Microgrids

Lecture 2: introduction to probabilistic forecasting

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Introduction to probabilistic forecasting

Lecture 2 - 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 probabilistic 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. Point-forecasts reminder

2. Probabilistic forecasts

3. Verification of probabilistic forecasts

4. Case study: probabilistic forecasting using normalizing flows

Introduction to probabilistic forecasting

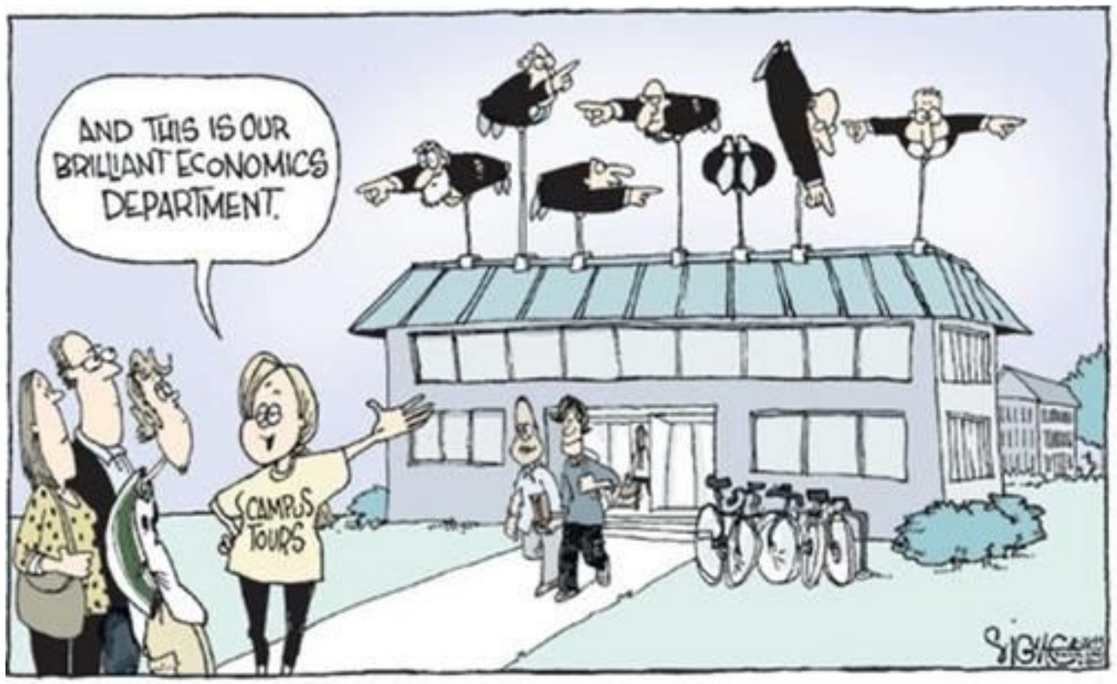
Quiz

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).

Quiz

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.

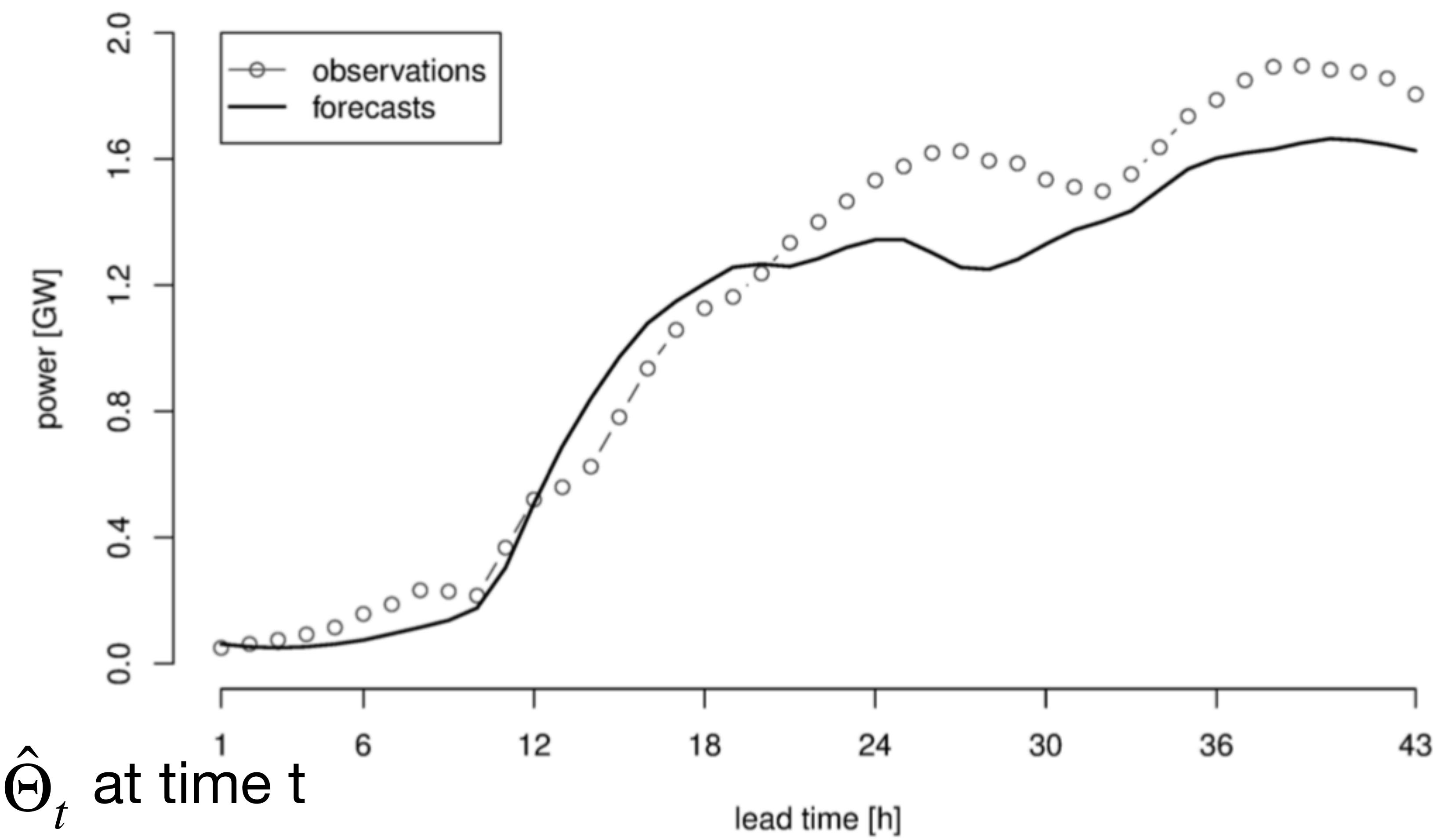
$$\hat{y}_{t+k|t} = \mathbb{E}\left[Y_{t+k|t} \,|\, g, \Omega_t, \hat{\Theta}_t\right]$$

given:

- the information set Ω;

- a model g

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



Introduction to probabilistic forecasting

Quiz

What are the strategies to assess forecasts?

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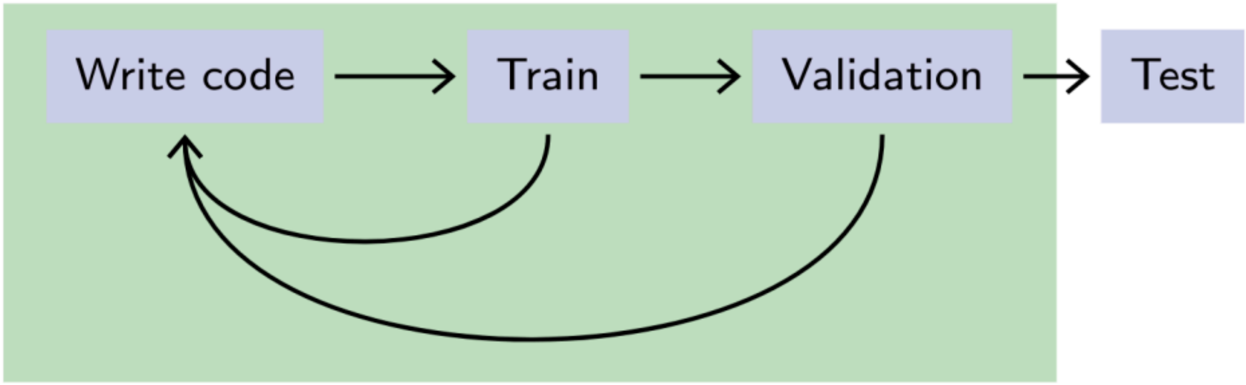
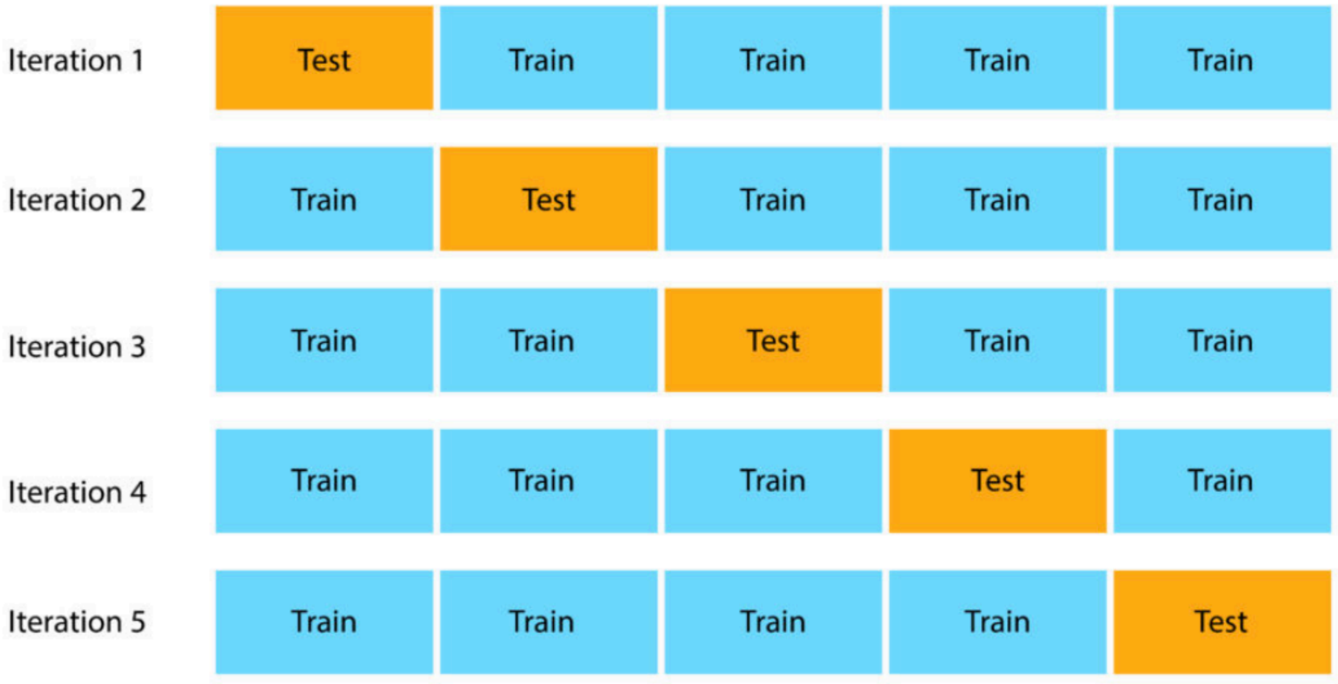
Reminder: strategy to assess forecasts

Several strategies to assess forecasts:

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

- k-cross fold validation.





Quiz

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

Introduction to probabilistic forecasting

Reminder: 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 probabilistic forecasting

Summary

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

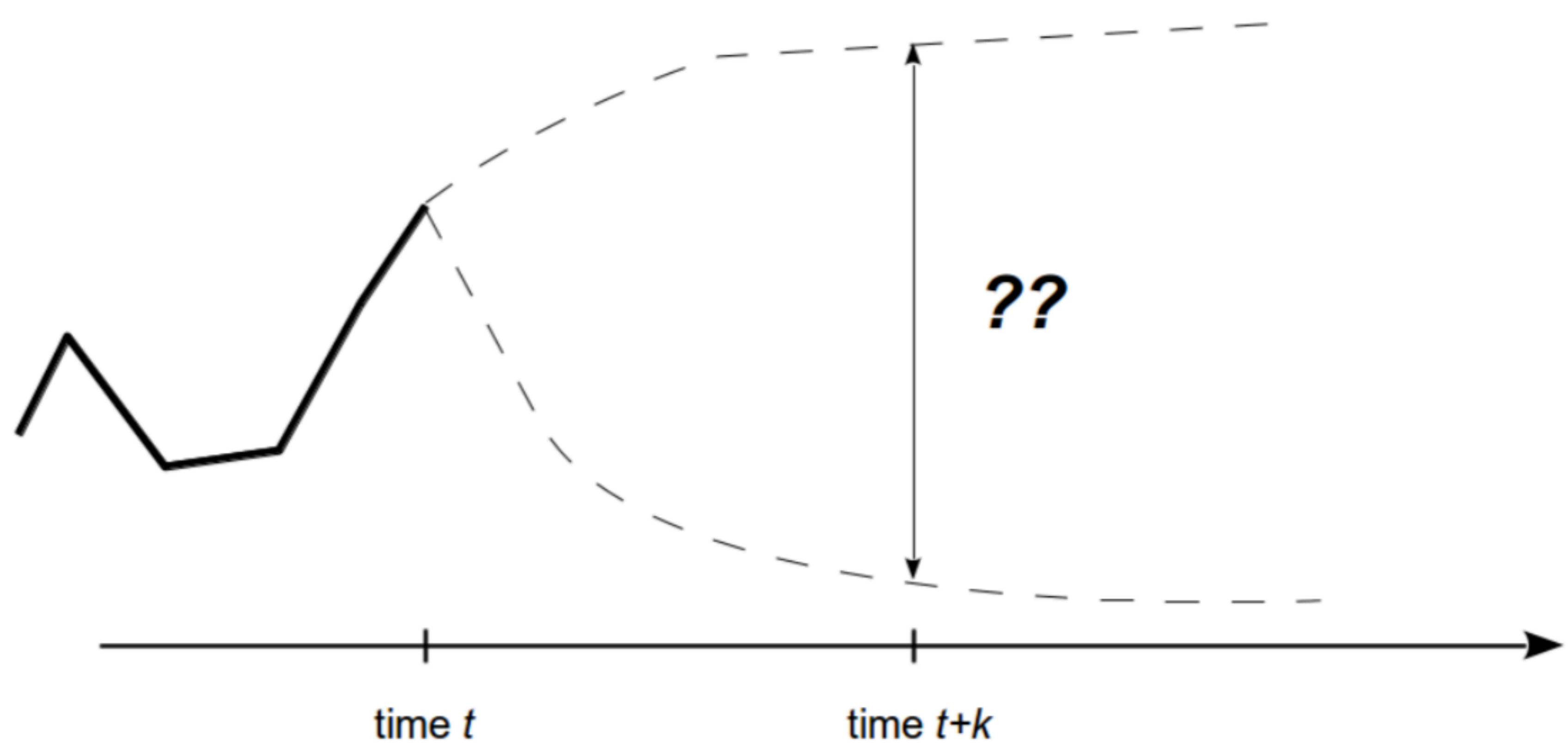
Quiz

Do you know the various types of probabilistic forecasts?

Introduction to probabilistic forecasting

Probabilistic forecasting

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



Introduction to probabilistic forecasting

Quiz

What is a quantile/percentile?

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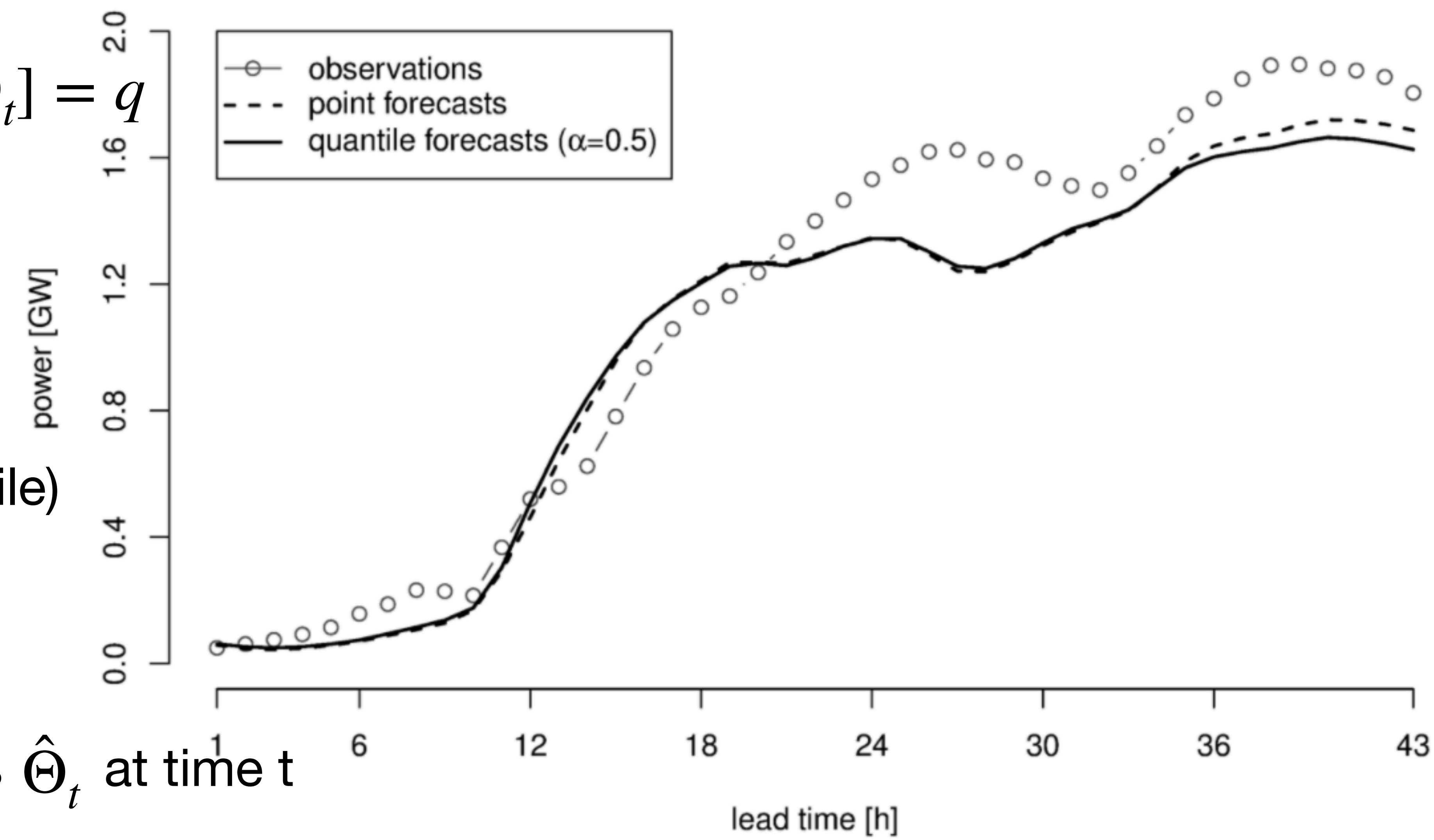
Quantile forecast definition

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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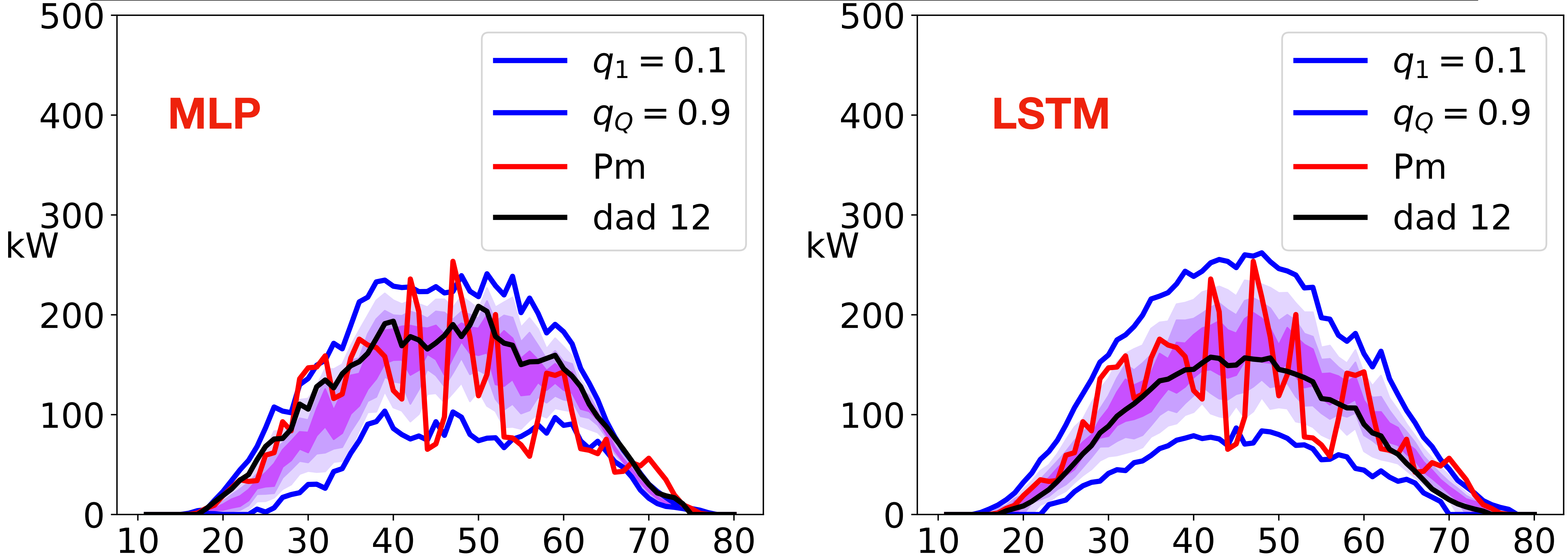
Quantile forecasts examples: PV generation



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

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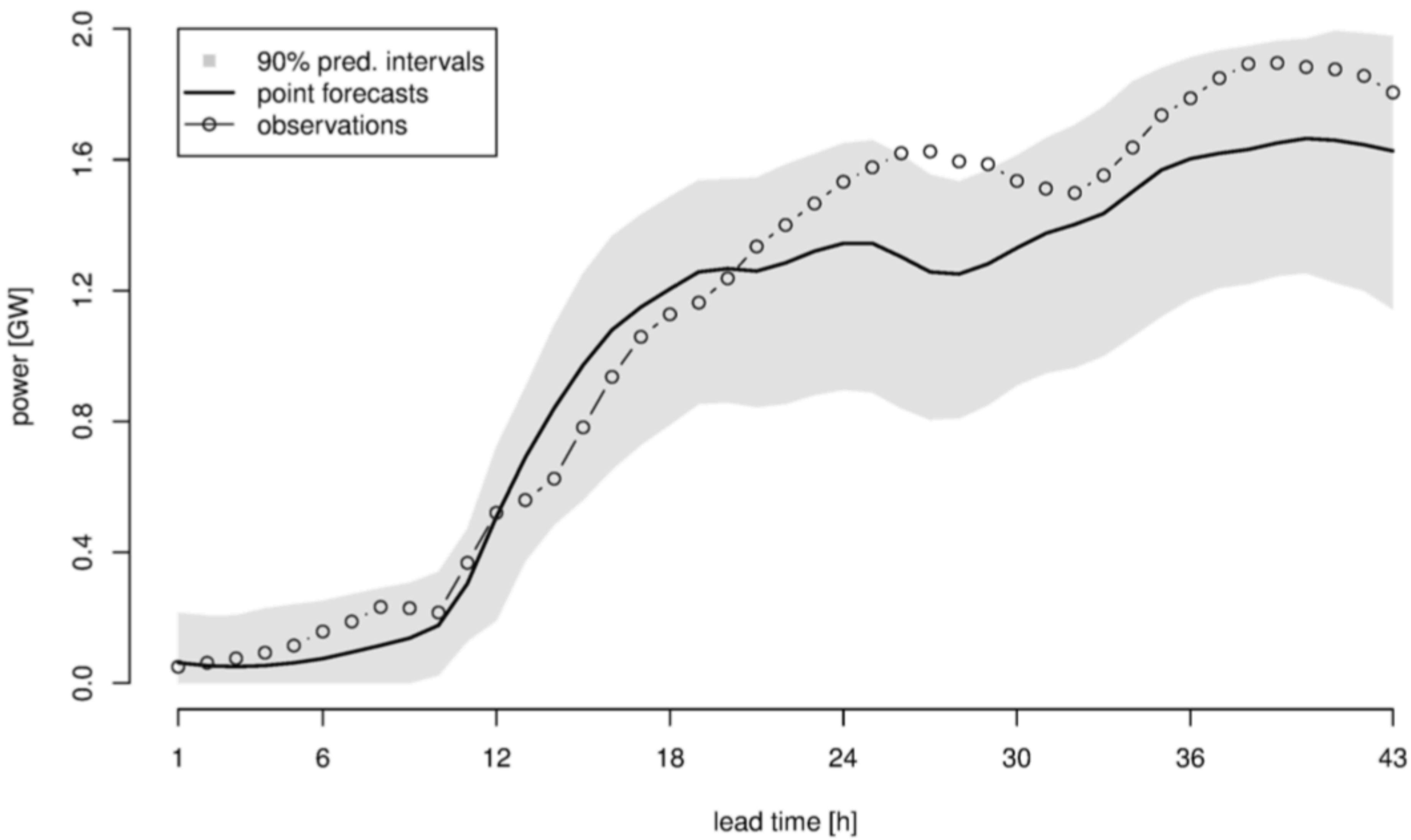
Prediction interval definition

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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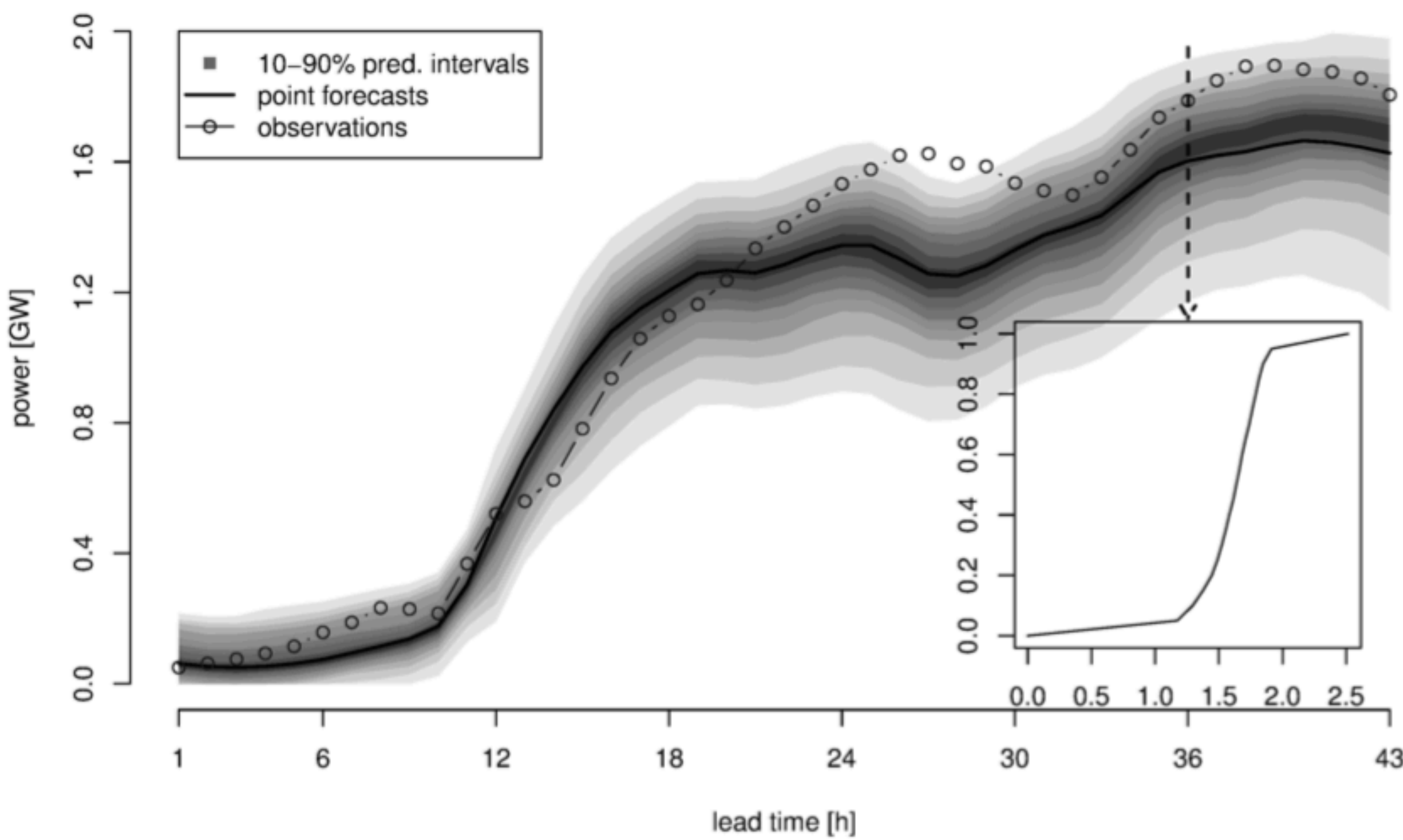
Predictive density definition

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



Quiz

What are scenarios?

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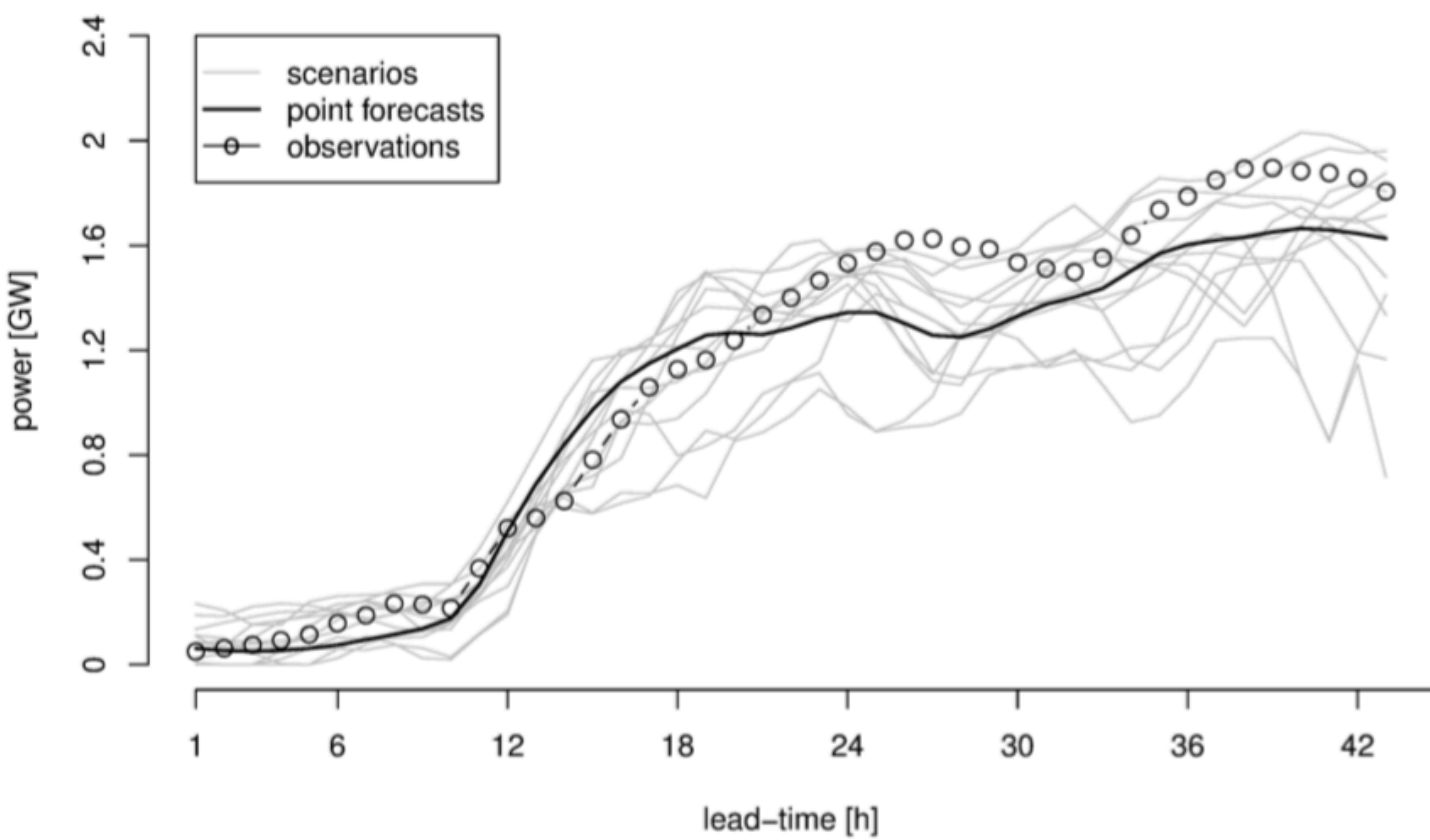
Trajectories (scenarios) definition

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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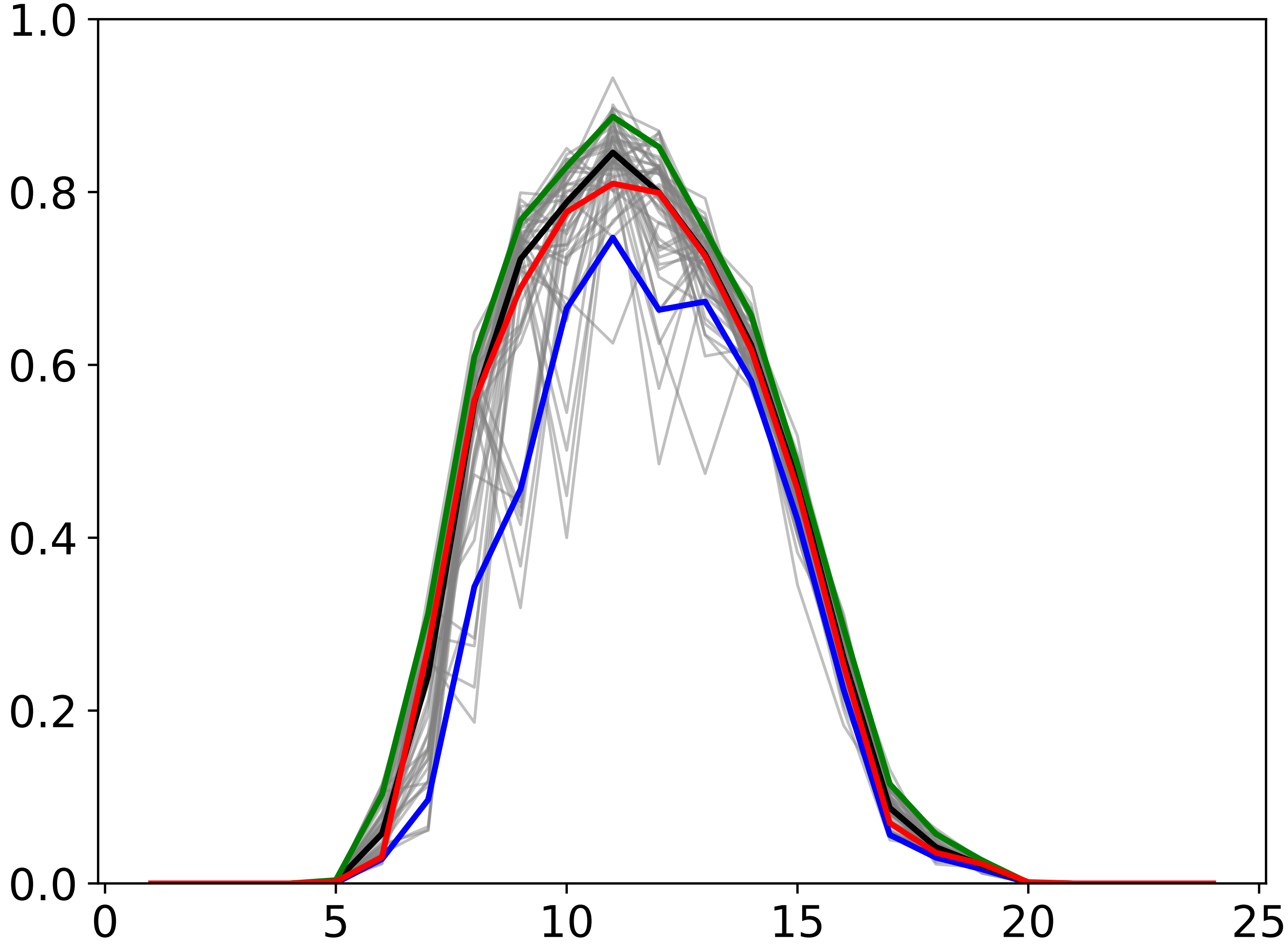
PV scenarios using a Normalizing Flow



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.

Summary

1. Reminder

2. Probabilistic forecasts

3. Verification of probabilistic forecasts

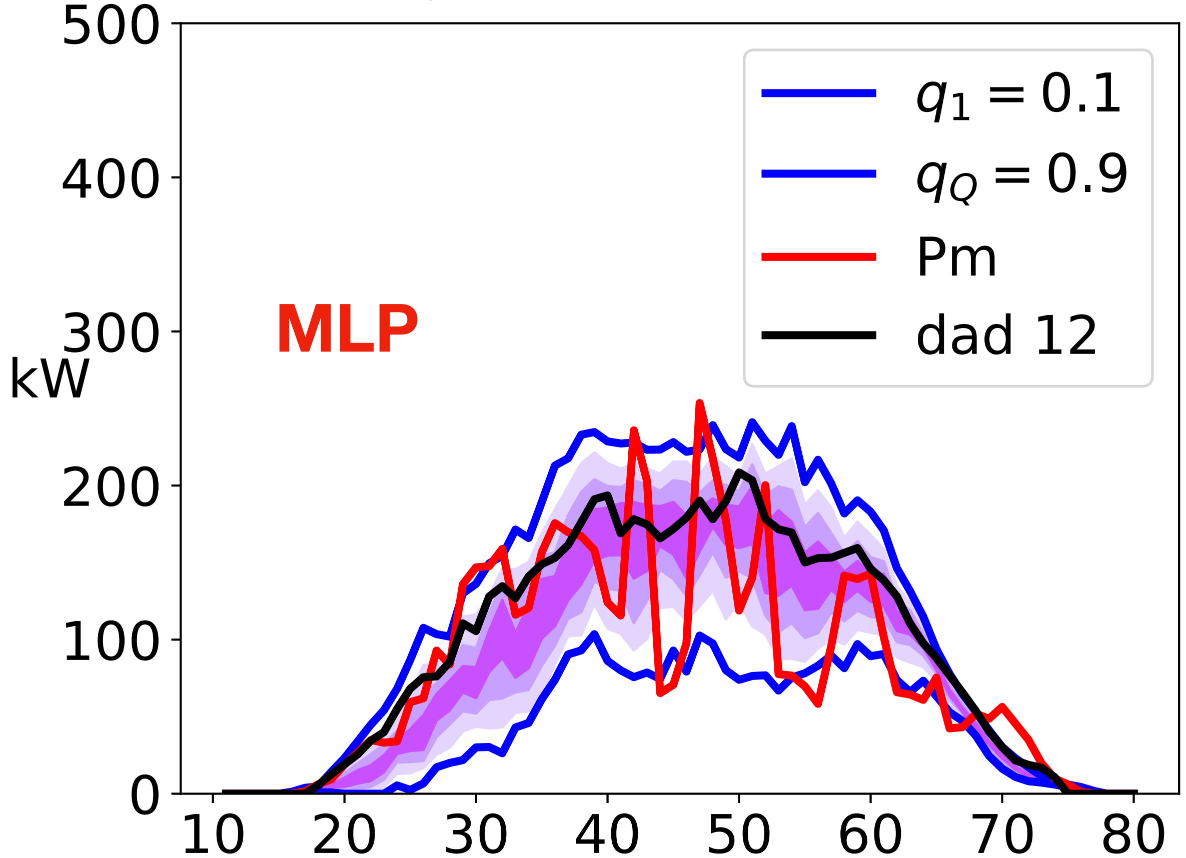
4. Case study: probabilistic forecasting using normalizing flows

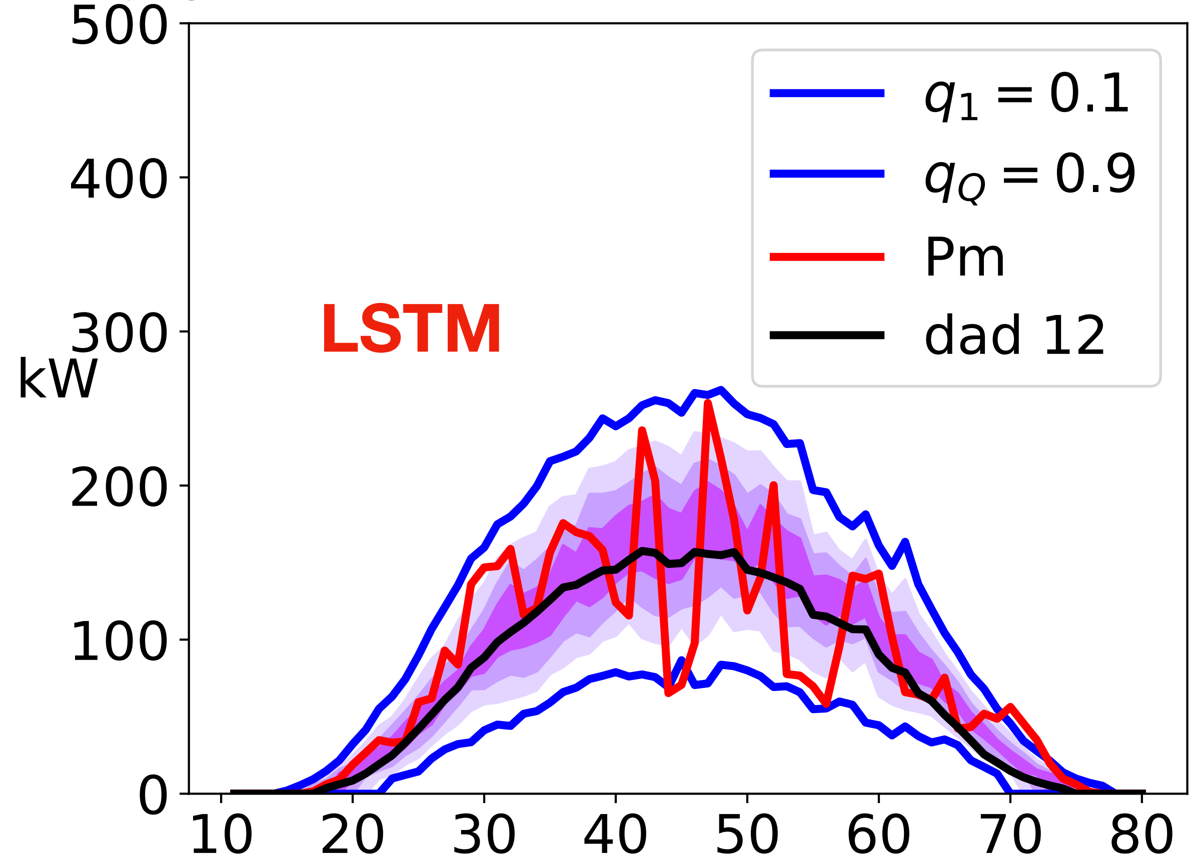
Introduction to probabilistic forecasting

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

Quiz

What is the difference between forecast quality and value?

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Forecast quality vs value

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

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

What is forecast calibration?

Introduction to probabilistic forecasting

Probabilistic calibration (reliability)

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!

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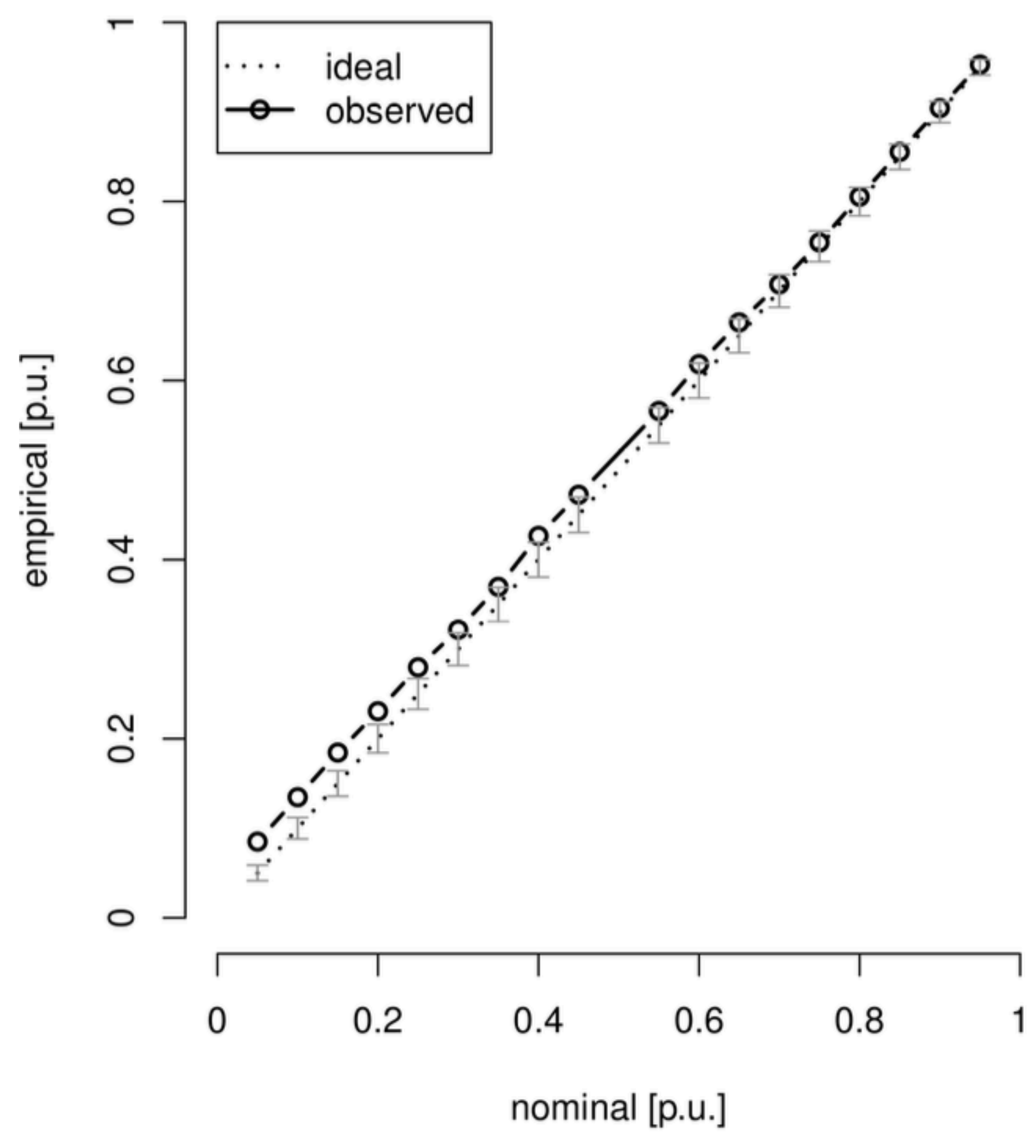
Reliability diagrams

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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What is the sharpness?

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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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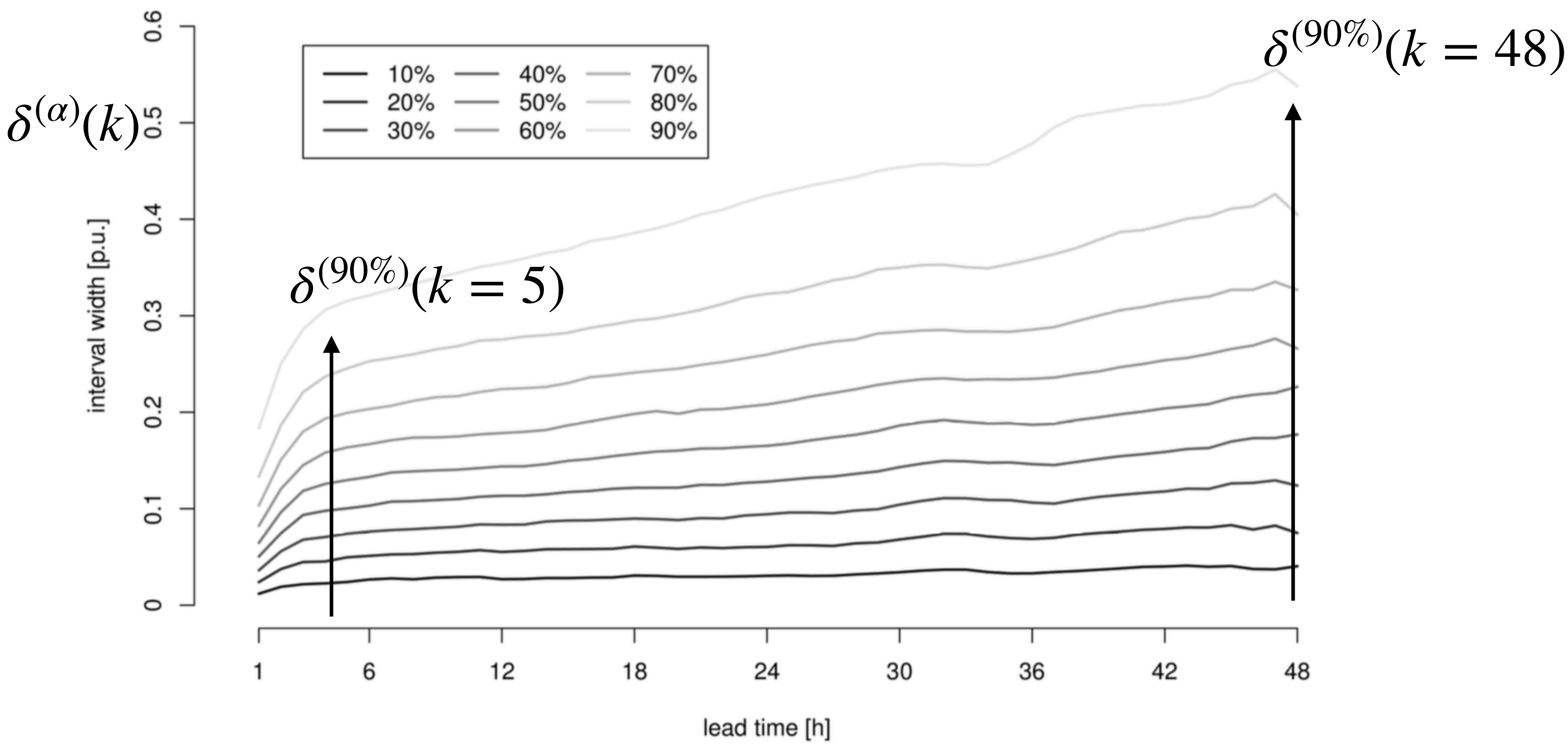
Sharpness

Predictive densities are composed 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



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Quiz

Do you know probabilistic forecasts metrics?

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Univariate skill score

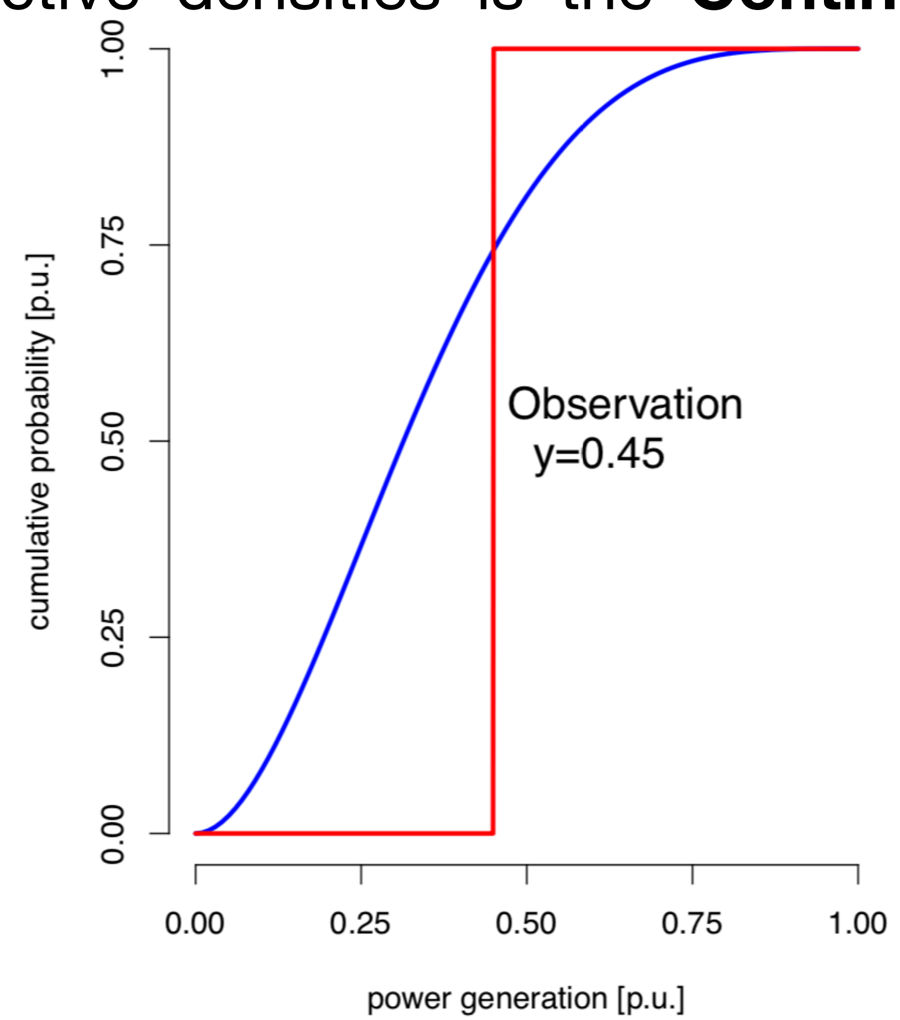
The skill of probabilistic forecasts can be assessed by scores, like MAE and RMSE for the deterministic forecasts.

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

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

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

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



[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.*

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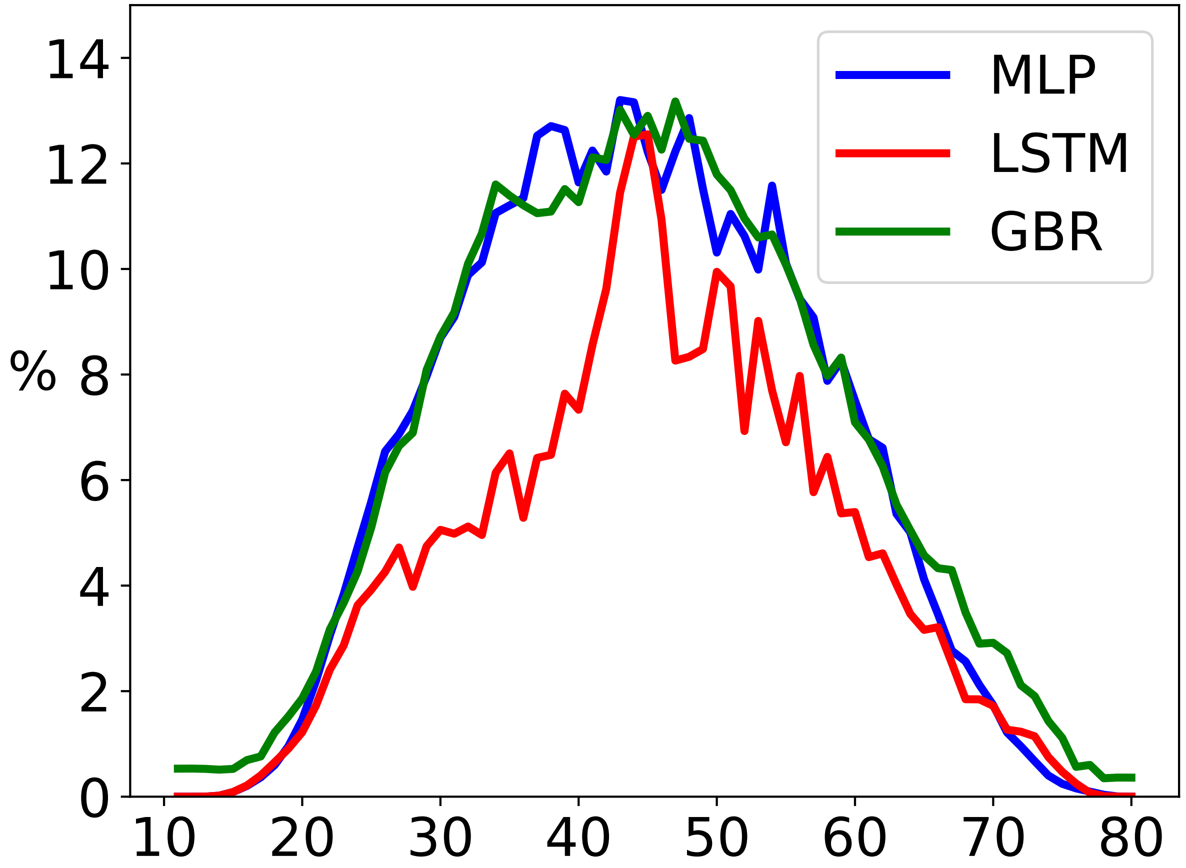
CRPS example



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

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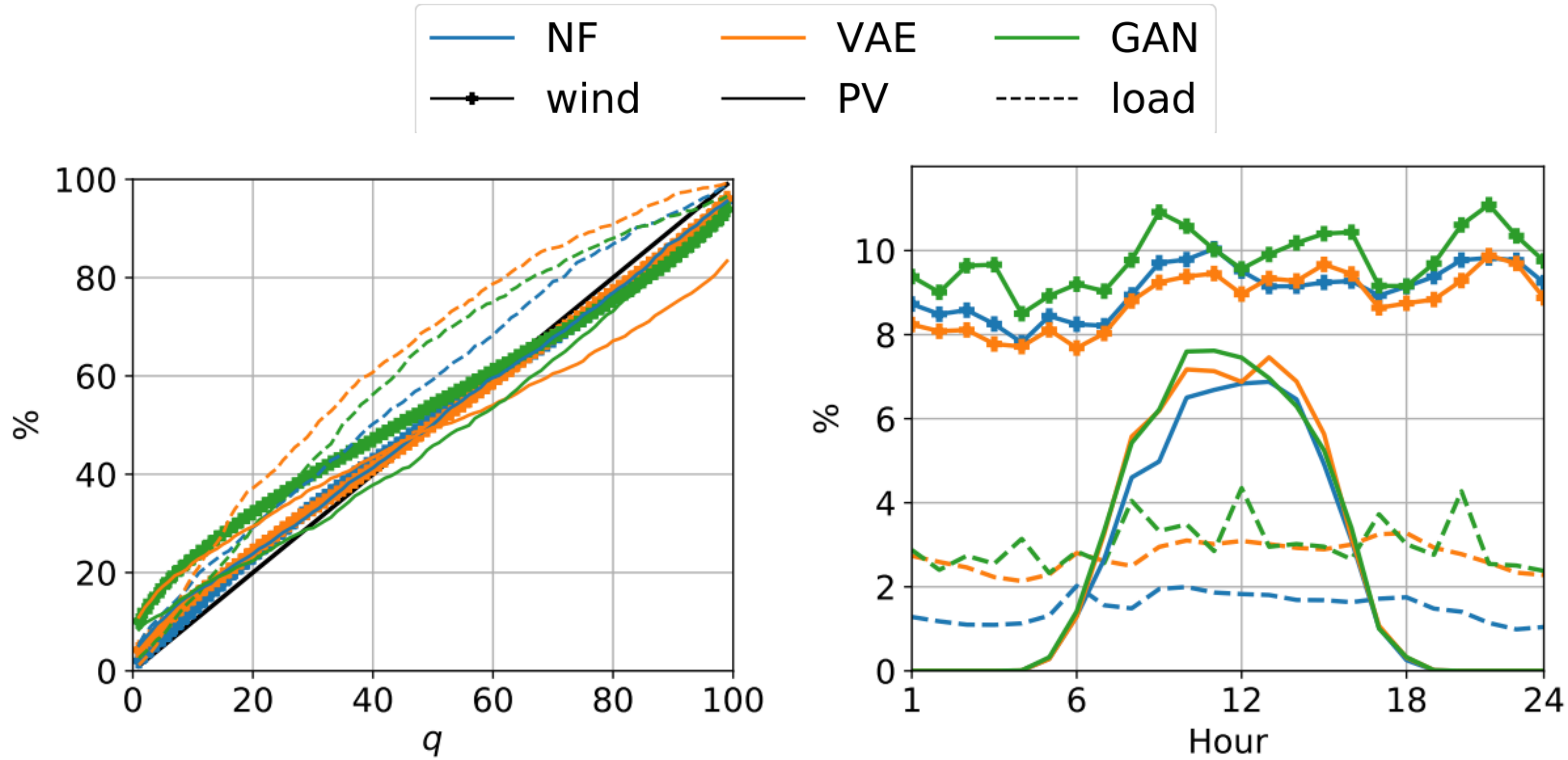
CRPS and reliability examples



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

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].

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

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

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

Summary

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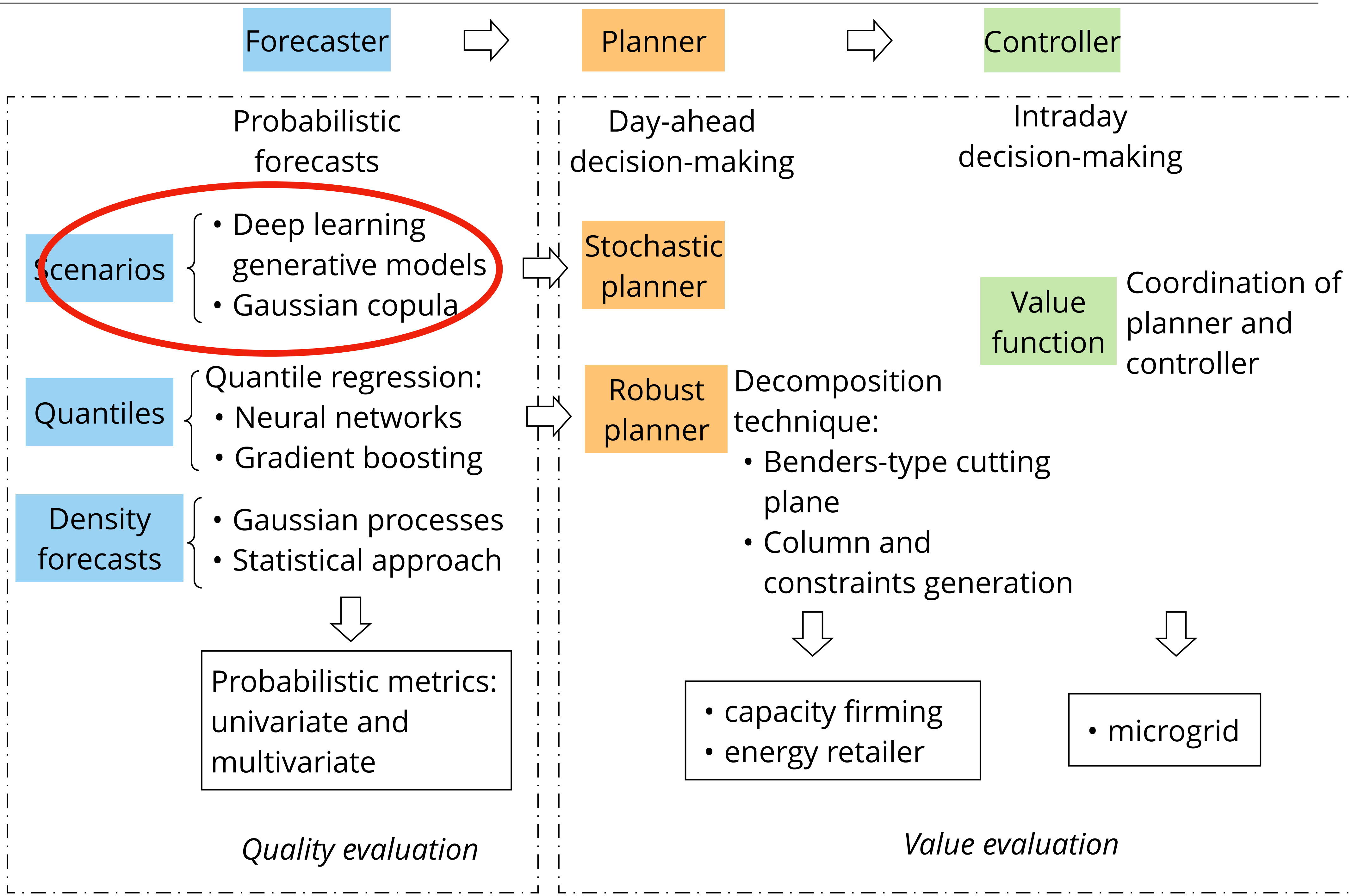
4. Case study: probabilistic forecasting using normalizing flows

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.

Case study summary

Introduction

Background

Value & quality assessment

Numerical results

Conclusions

Introduction to probabilistic forecasting

Overview

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

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.*

Framework of the study

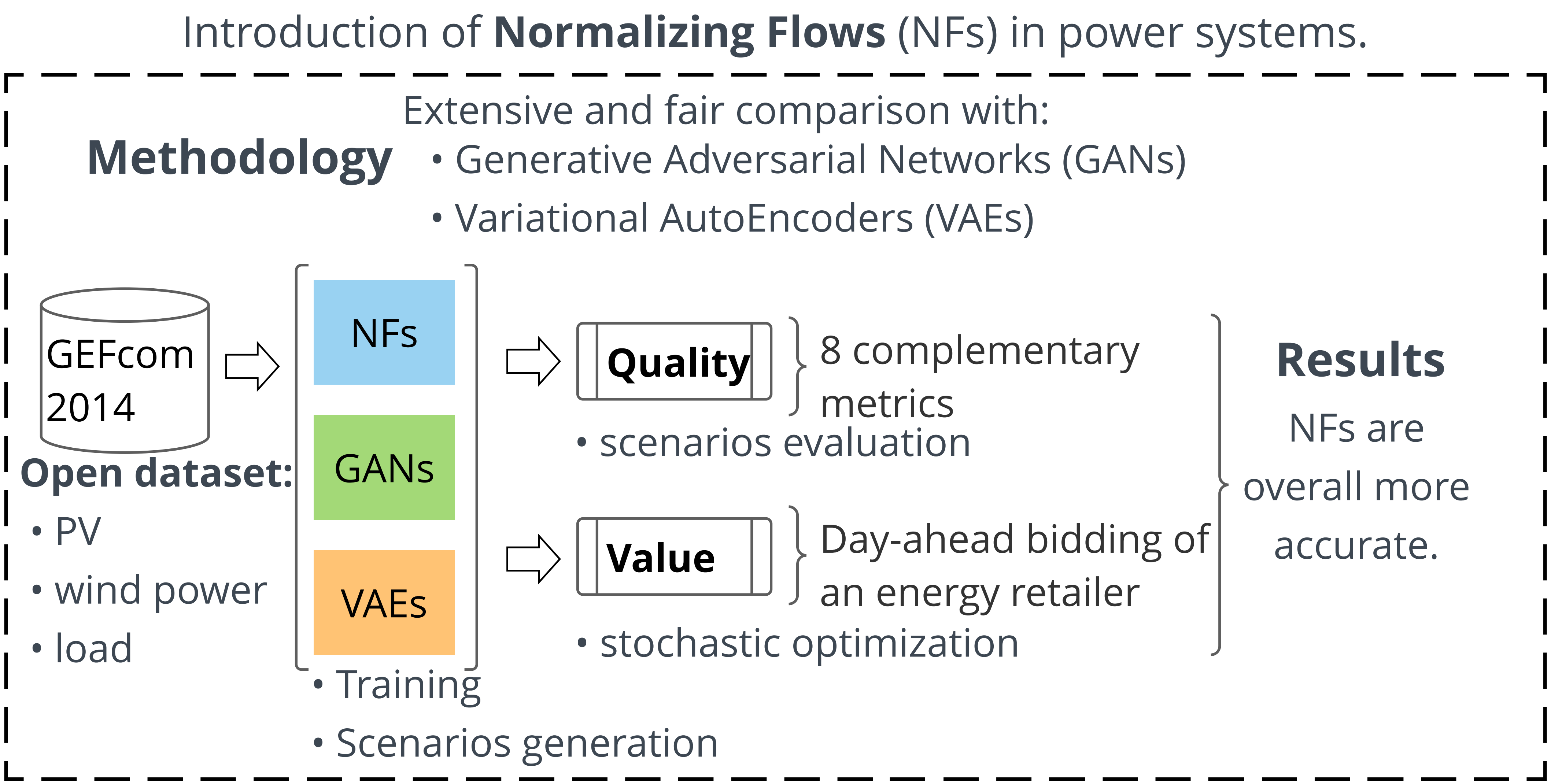


Figure I-1: The framework of the study.

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Framework of the study

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	×	×	×	✓

[1] *Wang, Yi, et al. "Modeling load forecast uncertainty using generative adversarial networks." Electric Power Systems Research 189 (2020): 106732.*

[2] *Qi, Yuchen, et al. "Optimal configuration of concentrating solar power in multienergy power systems with an improved variational autoencoder." Applied Energy 274 (2020): 115124.*

[2] *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.*

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

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**.

Normalizing flows

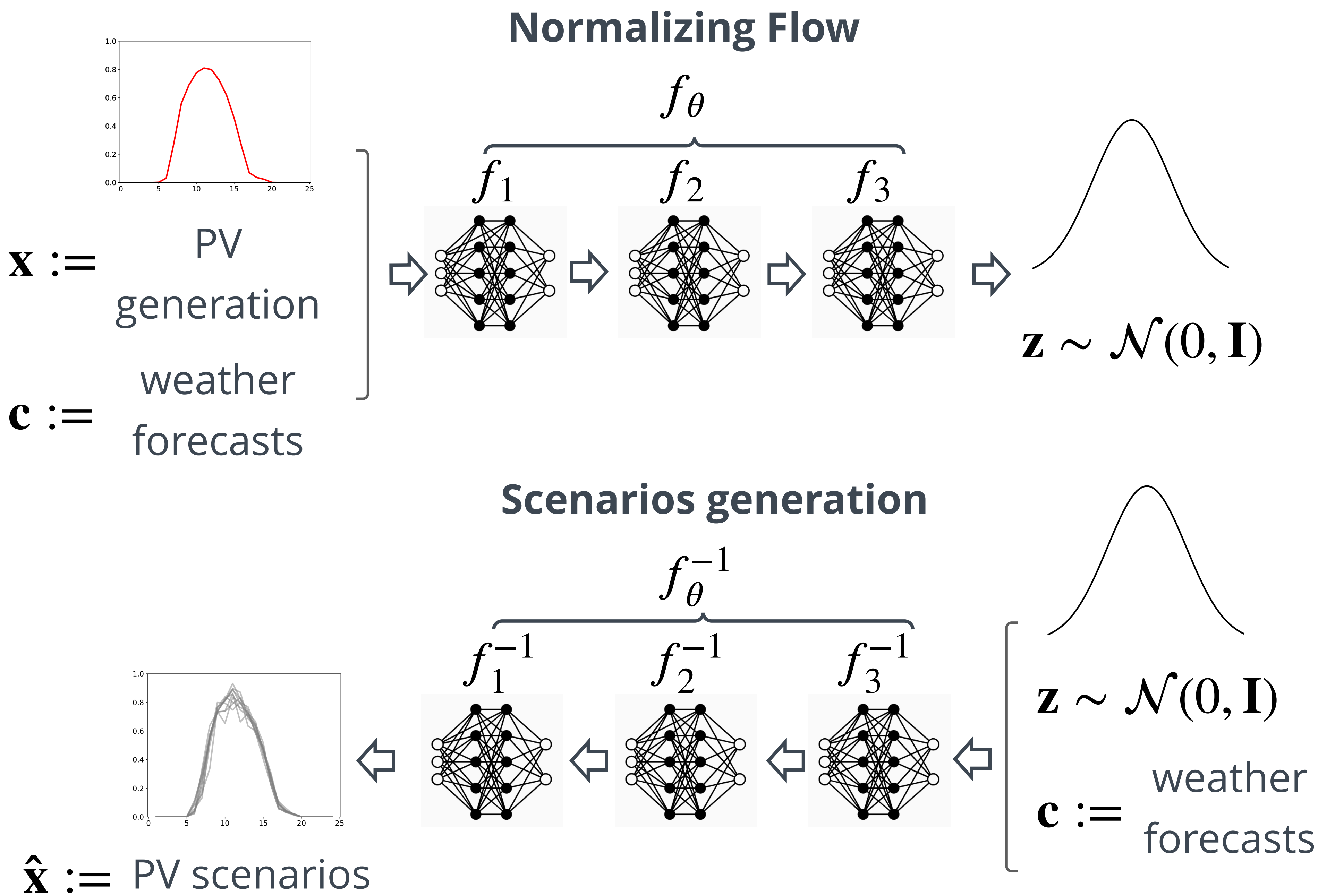

Figure I-2: A three-step conditional normalizing flows for PV generation.

Variational auto encoders

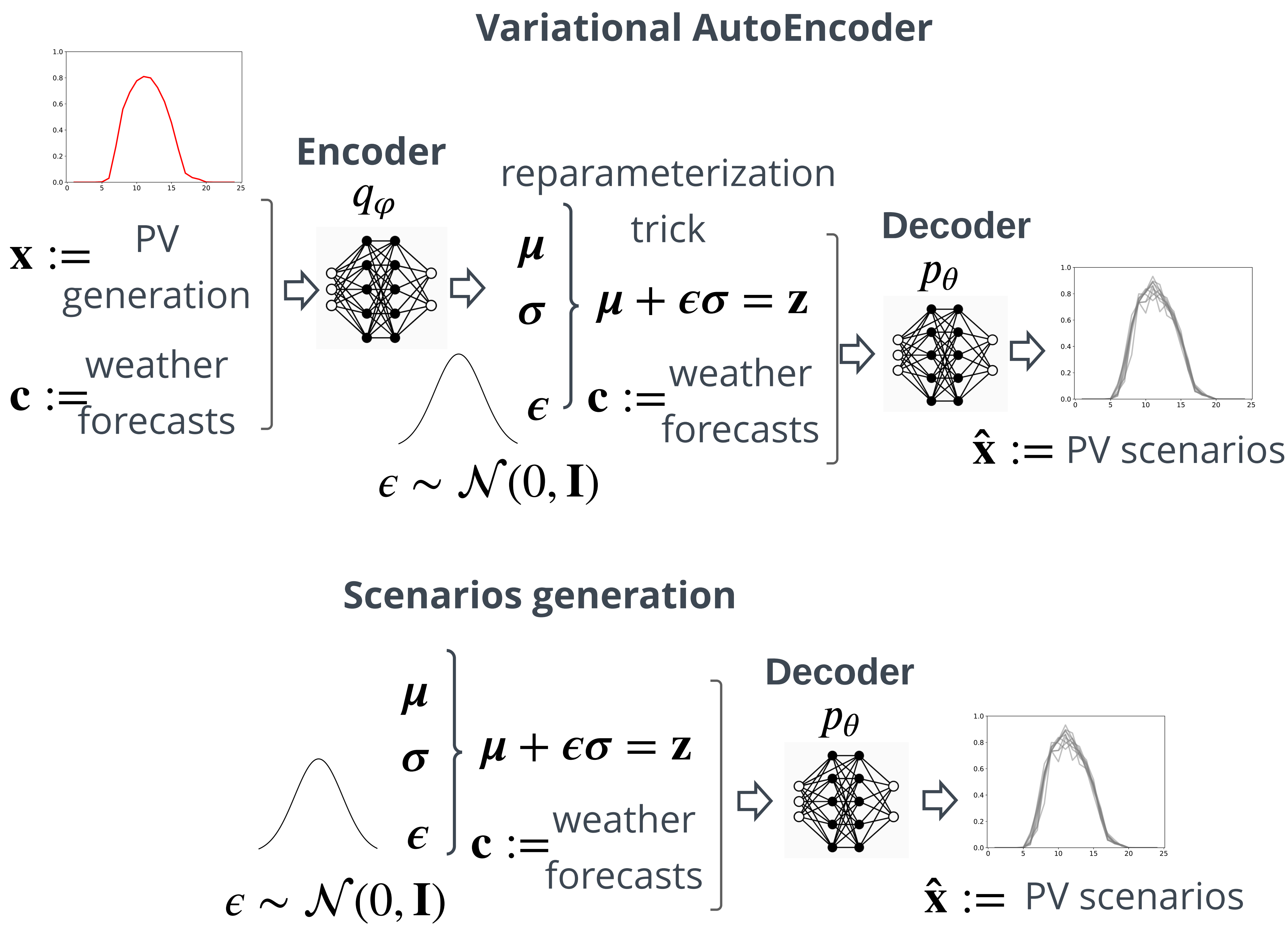

Figure I-3: A conditional variational autoencoder for PV generation.

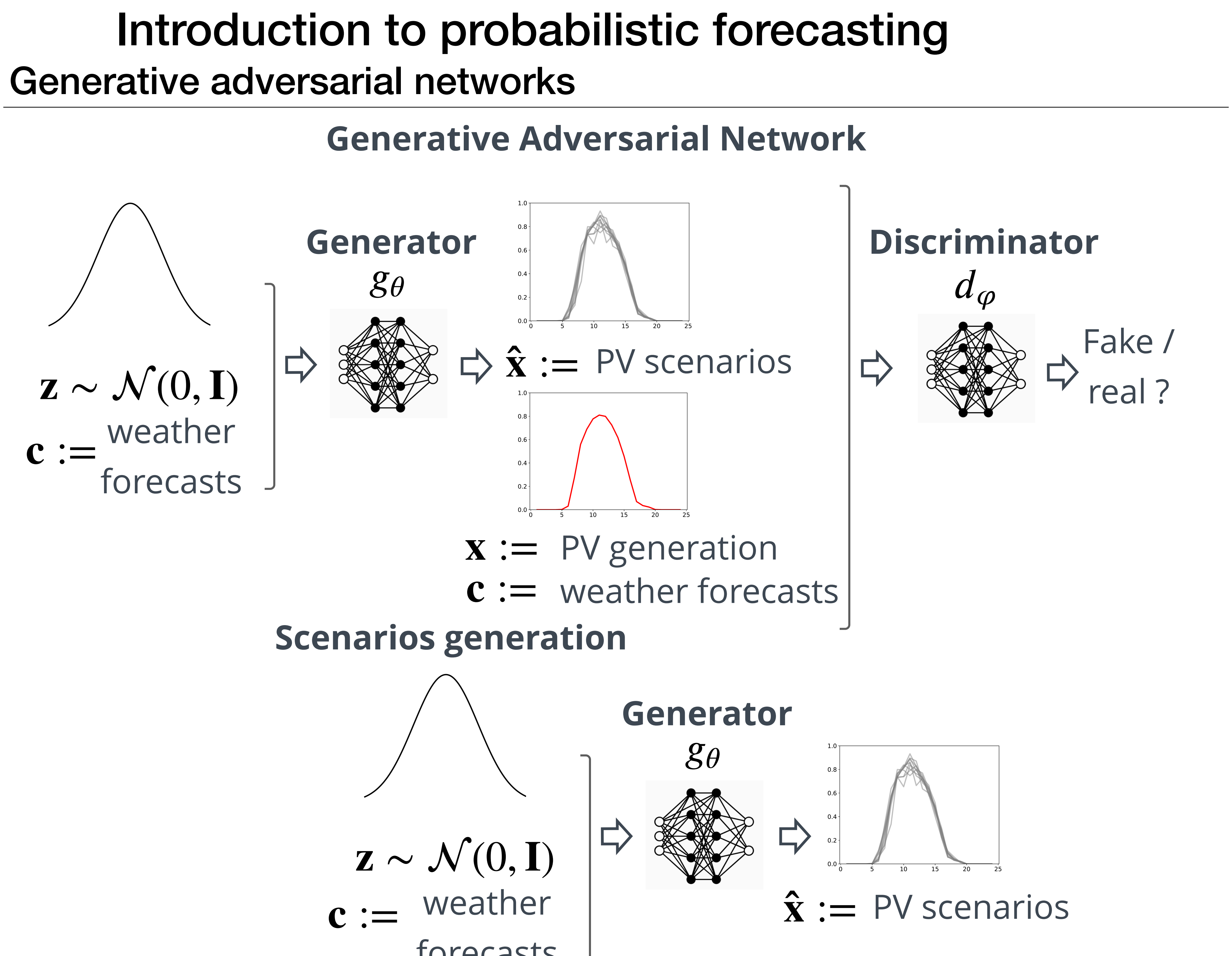

Figure I-3: A conditional generative adversarial network for PV generation.

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Comparison of the models

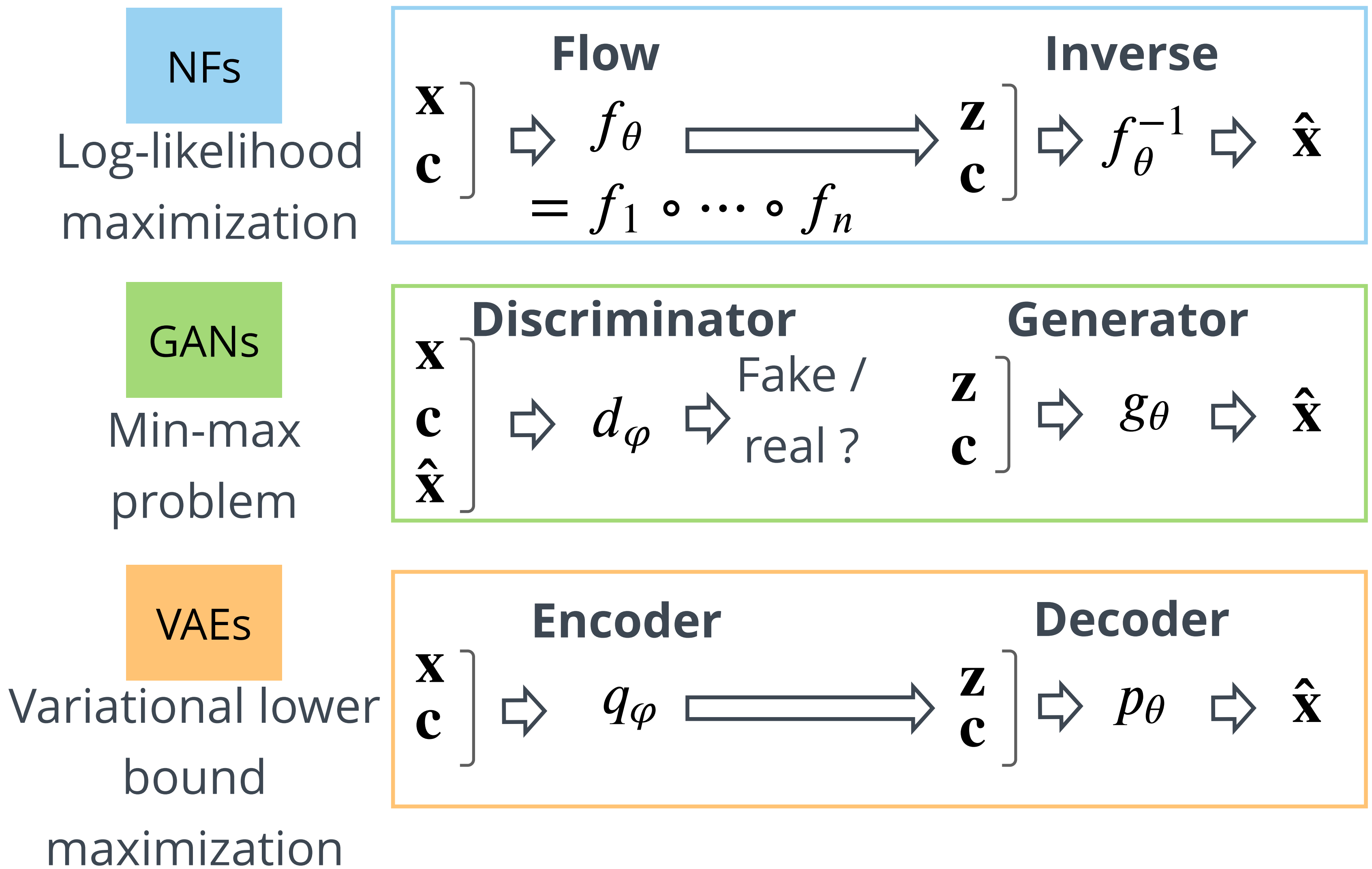

Figure I-4: High level comparison of the three models.

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Forecast quality vs. value

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

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

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

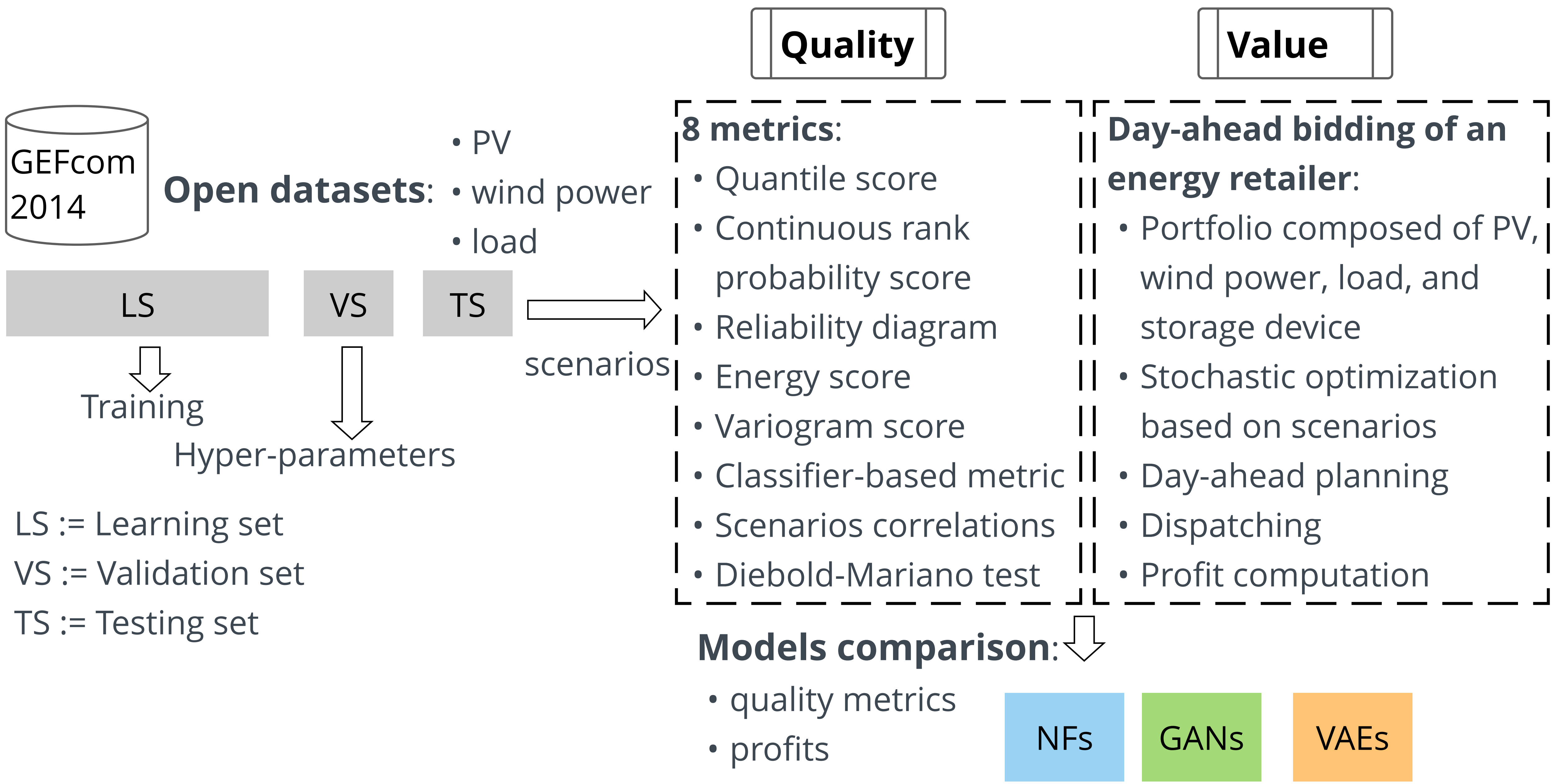

Figure I-5: Methodology.

Implementation details

	Wind	PV	Load
T periods	24	16	24
n_z zones	10	3	–
n_f features	10	5	25
$\mathbf{c}_d$ 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.

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Quality results: wind power scenarios

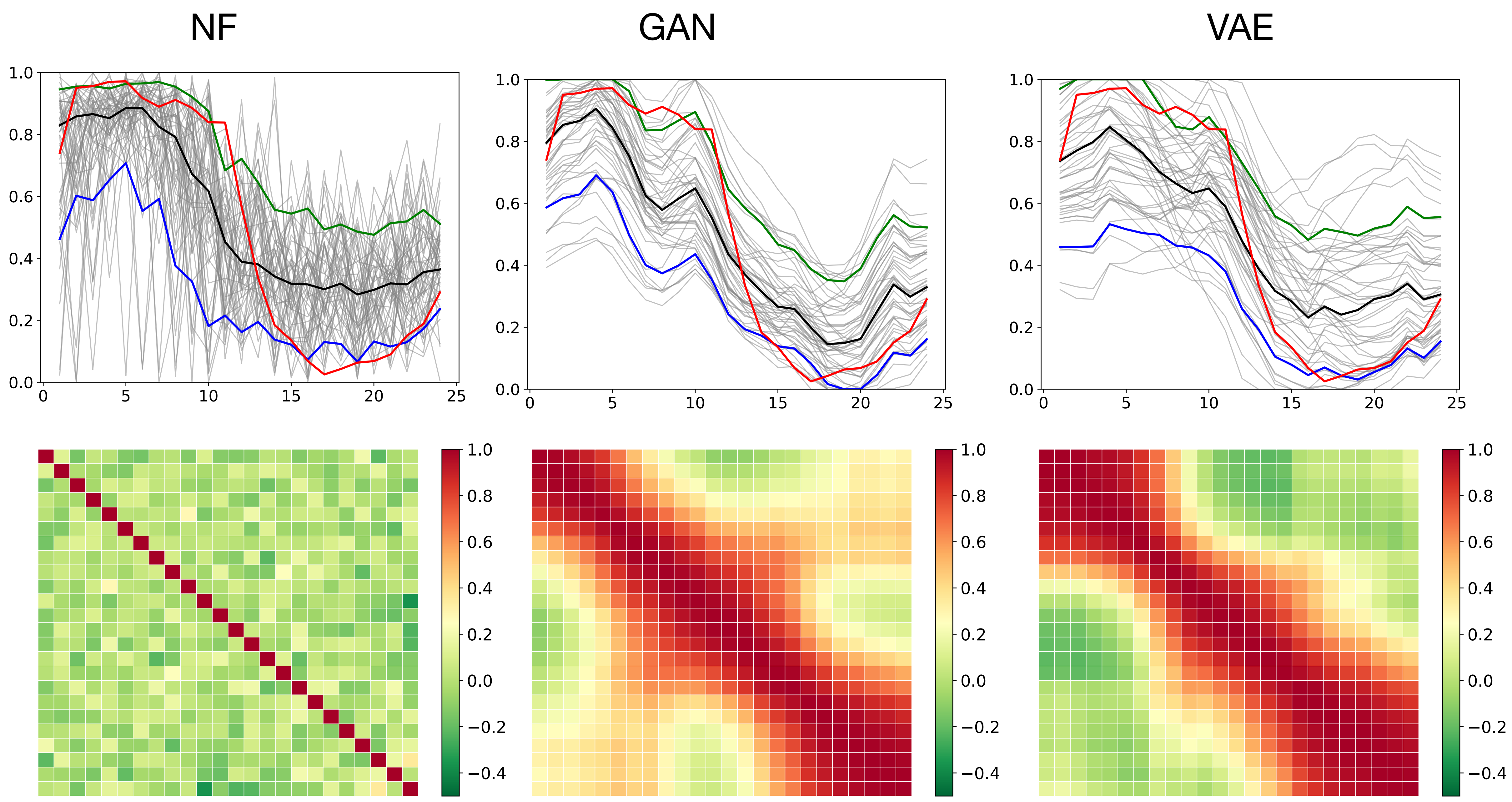

Figure I-6: Wind power scenarios shape comparison and analysis.

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Quality results: PV scenarios

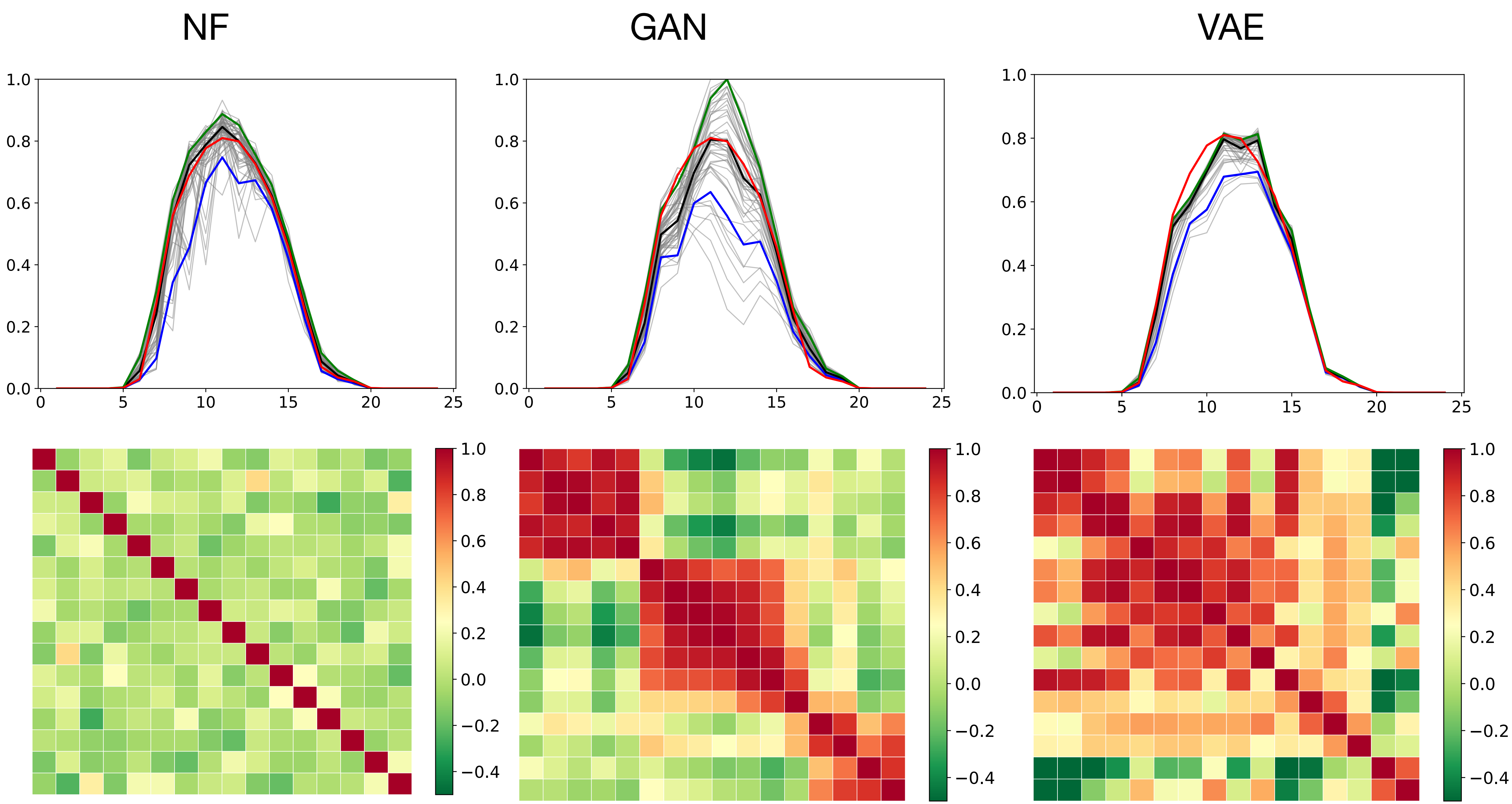

Figure I-7: PV scenarios shape comparison and analysis.

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Quality results: load scenarios

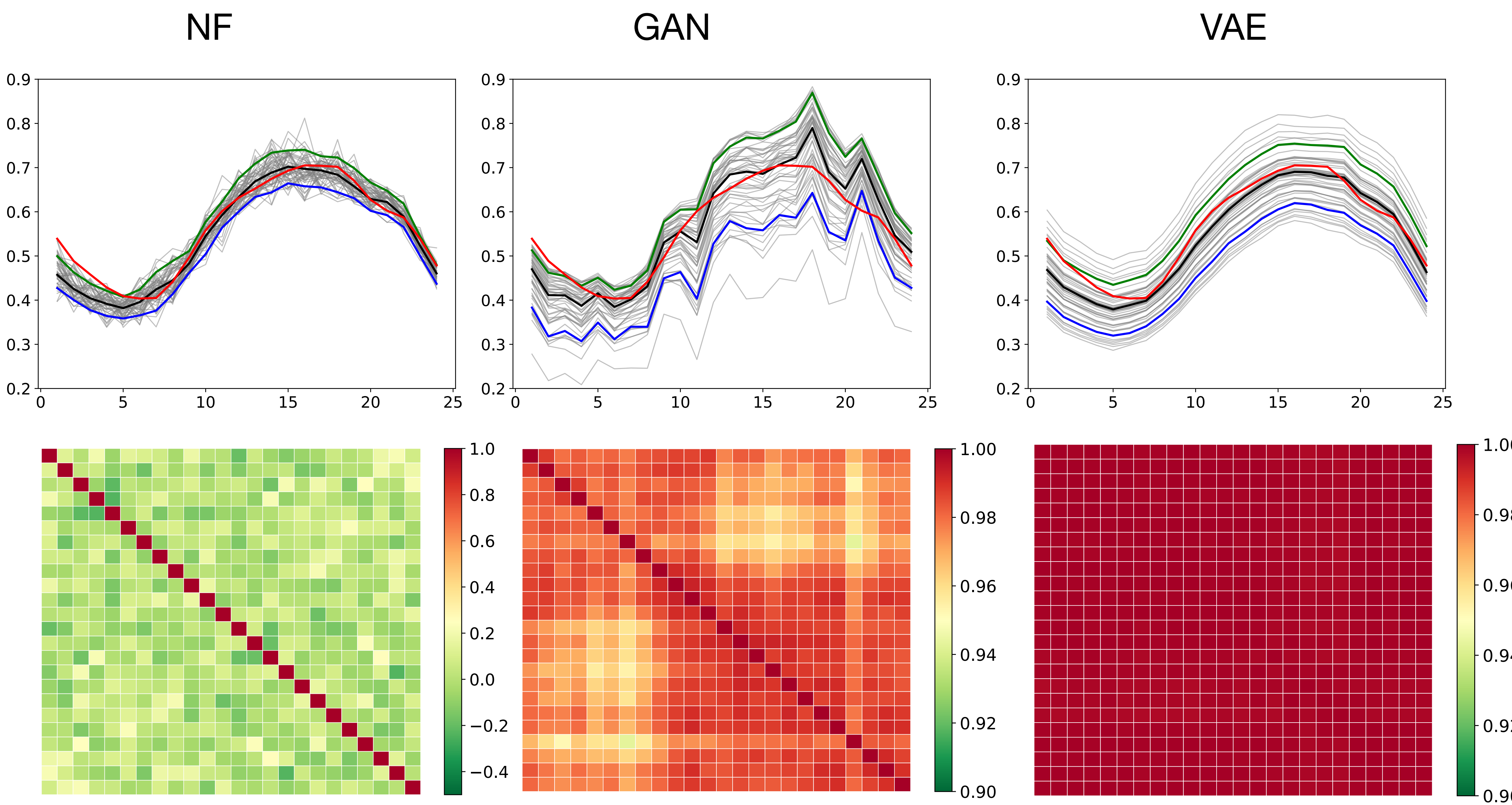

Figure I-8: Load scenarios shape comparison and analysis.

Quality results: averaged scores

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

Table I-2: Averaged quality score per dataset.

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Value results: methodology

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.

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Value results: data illustration

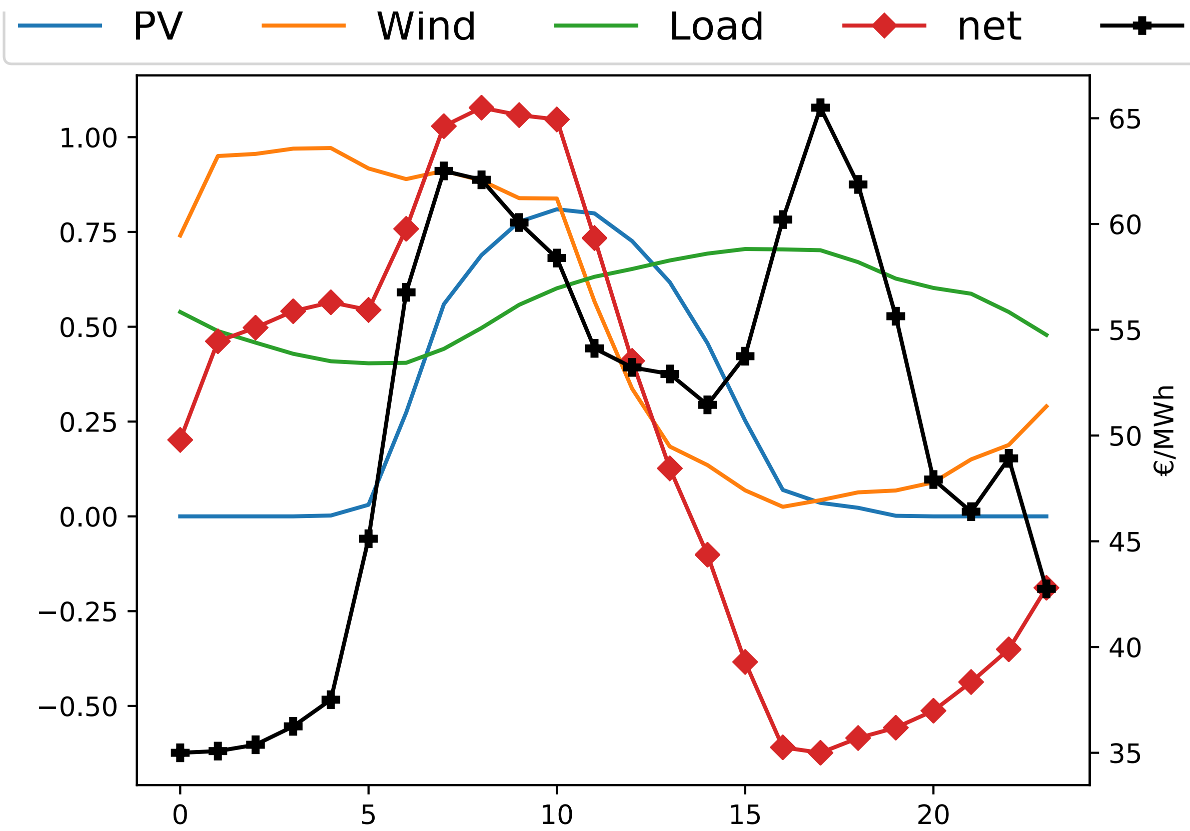

Figure I-9: Illustration of the observations on a random day of the testing set.

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Value results: profits comparison

Net profit = profit - penalty.

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

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

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

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Results: summary

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

Table I-4: Comparison between the generative models.

Conclusions

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.

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Perspectives

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.

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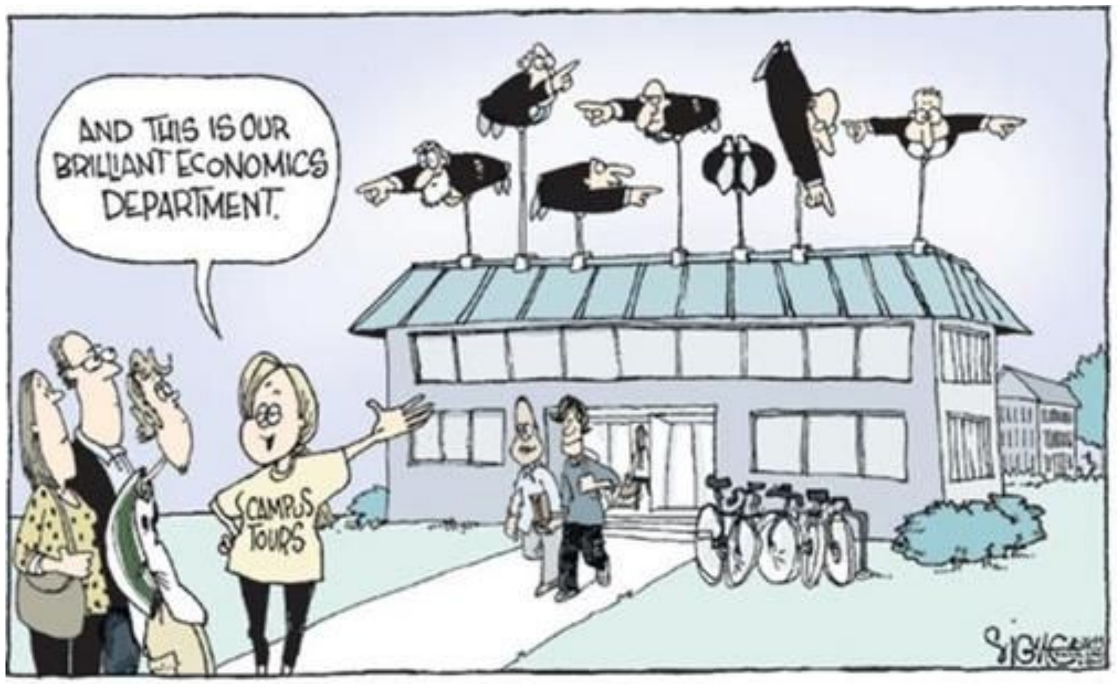
Conclusion: forecast for decision making

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).

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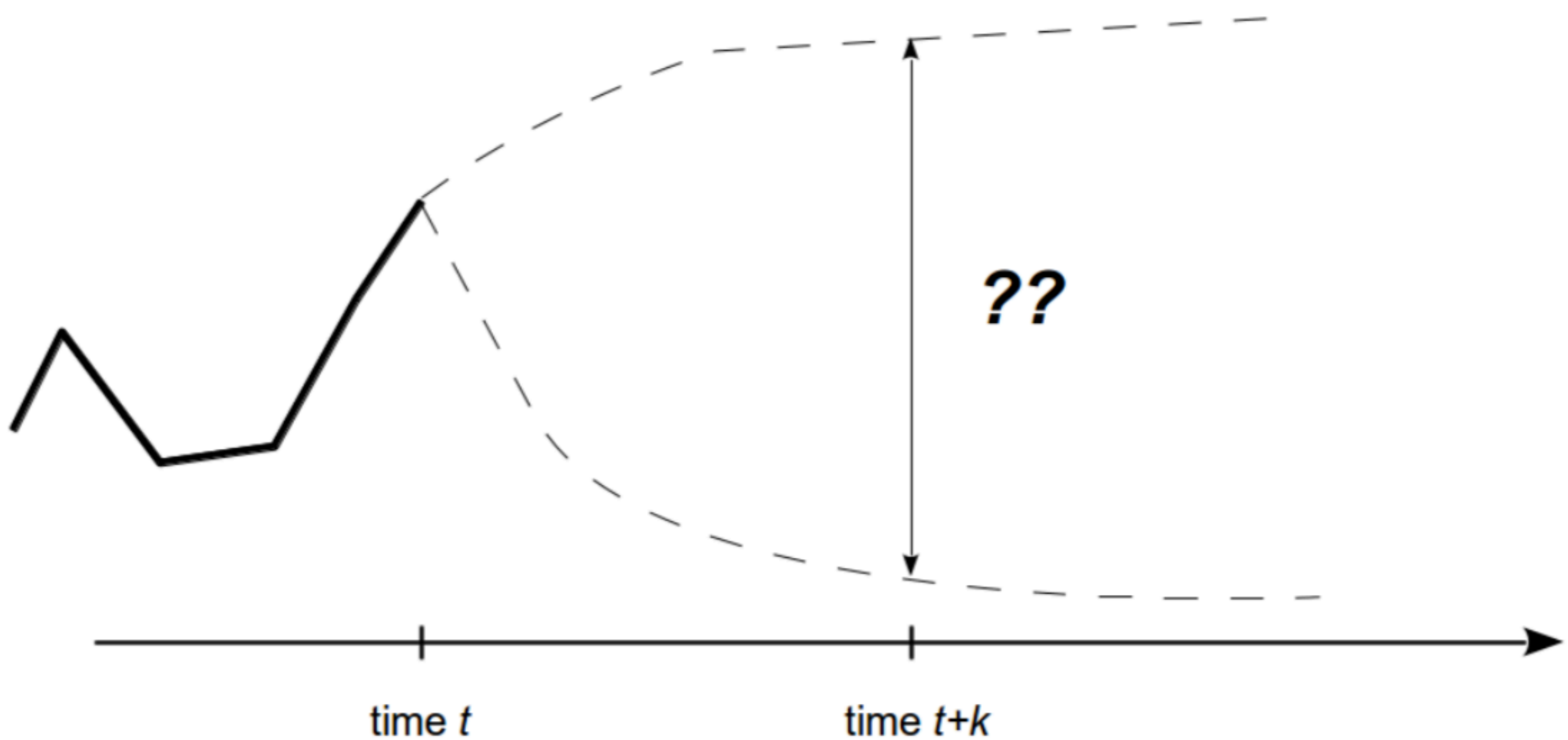
Conclusion: the various types of probabilistic forecasts

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



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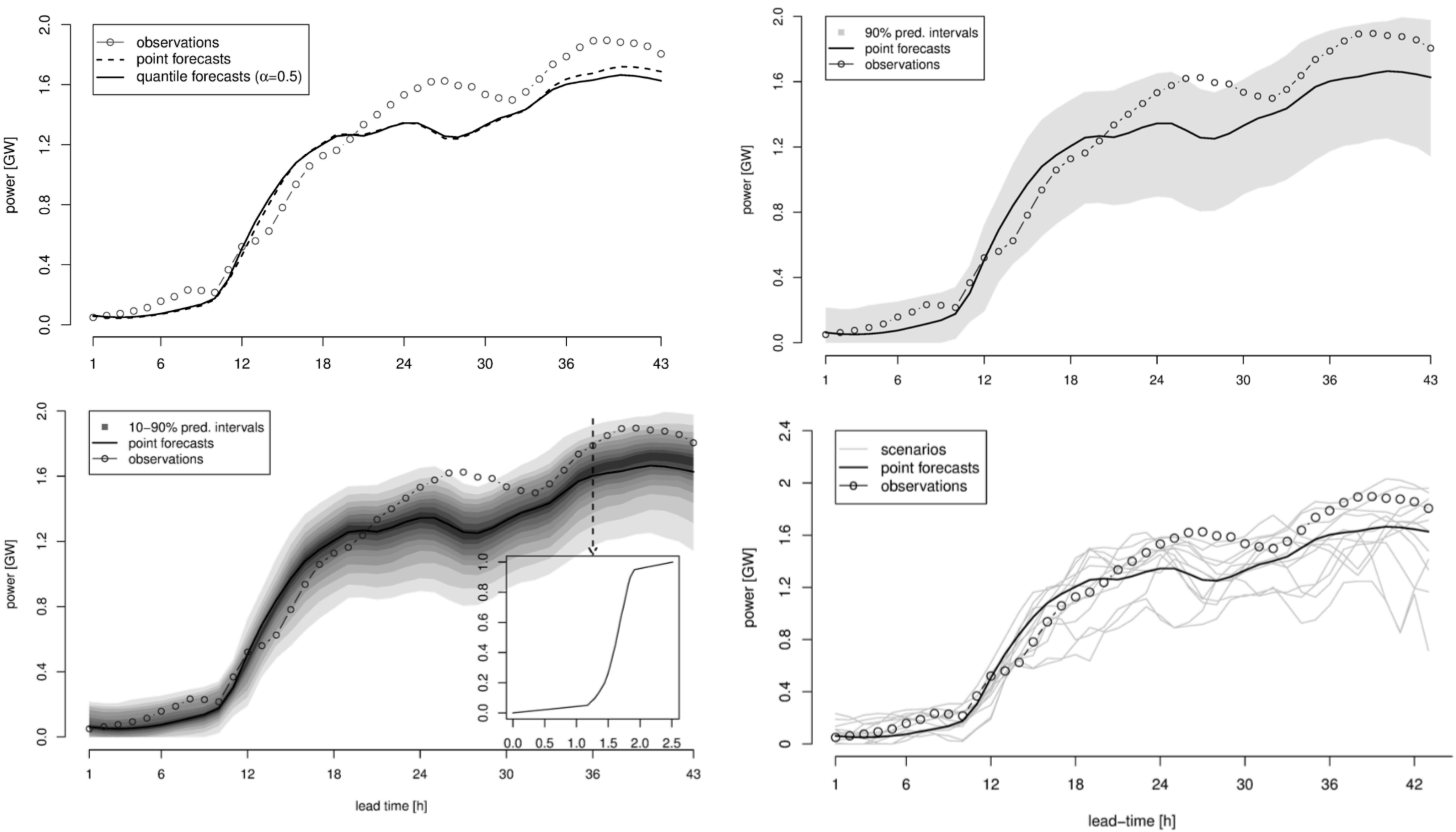
Conclusion: the various types of probabilistic forecasts



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Conclusion: forecast quality vs value

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.

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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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Conclusion: some quality metrics

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

- 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.