

# **Microgrids**

## **Lecture 2: introduction to probabilistic forecasting**



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# Introduction to probabilistic forecasting

## Lecture 2 - sources

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- 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 probabilistic forecasting

## Learning objectives

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

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

# Introduction to probabilistic forecasting

## Summary

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1. Point-forecasts reminder
2. Probabilistic forecasts
3. Verification of probabilistic forecasts
4. Case study: probabilistic forecasting using normalizing flows

# Introduction to probabilistic forecasting

## Quiz

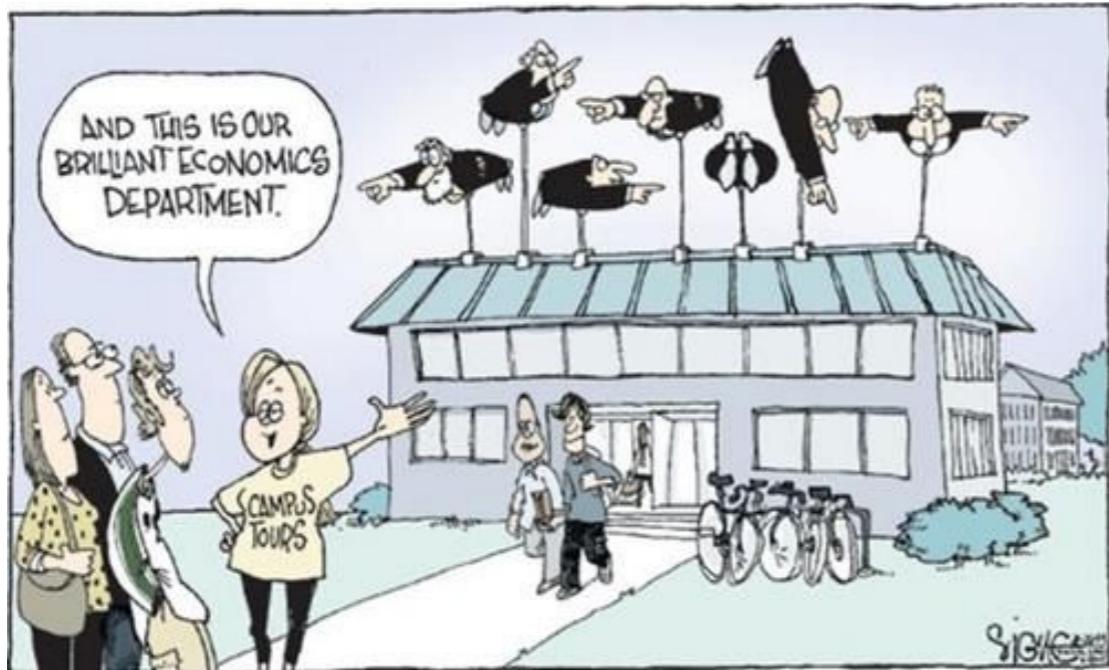
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Why forecasting?

# Introduction to probabilistic 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 probabilistic forecasting

## Quiz

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What is the point forecast definition?

# Introduction to probabilistic forecasting

Reminder: point forecast definition

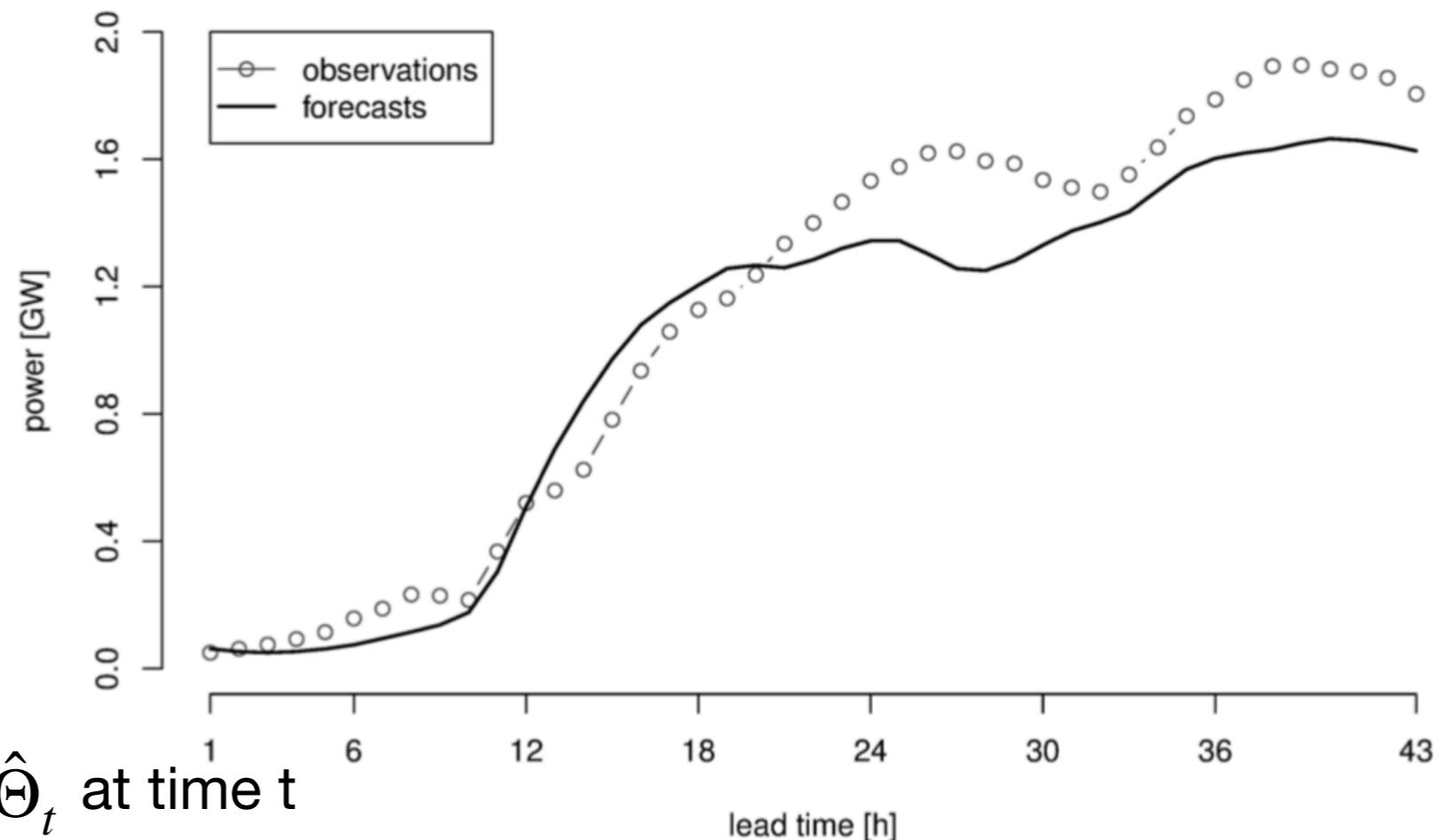
A forecast is an **estimate** for time  $t + k$ , conditional to information up to time  $t$ .

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

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

given:

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



# Introduction to probabilistic forecasting

## Quiz

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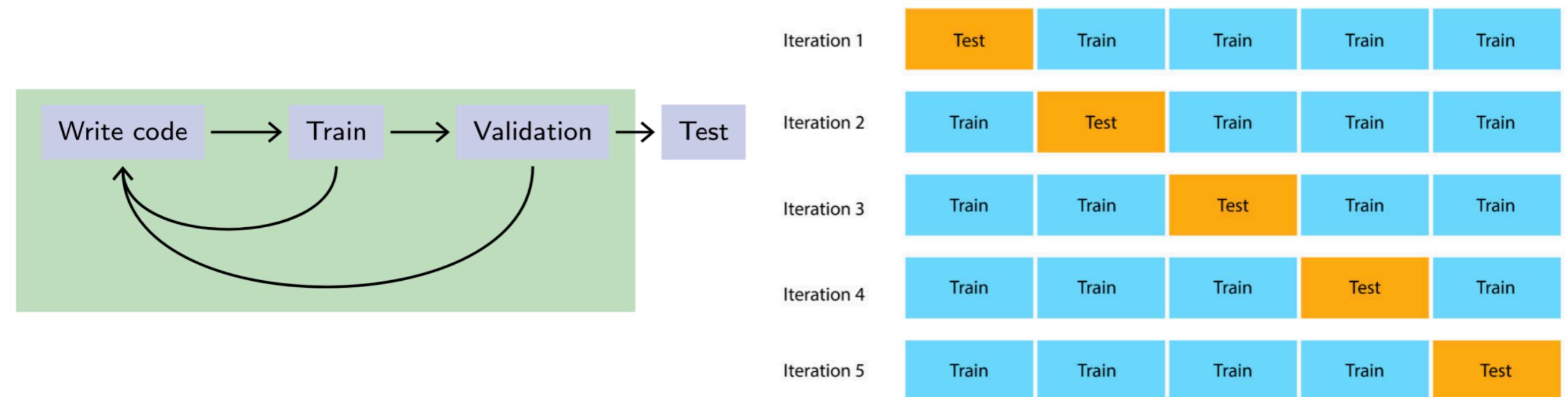
What are the strategies to assess forecasts?

# Introduction to probabilistic forecasting

## Reminder: 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 probabilistic forecasting

## Quiz

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Do you know some quantitative metrics to assess point-forecasts?

# Introduction to probabilistic forecasting

## Reminder: quantitative metrics

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**Bias** or Nbias, for the normalized version:

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

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

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

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

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

# Introduction to probabilistic forecasting

## Summary

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# Introduction to probabilistic forecasting

## Quiz

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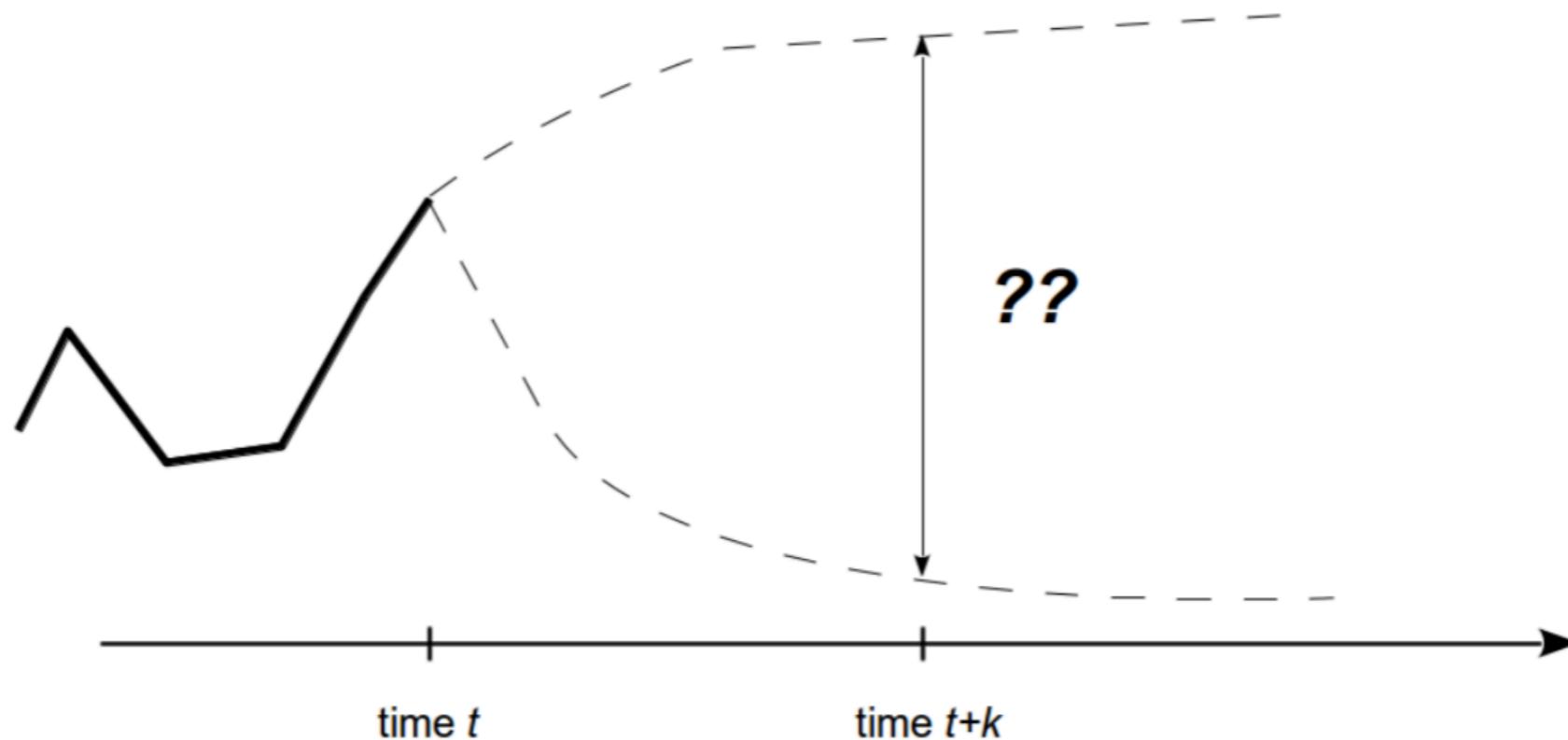
Do you know the various types of probabilistic forecasts?

# Introduction to probabilistic forecasting

## Probabilistic forecasting

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



# Introduction to probabilistic forecasting

## Quiz

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What is a quantile/percentile?

# Introduction to probabilistic forecasting

## Quantile forecast definition

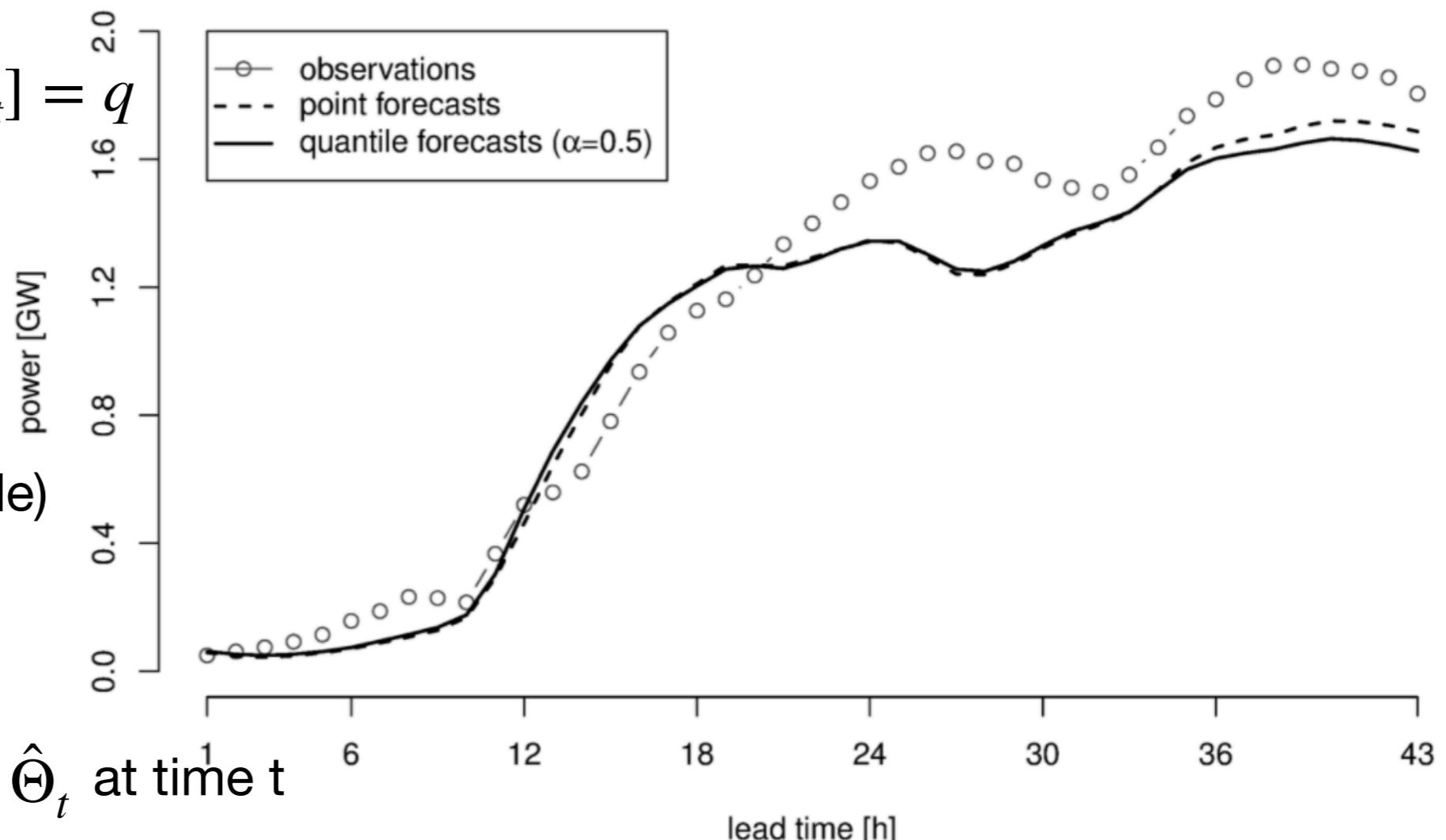
A **quantile** forecast is to be seen as a probabilistic **threshold** for power generation.

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

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

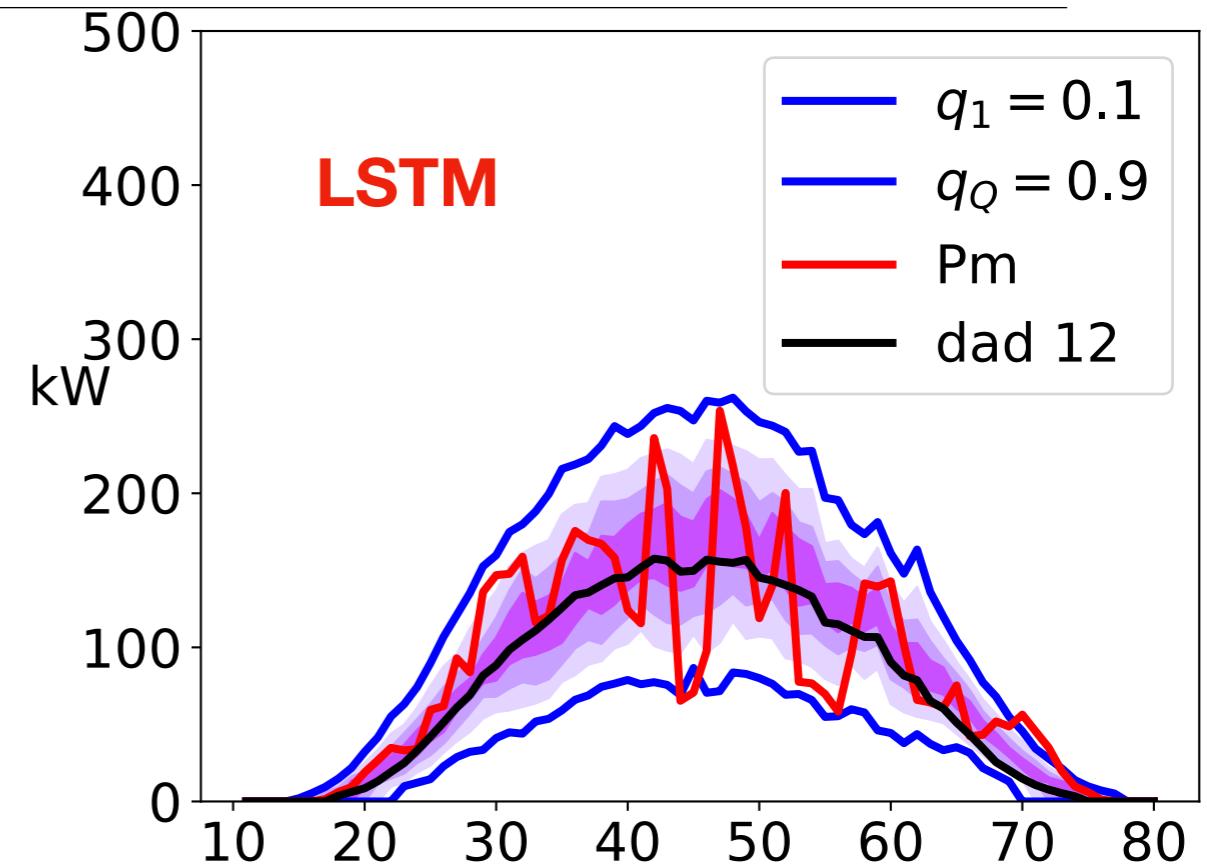
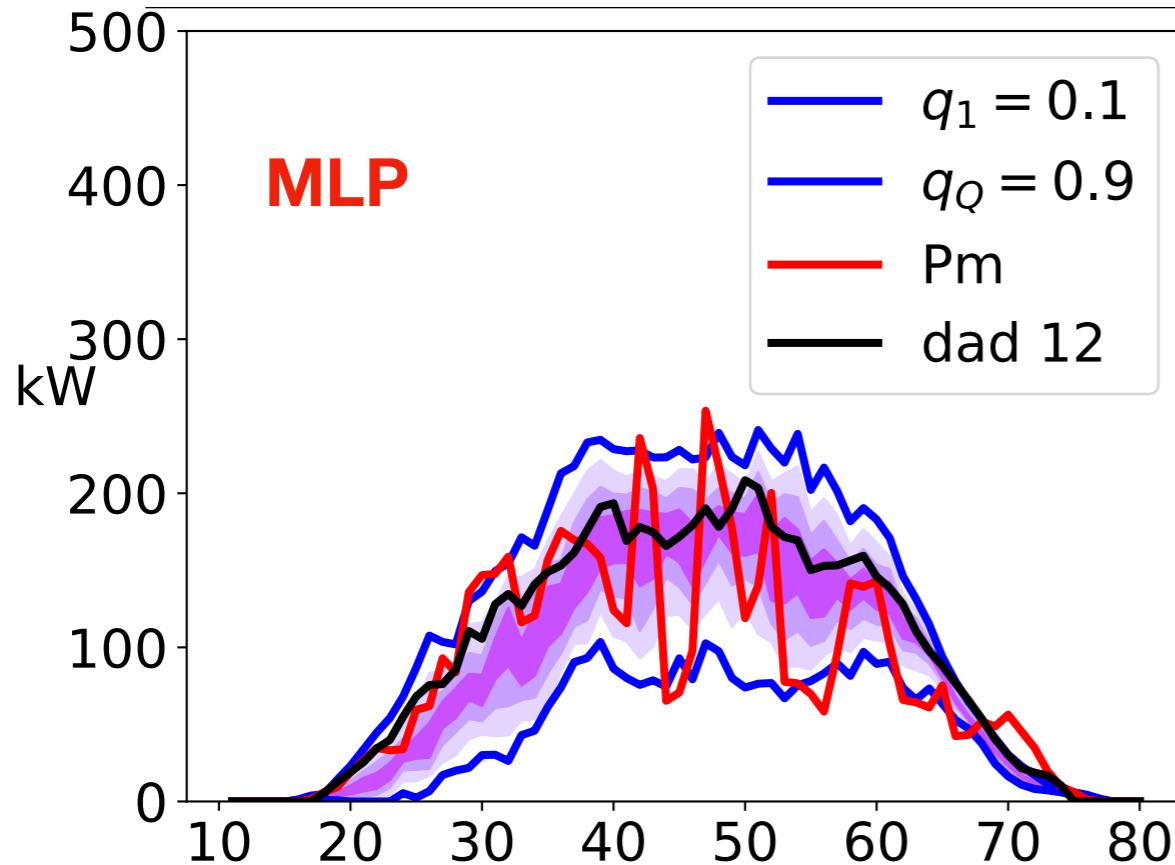
with:

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



# Introduction to probabilistic forecasting

## Quantile forecasts examples: PV generation



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

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

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 probabilistic forecasting

## Prediction interval definition

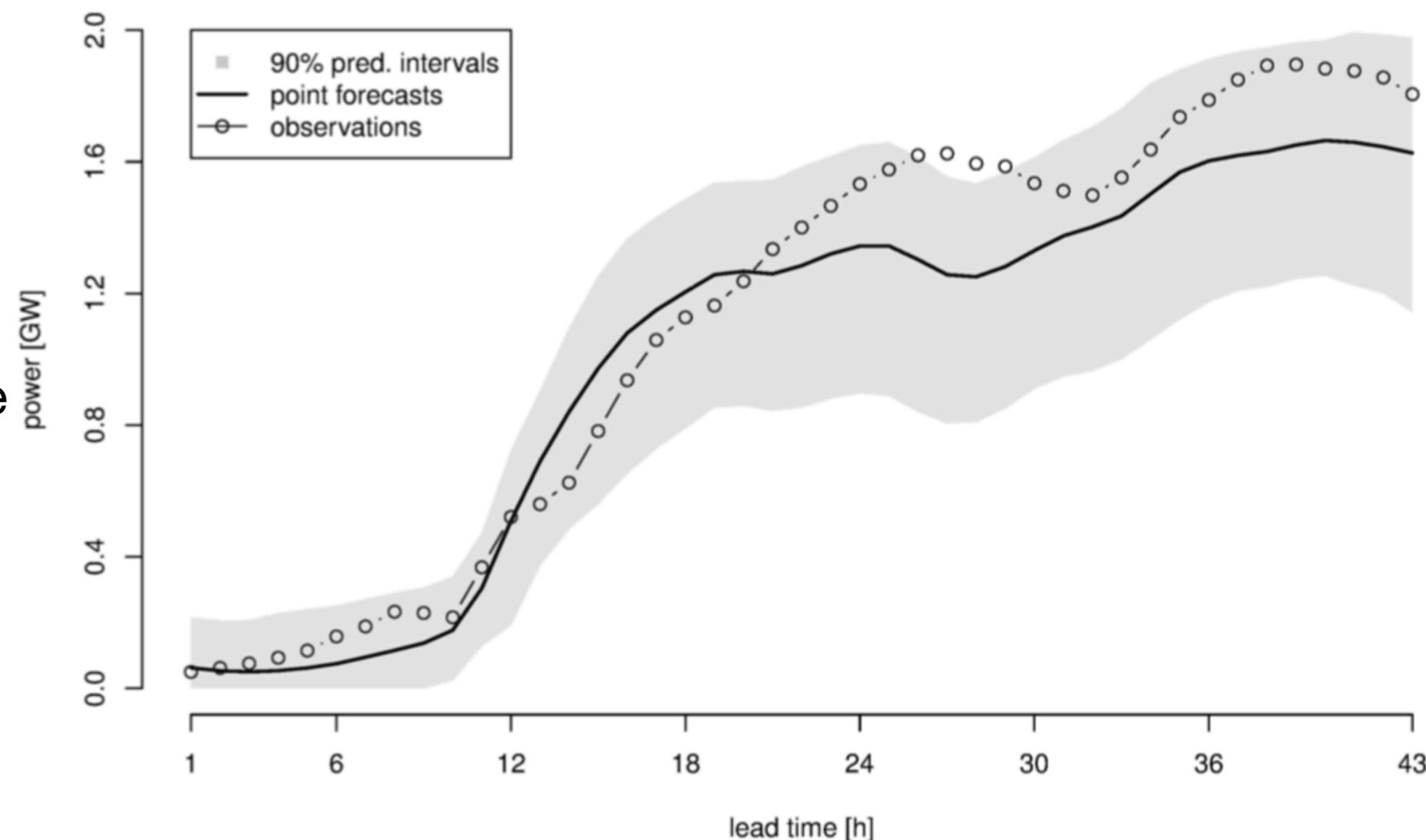
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A **prediction** interval is an **interval** within which power generation may lie, with a certain probability.

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

with:

- alpha the nominal coverage



# Introduction to probabilistic forecasting

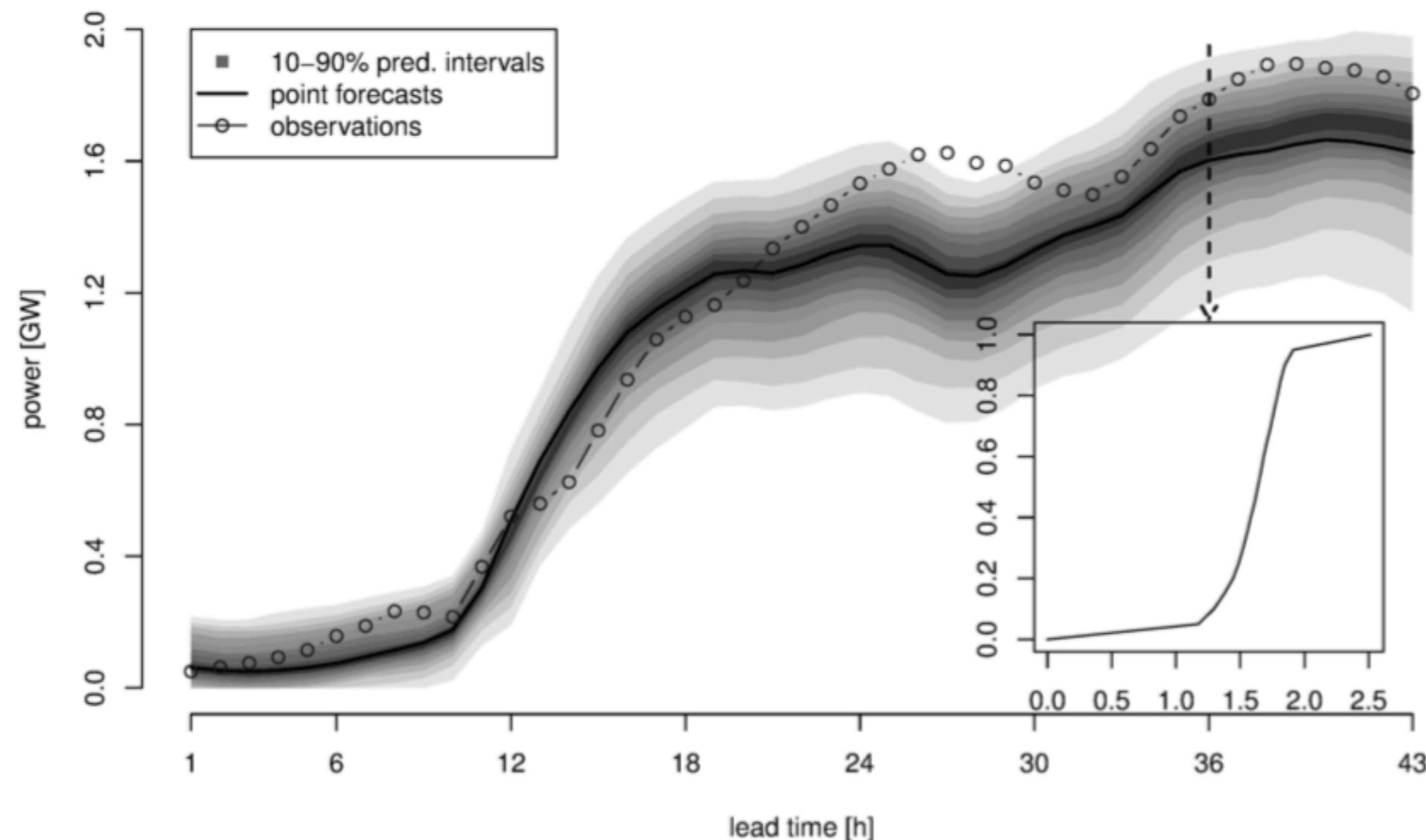
## Predictive density definition

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  $Y_{t+k}$



# Introduction to probabilistic forecasting

## Quiz

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What are scenarios?

# Introduction to probabilistic forecasting

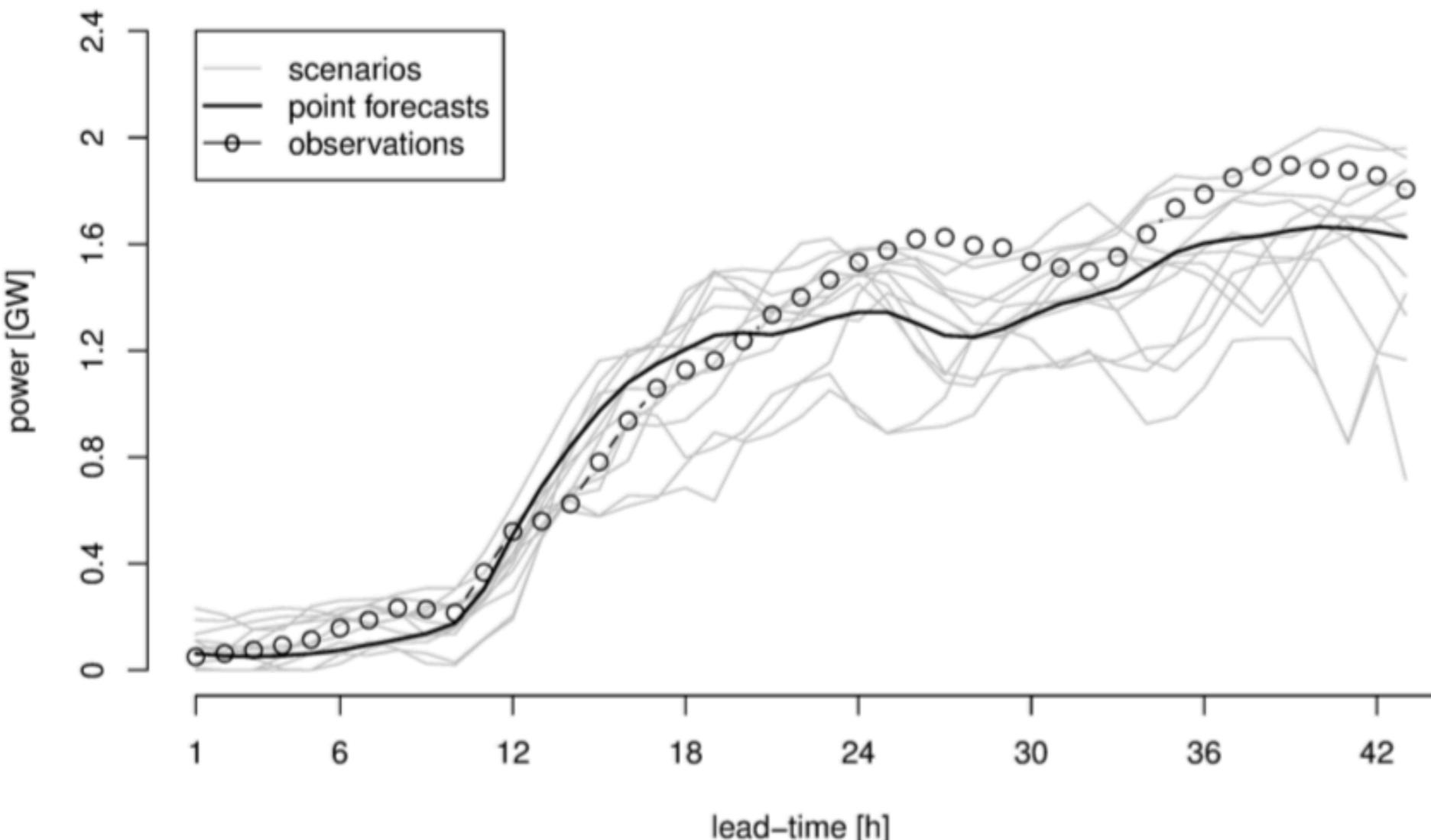
## Trajectories (scenarios) definition

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:

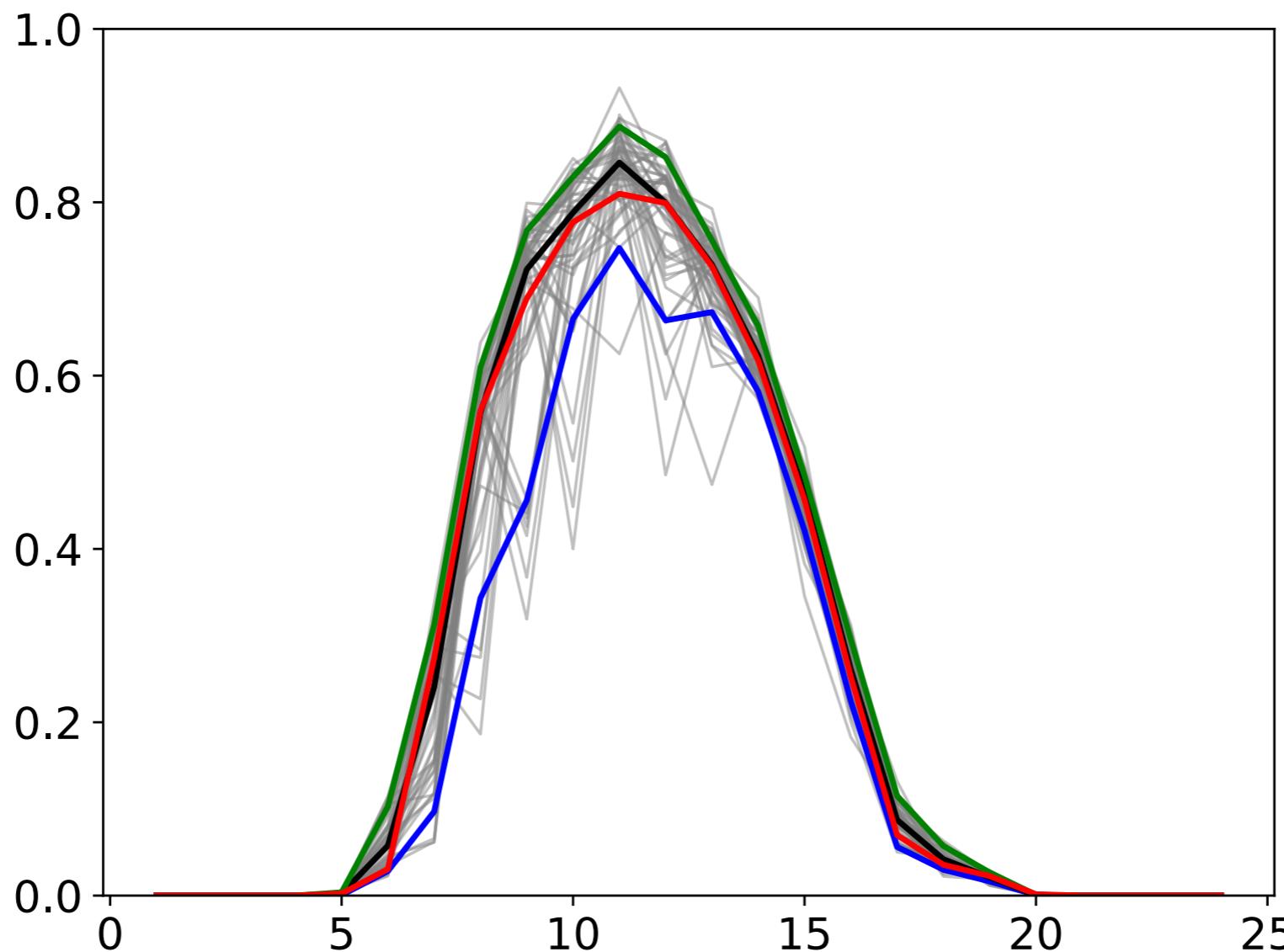
- $F$  the multivariate predictive cdf of  $Y_t$
- $z^j$  the  $j^{\text{th}}$  trajectory



# Introduction to probabilistic forecasting

## PV scenarios using a Normalizing Flow

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### Reference:

Jonathan Dumas, Antoine Wehenkel, Damien Lanaspeze, Bertrand Cornélusse, and Antonio Sutera. A deep generative model for probabilistic energy forecasting in power systems: normalizing flows. *Applied Energy*, 305:117871, 2022. ISSN 0306-2619. doi: <https://doi.org/10.1016/j.apenergy.2021.117871>.

# Introduction to probabilistic forecasting

## Summary

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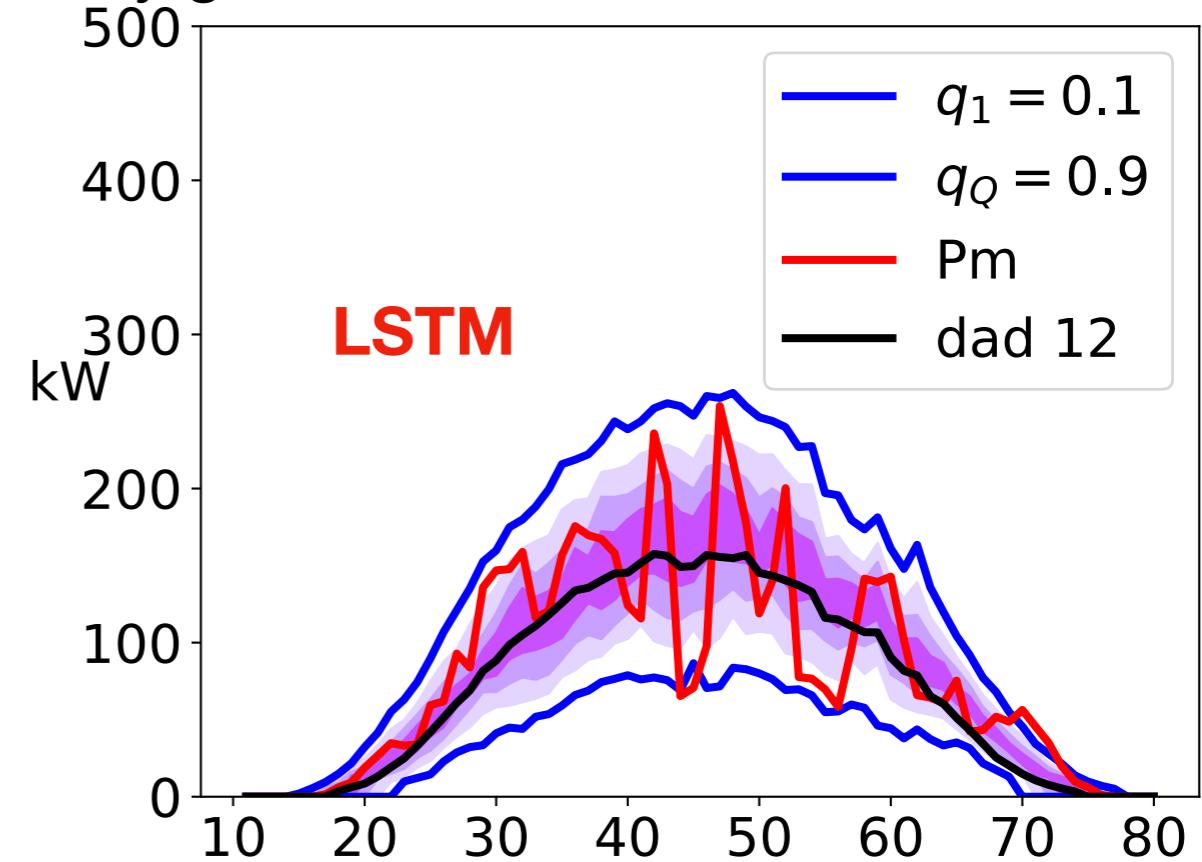
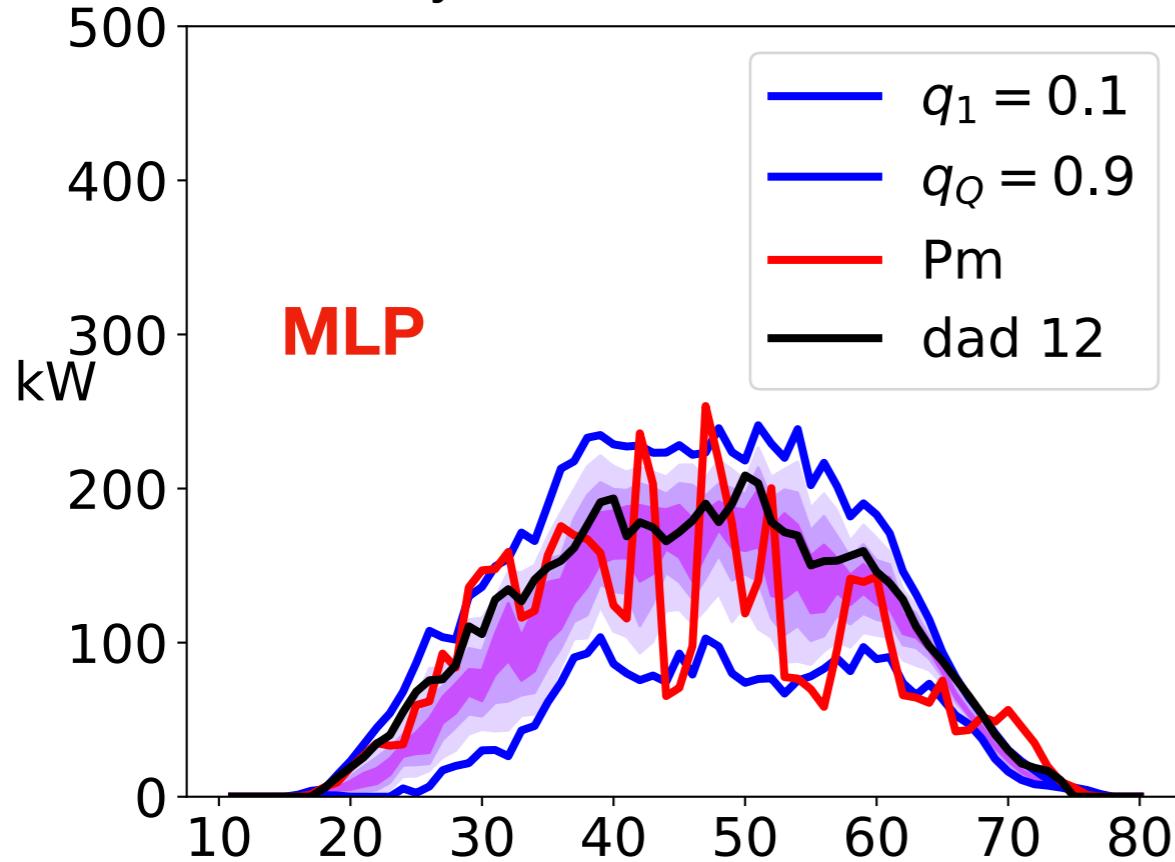
1. Reminder
2. Probabilistic forecasts
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# Introduction to probabilistic forecasting

## 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 1 August 2020 at noon for 2 August 2020.

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 probabilistic forecasting

## Quiz

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What is the difference between forecast quality and value?

# Introduction to probabilistic forecasting

## Forecast quality vs value

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For predictions in any form, one must differentiate between their quality and their value.

Forecast **quality** corresponds to the **ability** of the forecasts to genuinely inform of future events by **mimicking the characteristics of the processes involved**.

Forecast **value** relates, instead, to the **benefits from using forecasts in a decision-making process**, such as participation in the electricity market.

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

# Introduction to probabilistic forecasting

## Attribute of probabilistic forecast quality

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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)

# Introduction to probabilistic forecasting

## Quiz

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What is forecast calibration?

# Introduction to probabilistic forecasting

## Probabilistic calibration (reliability)

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**Calibration** is about respecting the probabilistic contract:

- **quantile** forecast with a nominal level  $q = 0.5$ , one expect that the observations are to be less than the forecast 50% of the time;
- **prediction** interval with a nominal coverage of 90%, one expect that 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!

# Introduction to probabilistic forecasting

## Reliability diagrams

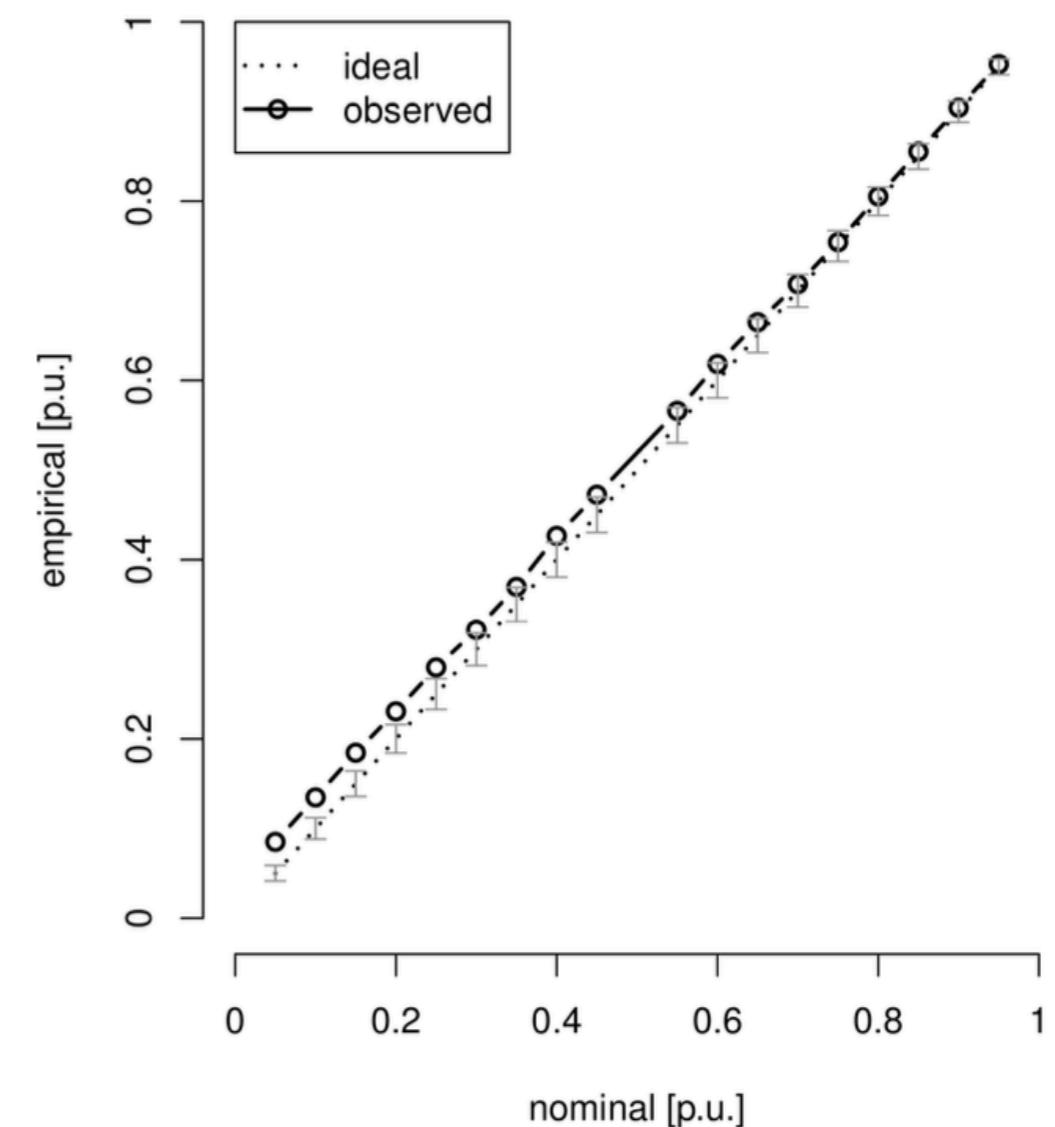
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The calibration assessment can be summarized in reliability diagrams.

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

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

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



# Introduction to probabilistic forecasting

## Quiz

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What is the sharpness?

# Introduction to probabilistic forecasting

## Sharpness

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

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

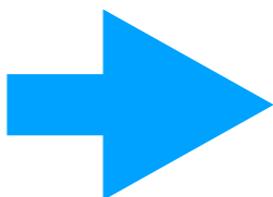
Consequently, a sharpness assessment boils down to **evaluating how tight the predictive densities are ...**

For a given interval forecast

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

The width is

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



Average over the validation set

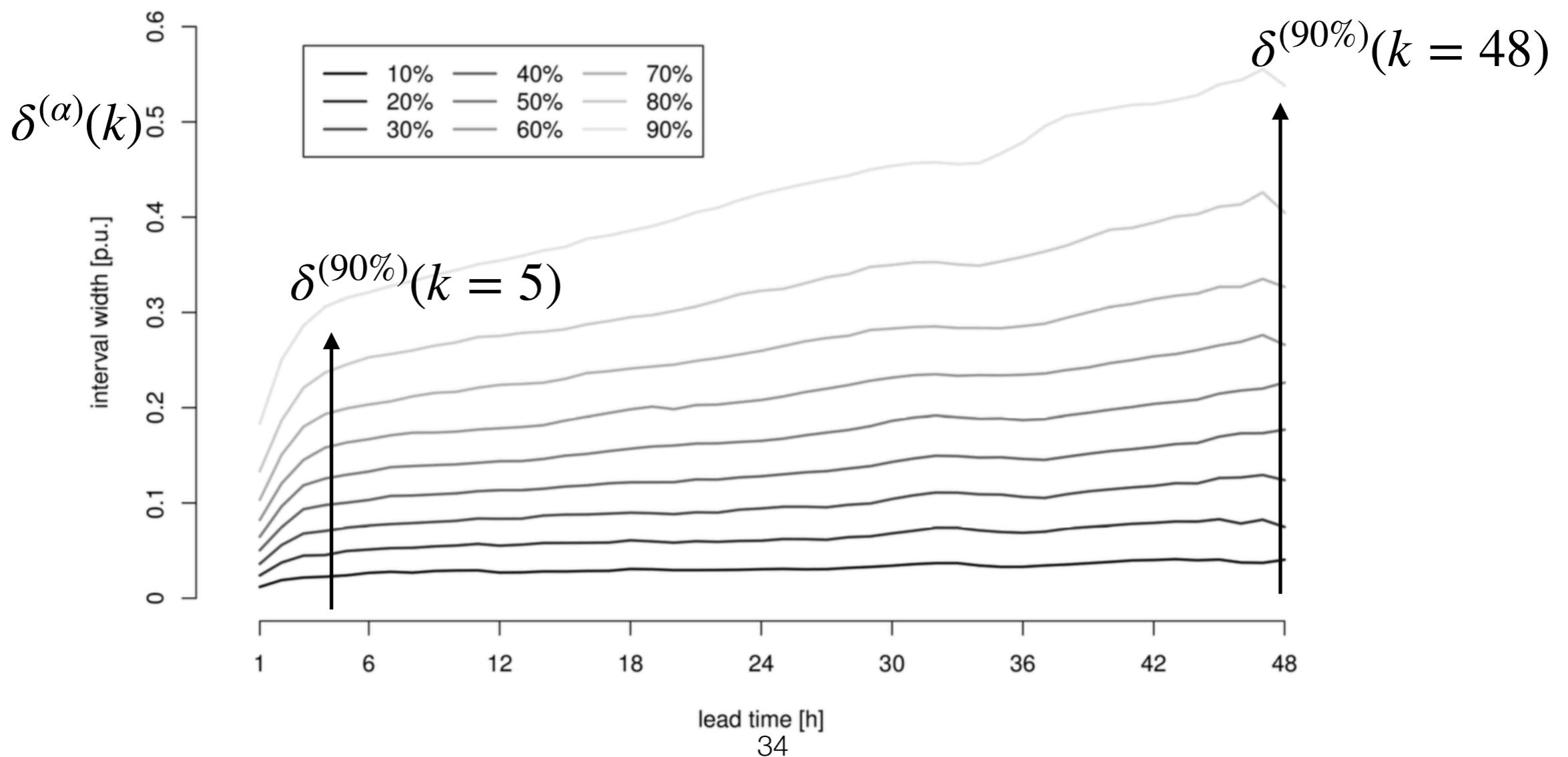
$$\delta^{(\alpha)}(k) = \frac{1}{T} \sum_{t=1}^T \delta_{t,k}^{(\alpha)}$$

# Introduction to probabilistic forecasting

## Sharpness

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

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



# Introduction to probabilistic forecasting

## Quiz

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Do you know probabilistic forecasts metrics?

# Introduction to probabilistic forecasting

## Univariate skill score

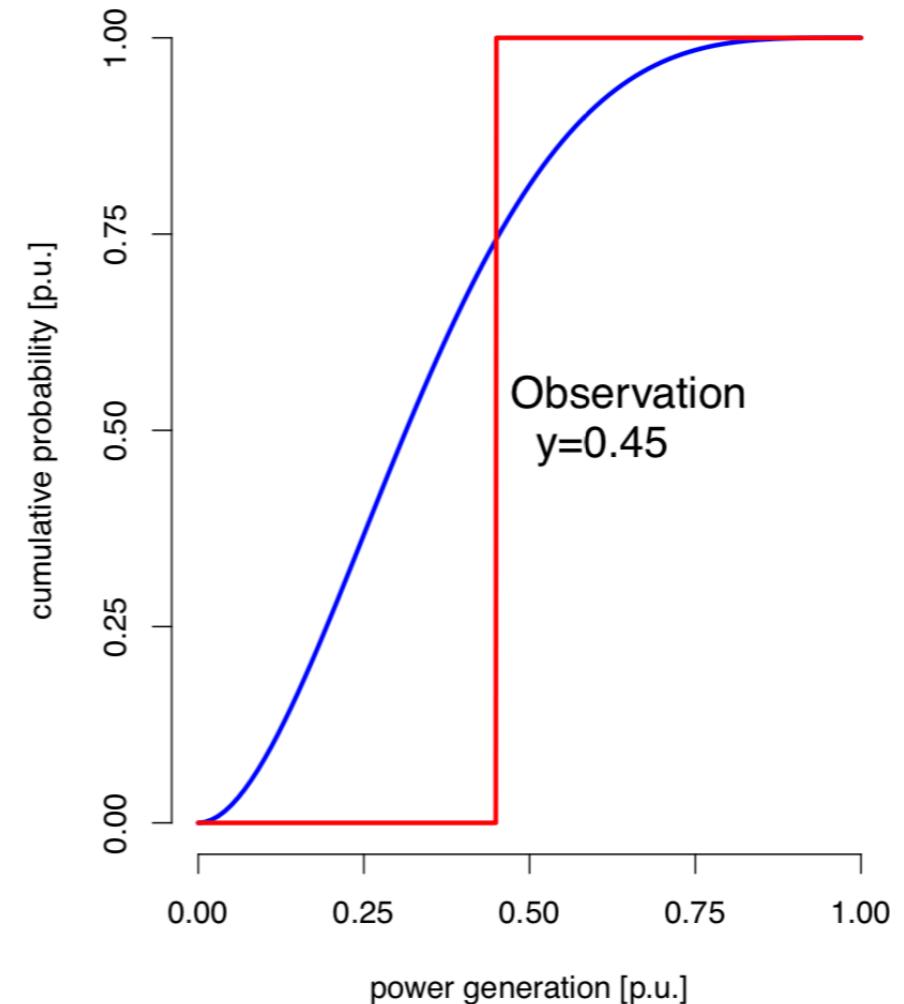
The skill of probabilistic forecasts can be assessed by scores, like MAE and RMSE for the deterministic forecasts.

The most common skill score for predictive densities is the **Continuous Ranked Probability Score (CRPS)** [1].

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

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

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

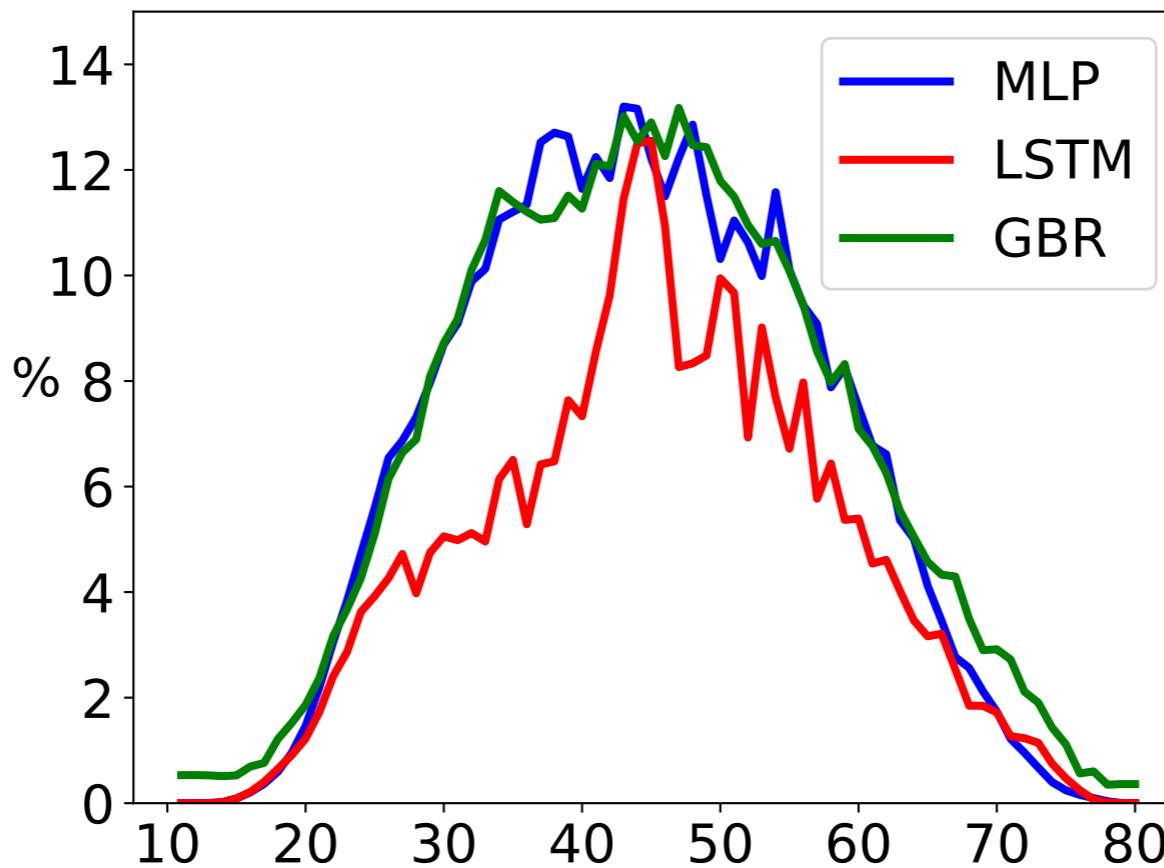


[1] Gneiting, Tilmann, and Adrian E. Raftery. "Strictly proper scoring rules, prediction, and estimation." *Journal of the American statistical Association* 102.477 (2007): 359-378.

# Introduction to probabilistic forecasting

## CRPS example

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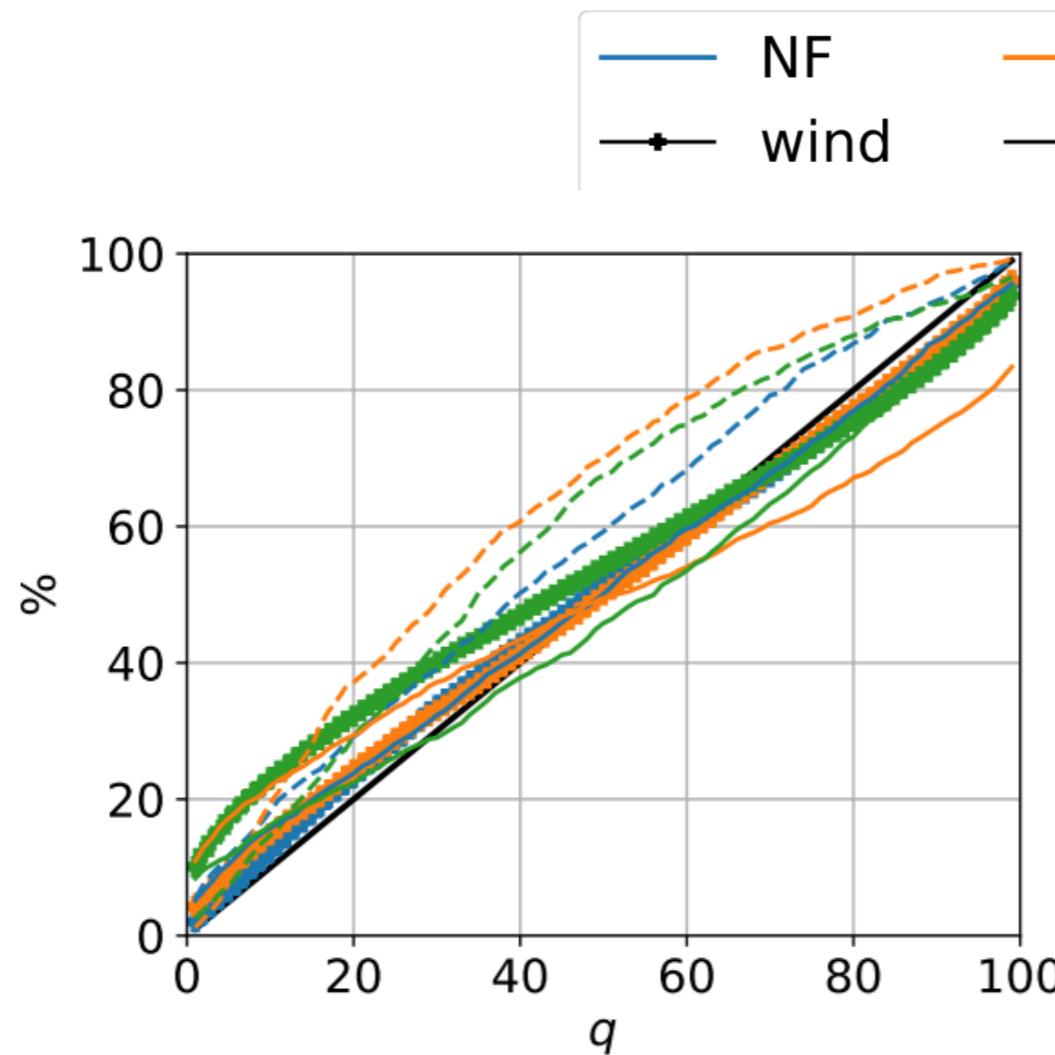


**CRPS** per lead time (univariate score), from 11-cross validation, of three forecasting models for PV quantile forecasts.

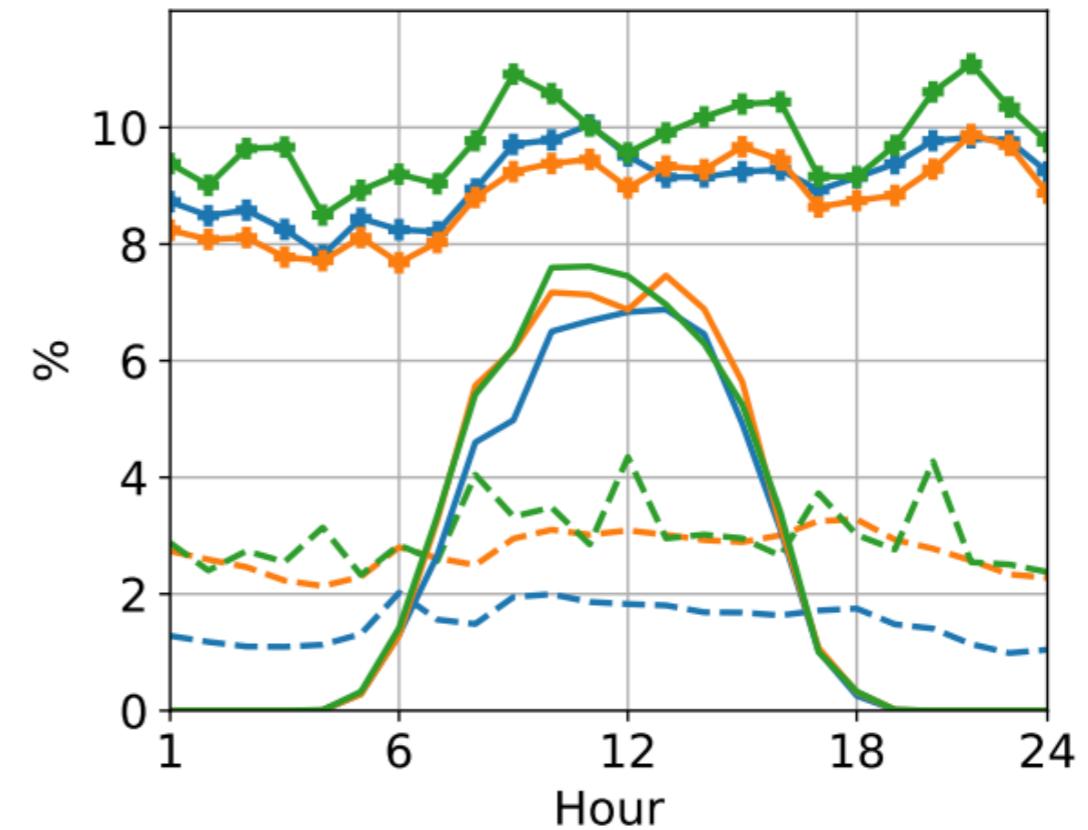
*J. Dumas, C. Cointe, X. Fettweis and B. Cornélusse, "Deep learning-based multi-output quantile forecasting of PV generation," 2021 IEEE Madrid PowerTech, 2021, pp. 1-6, doi: 10.1109/PowerTech46648.2021.9494976. <https://arxiv.org/abs/2106.01271>*

# Introduction to probabilistic forecasting

## CRPS and reliability examples



**Reliability diagram**



**CRPS**

### Reference:

Jonathan Dumas, Antoine Wehenkel, Damien Lanaspeze, Bertrand Cornélusse, and Antonio Sutera. A deep generative model for probabilistic energy forecasting in power systems: normalizing flows. *Applied Energy*, 305:117871, 2022. ISSN 0306-2619. doi: <https://doi.org/10.1016/j.apenergy.2021.117871>.

# Introduction to probabilistic forecasting

## Multivariate skill score

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The **energy score (ES)** is the most commonly used scoring rule when a finite number of **trajectories** represents distributions. It is a multivariate generalization of the CRPS and has been formulated and introduced by [1].

$$\text{ES} = \frac{1}{N} \sum_{t=1}^M \left[ \frac{1}{M} \sum_{i=1}^M \|\hat{\mathbf{x}}_t^i - \mathbf{x}_t\| - \frac{1}{2M^2} \sum_{i,j=1}^M \|\hat{\mathbf{x}}_t^i - \hat{\mathbf{x}}_t^j\| \right].$$

ES -> provides a single value for all the time periods (multivariate score).

[1] Gneiting, Tilman, and Adrian E. Raftery. "Strictly proper scoring rules, prediction, and estimation." *Journal of the American statistical Association* 102.477 (2007): 359-378.

# Introduction to probabilistic forecasting

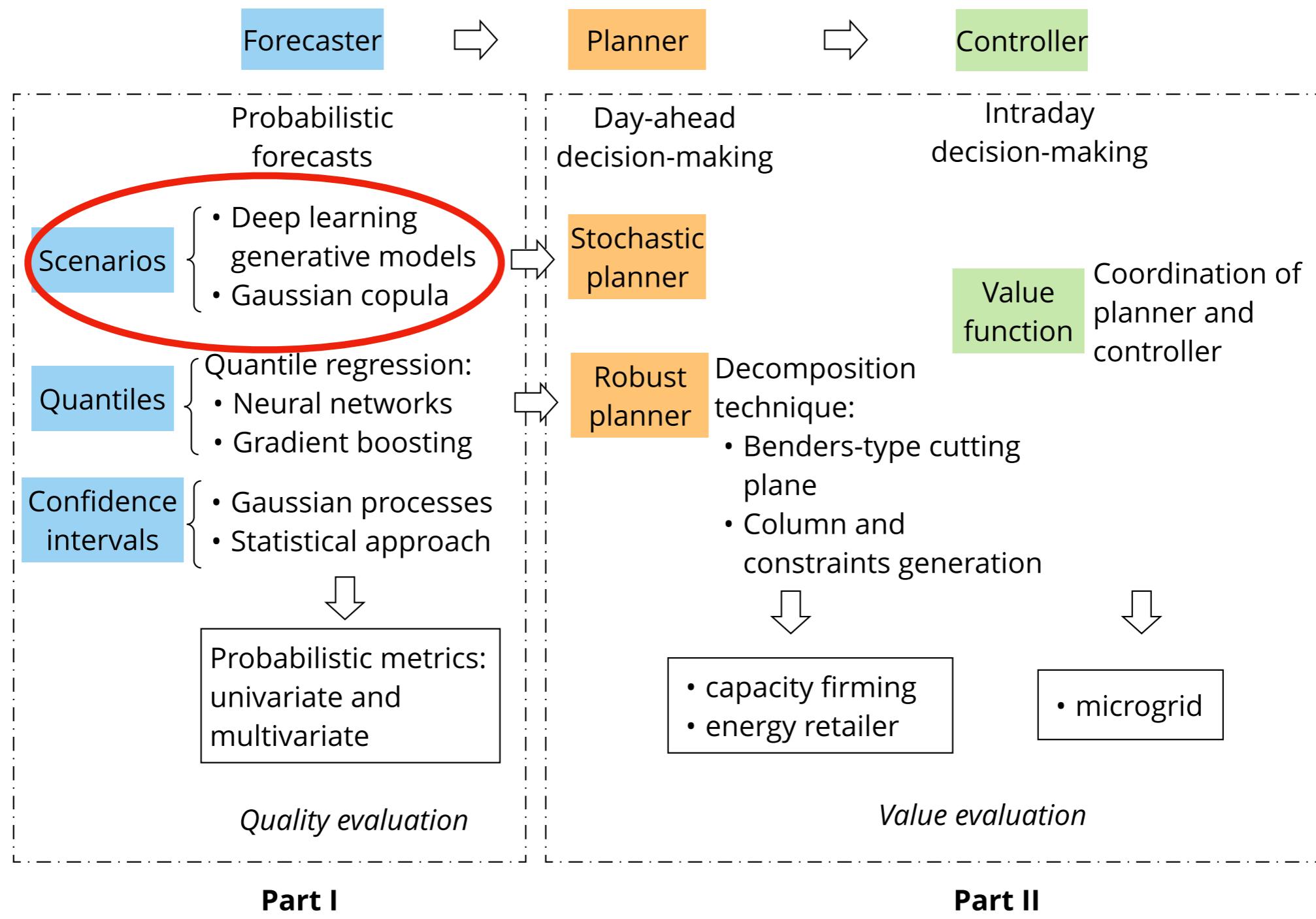
## Summary

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1. Reminder
2. Probabilistic forecasts
3. Verification of probabilistic forecasts
4. Case study: probabilistic forecasting using normalizing flows

# Introduction to probabilistic forecasting

## Thesis skeleton



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

# **Introduction to probabilistic forecasting**

## **Case study summary**

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**Introduction**

**Background**

**Value & quality assessment**

**Numerical results**

**Conclusions**

# Introduction to probabilistic forecasting

## Overview

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A recent deep learning technique: **normalizing flows (NFs)**.

**Comparison with generative adversarial networks and variational autoencoders.**

Implementation of **conditional generative models** using weather forecasts.

NFs are **more accurate in quality and value**.

Study published:

*Jonathan Dumas, Antoine Wehenkel, Damien Lanaspeze, Bertrand Cornélusse, and Antonio Sutera. A deep generative model for probabilistic energy forecasting in power systems: normalizing flows. Applied Energy, 305:117871, 2022. ISSN 0306-2619. doi: <https://doi.org/10.1016/j.apenergy.2021.117871>.*

<https://github.com/jonathandumas/generative-models>

# Introduction to probabilistic forecasting

## Research gaps

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Only [1] compared NFs to GANs and VAEs for the generation of daily load profiles.

Most of the studies that propose or compare forecasting techniques **only consider the forecast quality**.

The **conditional versions** of the models are not always addressed.

[1] Ge, Leijiao, et al. "Modeling daily load profiles of distribution network for scenario generation using flow-based generative network." *IEEE Access* 8 (2020): 77587-77597.

# Introduction to probabilistic forecasting

## Framework of the study

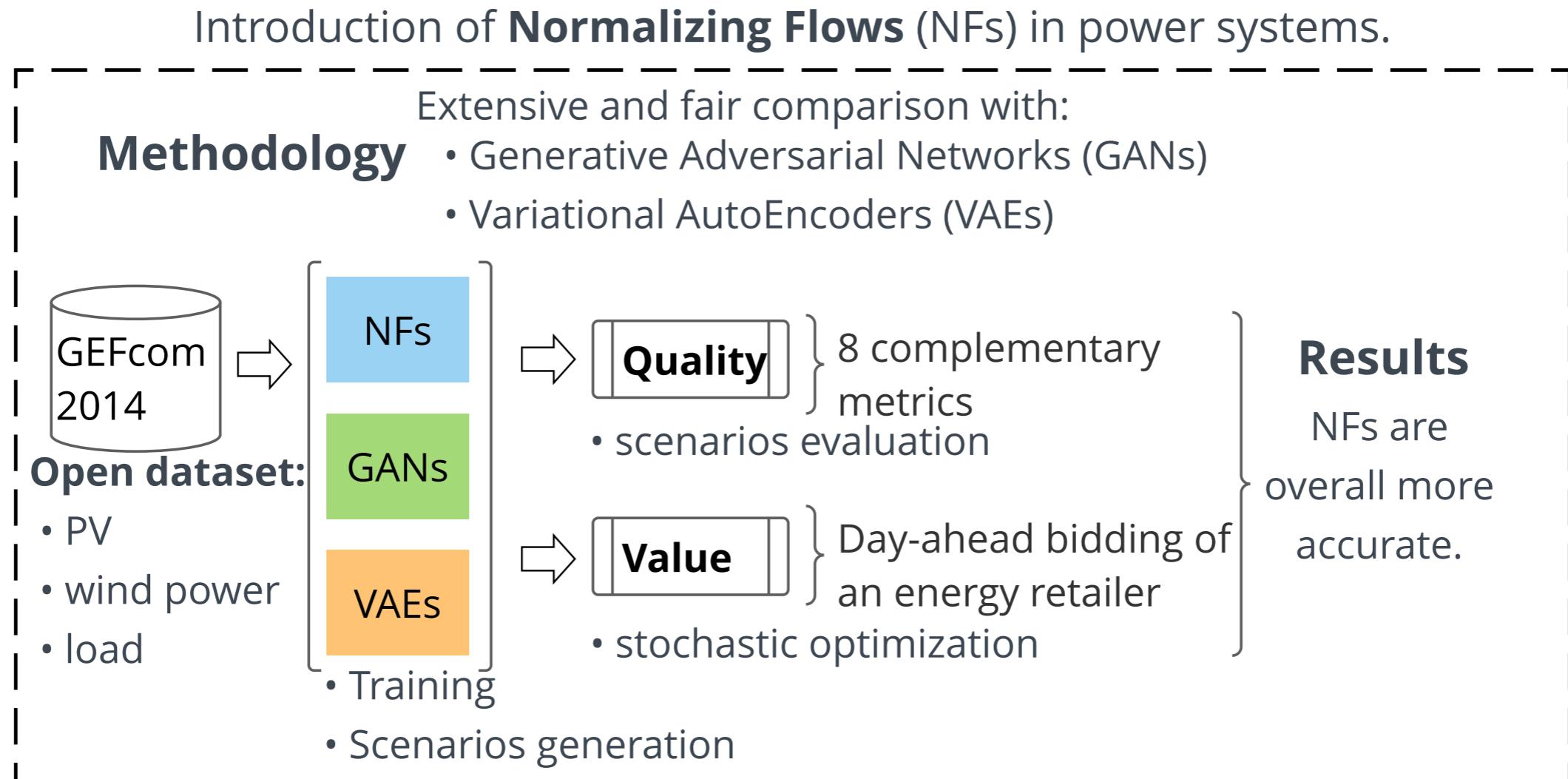


Figure I-1: The framework of the study.

# Introduction to probabilistic forecasting

## Framework of the study

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Criteria	[1]	[2]	[3]	study
GAN	✓	✗	✓	✓
VAE	✗	✓	✓	✓
NF	✗	✗	✓	✓
Number of models	4	1	3	3
PV	✗	✓	✗	✓
Wind power	✗	✓	✗	✓
Load	✓	~	✓	✓
Weather-based	✓	✗	✗	✓
Quality assessment	✓	✓	✓	✓
Quality metrics	5	3	5	8
Value assessment	✗	✓	✗	✓
Open dataset	~	✗	✓	✓
Value replicability	-	~	-	✓
Open-access code	✗	✗	✗	✓

Table I-1: Comparison of the study's contributions to three state-of-the-art studies using deep generative models.

# Introduction to probabilistic forecasting

## Applicability of the models

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1. The **forecasting module** of an energy management system (EMS).
2. **Stochastic unit commitment** models that employ scenarios to model the uncertainty of weather-dependent renewables.
3. **Ancillary services** market participation.
4. Compute **scenarios for any variable of interest**, e.g., energy prices, renewable generation, loads, water inflow of hydro reservoirs.
5. **Quantiles** can be derived from scenarios and used in **robust optimization**.

# Introduction to probabilistic forecasting

## Normalizing flows

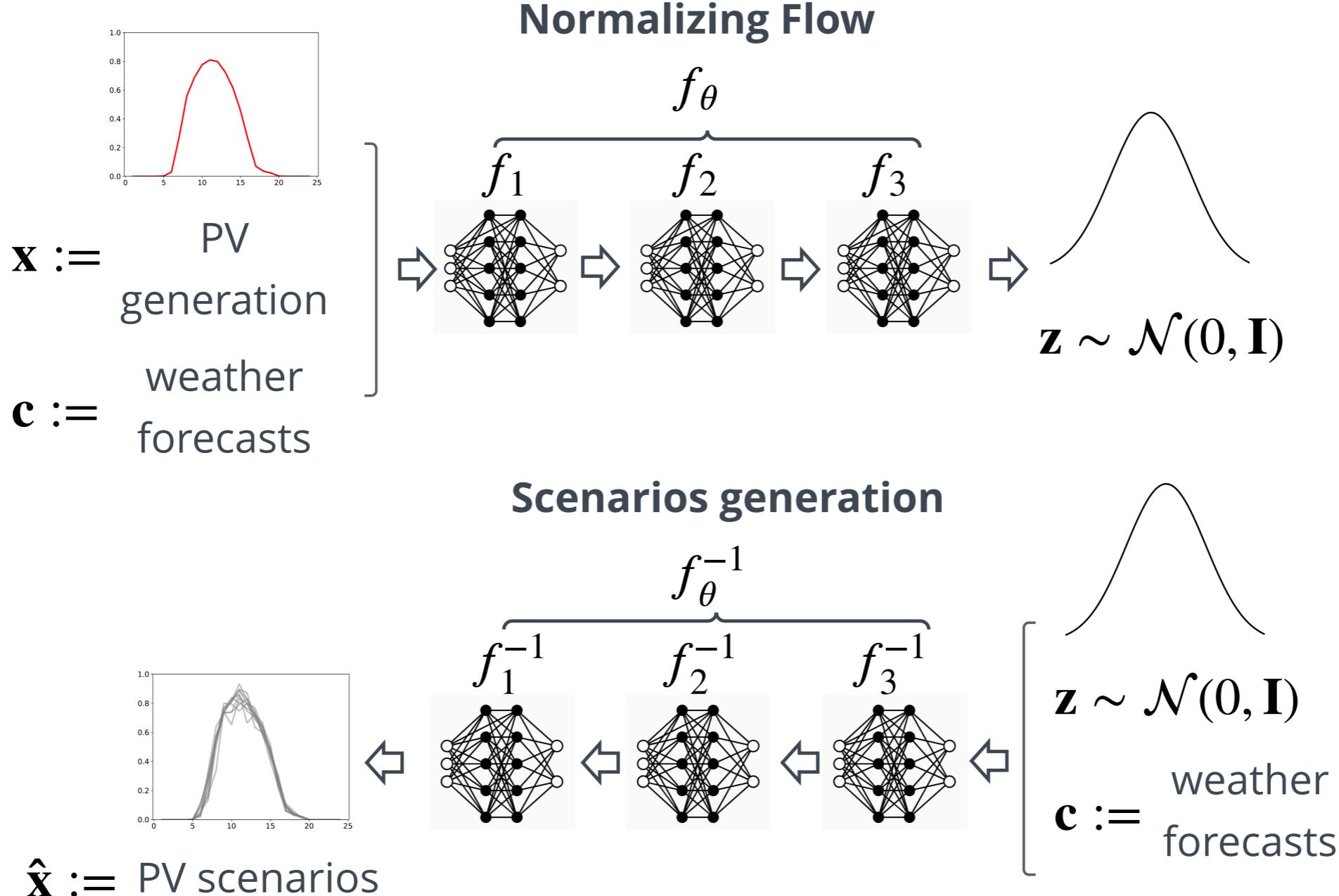


Figure I-2: A three-step conditional normalizing flows for PV generation.

# Introduction to probabilistic forecasting

## Variational auto encoders

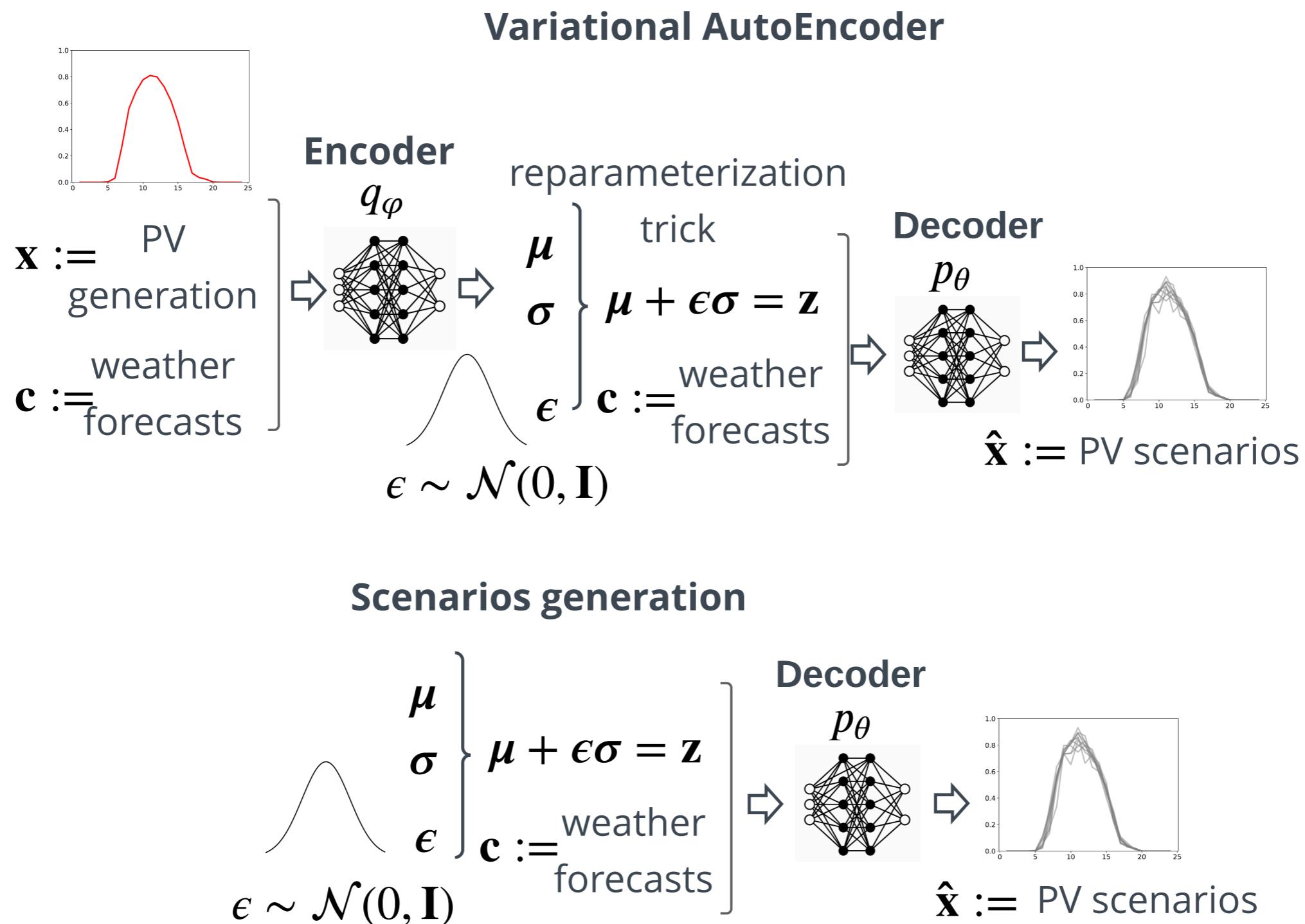
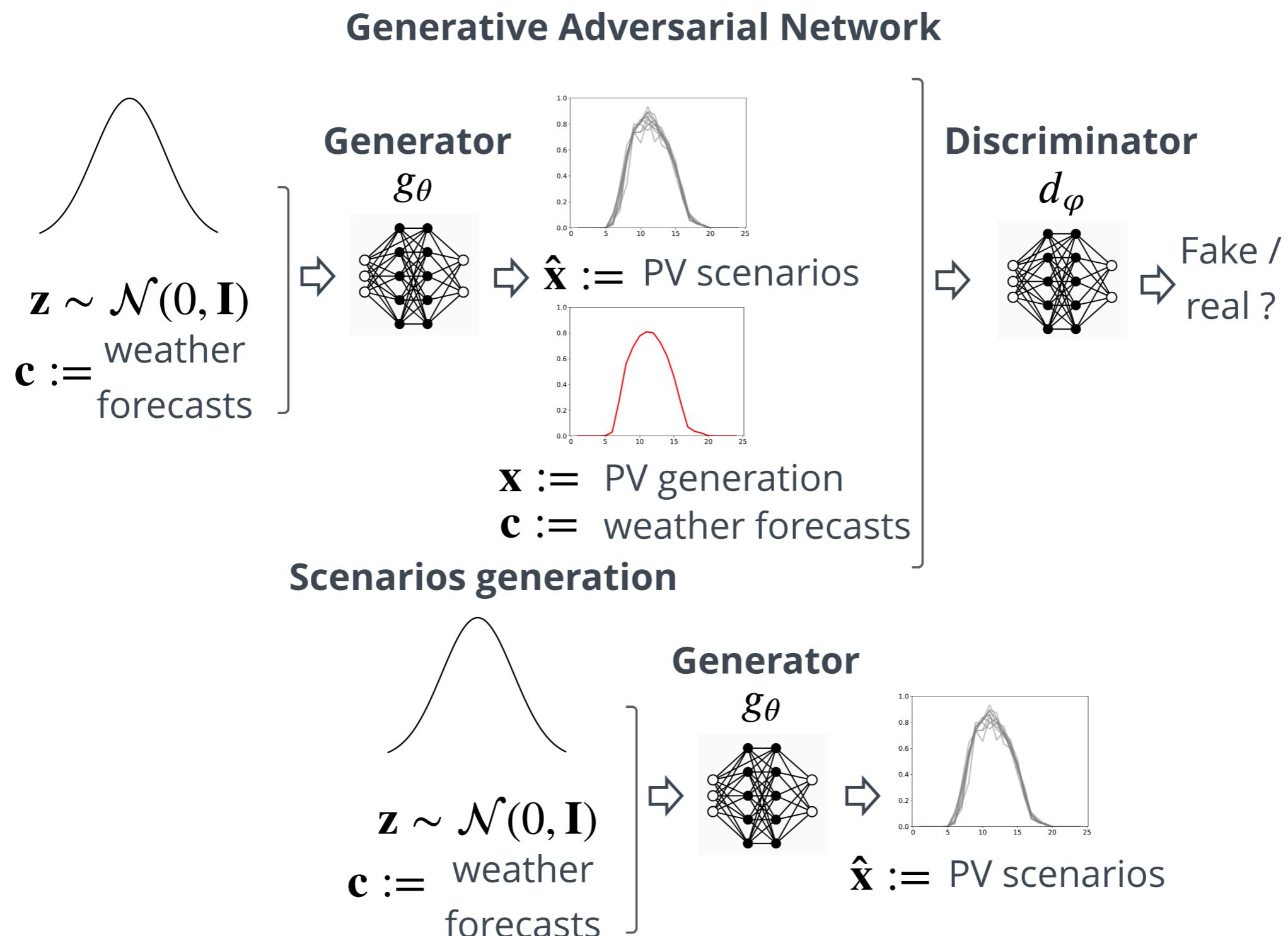


Figure I-3: A conditional variational autoencoder for PV generation.

# Introduction to probabilistic forecasting

## Generative adversarial networks



# Introduction to probabilistic forecasting

## Comparison of the models

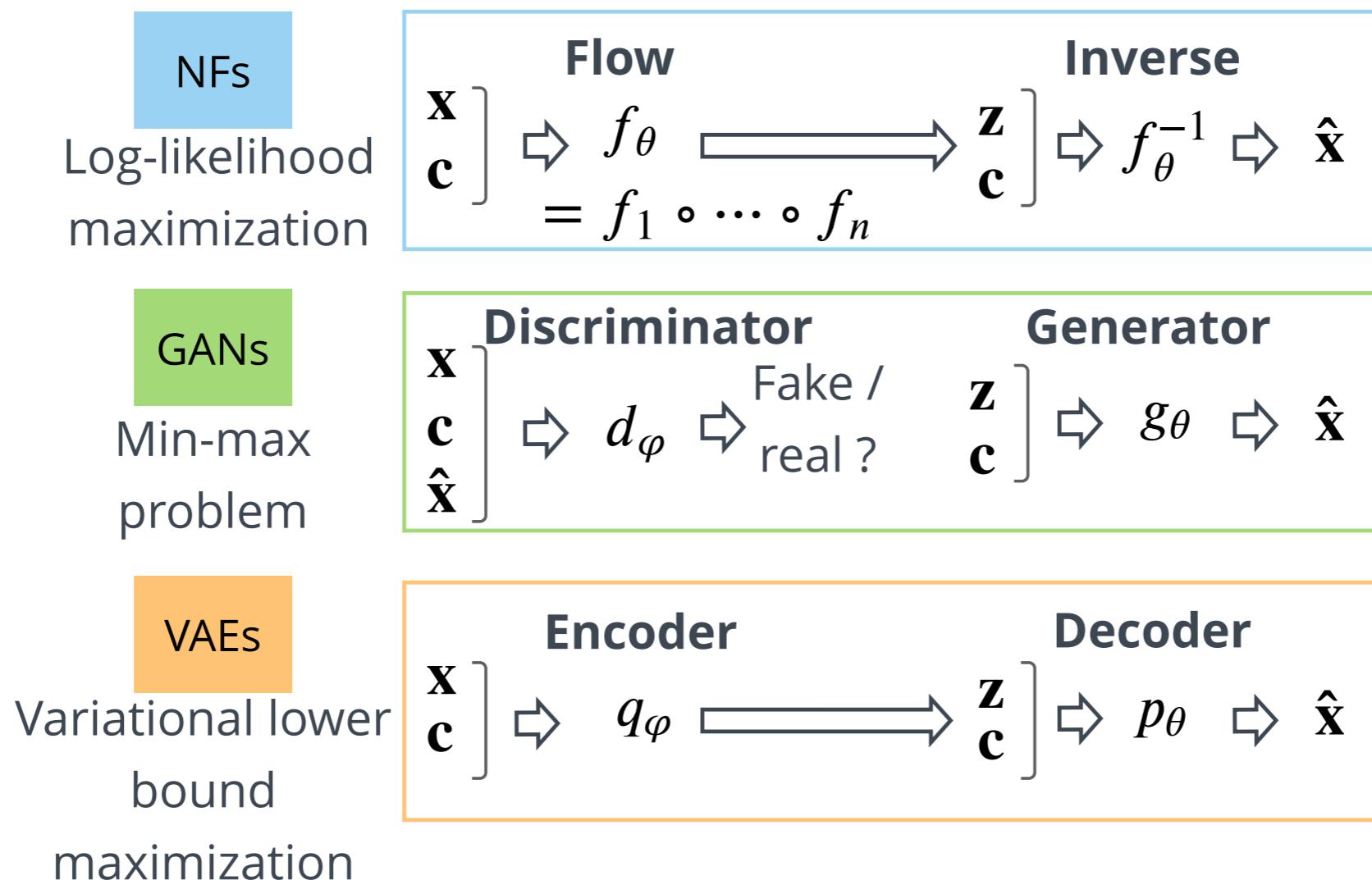


Figure I-4: High level comparison of the three models.

# Introduction to probabilistic forecasting

## Forecast quality vs. value

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Forecast **quality**: ability of the forecasts to genuinely inform of future events by mimicking the characteristics of the processes involved.

Forecast **value**: benefits from using forecasts in a decision-making process.

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

# Introduction to probabilistic forecasting

## Forecast quality: metrics

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### **Univariate** metrics:

- Continuous Ranked Probability Score (CRPS)
- Quantile Score (QS)
- Reliability diagrams

### **Multivariate** metrics:

- Energy Score (ES)
- Variogram Score (VS)

### **Specific** metrics:

- Classifier based
- Correlation between scenarios

### **Statistical** metric :

- Diebold and Mariano test

# Introduction to probabilistic forecasting

## Forecast value: energy retailer

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Day-ahead scheduling of an **energy retailer** portfolio composed of:

- **wind** power generation;
- **PV** generation;
- electrical **consumption**;
- A battery energy storage system (**BESS**).

Goal: **balance** the portfolio on an **hourly basis** to avoid financial penalties in case of imbalance by exchanging the surplus or deficit of energy in the **day-ahead electricity market**.

A **stochastic** planner with a **linear programming** formulation and linear constraints is implemented using a **scenario-based** approach.

# Introduction to probabilistic forecasting

## Methodology

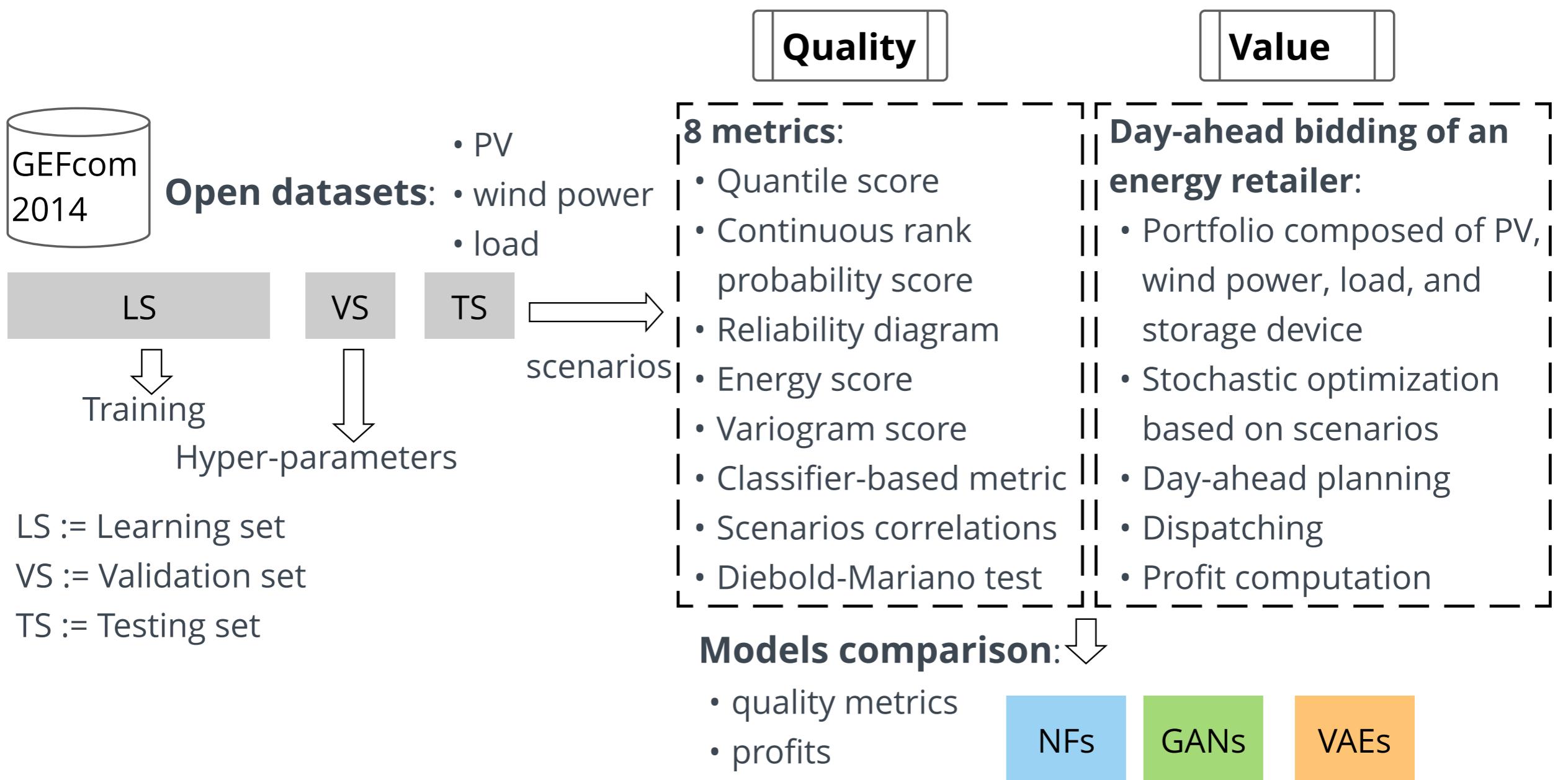


Figure I-5: Methodology.

# Introduction to probabilistic forecasting

## Implementation details

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	Wind	PV	Load
$T$ periods	24	16	24
$n_z$ zones	10	3	–
$n_f$ features	10	5	25
$c_d$ dimension	$n_f \cdot T + n_z$	$n_f \cdot T + n_z$	$n_f \cdot T$
# LS (days)	$631 \cdot n_z$	$720 \cdot n_z$	1999
# VS/TS (days)	$50 \cdot n_z$	$50 \cdot n_z$	50

Table I-2: Dataset and implementation details.

# Introduction to probabilistic forecasting

## Quality results: wind power scenarios

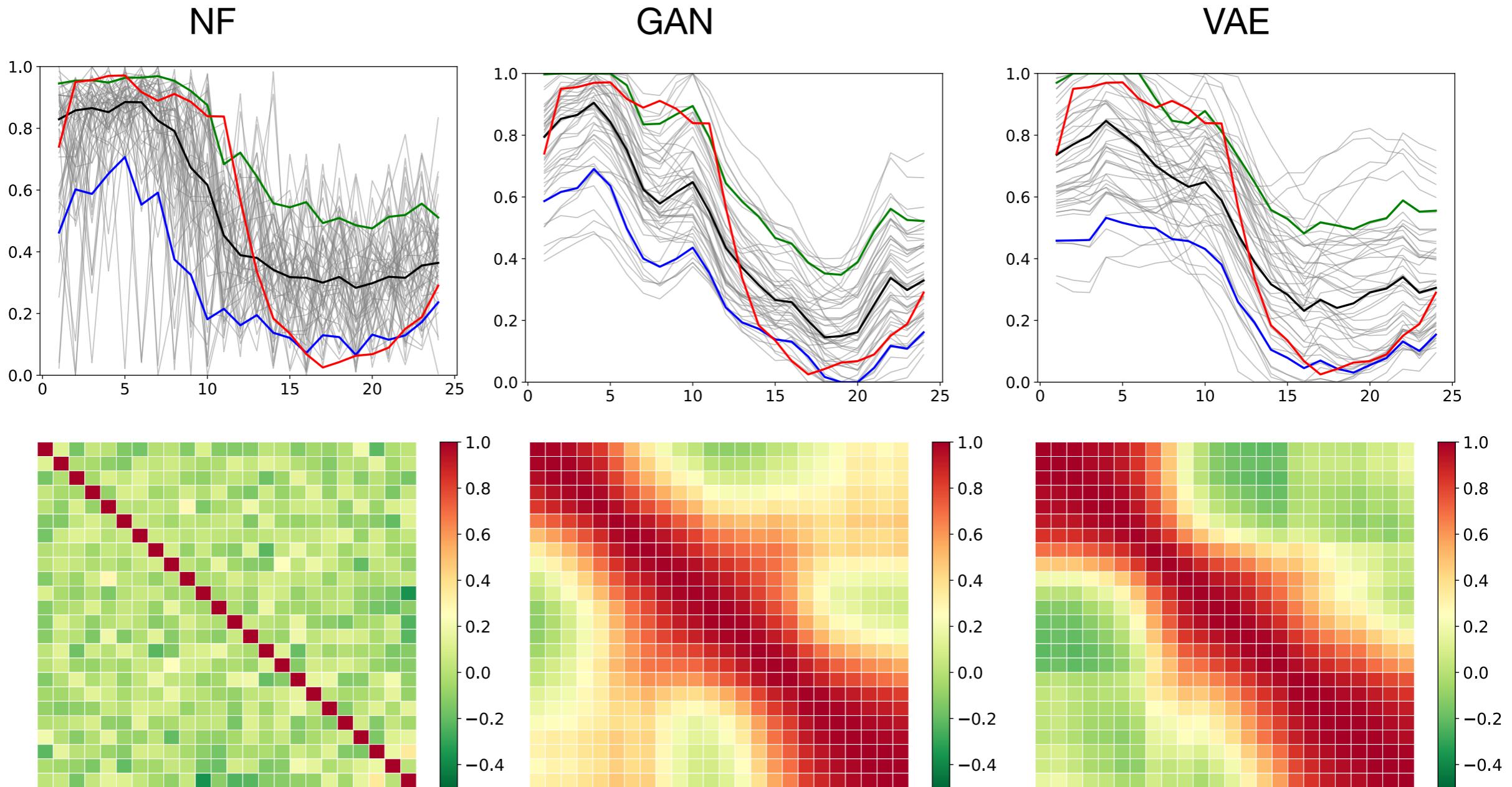


Figure I-6: Wind power scenarios shape comparison and analysis.

# Introduction to probabilistic forecasting

## Quality results: PV scenarios

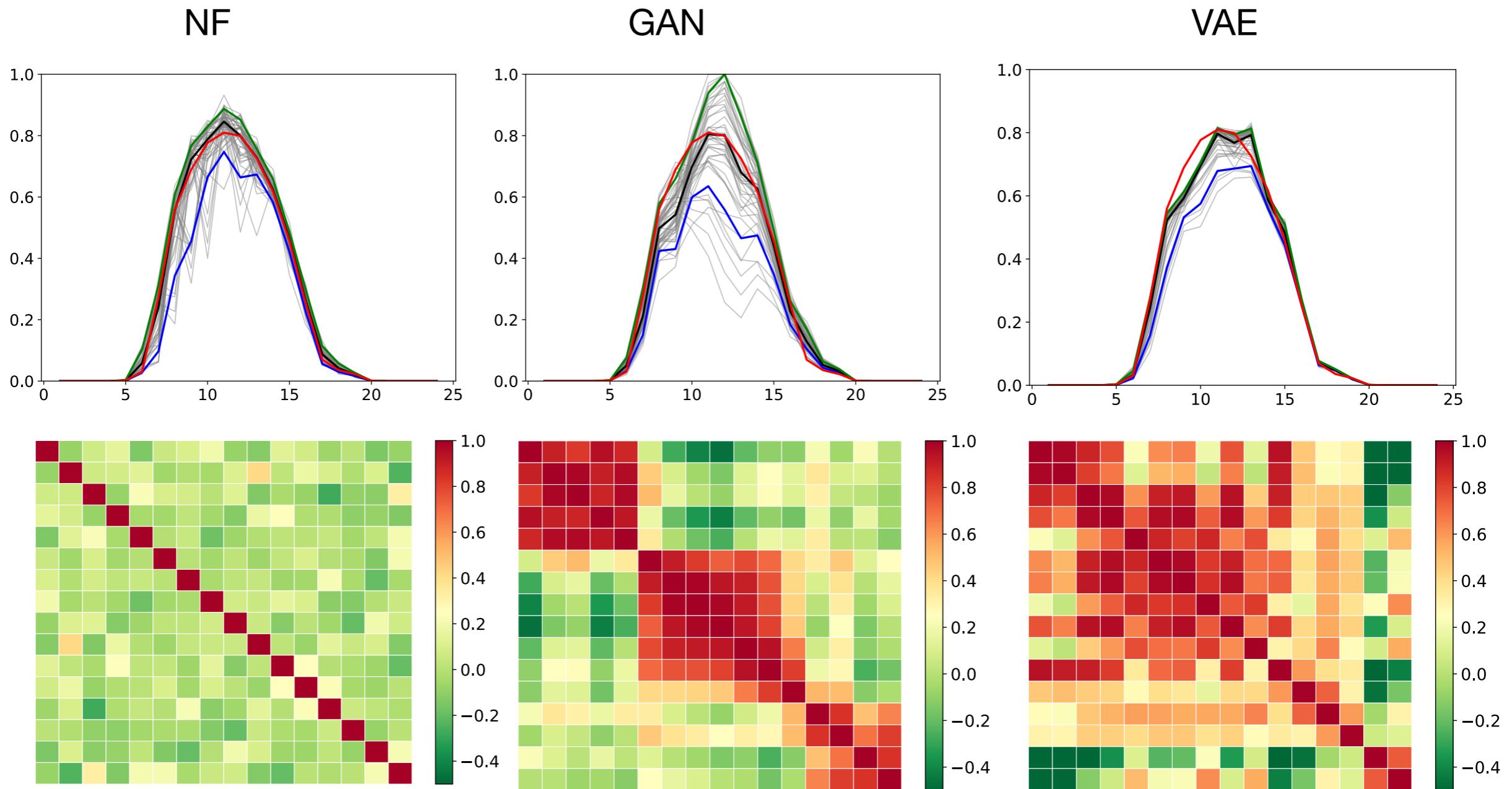


Figure I-7: PV scenarios shape comparison and analysis.

# Introduction to probabilistic forecasting

## Quality results: load scenarios

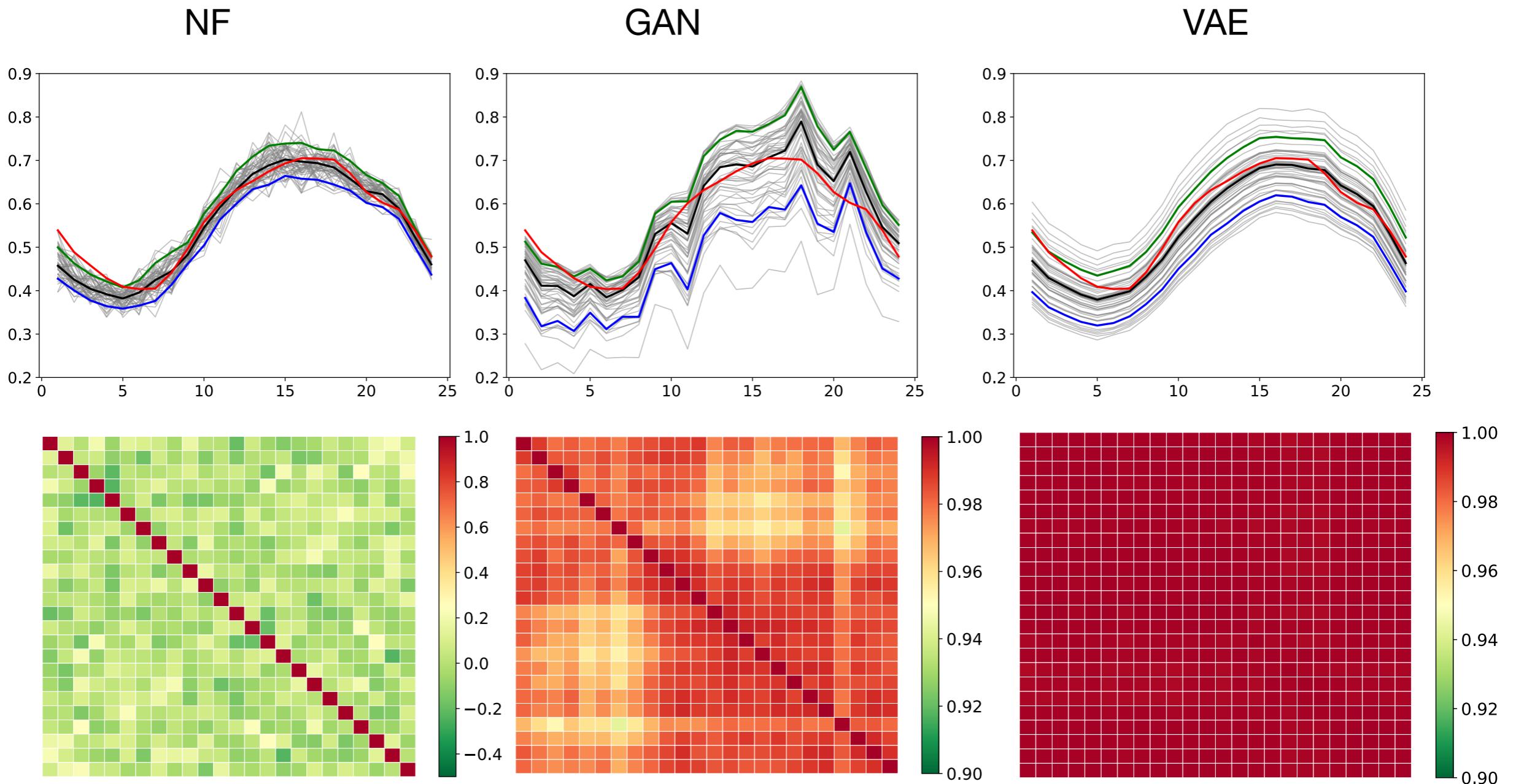


Figure I-8: Load scenarios shape comparison and analysis.

# Introduction to probabilistic forecasting

## Quality results: averaged scores

		NF	VAE	GAN	RAND
Wind	CRPS	9.07	<b>8.80</b>	9.79	16.92
	<u>QS</u>	4.58	<b>4.45</b>	4.95	8.55
	MAE-r	2.83	<b>2.67</b>	6.82	1.01
	AUC	0.935	<b>0.877</b>	0.972	0.918
	ES	56.71	<b>54.82</b>	60.52	96.15
	VS	18.54	<b>17.87</b>	19.87	23.21
PV	CRPS	<b>2.35</b>	2.60	2.61	4.92
	<u>QS</u>	<b>1.19</b>	1.31	1.32	2.48
	MAE-r	<b>2.66</b>	9.04	4.94	3.94
	AUC	<b>0.950</b>	0.969	0.997	0.947
	ES	<b>23.08</b>	24.65	24.15	41.53
	VS	<b>4.68</b>	5.02	4.88	13.40
Load	CRPS	<b>1.51</b>	2.74	3.01	6.74
	<u>QS</u>	<b>0.76</b>	1.39	1.52	3.40
	MAE-r	<b>7.70</b>	13.97	9.99	0.88
	AUC	<b>0.823</b>	0.847	0.999	0.944
	ES	<b>9.17</b>	15.11	17.96	38.08
	VS	<b>1.63</b>	1.66	3.81	7.28

Table I-2: Averaged quality score per dataset.

# Introduction to probabilistic forecasting

## Value results: methodology

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**Portfolio:** wind power (10 zones), PV generation (3 zones), load (1 zone), and a battery energy storage device.

**1500** independent simulated days = 50 days of testing \* 30 combinations of PV & wind generation zones.

A two-step approach:

- (1) the stochastic planner computes the **day-ahead bids** for each generative model and the 1500 days simulated;
- (2) a **real-time dispatch** is carried out using the observations, with the day-ahead decisions as parameters.

# Introduction to probabilistic forecasting

## Value results: data illustration

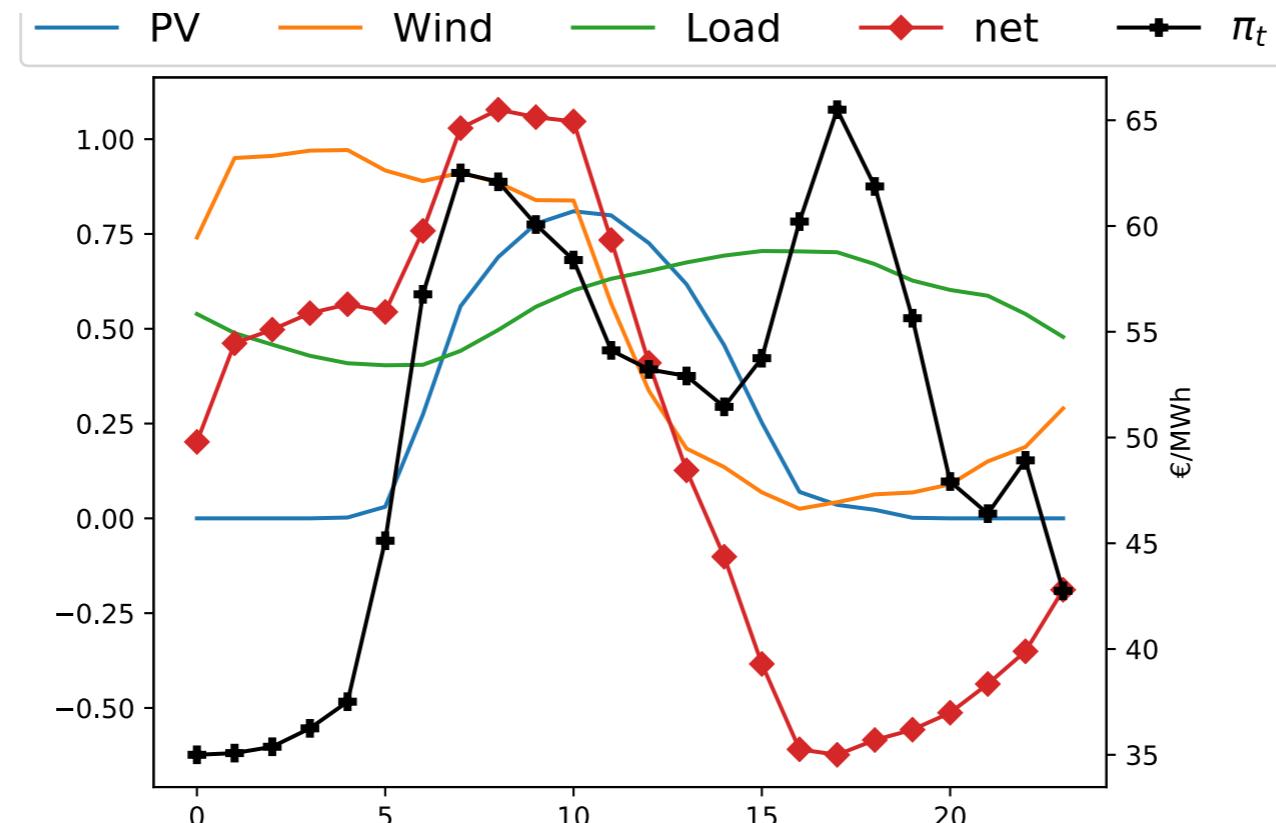


Figure I-9: Illustration of the observations on a random day of the testing set.

# Introduction to probabilistic forecasting

## Value results: profits comparison

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Net profit = profit - penalty.

Computed for the **1500 days** of the simulation and aggregated.

	NF	VAE	GAN
Net profit (k€)	<b>107</b>	97	93
1 (%)	<b>39.0</b>	31.8	29.2
1 & 2 (%)	<b>69.6</b>	68.3	62.1
1 & 2 & 3 (%)	100	100	100

Table I-3: Total net profit (k€) and cumulative ranking (%).

# Introduction to probabilistic forecasting

## Results: summary

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Criteria	VAE	GAN	NF
Train speed	★★★	★★★	★★★
Sample speed	★★★	★★★	★★★
Quality	★★★	★★★	★★★
Value	★★★	★★★	★★★
Hp search	★★★	★★★	★★★
Hp sensibility	★★★	★★★	★★★
Implementation	★★★	★★★	★★★

Table I-4: Comparison between the generative models.

# Introduction to probabilistic forecasting

## Conclusions

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A fair and thorough comparison (**quality** and **value**) of **normalizing flows** with **generative adversarial networks** and **variational autoencoders**.

Open data of the **Global Energy Forecasting Competition 2014**, where the generative models use the **conditional information** to compute improved weather-based **PV power, wind power, and load scenarios**.

Normalizing flows can challenge generative adversarial networks and variational autoencoders. Overall, they are **more accurate in quality and value** and can be used effectively by non-expert deep learning practitioners.

# Introduction to probabilistic forecasting

## Perspectives

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Normalizing flows **directly learn the stochastic multivariate distribution** of the underlying process by maximizing the likelihood:

- transfer scenarios from one location to another;
- importance sampling.

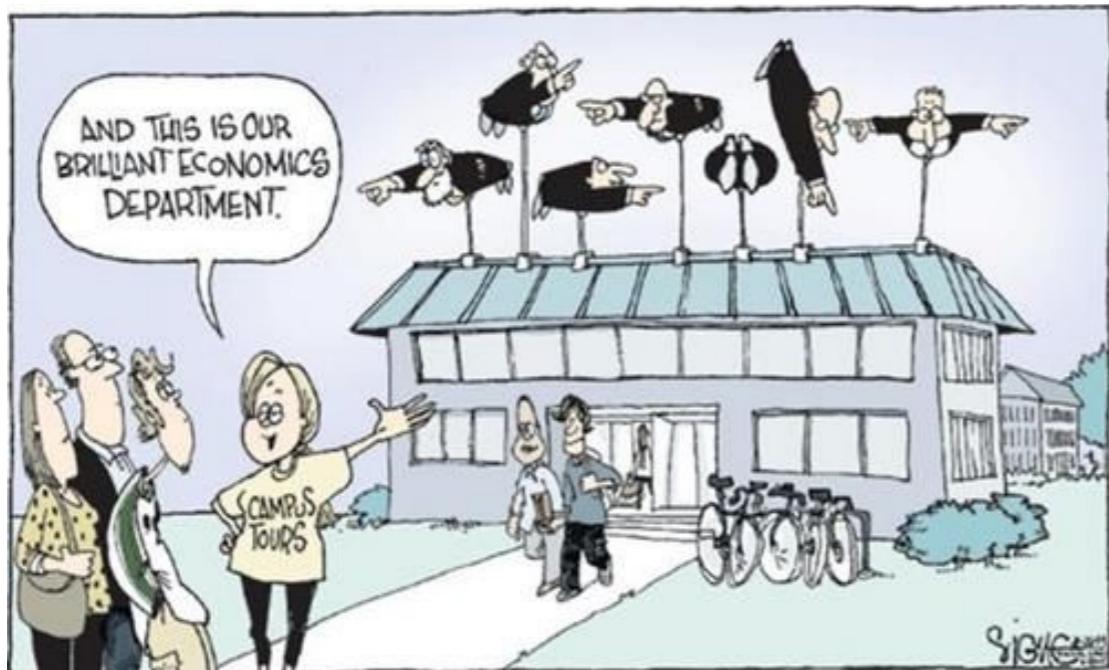
Normalizing flows are **easier to use by non-expert** deep learning practitioners once the libraries are available:

- more reliable and robust in terms of hyper-parameters selection;
- training is more stable than with generative adversarial networks.

# Introduction to probabilistic forecasting

**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

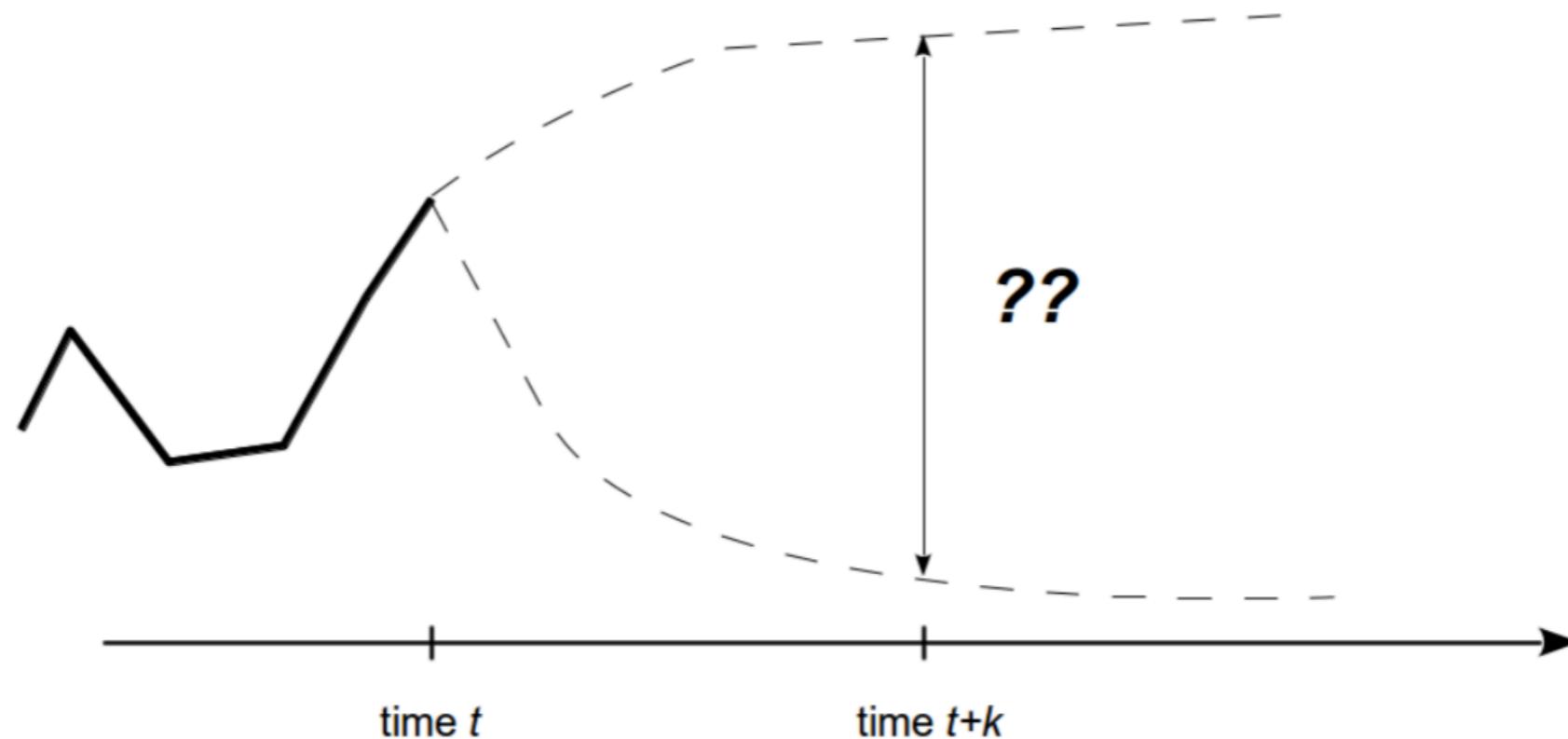
**Prices:** electricity, gas, (futures, day ahead, intraday, imbalances).

# Introduction to probabilistic forecasting

## Conclusion: the various types of probabilistic forecasts

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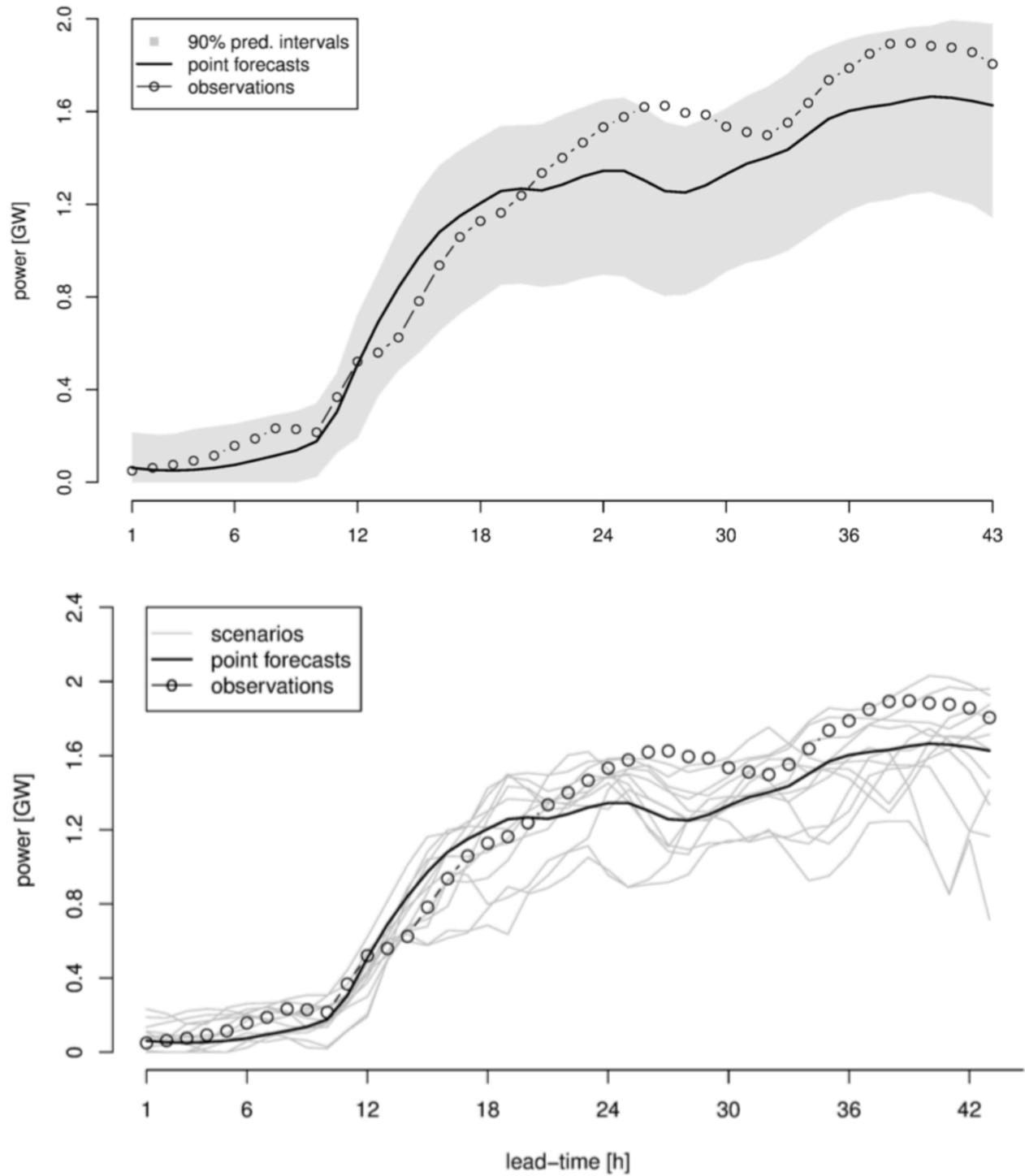
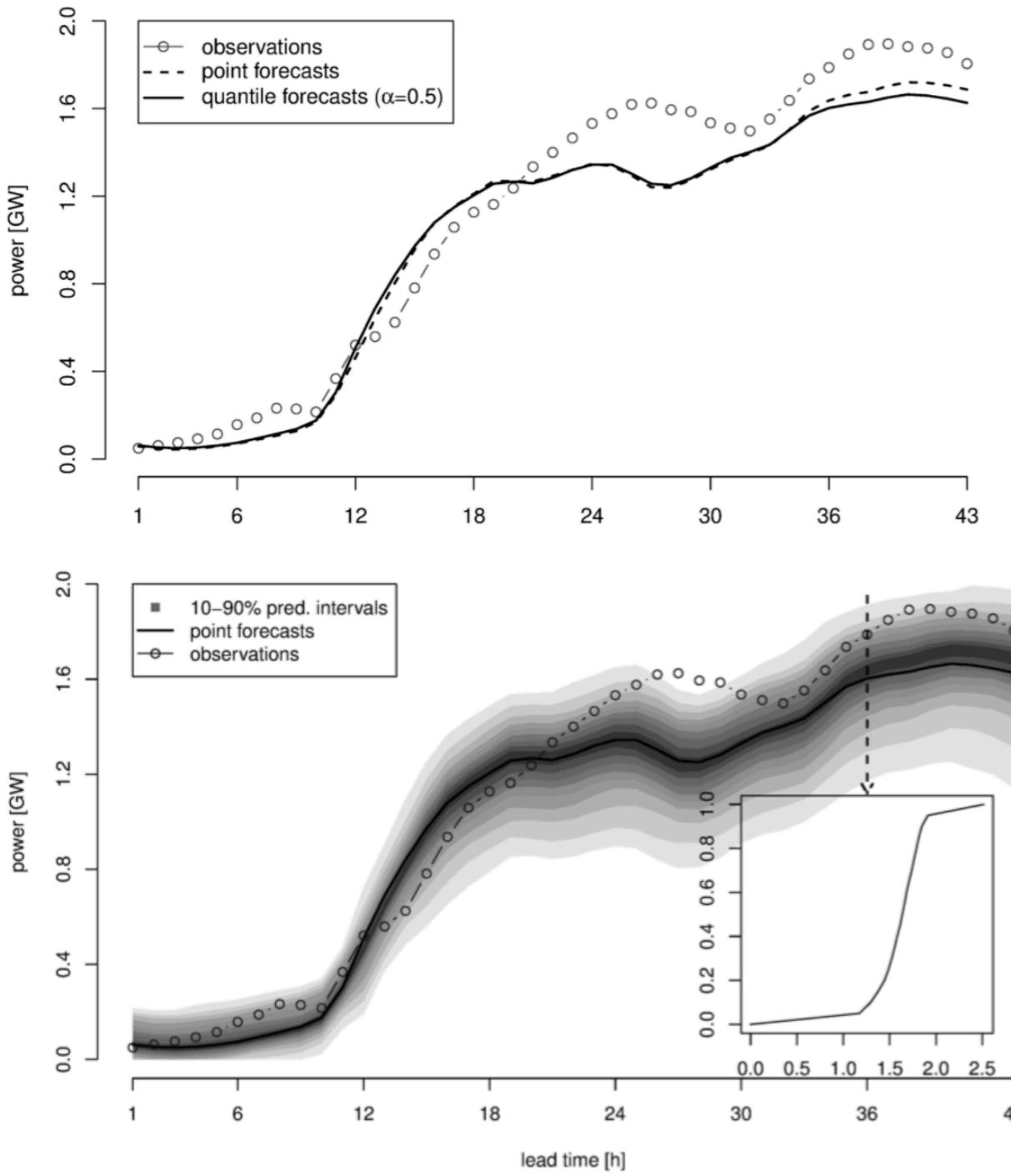
The various types of probabilistic forecasts range from **quantile** to **density** forecasts, **prediction intervals**, and **scenarios**.



# Introduction to probabilistic forecasting

## Conclusion: the various types of probabilistic forecasts

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# Introduction to probabilistic forecasting

## Conclusion: forecast quality vs value

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For predictions in any form, one must differentiate between their quality and their value.

Forecast **quality** corresponds to the **ability** of the forecasts to genuinely inform of future events by **mimicking the characteristics of the processes involved**.

Forecast **value** relates, instead, to the **benefits from using forecasts in a decision-making process**, such as participation in the electricity market.

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

# Introduction to probabilistic forecasting

## Conclusion: attribute of probabilistic forecast quality

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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

# Introduction to probabilistic forecasting

## Conclusion: some quality metrics

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### **Univariate** metrics:

- Continuous Ranked Probability Score (CRPS)
- Quantile Score (QS)
- Reliability diagrams

### **Multivariate** metrics:

- Energy Score (ES)
- Variogram Score (VS)

### **Specific** metrics:

- Classifier based
- Correlation between scenarios

### **Statistical** metric :

- Diebold and Mariano test

### Reference:

*Jonathan Dumas, Antoine Wehenkel, Damien Lanaspeze, Bertrand Cornélusse, and Antonio Sutera. A deep generative model for probabilistic energy forecasting in power systems: normalizing flows. Applied Energy, 305:117871, 2022. ISSN 0306-2619. doi: <https://doi.org/10.1016/j.apenergy.2021.117871>.*

# Introduction to probabilistic forecasting

## Lecture 2 - sources to dig the topic

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- 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>.