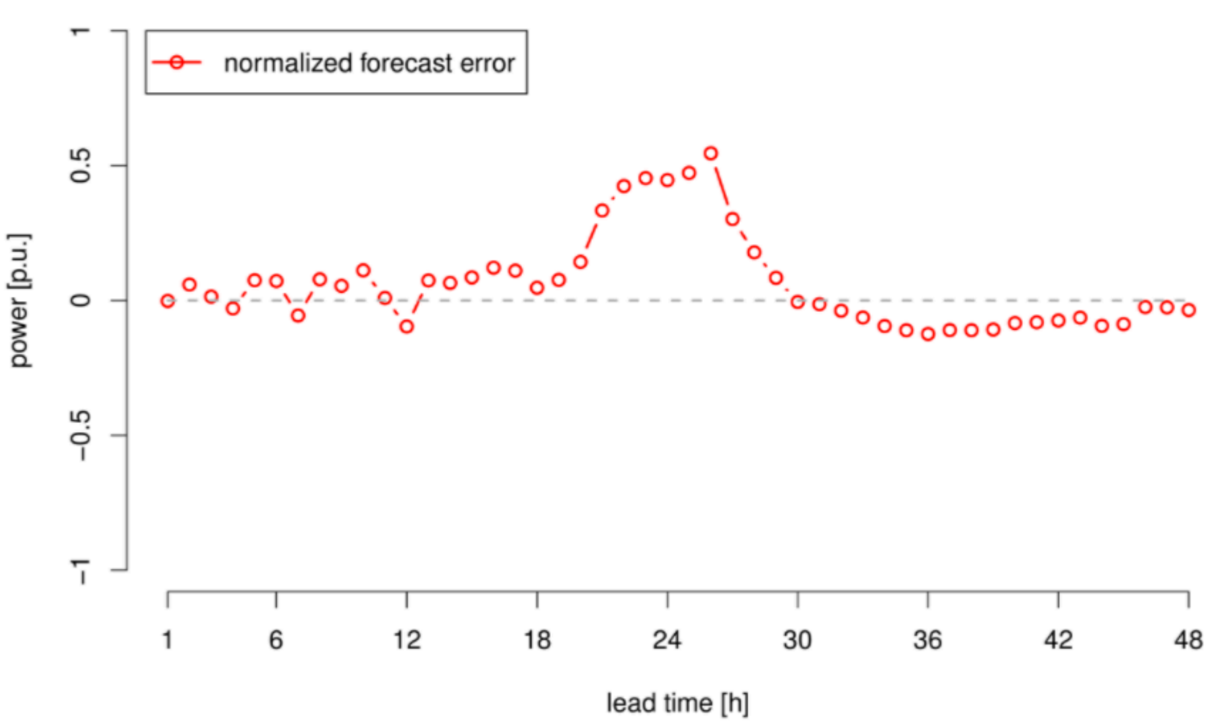
with Pn the nominal capacity.

Introduction to forecasting

Quantitative metrics

Example on a wind farm with the normalized error.





Introduction to forecasting

Quiz

Do you know some point-forecasts metrics to assess the forecasts quantitatively?

Quantitative metrics: most common point-forecasts metrics

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

The most common scores include, as a 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:

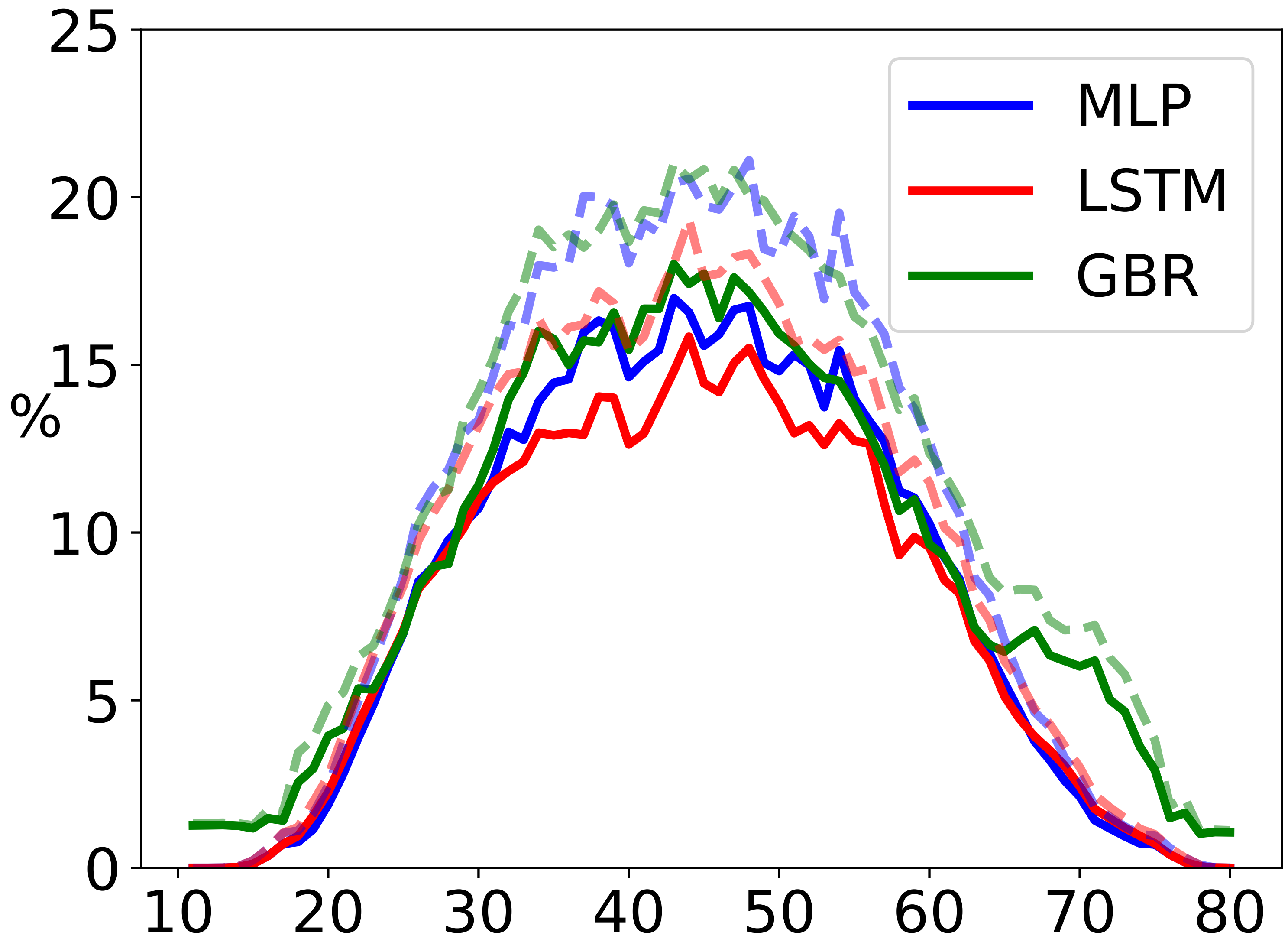
$$\textbf{MAE}(k) = \frac{1}{T} \sum_{t=1}^{T} |\epsilon_{t+k|t}|$$

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

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

Introduction to forecasting

Example on the case study



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

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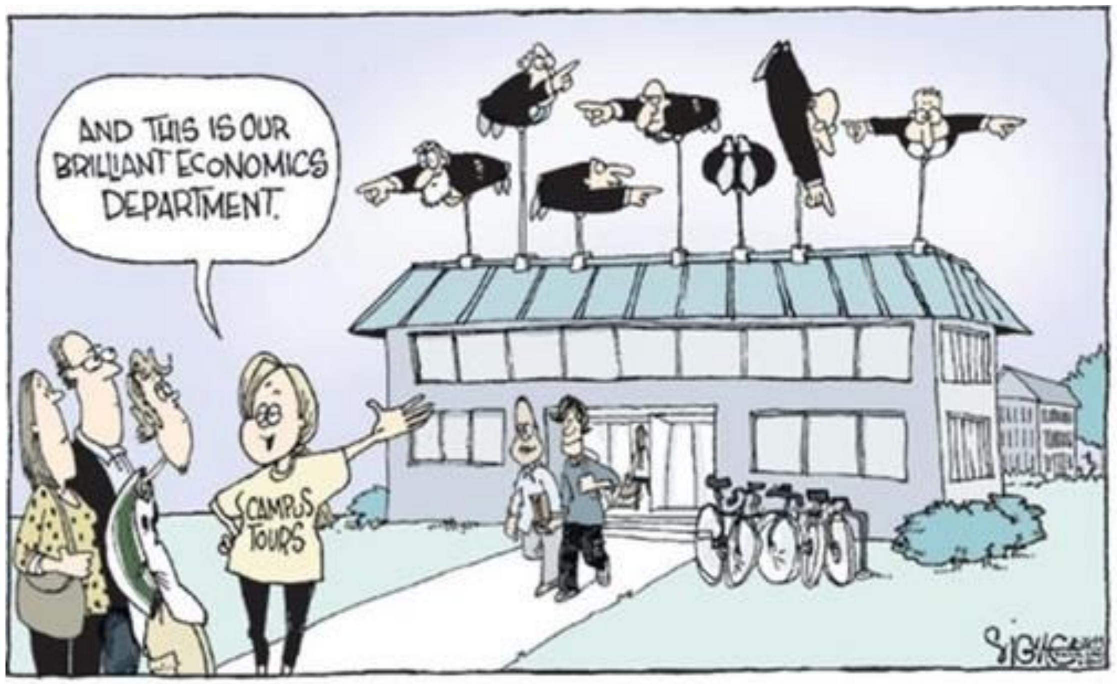
Conclusion: forecast for decision making

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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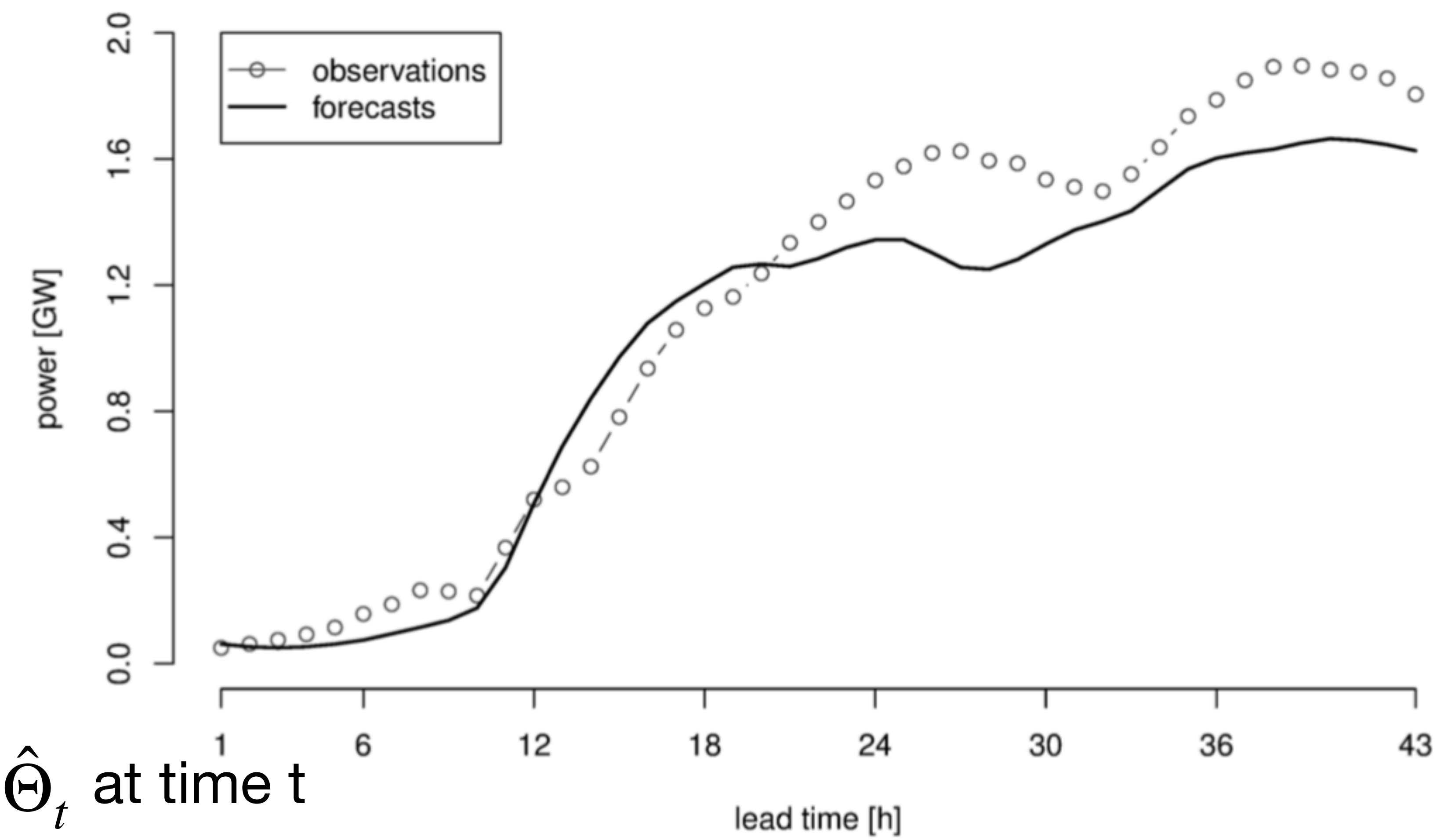

given:

- the information set Ω;

- a model g

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

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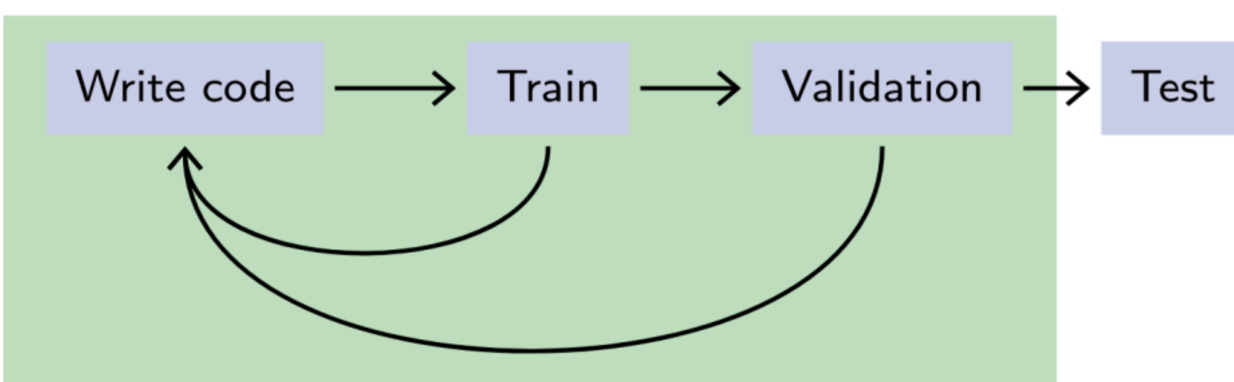
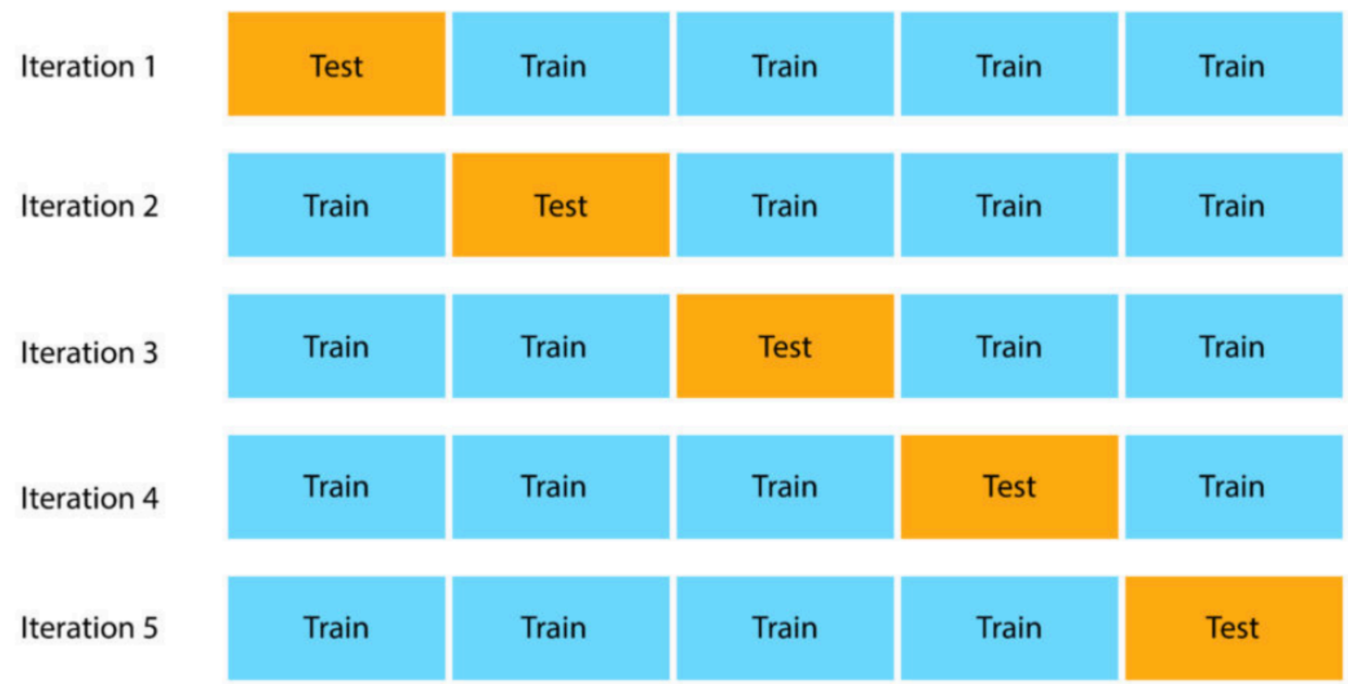
Conclusion: strategy to assess forecasts

Several strategies to assess forecasts:

- splitting the dataset into three random parts: learning, validation, and testing sets;

- k-cross fold validation.





Introduction to forecasting

Conclusion: 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:

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

Introduction to forecasting

Lecture 1 - sources to dig the topic

- Renewables in Electricity Markets online lectures (open-access): modules 8, 9, and 10. https://pierrepinson.com/index.php/teaching/

- The DTU CEE Summer School 2019 “Data-Driven Analytics and Optimization for Energy Systems”: Statistical and Machine Learning for Forecasting lecture https://energy-markets-school.dk/summer-school-2019/

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

- Dumas, Jonathan. "Weather-based forecasting of energy generation, consumption and price for electrical microgrids management." https://arxiv.org/abs/2107.01034.