Microgrid management with weather-based forecasting of energy generation, consumption and prices.

LIÈGE université

Ph.D. defense 15/11/2021

Jonathan Dumas

Jury members

Prof. Quentin Louveaux (President) University of Liège, Belgium.

Prof. Bertrand Cornélusse (Supervisor) University of Liège, Belgium.

Prof. Gilles Louppe University of Liège, Belgium.

Prof. Pierre Pinson Technical University of Denmark, Denmark.

Prof. Ricardo Bessa INESC TEC, Portugal.

Prof. Simone Paoletti University of Siena, Italy

Summary

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Part I: probabilistic forecasting using normalizing flows

Part II: day-ahead management of a microgrid using robust optimization

Conclusions & perspectives

Context

Climate change

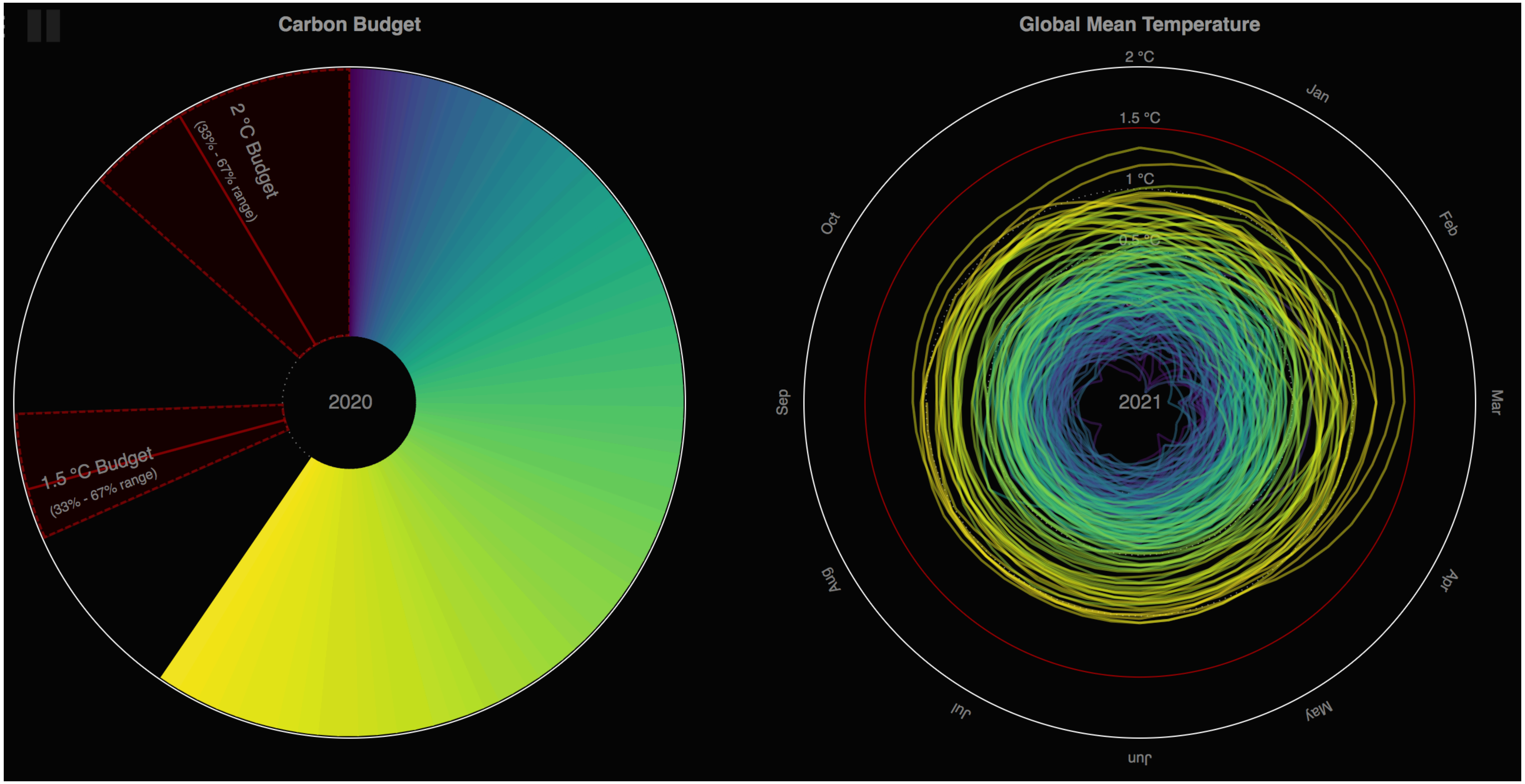
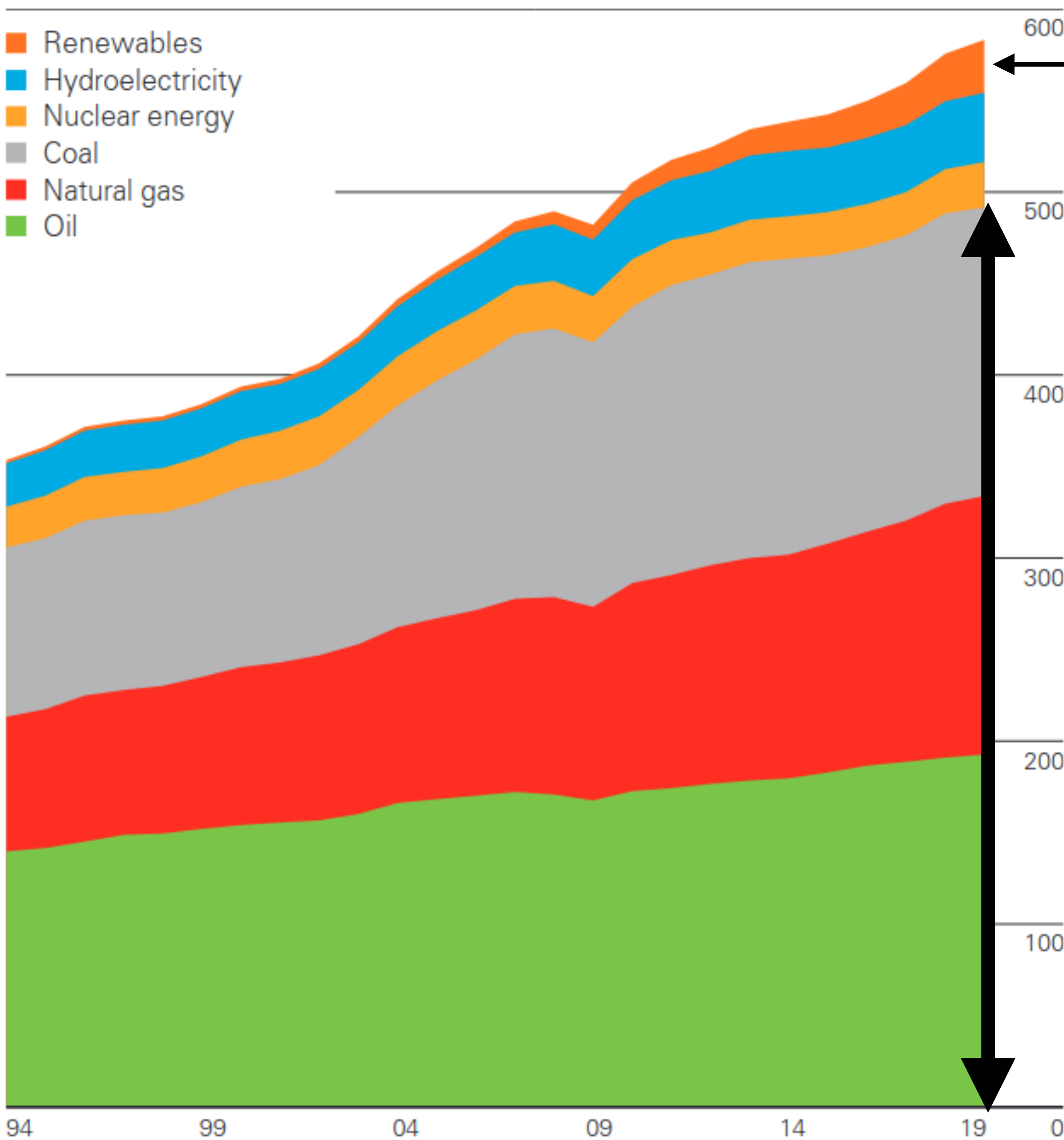


Figure 0-1. From emissions to Global Warming.
Credits: Original Climate Spiral by Ed Hawkins (Climate Lab Book), extended with Carbon Budget and Concentration Spiral by Robert Gieseke and Malte Meinshausen (PRIMAP Group, Potsdam Institute for Climate Impact Research, Germany & Australian-German Climate & Energy College, The University of Melbourne, Australia). link

Context

World consumption of primary energy



Renewables: 5%

Oil, natural gas, and coal: 84%

Figure 0-2: World consumption of primary energy from 1994 to 2020.
Credits: BP's Statistical Review of World Energy 2020. link

Context

The gap between rhetoric and reality on emissions

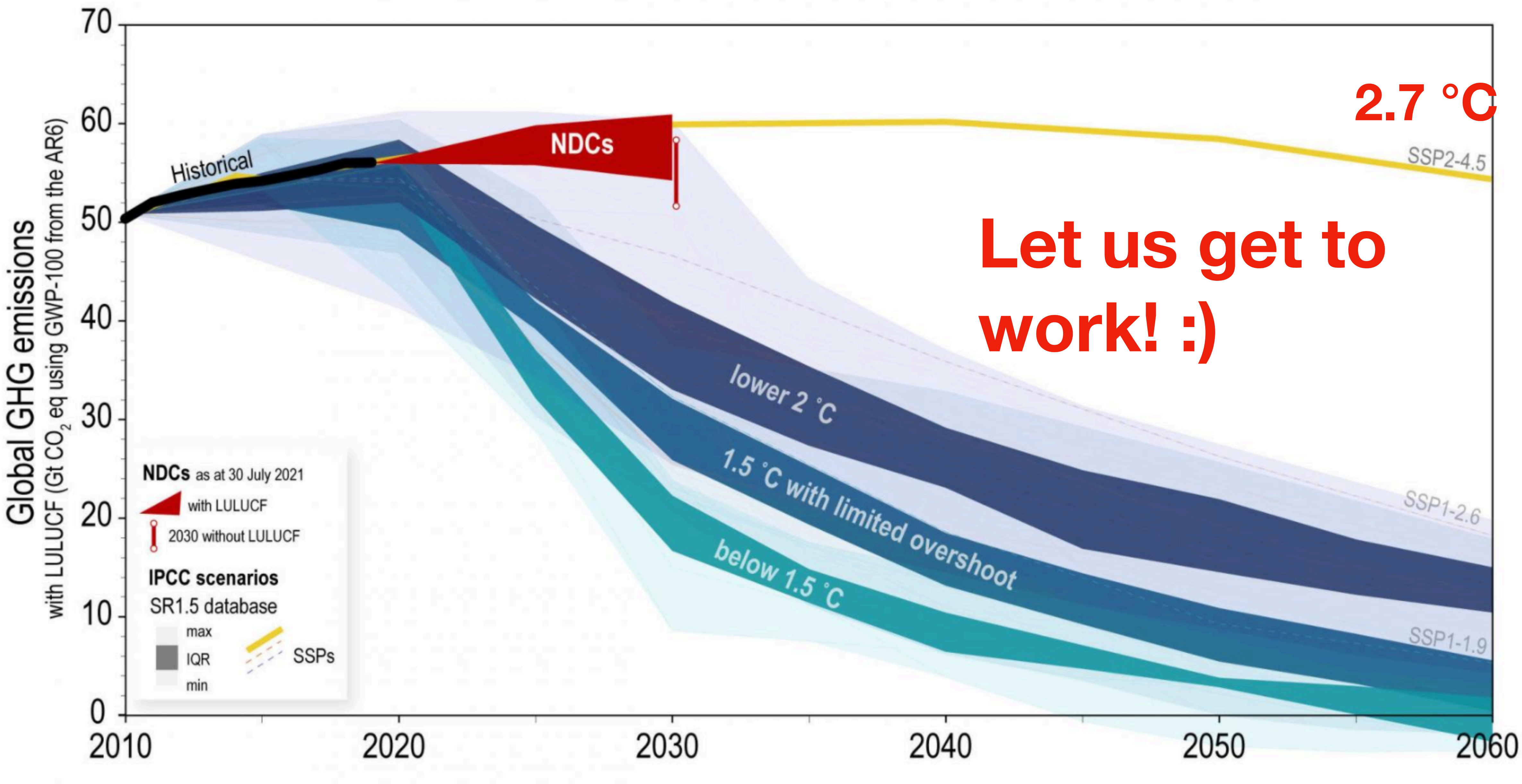


Figure 0-3: The gap between emissions and policies scenarios.
Credits: United Nations Framework Convention on Climate Change (UNFCCC), Nationally Determined Contributions Synthesis Report. link

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Introduction

How to reduce greenhouse gas emissions?

Wind and **solar** provide **70%** of total generation in **2050!**

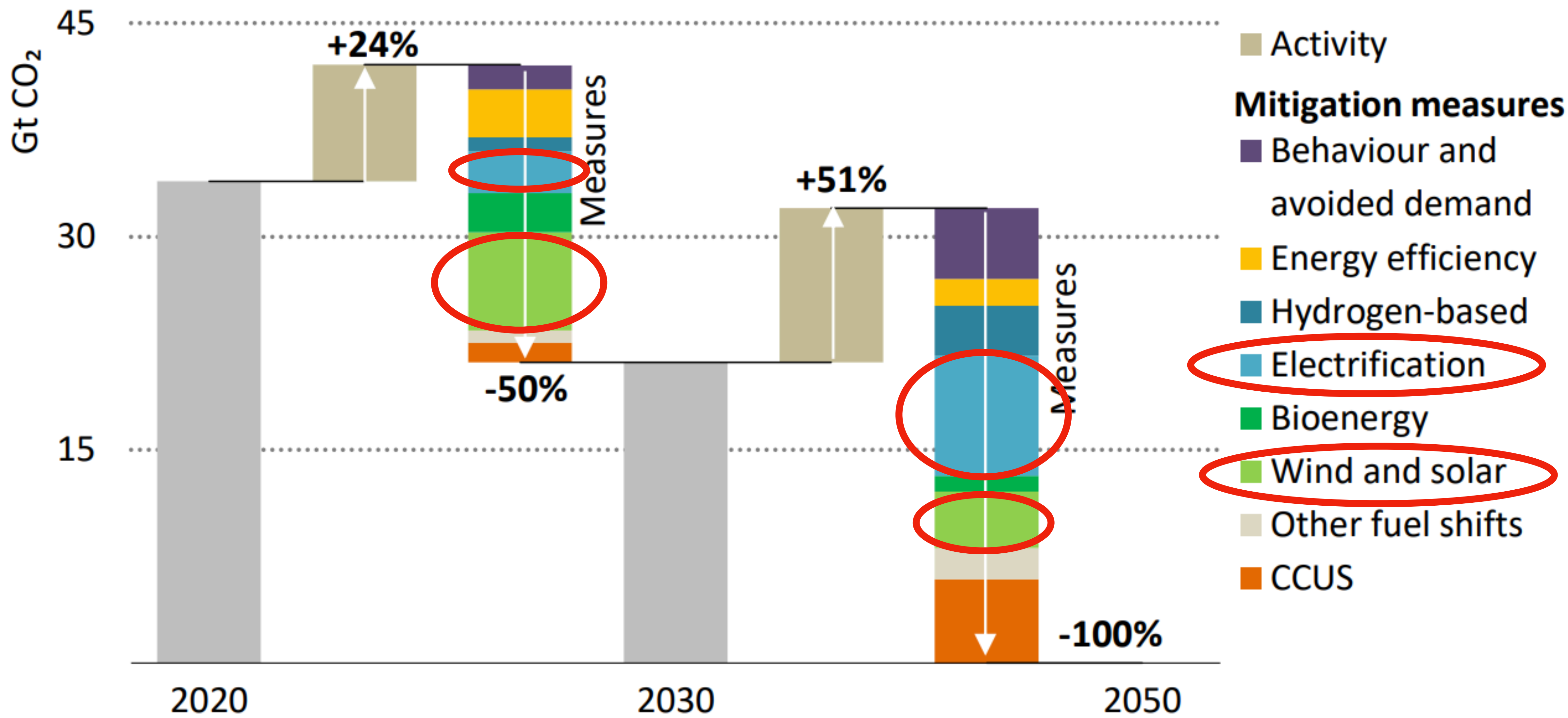

Figure intro-1: Emissions reductions by mitigation measure in the NZE, 2020-2050. *Credits: IEA (2021), Net Zero by 2050, IEA, Paris https://www.iea.org/reports/net-zero-by-2050*

Introduction

How to cope with uncertainty?

Renewable energies are **uncertain**!
-> challenges to the **electricity system's adequacy** when conventional capacities are reduced, and renewable energies are increasing.

In parallel: ***digitization*** *of energy systems, a process towards decentralization, liberalization of electricity markets.*

-> increased focus on **data-driven decision** approaches including:

- **forecasting** of the renewable generation and the consumption;
- **optimization** and **control** of energy systems;

to cope with the uncertainty.

Introduction

Forecasting

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

Key parameters to forecast:

- **Generation:** PV, wind power, hydraulic power …
- **Consumption**: office, industrial, residential …
- **Prices**: electricity, gas …

Figure intro-2: humoristic picture about forecasting.

Introduction

Optimization and management

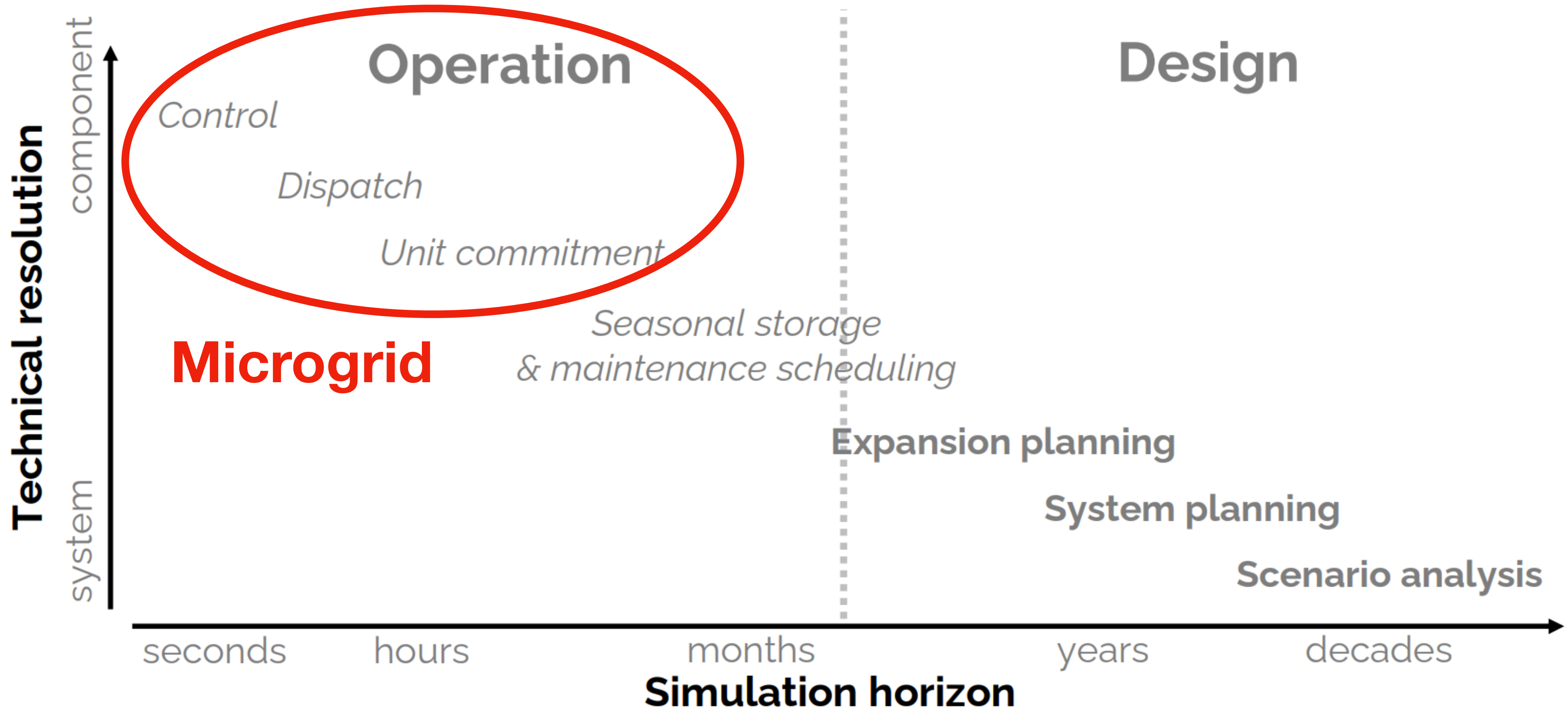

Figure intro-3: Overview of the different scopes of models.
Credits: Limpens, Gauthier. Generating energy transition pathways: application to Belgium. Diss. UCL-Université Catholique de Louvain, 2021.

Introduction

Microgrids

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

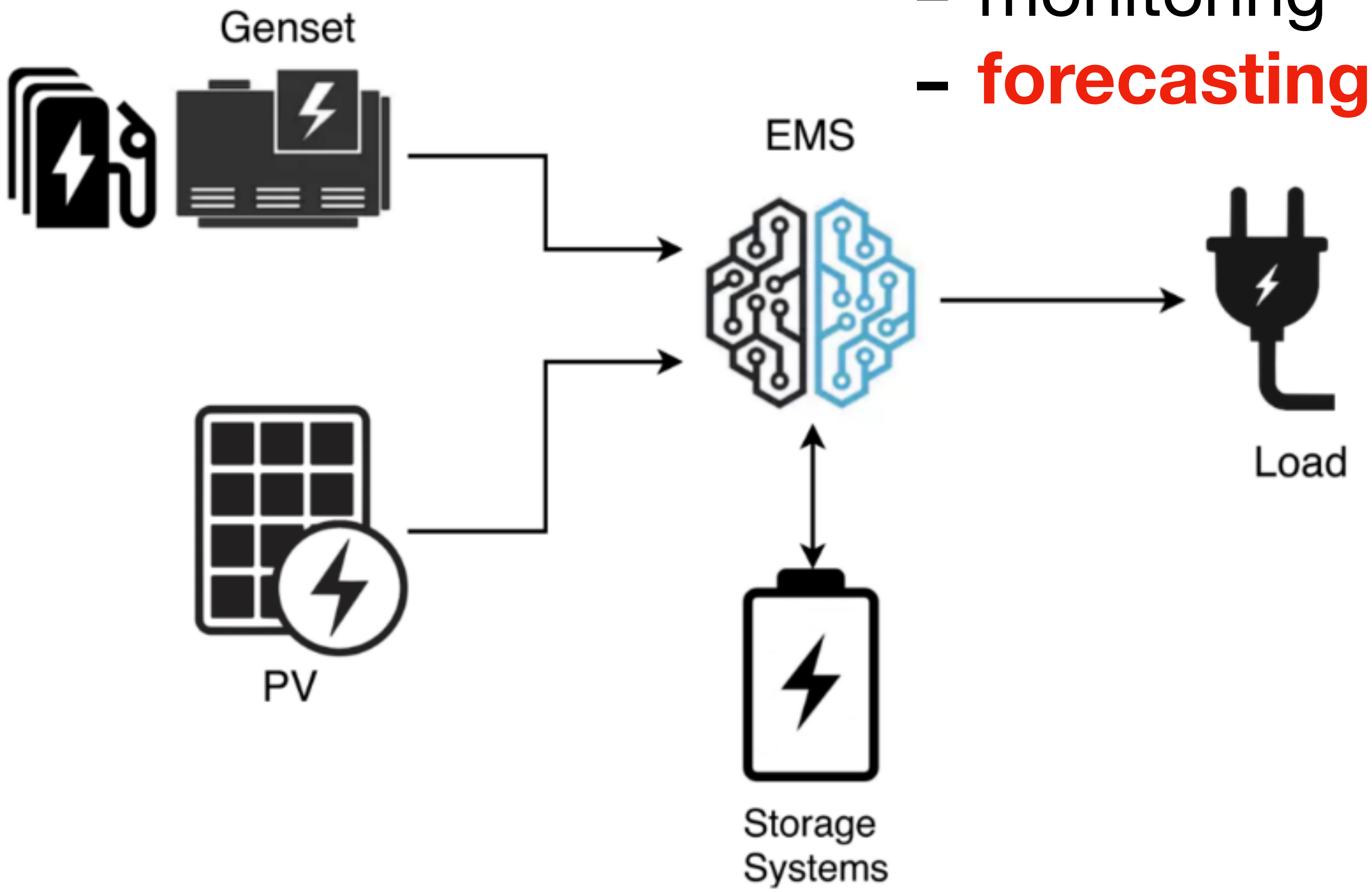

Figure intro-4: Microgrid scheme.
Credits: ELEN0445 Microgrids course link, Liège University.

Introduction

Research questions

1. How to **produce reliable probabilistic forecasts** of renewable generation, consumption, and electricity prices?

2. How to **make decisions with uncertainty** using probabilistic forecasts to improve scheduling?

Introduction

Model simplifications

Microgrids considered are composed of **a few nodes** (generation, consumption, and storage).

Power flows are **not** considered.

Static and **linear** model of the battery energy storage system (BESS).

No degradation of the microgrid components.

Day-ahead planning: the horizon is **cropped to 24** hours.

Introduction

Forecast quality *vs*. value

Forecast **quality**:

-> the ability of the forecasts to **mimic the characteristics** of the processes involved: assessed by quality metrics.

Forecast **value**:

-> 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

Thesis contributions

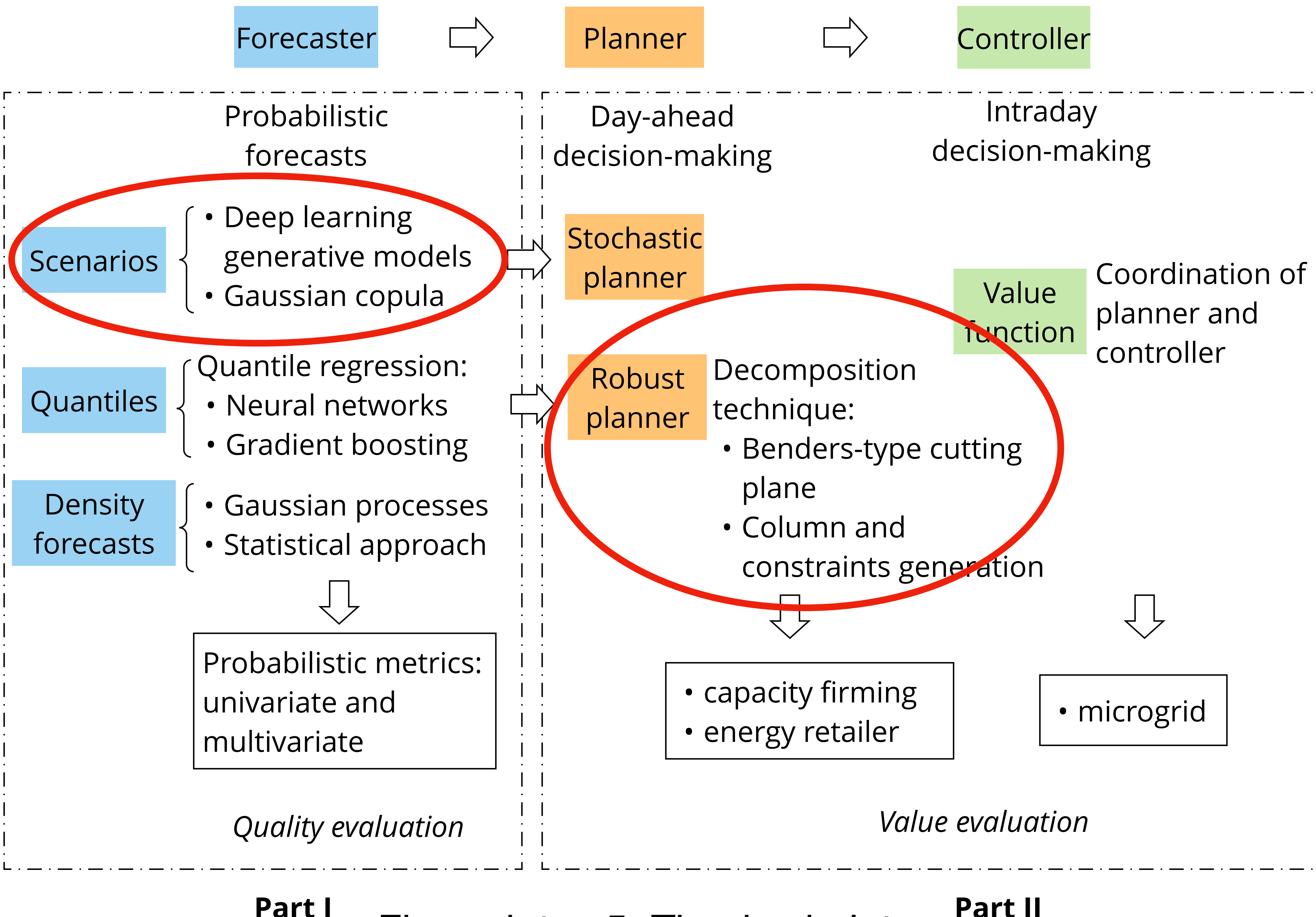

Figure intro-5: Thesis skeleton.

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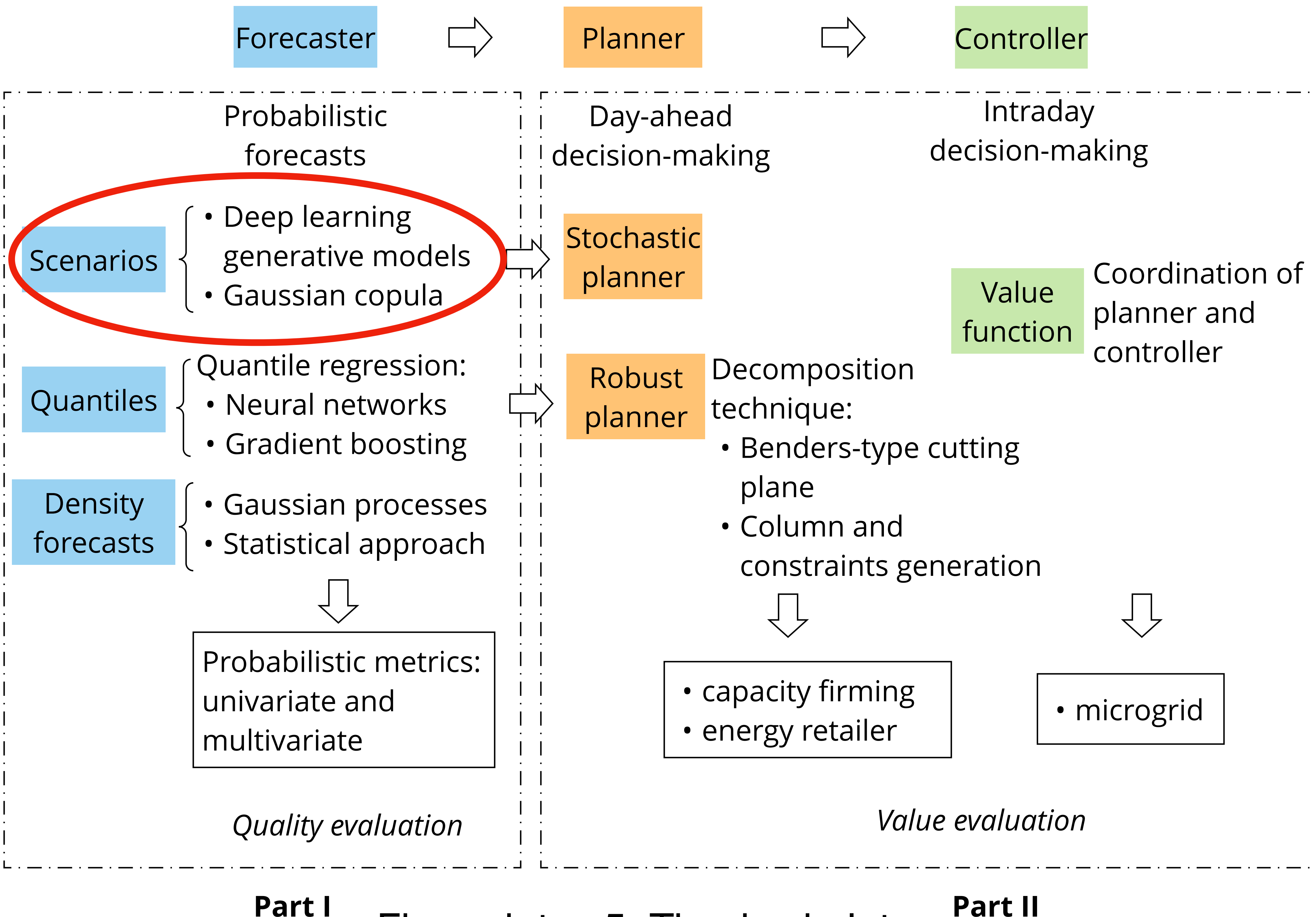

Figure intro-5: Thesis skeleton.

Part I

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Part I - Introduction

Overview

Normalizing flows (NFs) *vs.* **generative adversarial networks** (GANs) & **variational autoencoders** (VAEs).

Conditional generative models using weather forecasts.

Open data of the Global Energy Forecasting Competition 2014: PV, wind power, and load tracks.

-> NFs are more **accurate** in **quality** & **value**.

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.*

Python code: *https://github.com/jonathandumas/generative-models*

Part I - Introduction

Motivations

Research gaps:

- only [ref] 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.

[ref] *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.*

Part I - Introduction

Framework of the study

Introduction of **Normalizing Flows** (NFs) in power systems.

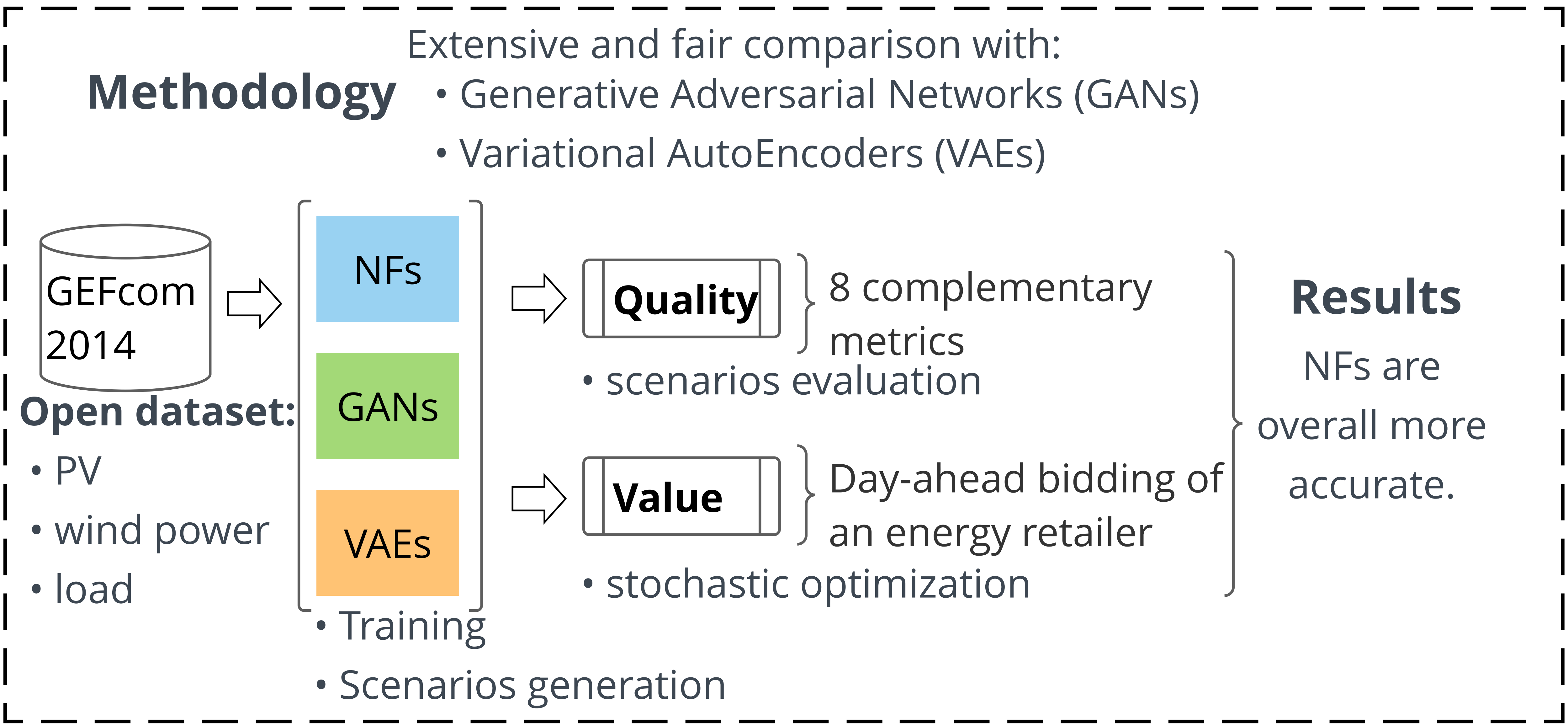

Figure I-1: The framework of the study.

Part I

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Part I - Background

Comparison of the models

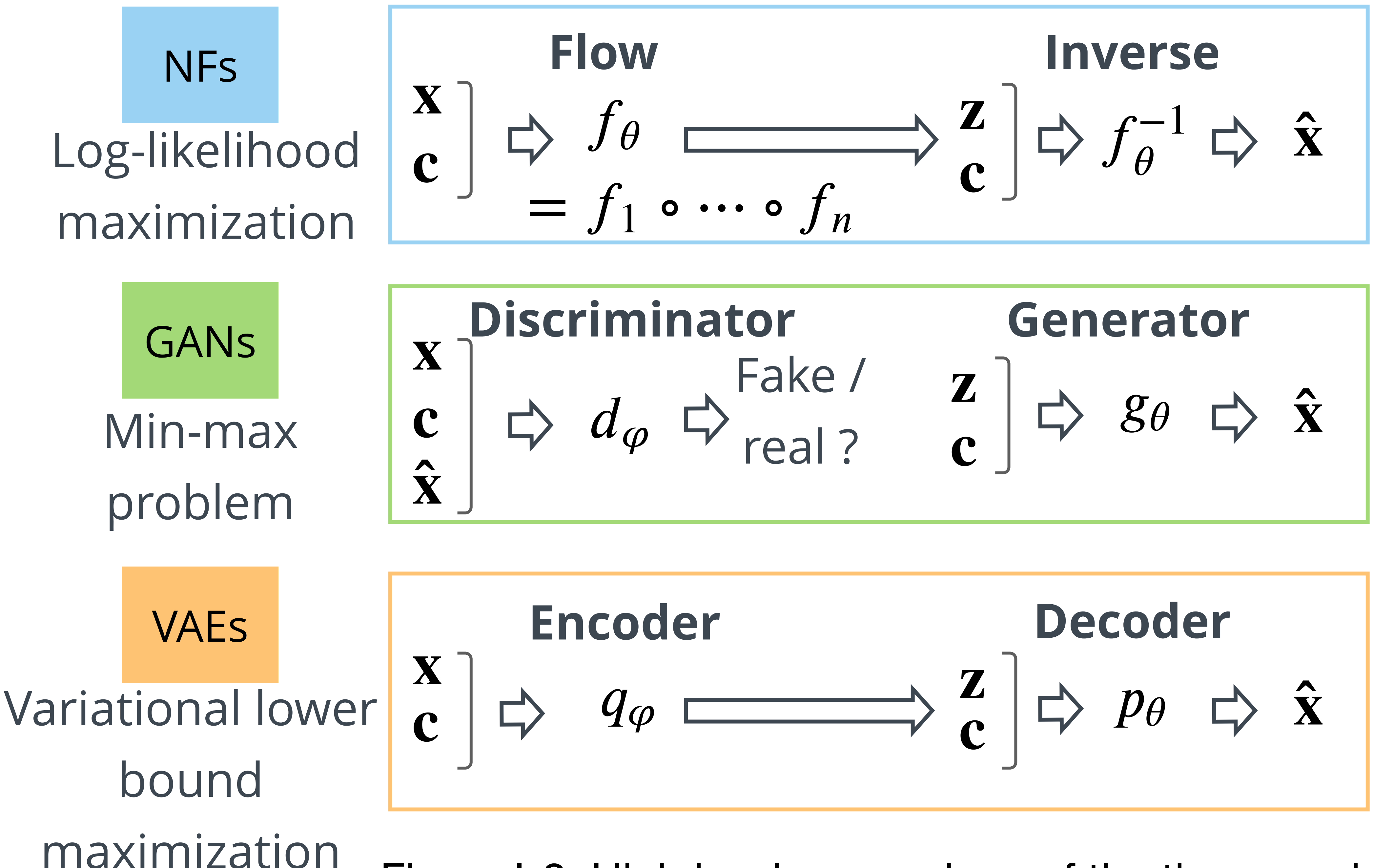

Figure I-2: High level comparison of the three models.
Mathematical formulations are provided in the Ph.D. thesis.

Part I summary

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Part I - Numerical results

Evaluation methodology

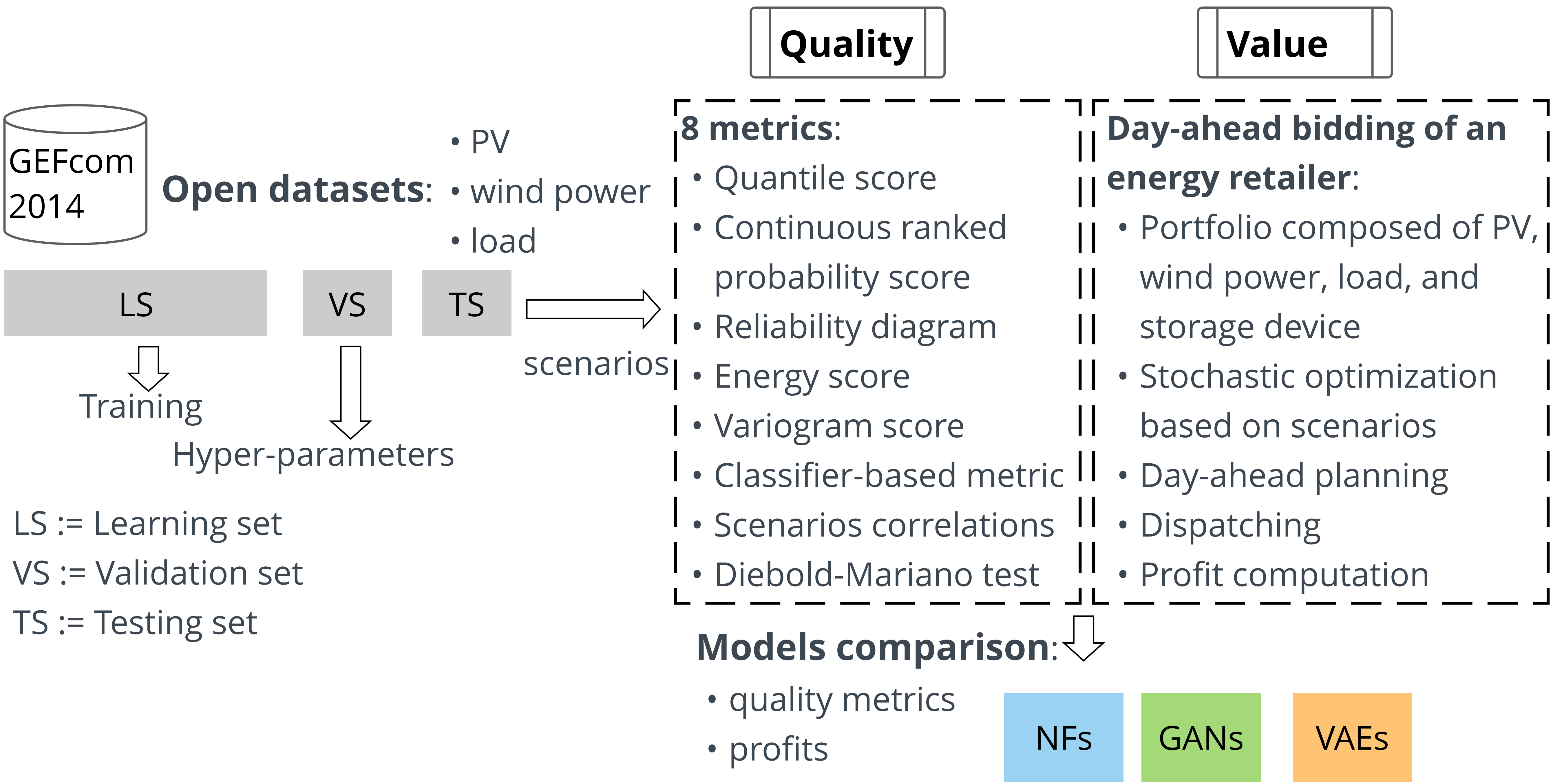

Figure I-3: Methodology: quality and value evaluation.

Part I - Numerical results

Evaluation methodology

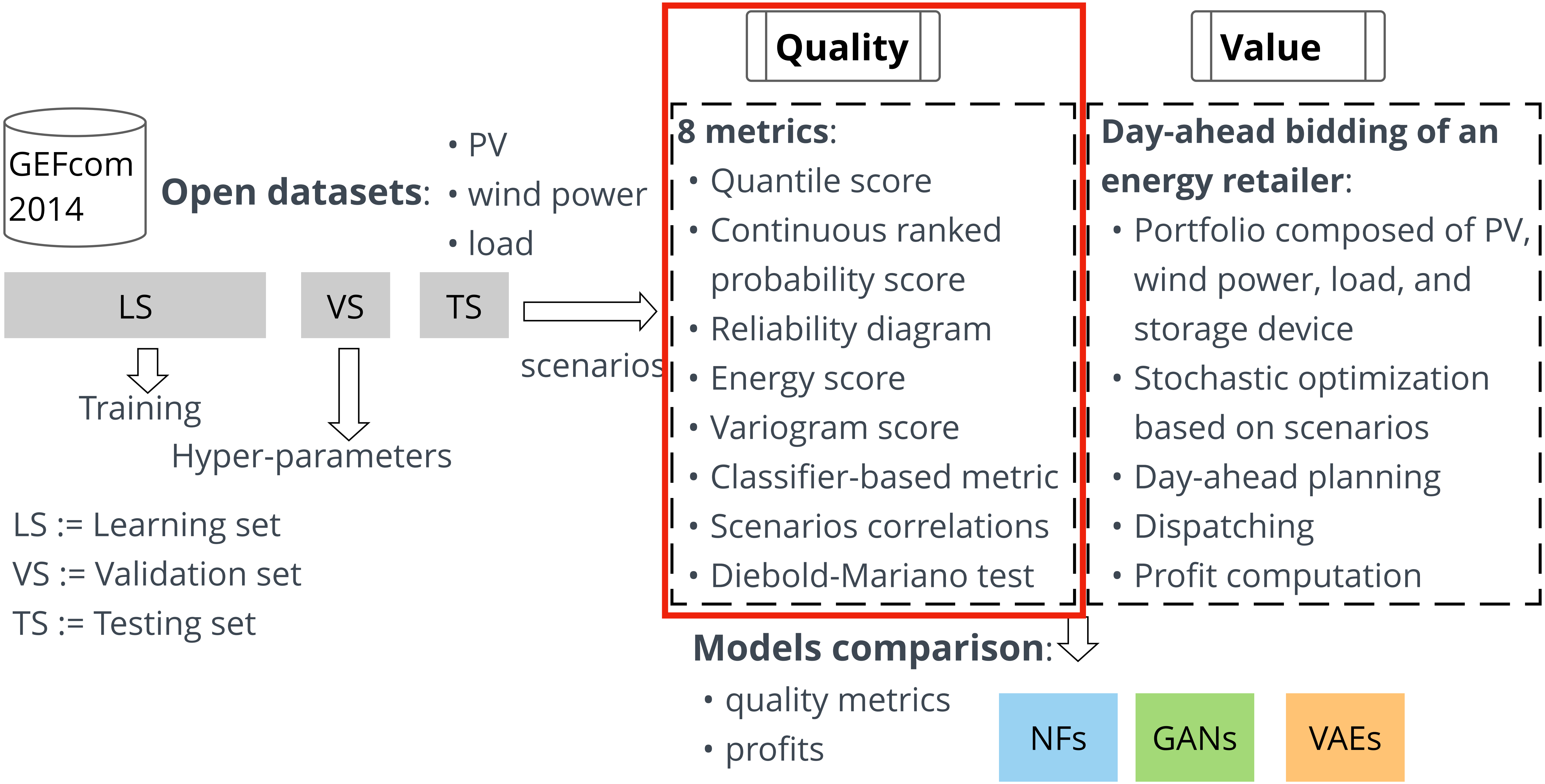

Figure I-3: Methodology: quality and value evaluation.

Part I - Numerical results

Wind power scenarios

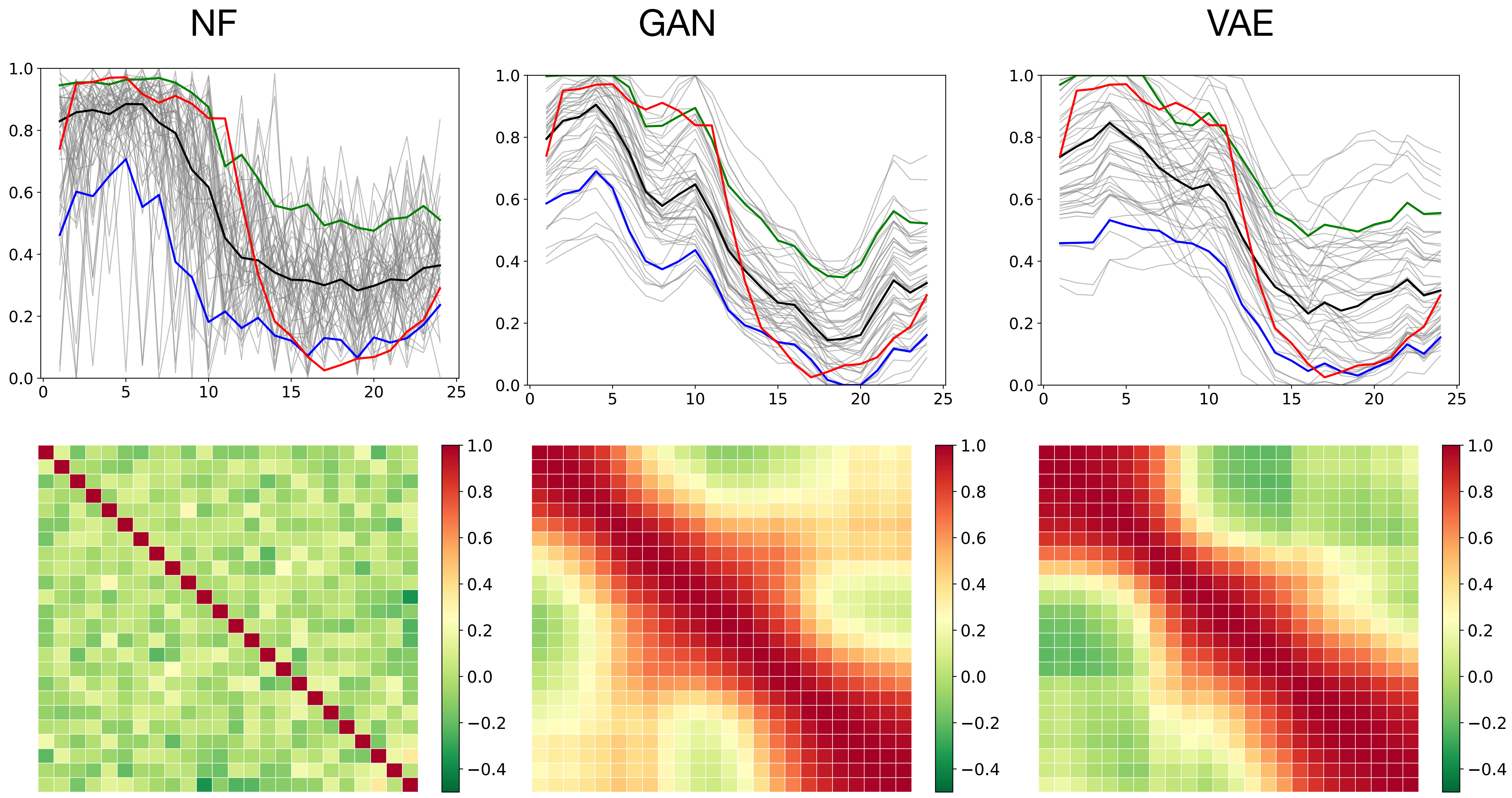

Figure I-4: Wind power scenarios shape comparison and analysis.

Part I - Numerical results

PV scenarios

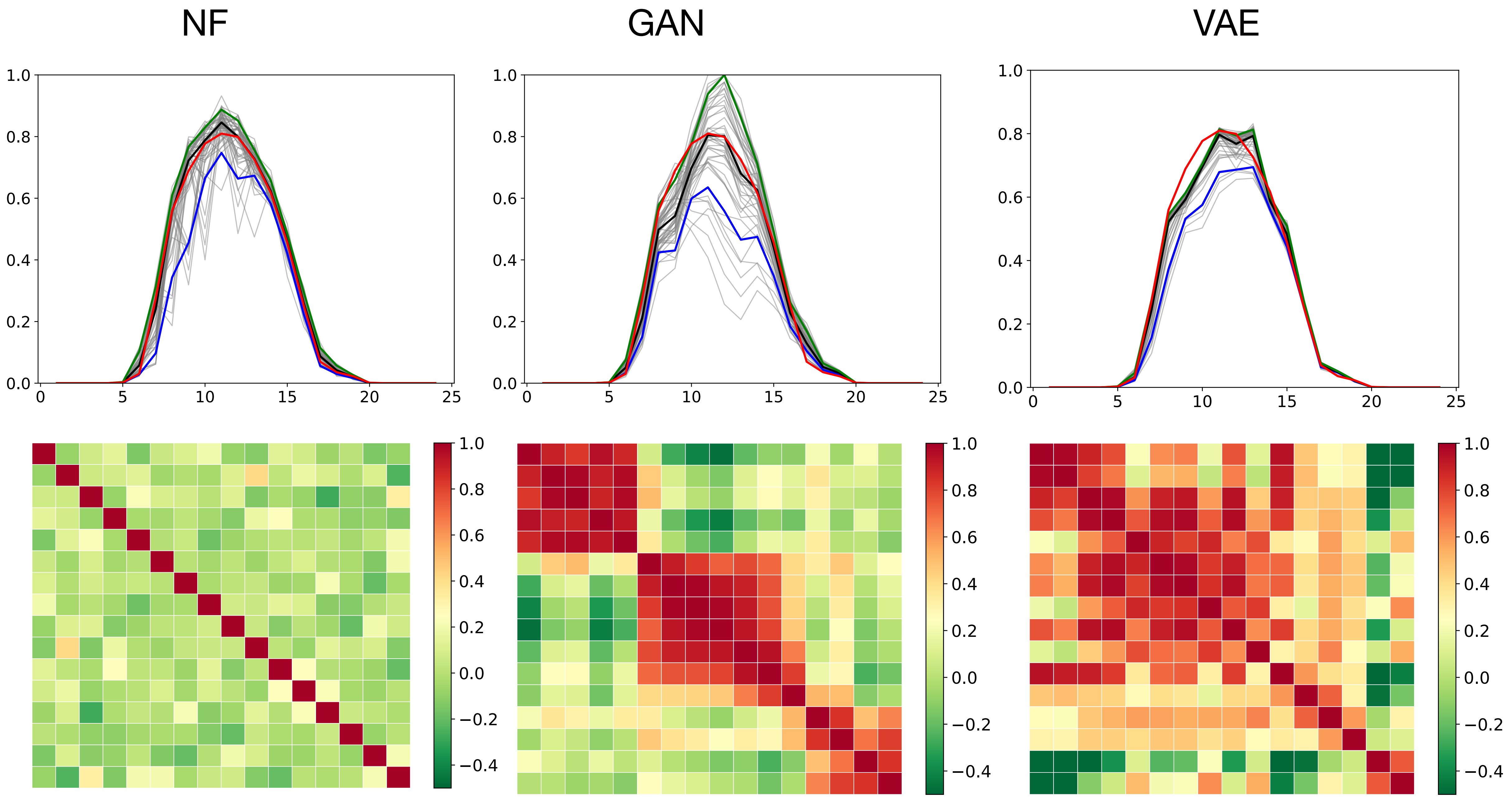

Figure I-5: PV scenarios shape comparison and analysis.

Part I - Numerical results

Load scenarios

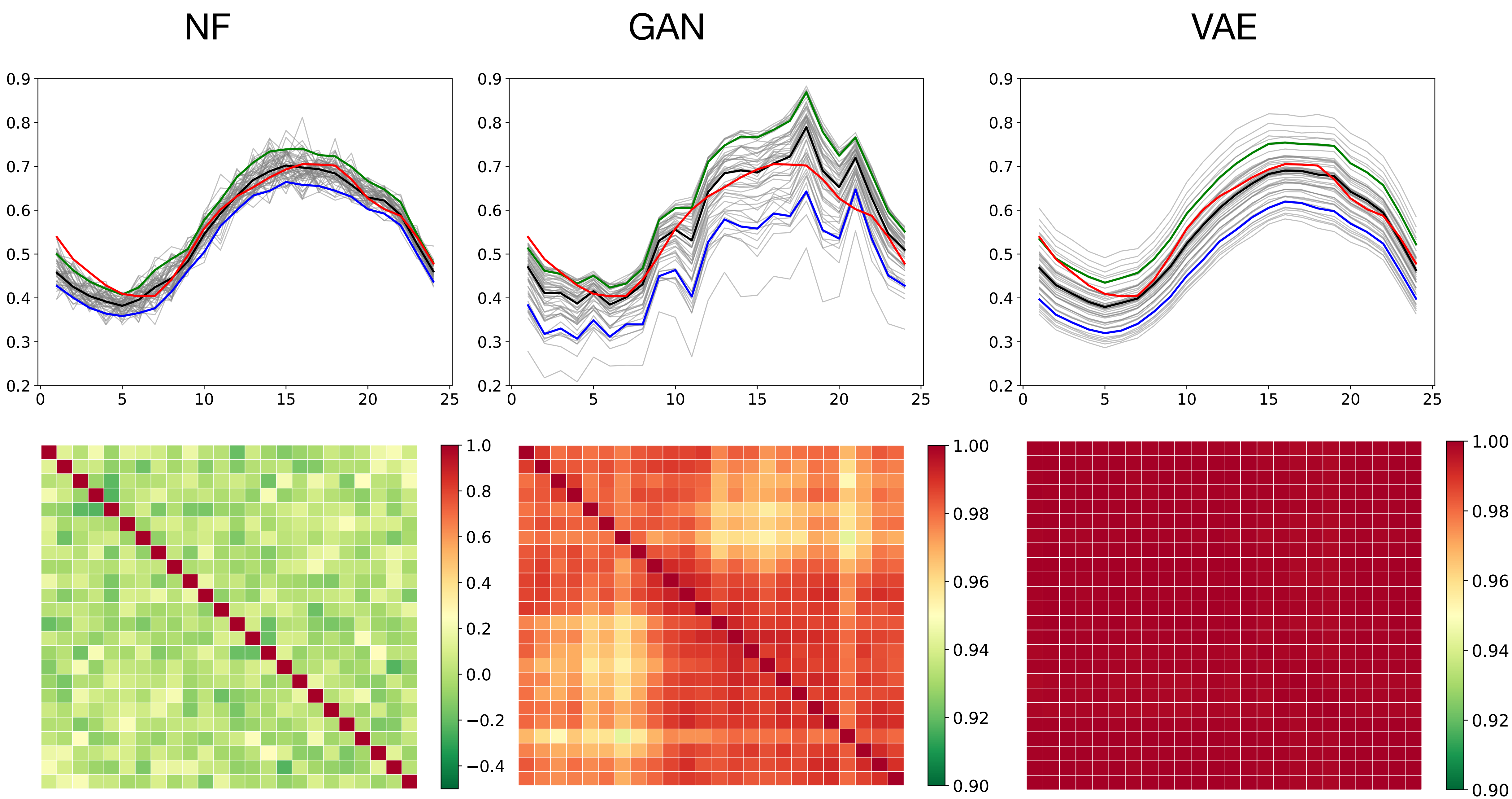

Figure I-6: Load scenarios shape comparison and analysis.

Part I - Numerical results

Quality results

		NF	VAE	GAN
Wind	$\overline{\text{CRPS}}$	9.07	**8.80**	9.79
	$\overline{\text{QS}}$	4.58	**4.45**	4.95
	MAE-r	2.83	**2.67**	6.82
	$\overline{\text{AUC}}$	0.935	**0.877**	0.972
	ES	56.71	**54.82**	60.52
	VS	18.54	**17.87**	19.87
PV	$\overline{\text{CRPS}}$	**2.35**	2.60	2.61
	$\overline{\text{QS}}$	**1.19**	1.31	1.32
	MAE-r	**2.66**	9.04	4.94
	$\overline{\text{AUC}}$	**0.950**	0.969	0.997
	ES	**23.08**	24.65	24.15
	VS	**4.68**	5.02	4.88
Load	$\overline{\text{CRPS}}$	**1.51**	2.74	3.01
	$\overline{\text{QS}}$	**0.76**	1.39	1.52
	MAE-r	**7.70**	13.97	9.99
	$\overline{\text{AUC}}$	**0.823**	0.847	0.999
	ES	**9.17**	15.11	17.96
	VS	**1.63**	1.66	3.81

Table I-1: Averaged quality score per dataset.

Part I - Numerical results

Evaluation methodology

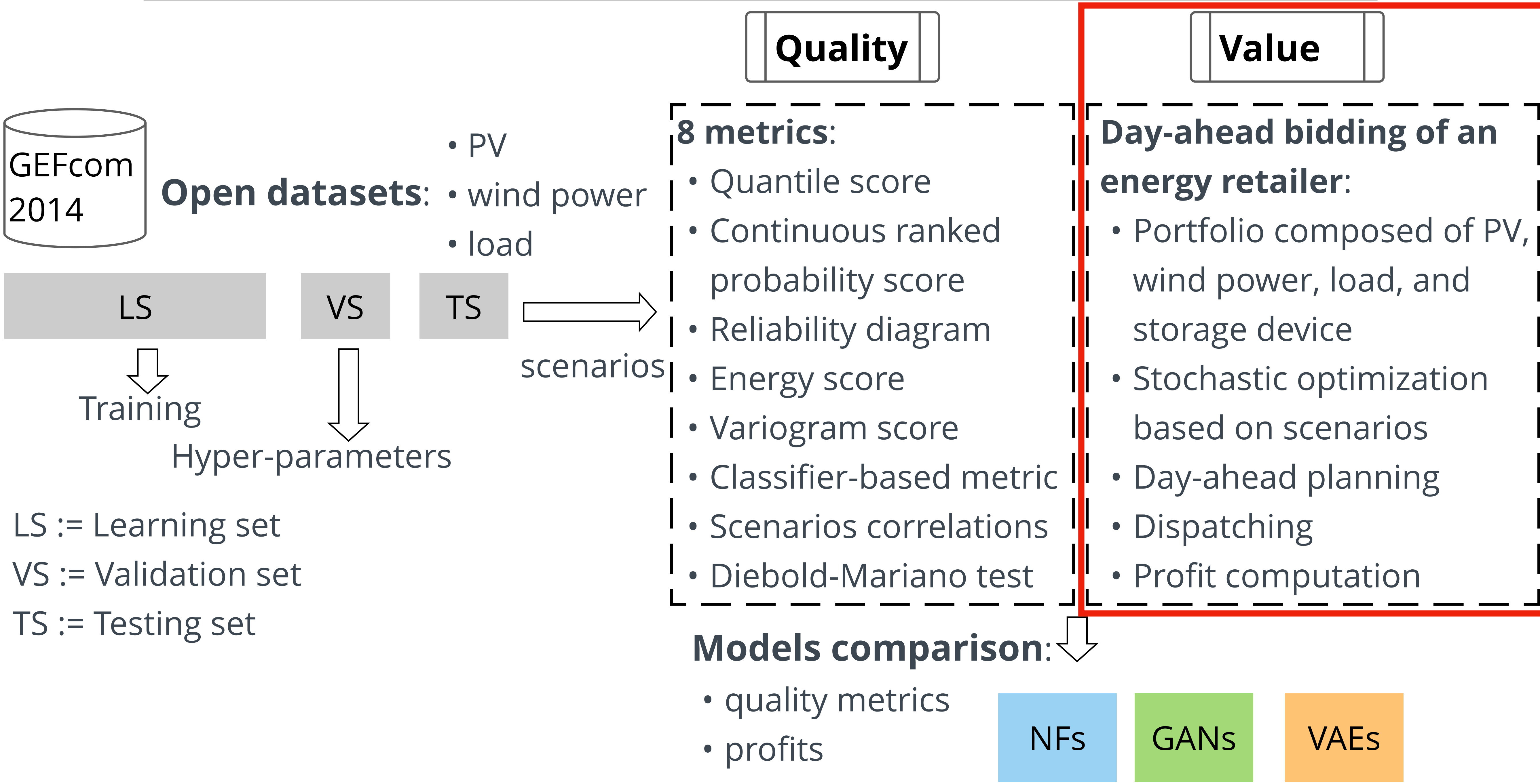

Figure I-3: Methodology: quality and value evaluation.

Part I - Numerical results

Energy retailer formulation: scenario-based approach

Net profit = profit - penalty. (k€)

$$\max_{e_t \in \mathcal{X}, y_{t,\omega} \in \mathcal{Y}(e_t)} \sum_{\omega \in \Omega} \alpha_\omega \sum_{t \in \mathcal{T}} \Big[\underbrace{\pi_t e_t}_{\text{day-ahead bid}} - \bar{q}_t d^-_{t,\omega} - \bar{\lambda}_t d^+_{t,\omega} \Big]$$

day-ahead bid Short & long deviations

e = ***first***-*stage variables: day-ahead bid*
y = ***second***-*stage variables: deviations, dispatch, BESS charge/ discharge, BESS state of charge, PV and wind power generation.*

Part I - Numerical results

Value results: profits comparison

Net profit = profit - penalty. (k€)

-> 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-2: Total net profit (k€) and cumulative ranking (%).

Part I - Numerical results

Results: summary

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

Table I-3: Comparison between the generative models.

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Part I - Conclusions

Introduction of **Normalizing Flows** (NFs) in power systems.

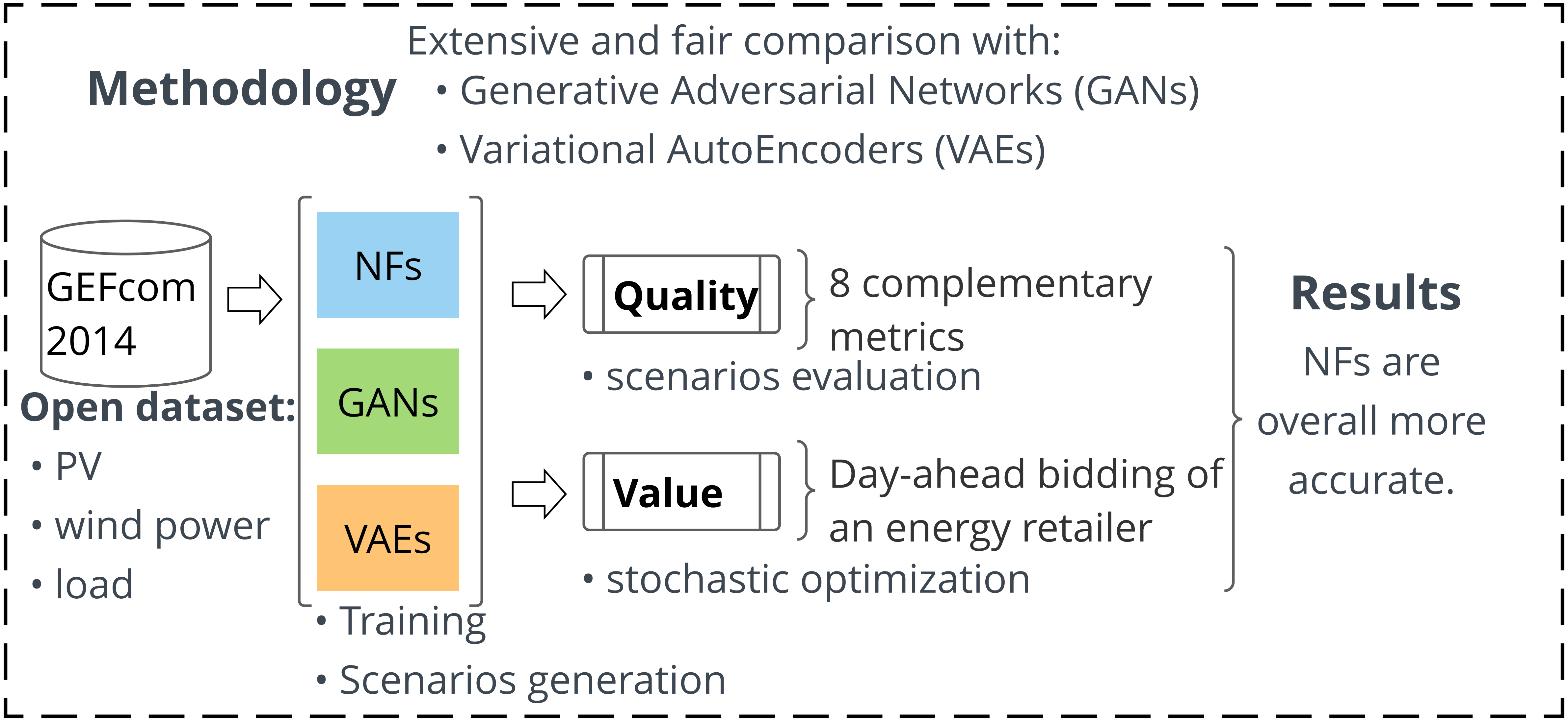

Figure I-1: The framework of the study.

- **Normalizing flows** can **challenge** GANs and VAEs.
- They can be used effectively by **non-expert** deep learning practitioners.

Part I - Conclusions

Perspectives

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

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

Investigate **graphical normalizing flows** [1] that could take advantage of **spatial** dependencies between plants.

[1] *Wehenkel, Antoine, and Gilles Louppe. "Graphical normalizing flows." International Conference on Artificial Intelligence and Statistics. PMLR, 2021.*

Compare NFs to other recent generative models such as **diffusion** models [2].

[2] *Dhariwal, Prafulla, and Alex Nichol. "Diffusion models beat gans on image synthesis." arXiv preprint arXiv:2105.05233 (2021).*

Part I - Conclusions

Perspectives

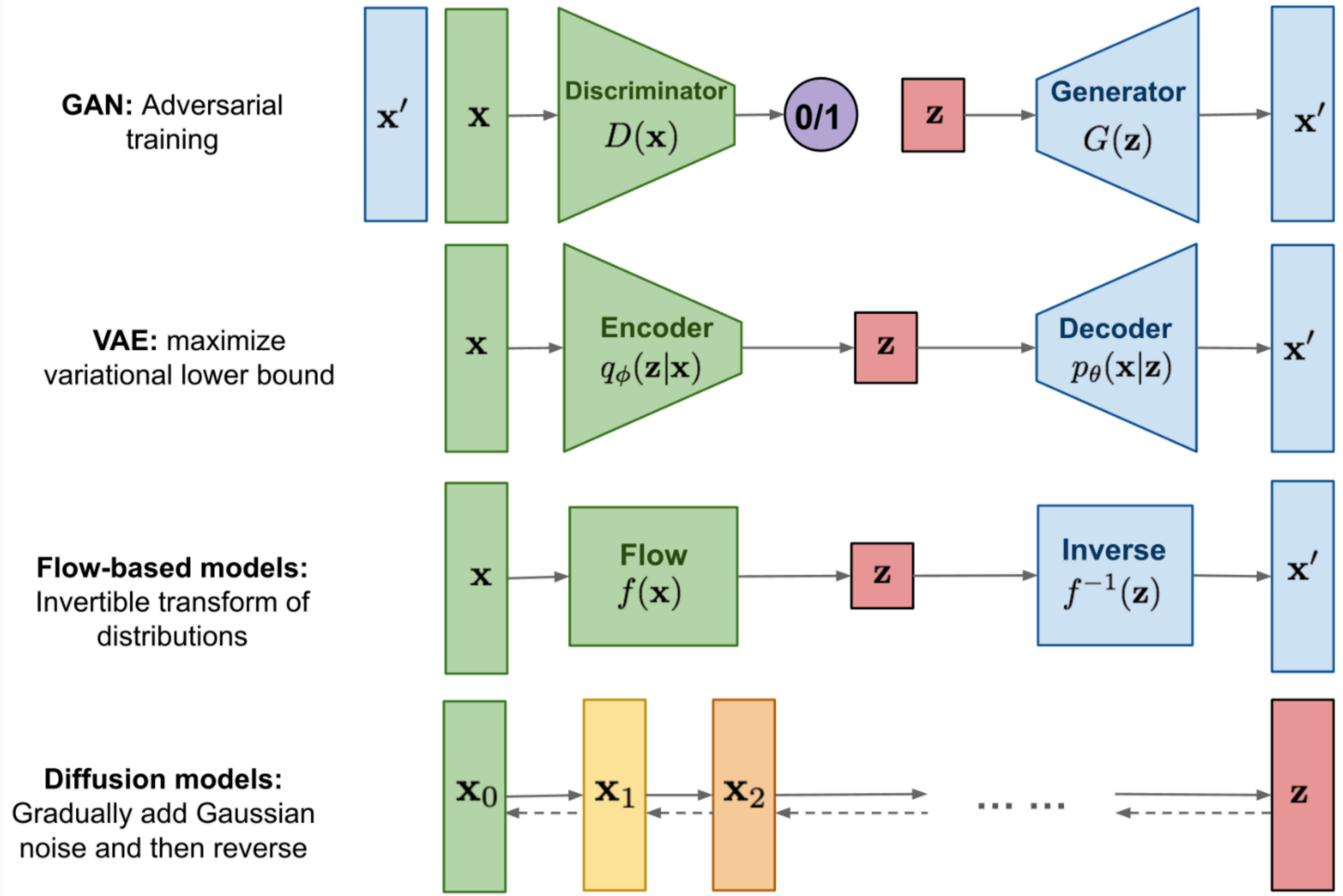

Figure I-7: Overview of different types of generative models.
Credits: https://lilianweng.github.io/lil-log/2021/07/11/diffusion-models.html

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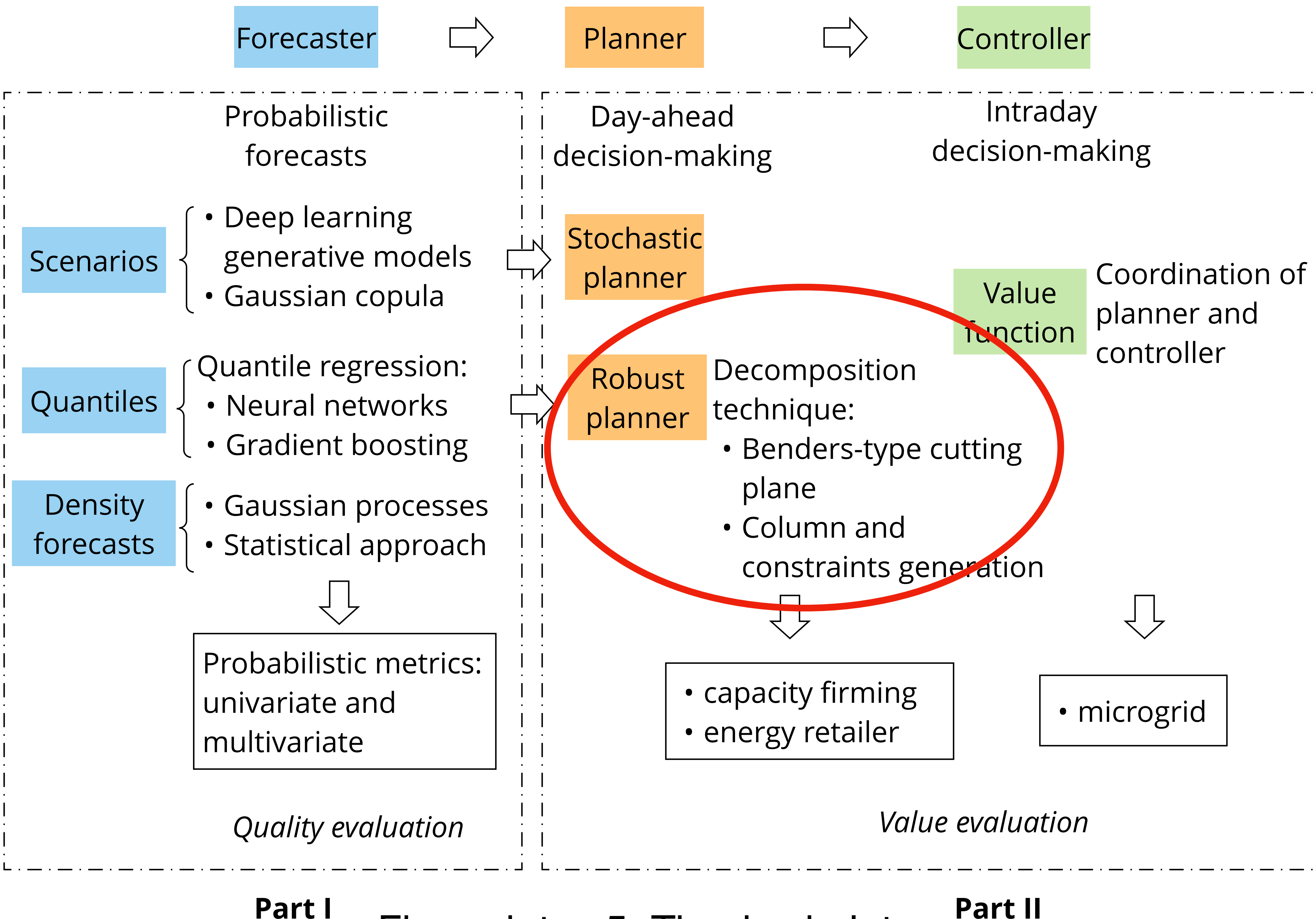

Figure intro-5: Thesis skeleton.

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Part II - Introduction

Overview

System:
-> a **grid-connected renewable generation** plant & a battery energy storage system (BESS) in the **capacity firming** market.

Methodology:
-> a **min-max-min robust optimization** problem with recourse.

Decomposition techniques:
-> **Benders-dual cutting plane** & **column and constraints generation** algorithms.

*J. Dumas, C. Cointe, A. Wehenkel, A. Sutera, X. Fettweis and B. Cornelusse, "**A Probabilistic Forecast-Driven Strategy for a Risk-Aware Participation in the Capacity Firming Market**," in IEEE Transactions on Sustainable Energy, doi: 10.1109/TSTE.2021.3117594.*

Python code: *https://github.com/jonathandumas/capacity-firming-ro*

Part II - Introduction

Capacity firming framework

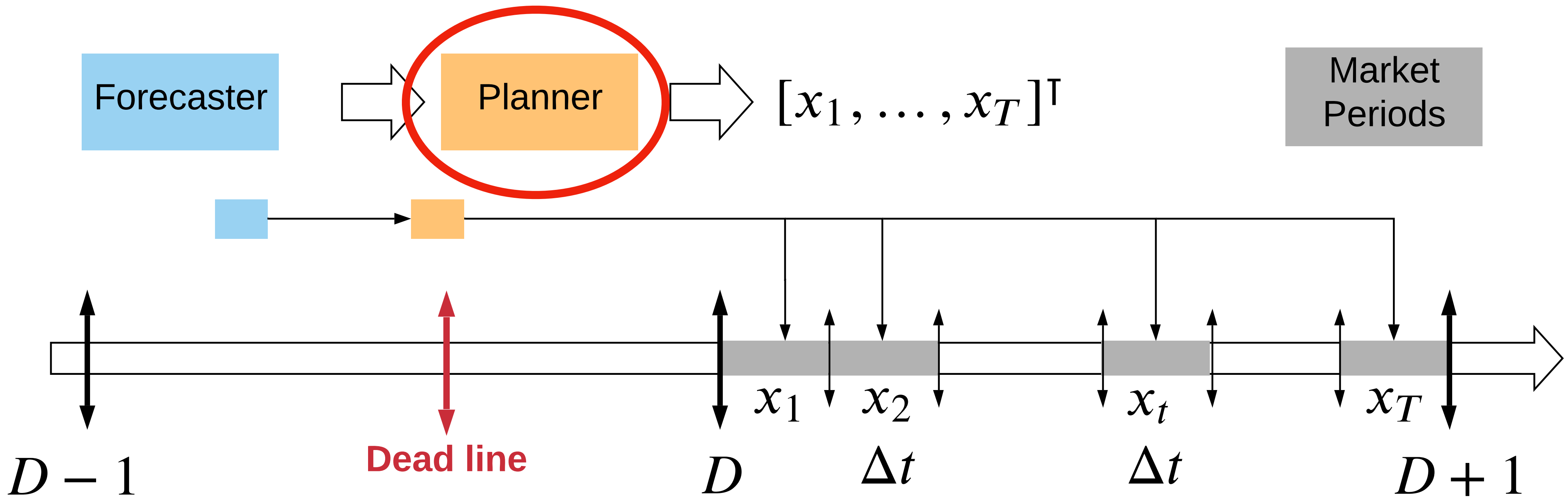


Figure II-1: Day-ahead nomination process.

System = a grid connected **PV plant + BESS.**

Nomination on a **day-ahead** basis with ramping power constraints.

Remuneration = gross revenue - penalties.

Penalties = **deviations** of the realized imports/exports from the engagements.

Part II - Introduction

Day-ahead planning strategies

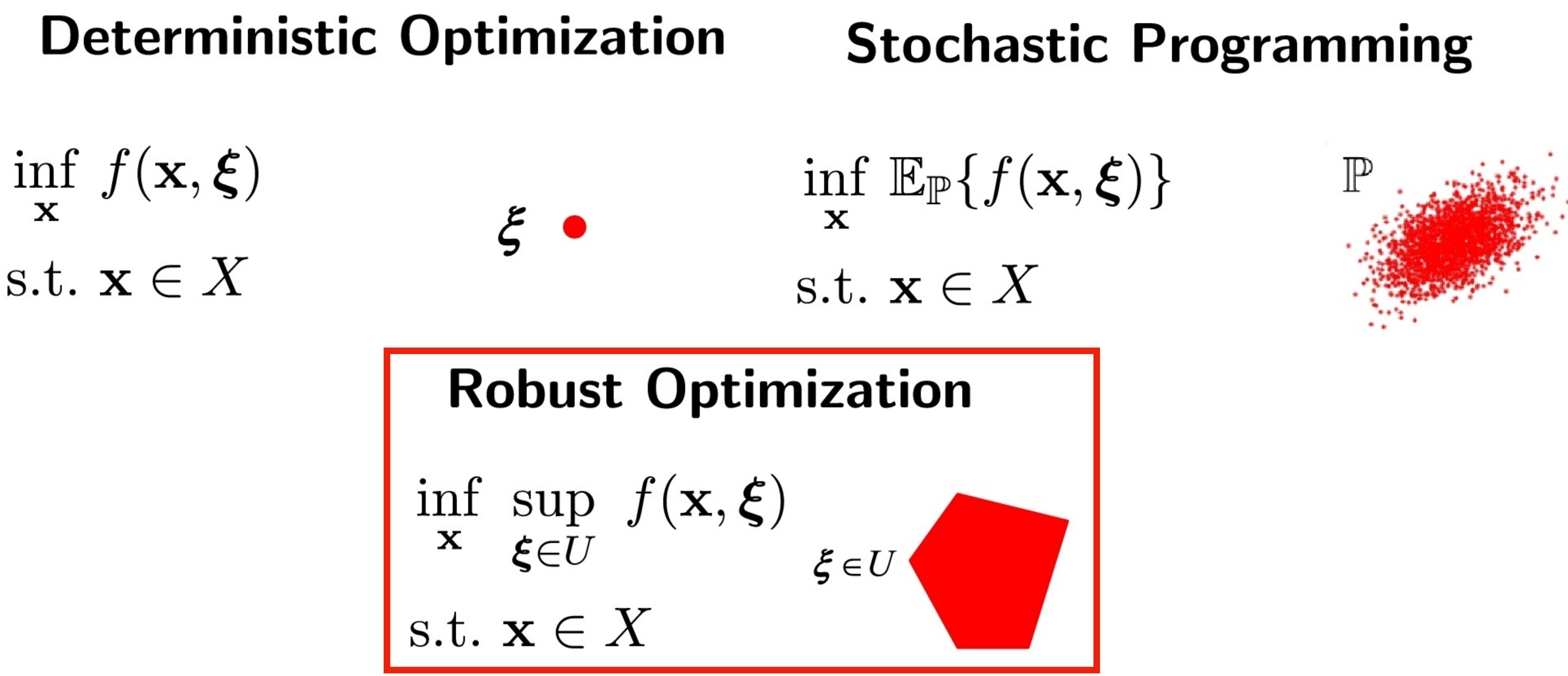
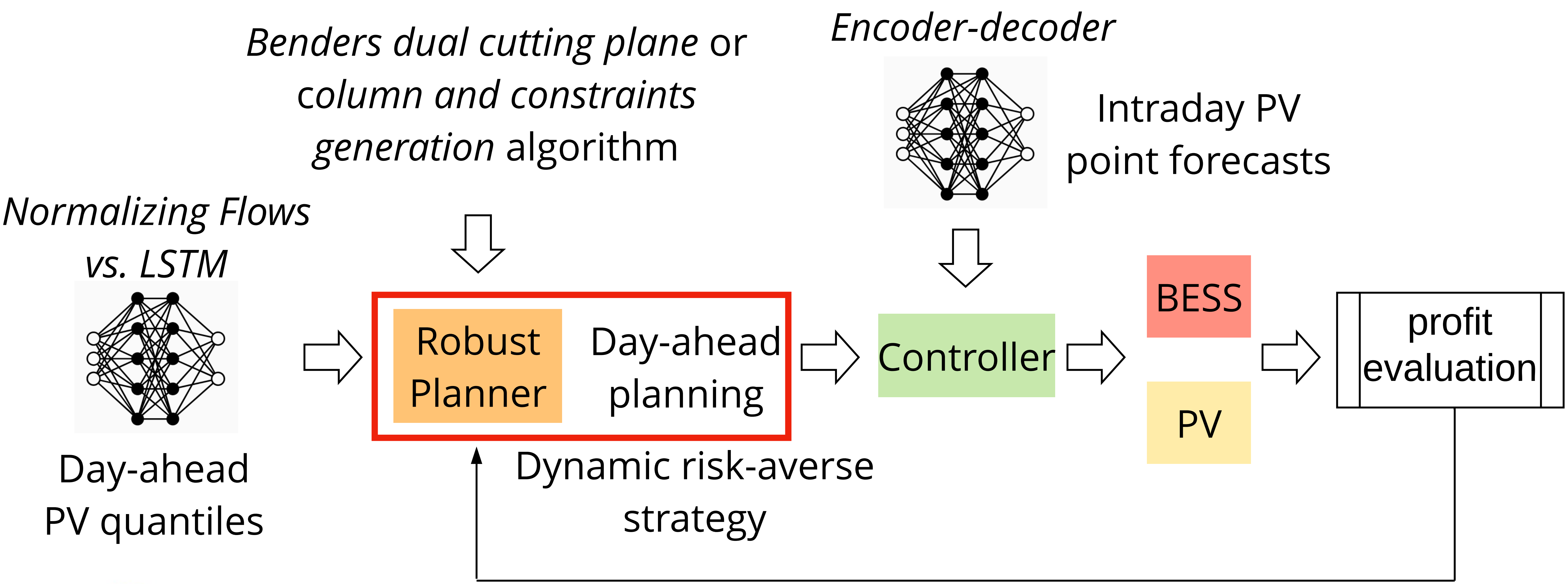


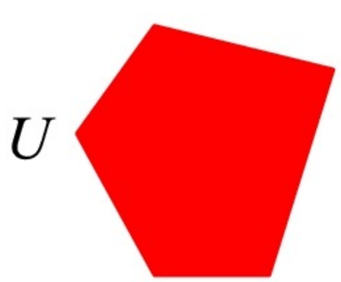
Figure II-2: Comparison of various optimization schemes.

Credits: Shang, Chao, and Fengqi You. "Distributionally robust optimization for planning and scheduling under uncertainty." Computers & Chemical Engineering 110 (2018): 53-68.

Part II - Introduction

Framework of the study





PV uncertainty set

Figure II-3: Forecast-driven robust optimization strategy.

Part II

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Part II - Problem formulation

Day-ahead planning strategies

Deterministic Optimization

$$\inf_{\mathbf{x}} \; f(\mathbf{x}, \boldsymbol{\xi})$$

$$\text{s.t. } \mathbf{x} \in X$$

$\boldsymbol{\xi}$

PV point forecast

Robust Optimization

$$\inf_{\mathbf{x}} \; \sup_{\boldsymbol{\xi} \in U} \; f(\mathbf{x}, \boldsymbol{\xi})$$

$$\text{s.t. } \mathbf{x} \in X$$

$\boldsymbol{\xi} \in U$

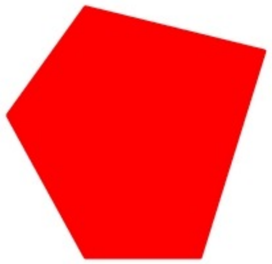


Figure II-2: Comparison of various optimization schemes.
Credits: Shang, Chao, and Fengqi You. "Distributionally robust optimization for planning and scheduling under uncertainty." Computers & Chemical Engineering 110 (2018): 53-68.

Part II - Problem formulation

Two-stage deterministic formulation

J := - **net revenue** = - (gross revenue - penalties) [EUR]

$$J\left(x_t, y_t\right) = \sum_{t \in \mathcal{T}} \pi_t \Delta t[-y_t + \beta(d_t^- + d_t^+)]. \quad \text{Eq. (II-1)}$$

symmetric, convex & piecewise-linear **penalty**

Mixed-integer linear program (**MILP**):

$$\boxed{\min_{x_t \in \mathcal{X}, y_t \in \Omega(x_t, \hat{y}_t^{\mathrm{pv}})} J(x_t, y_t)} \quad \text{Eq. (II-2)}$$

$\mathcal{X} =$ *Set of feasible engagements =* ***first-stage*** *variables*

$\Omega(x_t, \hat{y}_t^{\mathrm{pv}}) =$ *Set of* ***feasible dispatch*** *variables =* ***second-stage*** *variables: import/export, BESS charge/discharge, BESS state of charge, PV generation, short/long deviations.*

$\hat{y}_t^{\mathrm{pv}}$ = *PV point forecast*

Part II - Problem formulation

Day-ahead planning strategies

Deterministic Optimization

$$\inf_{\mathbf{x}} \ f(\mathbf{x}, \boldsymbol{\xi})$$

$$\text{s.t. } \mathbf{x} \in X$$

ξ 

Robust Optimization

$$\inf_{\mathbf{x}} \ \sup_{\boldsymbol{\xi} \in U} \ f(\mathbf{x}, \boldsymbol{\xi})$$

$$\text{s.t. } \mathbf{x} \in X$$

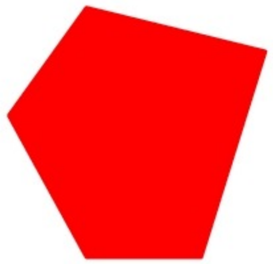
$\xi \in U$ 

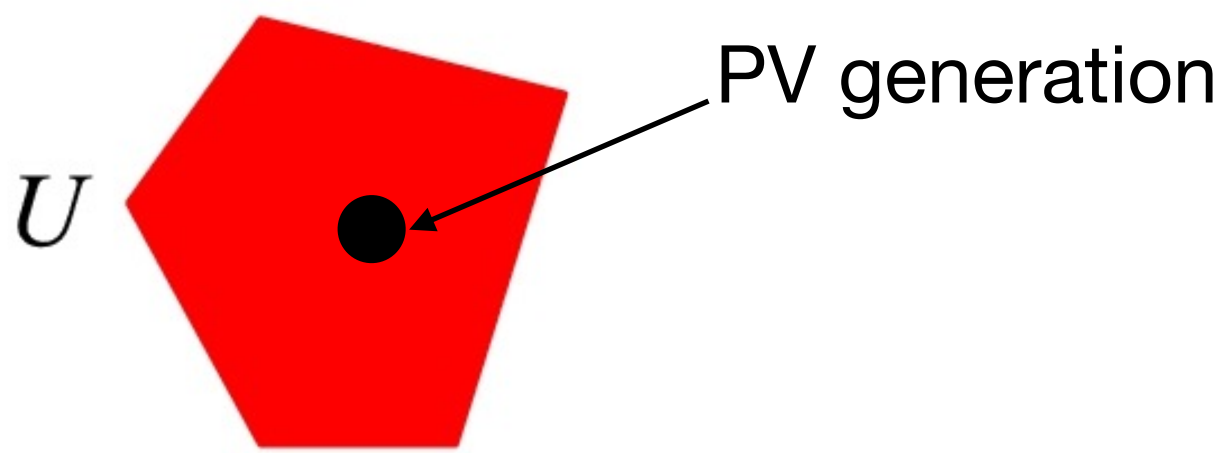
Figure II-2: Comparison of various optimization schemes.
Credits: Shang, Chao, and Fengqi You. "Distributionally robust optimization for planning and scheduling under uncertainty." Computers & Chemical Engineering 110 (2018): 53-68.

Part II - Problem formulation

PV uncertainty set

PV generation is within an **uncertainty interval**:

$$\mathcal{U} = \left\{u_t \in \left[u_t^{min}, u_t^{max}\right] \forall t \in \mathcal{T}\right\}$$



PV uncertainty set

$$u_t^{min}, u_t^{max} = \hat{y}_t^{pv,(q)}, \hat{y}_t^{pv,(1-q)}$$

PV quantiles **q**-> **marginal prediction intervals**!

Part II - Problem formulation

PV uncertainty set

Only **downward** deviations: $u_t^{max} = \hat{y}_t^{pv,(q=50\%)}$

*Demonstration in the Ph.D. thesis (thank you **Quentin** :))*

$$\mathcal{U} = \left\{ u_t \in \left[u_t^{min}, \hat{y}_t^{pv,(q=50\%)} \right] \forall t \in \mathcal{T} \right\}$$

Only **lower** or **upper bounds** [ref]:

$$\boxed{\begin{gathered} \mathcal{U} = \left\{ u_t \in \left\{ u_t^{min}; \hat{y}_t^{pv,(q=50\%)} \right\} \forall t \in \mathcal{T} \right\} \\ u_t^{min} = \hat{y}_t^{pv,(q=50\%)} - \hat{y}_t^{pv,(q)} \end{gathered}}$$

[ref] *Zhao, Long, and Bo Zeng. "Robust unit commitment problem with demand response and wind energy." 2012 IEEE power and energy society general meeting. IEEE, 2012.*

Part II - Problem formulation

Risk-aversion

2 parameters define the PV uncertainty set [Ref]:

- PV quantile **q**;
- the uncertainty budget **Γ**.

-> Γ **restricts** the number of periods where uncertainty is allowed:
- Γ = T -> full uncertainty;
- Γ = 0 -> no uncertainty.

$$\mathcal{U} = \Big\{ u_t : \sum_{t \in \mathcal{T}} z_t \leq \Gamma,\ z_t \in \{0; 1\}, \quad u_t = \hat{y}_t^{pv,(q=50\%)} - z_t u_t^{min}\ \forall t \in \mathcal{T} \Big\}$$

$$u_t^{min} = \hat{y}_t^{pv,(q=50\%)} - \hat{y}_t^{pv,(q)}$$

[Ref] *Bertsimas, Dimitris, et al. "Adaptive robust optimization for the security constrained unit commitment problem." IEEE transactions on power systems 28.1 (2012): 52-63.*

Part II - Problem formulation

Two-stage robust formulation

Minimizing J over the **worst** **PV trajectory**:

$$\max_{u_t \in \mathcal{U}} \left[\min_{x_t \in \mathcal{X},\ y_t \in \Omega(x_t, u_t)} J\Big(x_t, y_t\Big) \right] \qquad \text{Eq. (II-3)}$$

$$= \min_{x_t \in \mathcal{X}} \left[\max_{u_t \in \mathcal{U}} \min_{y_t \in \Omega(x_t, u_t)} J\Big(x_t, y_t\Big) \right]. \qquad \text{Eq. (II-4)}$$

$$\min_{y_t \in \Omega(x_t, u_t)} J\Big(x_t, y_t\Big)$$

Economic dispatch for a given engagement & PV trajectory [MILP]

$$\max_{u_t \in \mathcal{U}} \min_{y_t \in \Omega(x_t, u_t)} J\Big(x_t, y_t\Big)$$

Worst case economic dispatch for a given engagement over the PV uncertainty set [MILP]

Part II - Problem formulation

Second-stage planner transformation

$$\min_{y_t \in \Omega(x_t, u_t)} J\left(x_t, y_t\right) \quad \Rightarrow \quad \max_{\phi_t \in \Phi} G\left(x_t, u_t, \phi_t\right) \quad \text{[LP]}$$

Relaxation (BESS binary variables): [MILP] -> [LP]

Dual of the economic dispatch

$$\Rightarrow \quad \min_{x_t \in \mathcal{X}} \left[\max_{u_t \in \mathcal{U}} \min_{y_t \in \Omega(x_t, u_t)} J\left(x_t, y_t\right) \right].$$

$$= \quad \boxed{\min_{x_t \in \mathcal{X}} \left[\max_{u_t \in \mathcal{U},\ \phi_t \in \Phi} G\left(x_t, u_t, \phi_t\right) \right]} \quad \text{Eq. (II-5)}$$

-> A **decomposition technique** is used to solve this problem.

Part II

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Part II - Decomposition techniques

Decomposition of the min max problem

$$\min_{x_t \in \mathcal{X}} \left[\max_{u_t \in \mathcal{U},\ \phi_t \in \Phi} G\Big(x_t, u_t, \phi_t\Big) \right] \quad \text{Eq. (II-5)}$$

Master Problem (MP): first-stage variables -> **min**

Sub Problem (SP): dispatch variables -> **max**

2 algorithms:
- Benders-dual cutting plane algorithm (BD) -> SP provides **constraints**;
- Column and constraints generation algorithm (CCG) -> SP provides **variables & constraints**.

Part II - Decomposition techniques

BD algorithm

$$\mathbf{MP}: \min_{x_t \in \mathcal{X},\ \theta} \theta$$

New constraints! (cuts)

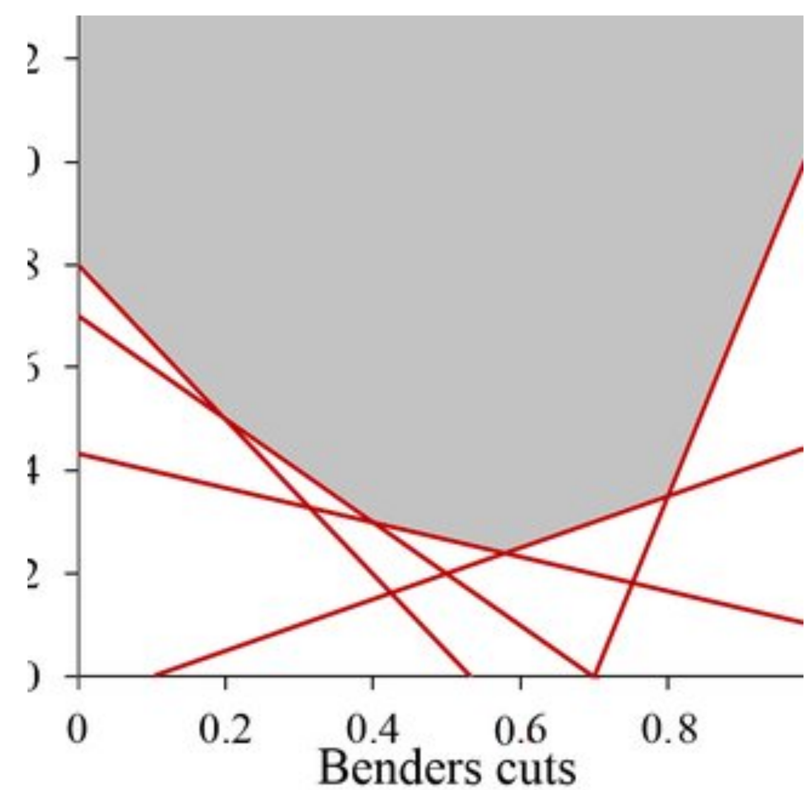
$$\boxed{\begin{aligned} &\theta \geq G\Big(x_t, \alpha_{t,l}, \phi_{t,l}\Big), \quad \forall l \leq j \\ &G\Big(x_t, \tilde{\alpha}_{t,k}, \tilde{\phi}_{t,k}\Big) \leq 0, \quad \forall k \leq j, \end{aligned}}$$

optimality cuts

feasibility cuts

Eq. (II-6)

$$\mathbf{SP}: R(x_t) = \max_{u_t \in \mathcal{U},\ \phi_t \in \Phi} G\Big(x_t, u_t, \phi_t\Big).$$



Value function of the first-stage variables

At iteration j:
- SP^j -> upper bound;
- MP^j -> lower bound.

Note: BD implemented uses a warm-start (initial set of cuts)

Part II - Decomposition techniques

CCG algorithm

$$\mathbf{MP}: \quad \min_{x_t \in \mathcal{X},\ \theta,\ \{y_t^s\}_{0 \le s \le j}} \quad \theta$$

$$\boxed{\begin{aligned} &\theta \geq J\Big(x_t, y_t^s\Big), \quad && s = 0 \ldots j \\ &y_t^s \in \Omega(x_t, u_t^{\star,s}), \quad && s = 0 \ldots j; \end{aligned}}$$

Eq. (II-7)

New constraints & second-stage variables!

$$\mathbf{SP}: R(x_t) = \max_{u_t \in \mathcal{U},\ \phi_t \in \Phi} \ G\Big(x_t, u_t, \phi_t\Big).$$

At iteration j:

- SP^j -> upper bound;
- MP^j -> lower bound.

Part II

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Part II - Case study

Numerical settings

Testing set: **30 days**

-> results are aggregated and normalized (%)

PV quantiles:
- NF
- LSTM

Decomposition technique:
- BD
- CCG

4 robust planners:
- BD-LSTM
- BD-NF
- CCG-LSTM
- CCG-NF

PV quantiles:
- NF
- LSTM

PV point-forecasts

Perfect forecasts

4 deterministic planners:
- Quantile-LSTM
- Quantile-NF
- nominal
- oracle

Part II - Case study

Risk-averse strategy

Γ and **q** control the risk-aversion.

2 strategies:

- **fixed Γ** and **q,** for **all** day of the dataset;
- **dynamic Γ** and **q,** for **each** day of the dataset.

Sensitivity analysis:

- q = 10, 20, 30, 40%
- Γ = 12, 24, 36, 48

Part II - Case study

Constant risk-averse parameters strategy

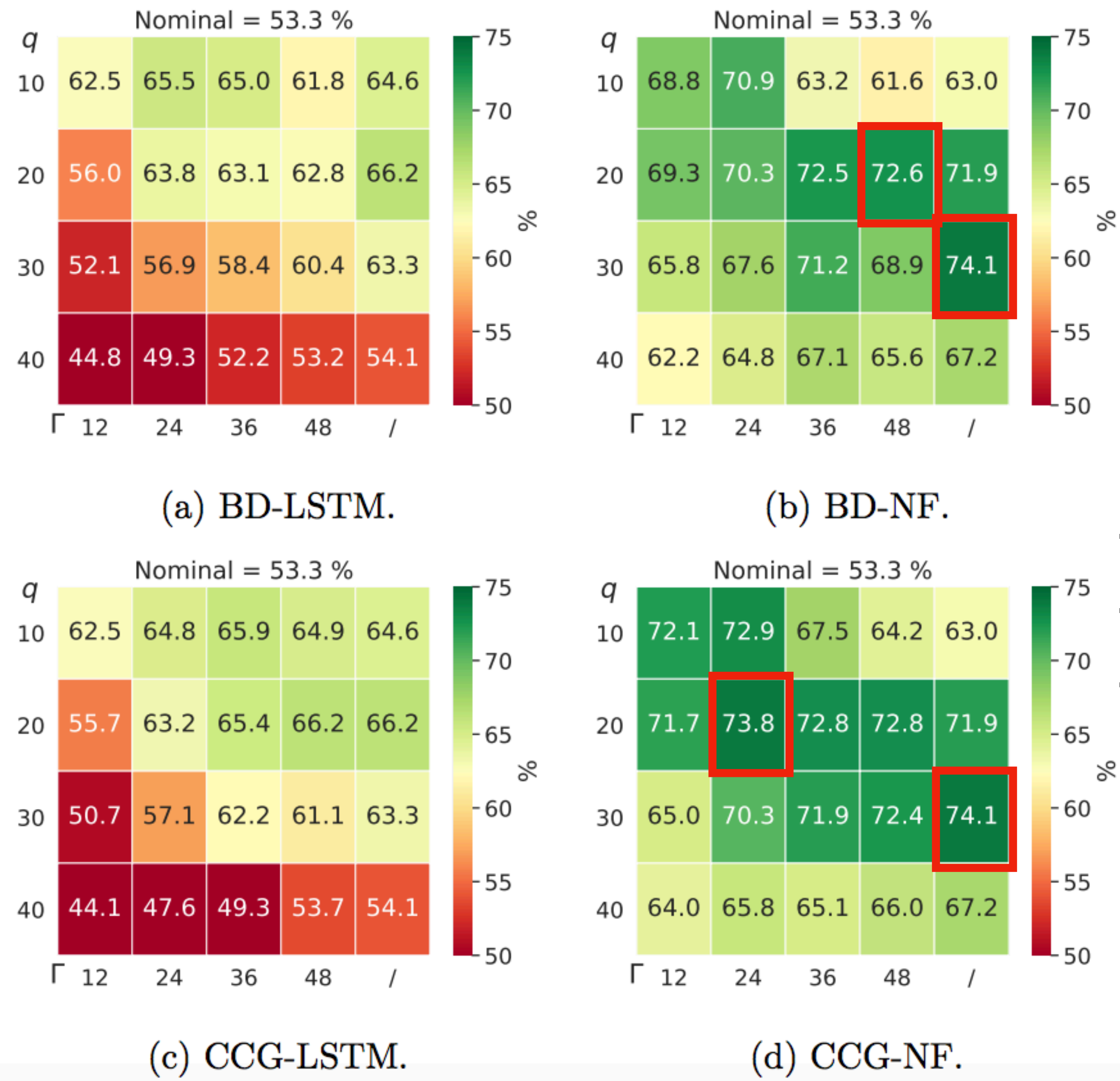


Figure II-5: Results with constant risk-averse parameters.

The **greener** the **better**!

Best results:
- BD-NF: **72.6**%
- CCG-NF: **73.8** %
- Deterministic planner: **74.1**%

Part II - Case study

Risk-averse strategy

Γ and **q** control the risk-aversion.

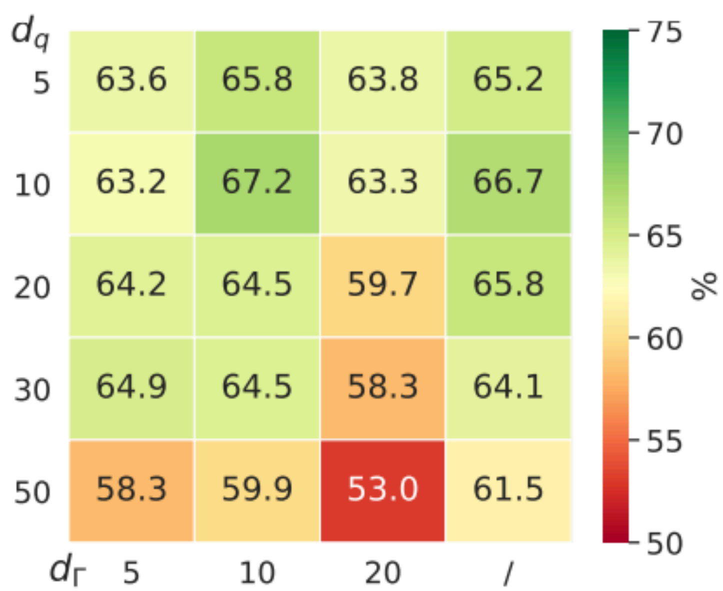
2 strategies:

- **fixed Γ** and **q,** for **all** day of the dataset;
- **dynamic Γ** and **q,** for **each** day of the dataset.

*A set of rules, detailed in the Ph.D. thesis, details how **Γ** and **q** are dynamically set.*

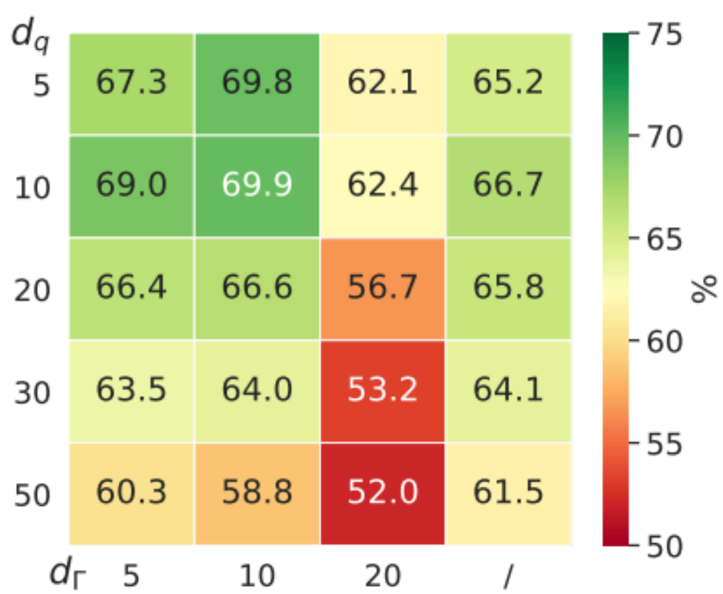
Part II - Case study

Dynamic risk-averse parameters strategy

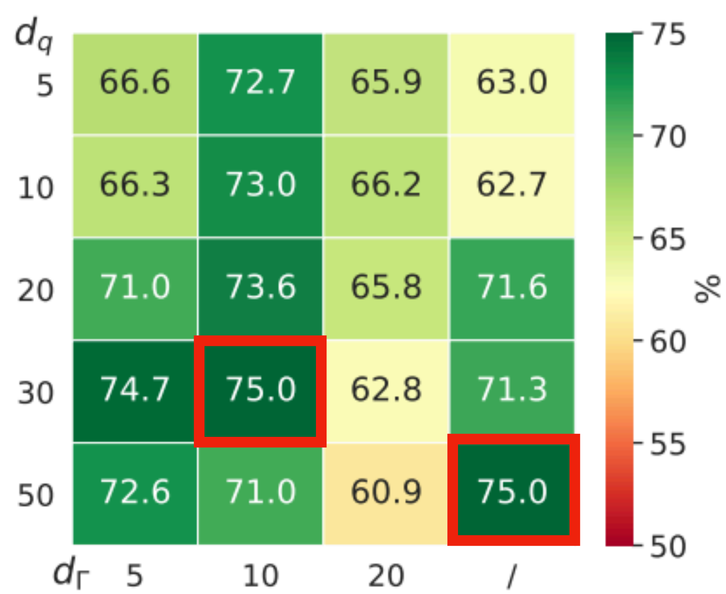


(a) BD-LSTM.

(b) BD-NF.



(c) CCG-LSTM.



(d) CCG-NF.

Figure II-6: Results with dynamic risk-averse parameters.

The **greener** the **better**!

Best results:

- BD-NF: **72.3**%
- CCG-NF: **75.0** %
- Deterministic planner: **75.0**%

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Part II - Conclusions

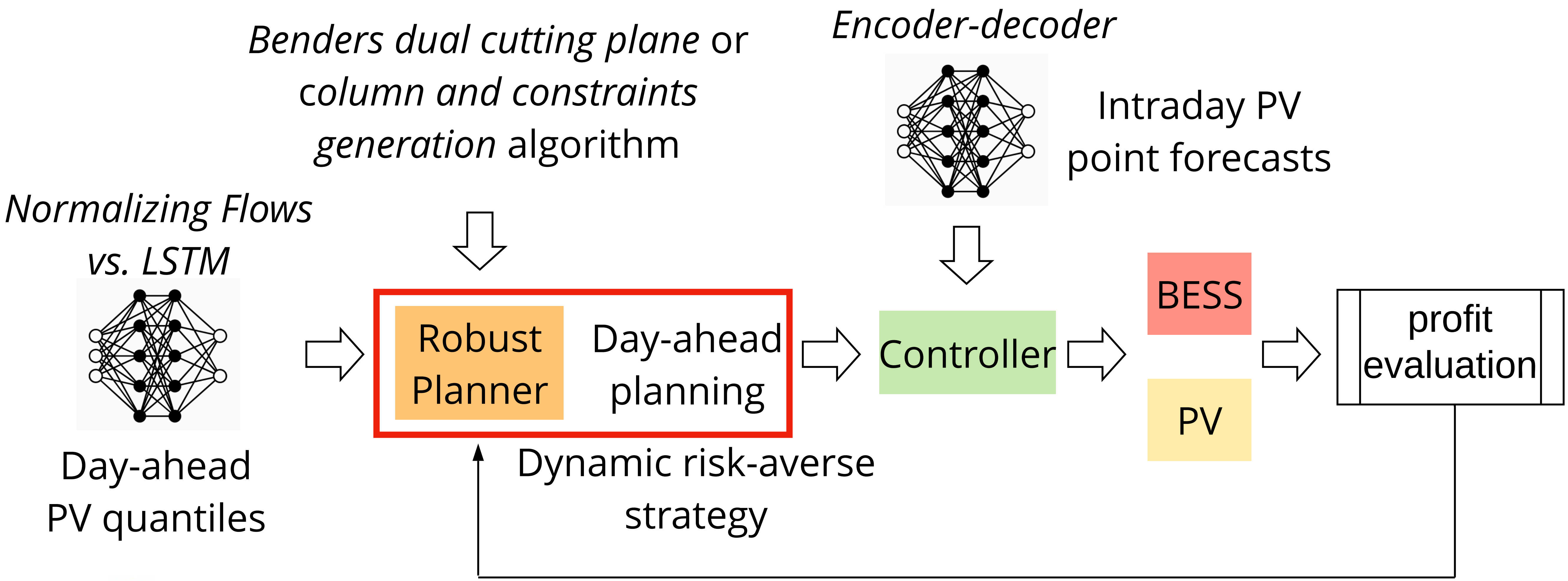
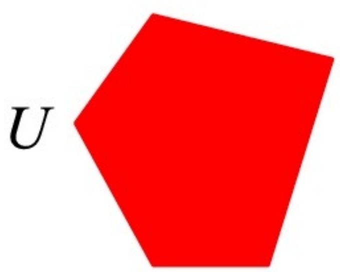


Figure II-3: Forecast-driven robust optimization strategy.



PV uncertainty set

Robust approach allows finding **a trade-off** between **conservative** and **risk-seeking** policies.

-> the **dynamic risk-averse strategy** improved the results.

Part II - Conclusions

Perspectives: uncertainty set

Representations of the **uncertainty set**:

- **Simultaneous** prediction intervals instead of Marginal prediction intervals [1];
- **Multivariate** polyhedra [2].

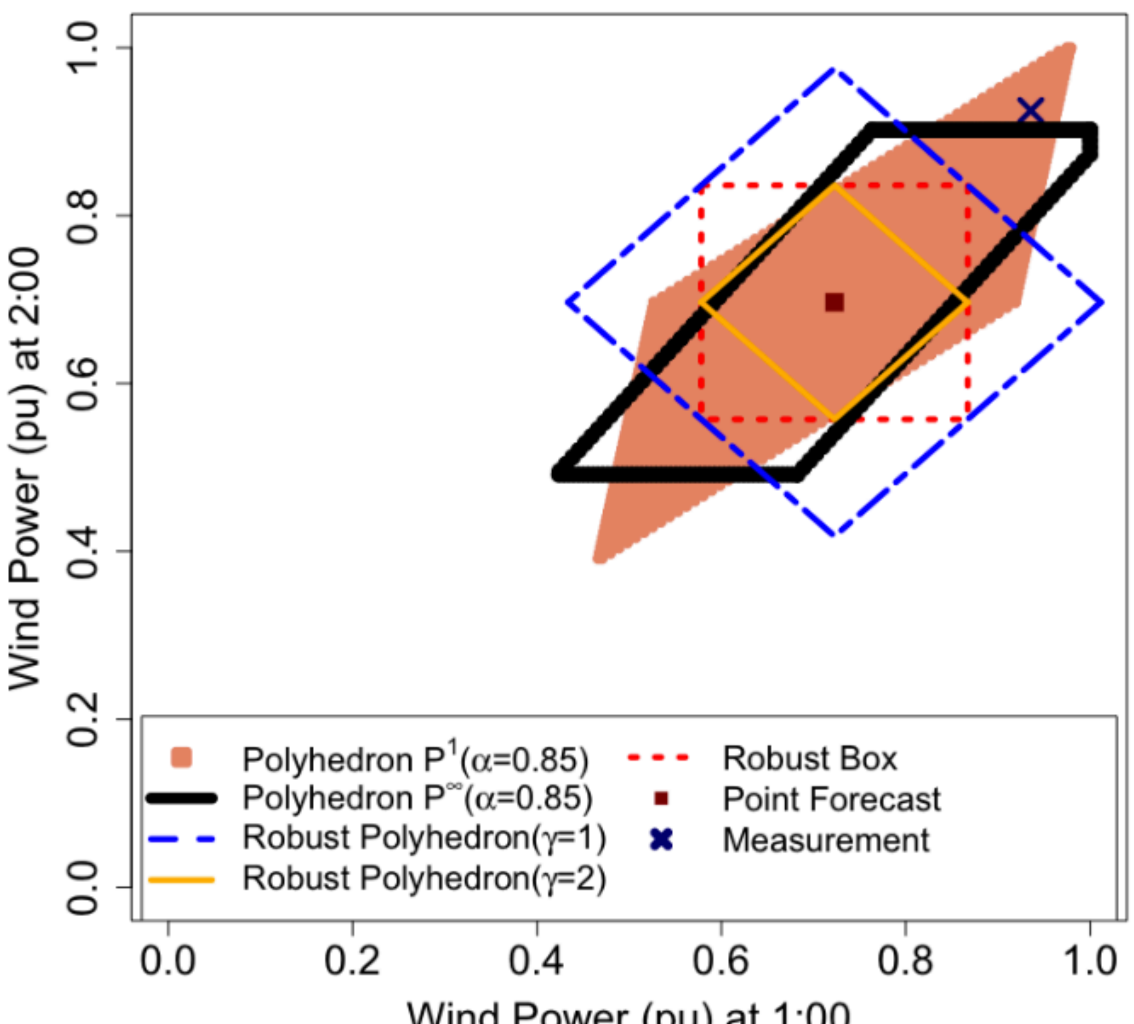


Figure II-7: Different uncertainty sets in dimension 2.
Credits: [2]

[1] Bessa, Ricardo J. "From marginal to simultaneous prediction intervals of wind power." 2015 18th International Conference on Intelligent System Application to Power Systems (ISAP). IEEE, 2015.

[2] Golestaneh, Faranak, Pierre Pinson, and Hoay Beng Gooi. "Polyhedral predictive regions for power system applications." IEEE Transactions on Power Systems 34.1 (2018): 693-704.

Part II - Conclusions

Perspectives: risk-averse strategy using machine learning

Design an improved **dynamic risk-averse** strategy using a machine learning tool.

-> machine learning model **outputs** the risk-averse parameters based on weather forecasts, …

Part II - Conclusions

Perspectives: RO vs. SP & COO

1. **Stochastic programming (SP)**:
- risk-**neutral**: maximization of the expected value of the objective;
- risk **management**: Conditional Value-at-Risk (**CVaR**).

$$\min_{x} \ (1-k)\mathop{\mathbb{E}}_{\omega}\{J(x,y_\omega)\} + k\mathbf{CVaR}_{1-\alpha}(x)$$

2. **Chance constrained optimization (COO)** using a scenario approach.

-> conduct a **proper comparison** of **RO vs. SP** & **COO** with using scenarios from generative models: NFs, GANs, VAEs, …)

3. Extend the case study to an **energy community:**
-> consider **power flows**, **non-linear model** of BESS, component **degradations** …

Summary

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Conclusions & perspectives

Conclusions & perspectives

Conclusions

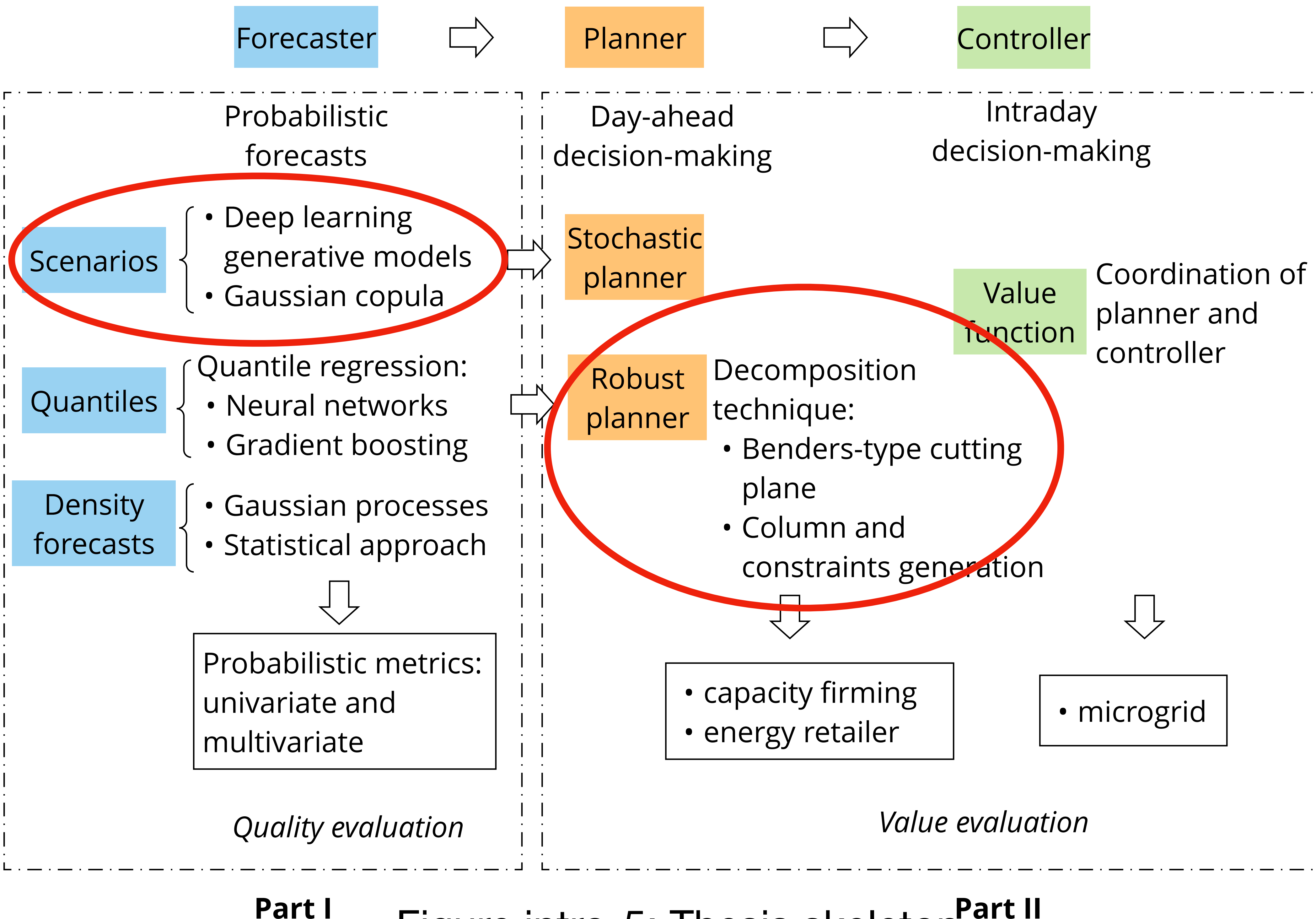


Figure intro-5: Thesis skeleton.

Conclusions & perspectives

Perspectives

(1) **Forecasting techniques of the future**

-> taking advantage of the underlying physical process/domain-specific insight;
-> new forecasting techniques (diffusion models …);
-> improve probabilistic forecasts assessment (quality & value).

(2) **Machine learning for optimization**

-> simplifying optimization problems by learning a sub-optimal space;
-> physics-informed neural networks in power system applications.

Conclusions & perspectives

Perspectives

(3) **Modeling & simulation of energy systems**

-> applying forecasting & decomposition techniques in energy system models (EnergyScope TD, …)
-> multi-criterion optimization, consider new metrics to optimize (EROI, emission, …).

(4) **Machine learning & psychology**

-> use algorithms to influence behavior towards sustainability?
-> integrate psychology into the algorithms;
-> address the rebound effect;
-> facilitating behavior changes (carbon footprint …).

Thank you for your attention!

Appendix

Appendix summary

Context

Part I: probabilistic forecasting using normalizing flows

Part II: day-ahead management of a microgrid using robust optimization

Context

Climate change

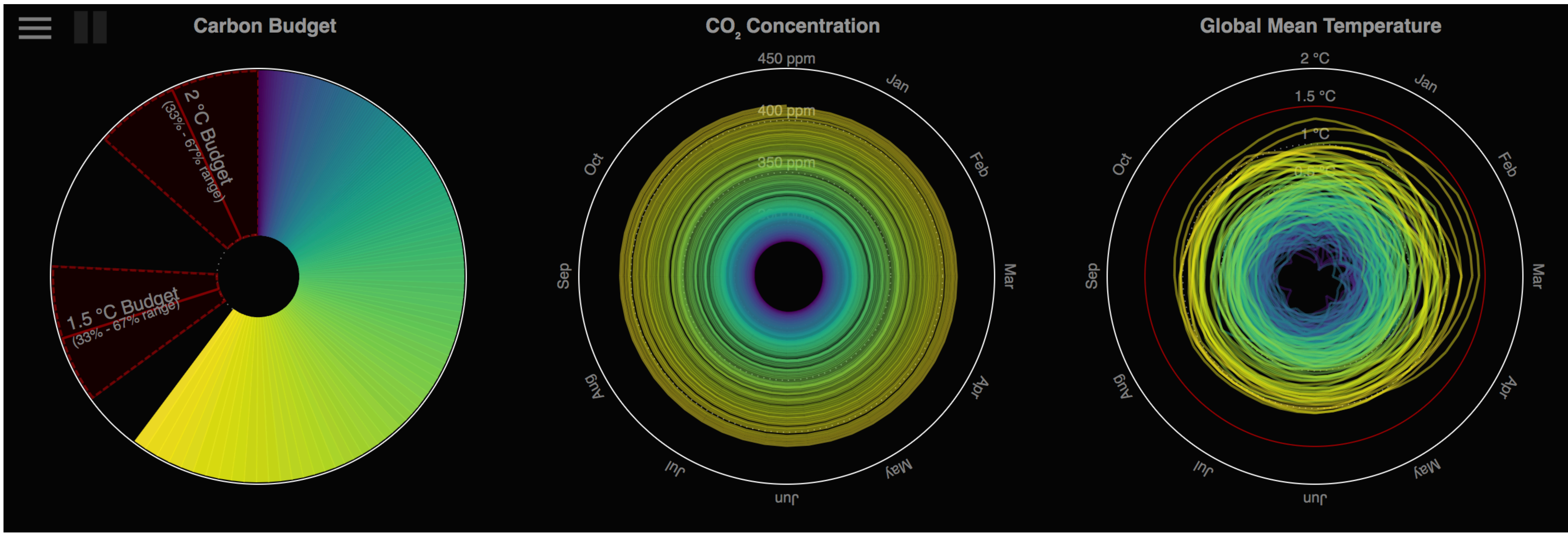


Figure 0-1. From emissions to Global Warming.
Credits: Original Climate Spiral by Ed Hawkins (Climate Lab Book), extended with Carbon Budget and Concentration Spiral by Robert Gieseke and Malte Meinshausen (PRIMAP Group, Potsdam Institute for Climate Impact Research, Germany & Australian-German Climate & Energy College, The University of Melbourne, Australia). link

Context

CO2 and global surface temperature

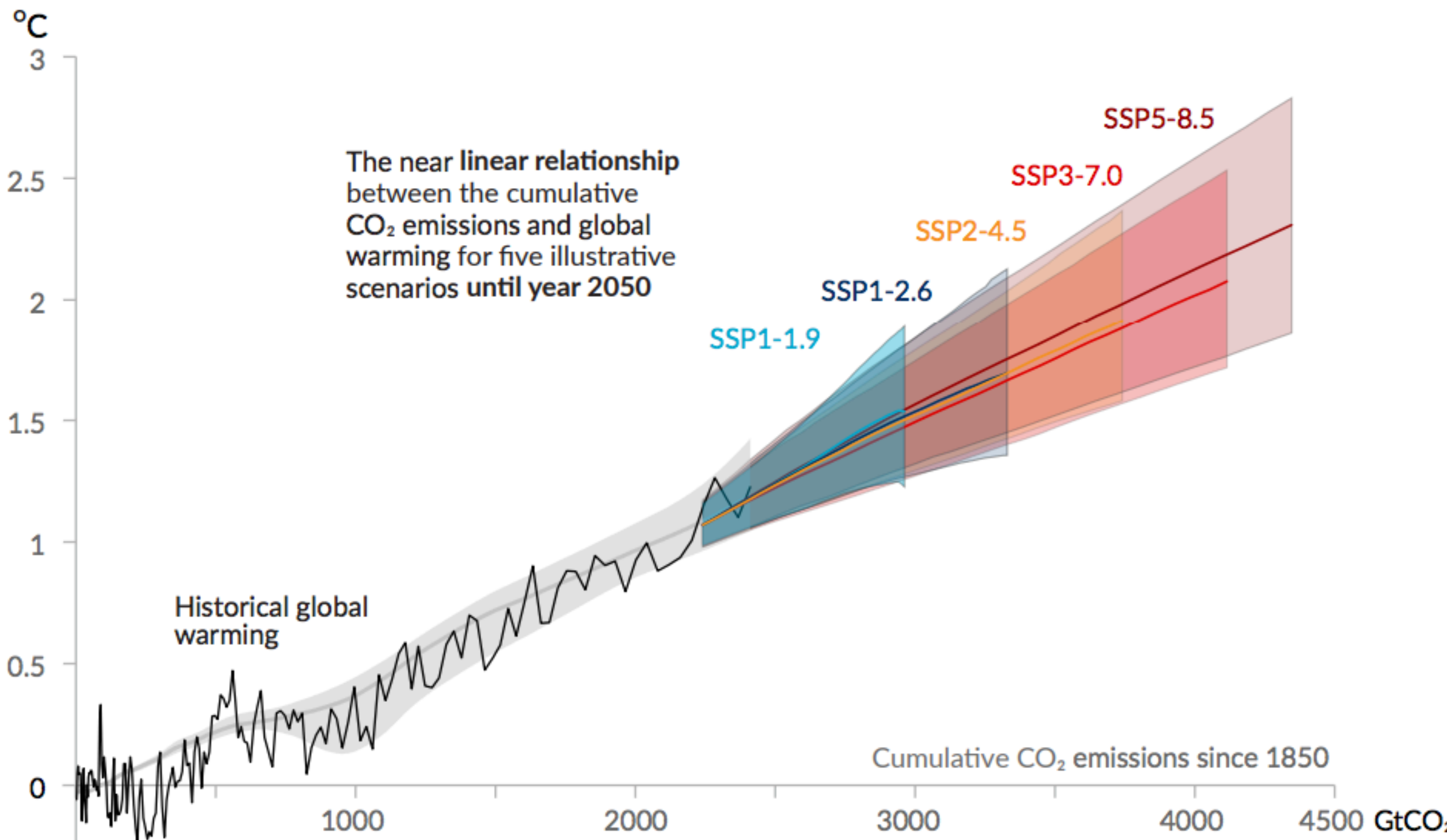


Figure 0-2: Near-linear relationship between cumulative CO2 emissions and the increase in global surface temperature.

Credits: AR6 Climate Change 2021: The Physical Science Basis, Summary for policymakers (SPM). link

Context

50-years event intensity & frequency of hot extreme events

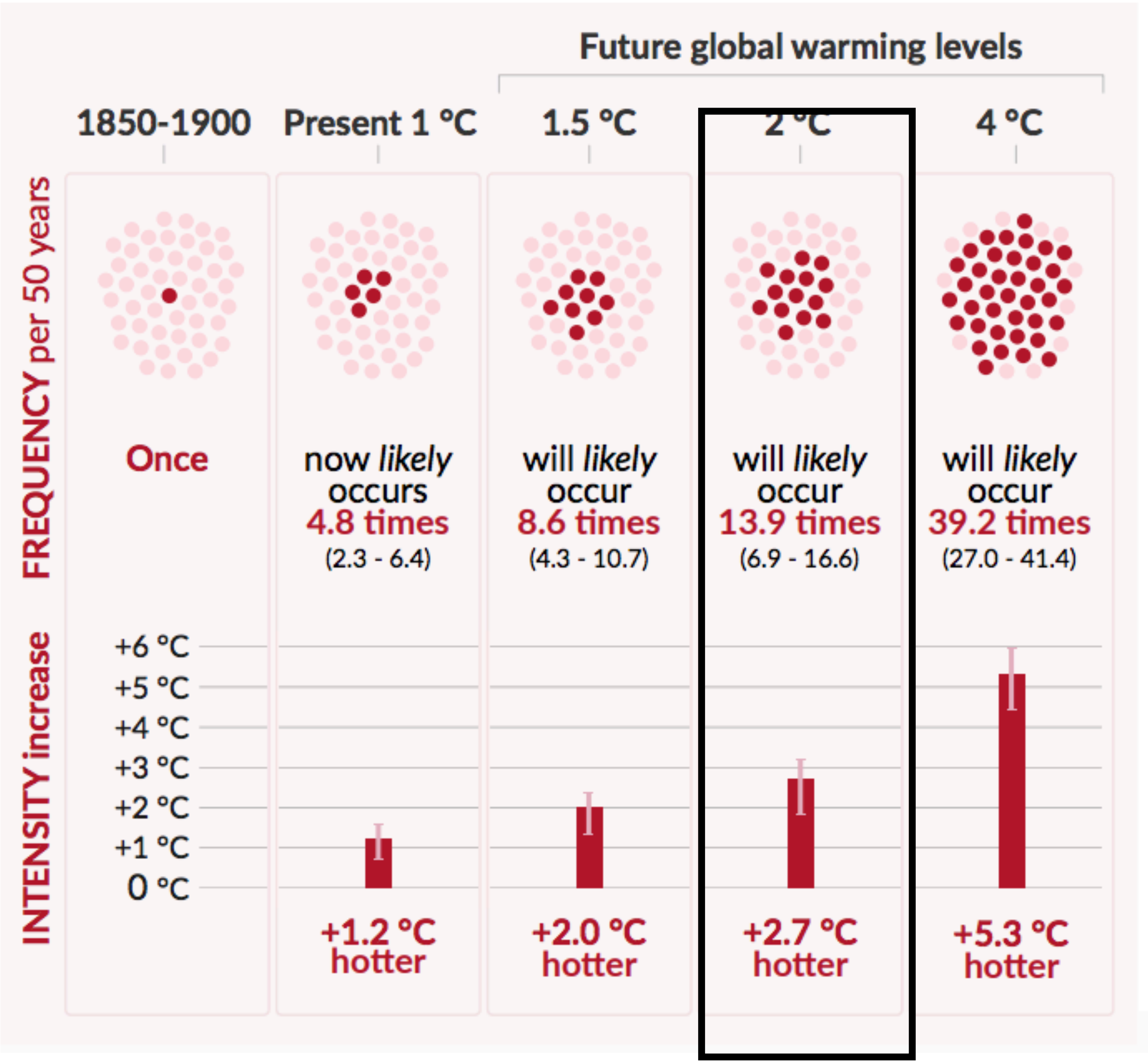


Figure 0-2: Projected changes in the intensity and frequency of hot temperature extremes over land.
Credits: AR6 Climate Change 2021: The Physical Science Basis, Summary for policymakers (SPM). link

Introduction

Thesis scope

How to meet **the IPCC targets?**

Net Zero by 2050 [ref] key pillars:

- **wind** & **solar** **energies** -> in **power systems** (thesis scope);
- reduce fossil energy consumption;
- behavior and avoided demand;
- **electrification** -> address the **uncertainty** (thesis scope);
- hydrogen-based;
- energy efficiency;
- carbon capture, utilisation and storage;
- …

-> Difficulty: renewable energies are **uncertain**!

[ref] *International Energy Agency (IEA): Net Zero by 2050 report A Roadmap for the Global Energy Sector* *https://www.iea.org/reports/net-zero-by-2050*

Appendix

Appendix summary

Context

Part I: probabilistic forecasting using normalizing flows

Part II: day-ahead management of a microgrid using robust optimization

Part I - Introduction

Applicability of the models

1. **Forecasting** module of an energy management system (EMS).

2. **Stochastic/robust unit commitment**.

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.

Part I - Introduction

Study contributions

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

[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.*

Part I - Background

Normalizing flows

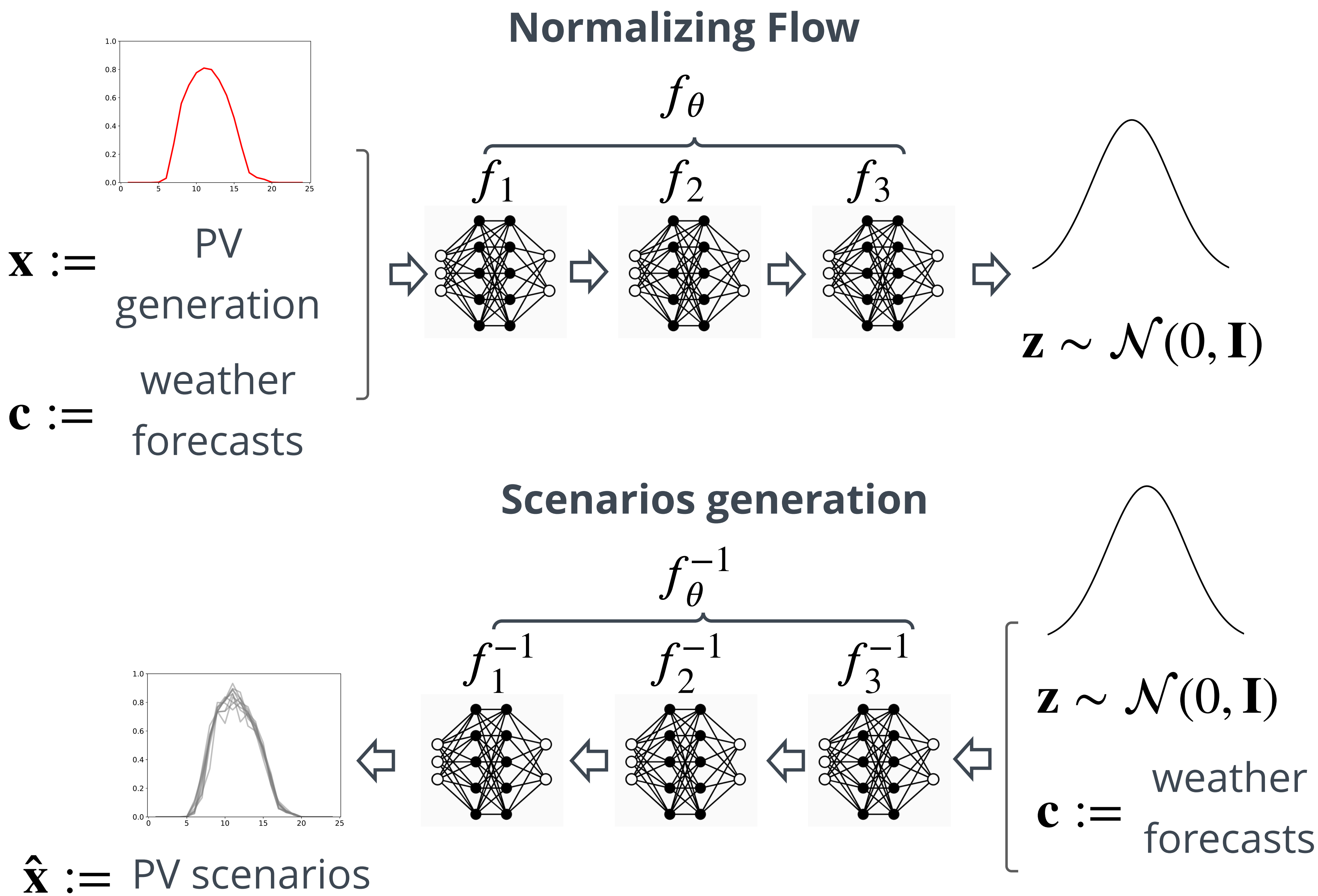
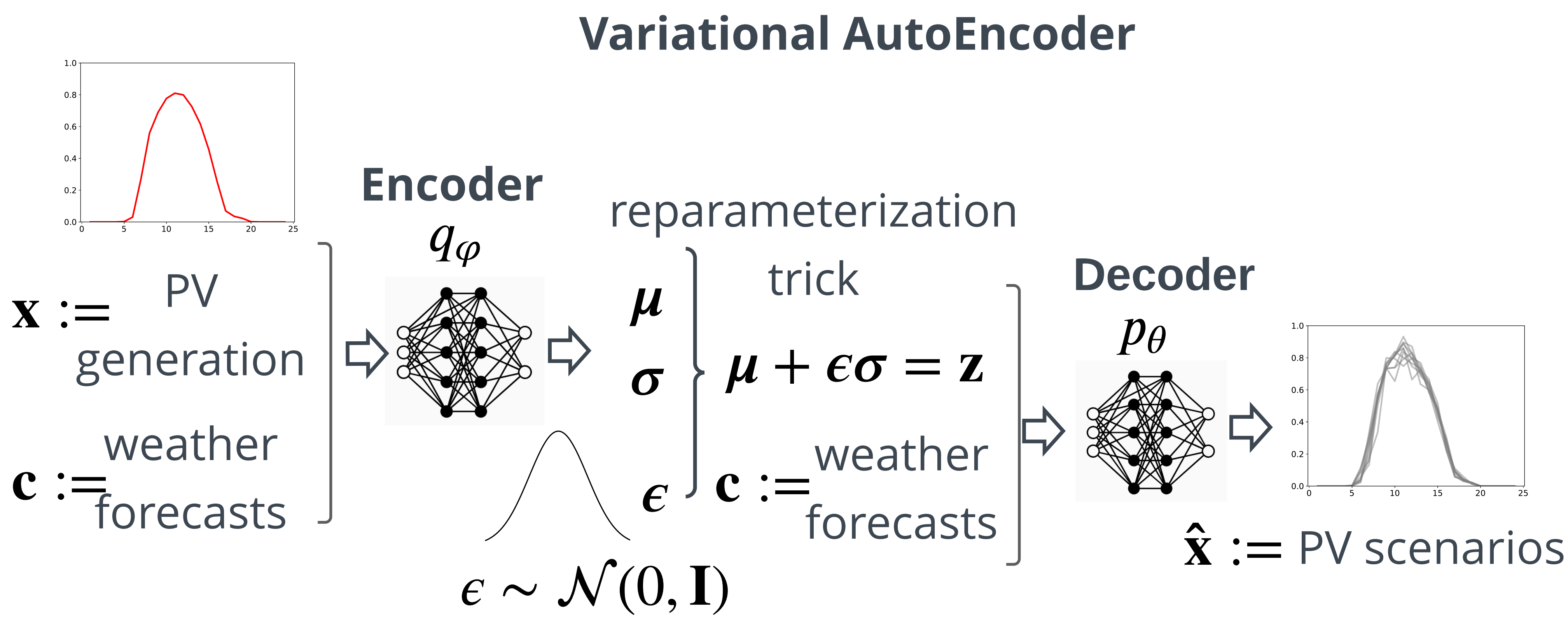


Figure appendix-I-1: A three-step conditional normalizing flows for PV generation.

Variational auto encoders



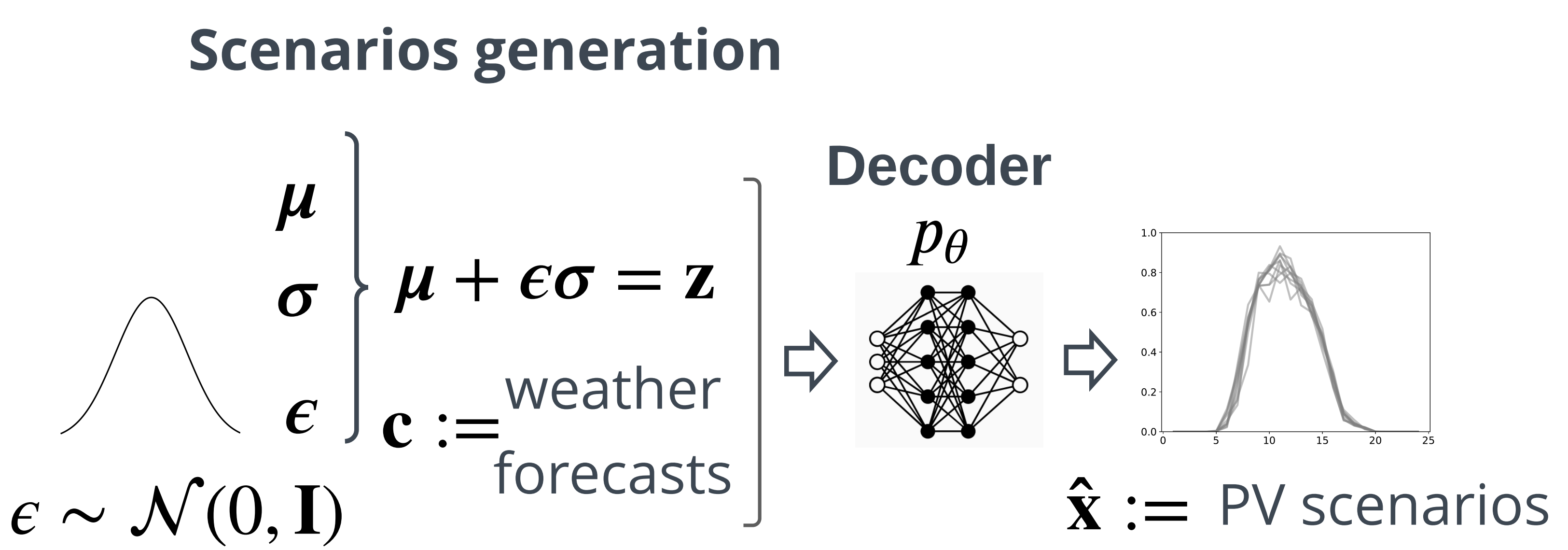


Figure appendix-I-2: A conditional variational autoencoder for PV generation.

Generative adversarial networks

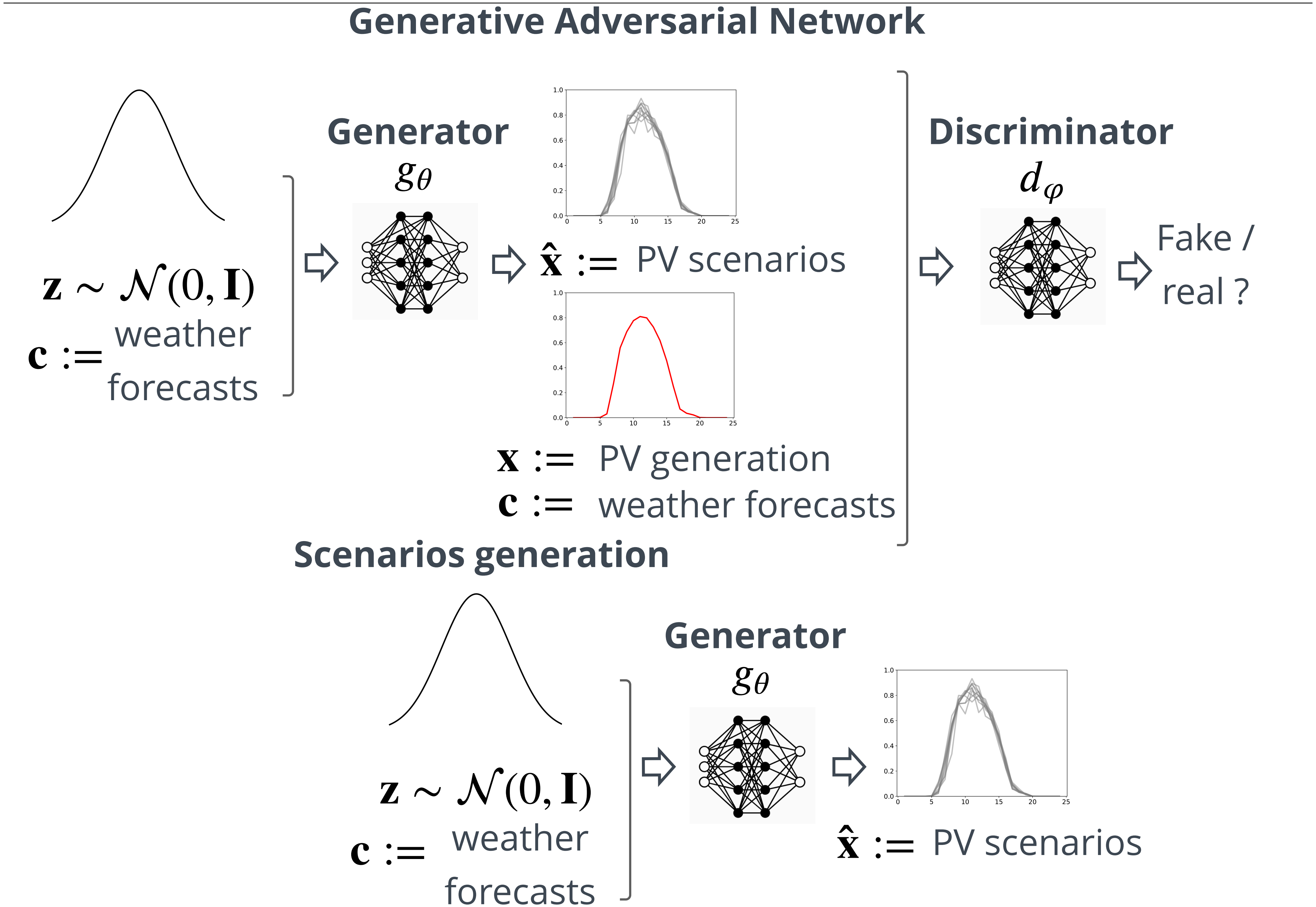


Figure appendix-I-3: A conditional generative adversarial network for PV generation.

Part I - Background

Theoretical comparison

NFs:
- Pros: exact likelihood calculation, efficiently parallelizable;
- Cons: requires bijective transformations, Jacobian computation issues.

VAEs:
- Pros: handle non-invertible generators & arbitrary latent space dimension;
- Cons: scenarios may be unrealistic -> limited approximation of the true posterior with a normally distributed prior with diagonal covariance.

GANs:
- Pros: does not rely on estimates of the likelihood or latent variable.
- Cons: training issues, mode collapsing, hyper parameters selection issues.

Part I - Numerical results

Quality metrics

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

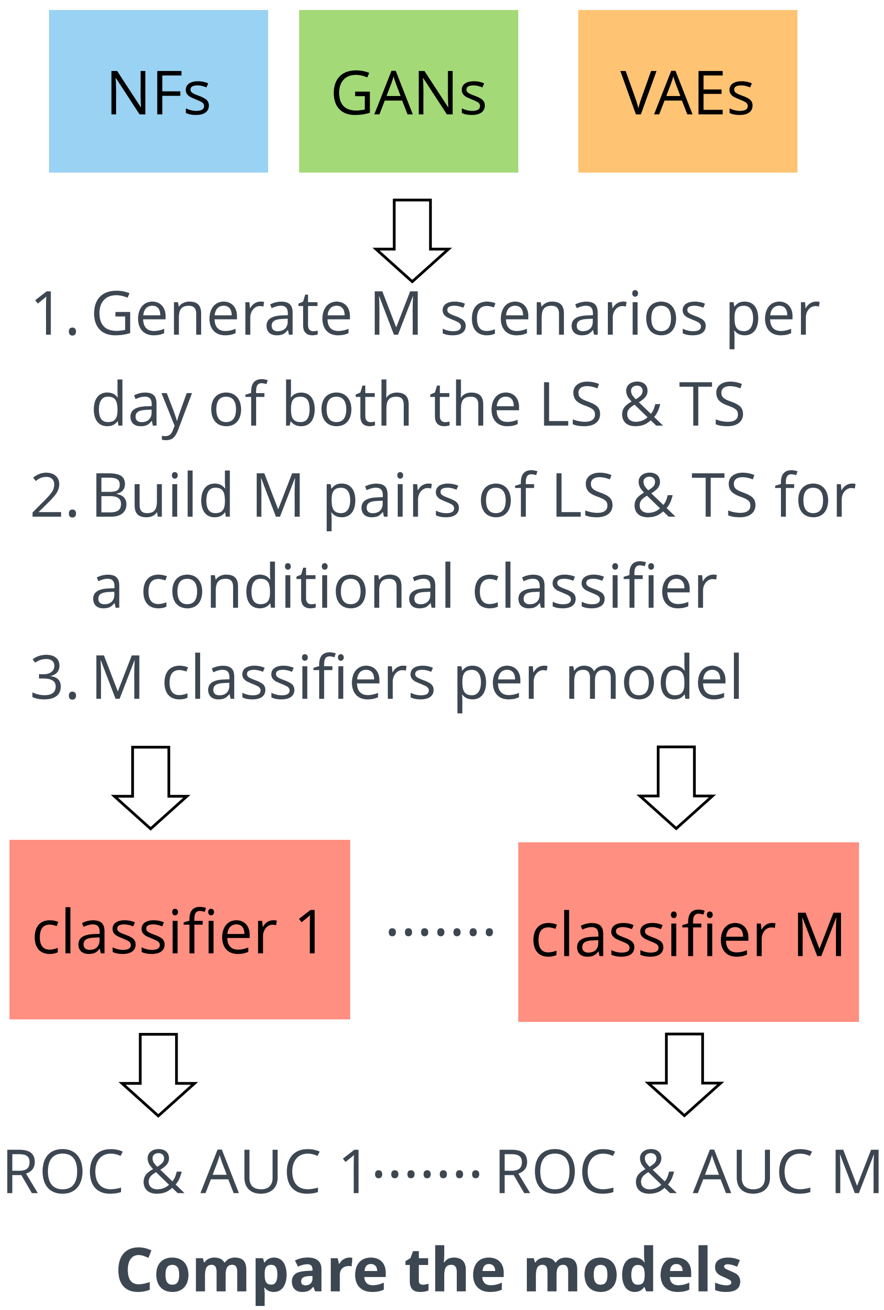
Multivariate metrics:
- Energy Score (ES) -> multivariate generalization of the CRPS
- Variogram Score (VS) -> captures the correlations between multivariate components in contrats to the ES

Specific metrics:
- Classifier based
- Correlation between scenarios

Statistical metric :
- Diebold and Mariano test -> CRPS, QS, ES & VS

Part I - Numerical results

Classifier-based metric



Goal: assess whether a **scenario** can be **distinguished** from an **observation**.

ROC curve: measure the ability of a classifier to produce good relative instance scores.

Area under the ROC curve = **AUC**
-> equivalent to the probability that the classifier will rank randomly chosen positive instance higher than a randomly chosen negative instance

AUC = 0.5 for a random classifier

Figure appendix-I-4: Classifier-based metric methodology.

Part I - Numerical results

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 A-I-2: Dataset and implementation details.

Part I - Numerical results

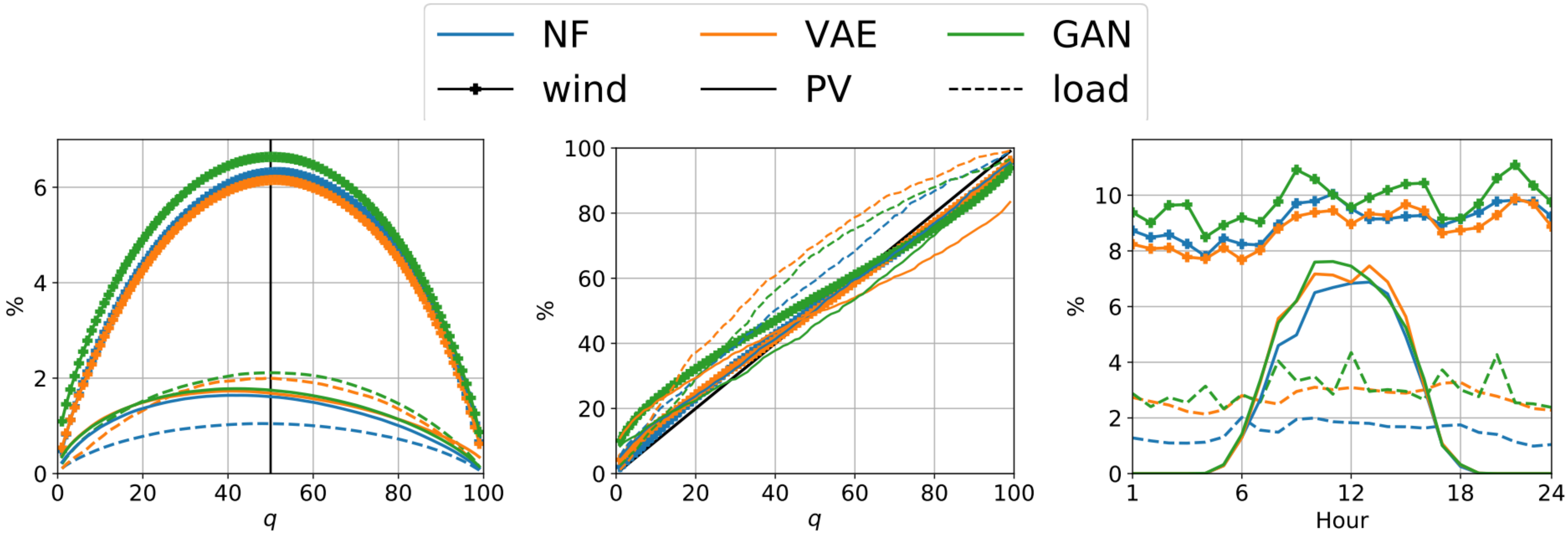
Hyper-parameters

		Wind	PV	Load
(a)	Embedding Net	4×300	4×300	4×300
	Embedding size	40	40	40
	Integrand Net	3×40	3×40	3×40
	Weight decay	5.10^{-4}	5.10^{-4}	5.10^{-4}
	Learning rate	10^{-4}	5.10^{-4}	10^{-4}
(b)	Latent dimension	20	40	5
	E/D Net	1×200	2×200	1×500
	Weight decay	$10^{-3.4}$	$10^{-3.5}$	10^{-4}
	Learning rate	$10^{-3.4}$	$10^{-3.3}$	$10^{-3.9}$
(c)	Latent dimension	64	64	256
	G/D Net	2×256	3×256	2×1024
	Weight decay	10^{-4}	10^{-4}	10^{-4}
	Learning rate	2.10^{-4}	2.10^{-4}	2.10^{-4}

Table A-I-3: NF (a), VAE (b) & GAN (c) hyper-parameters.

Part I - Numerical results

Quality results: QS, CRPS, and reliability diagrams

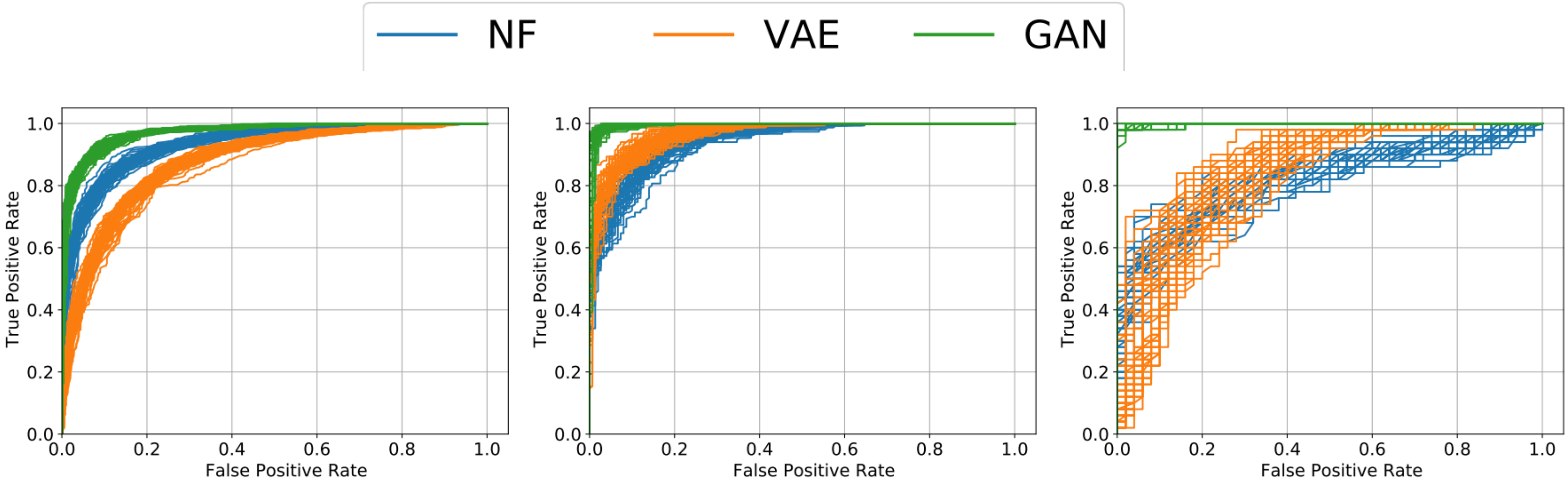


(a) Quantile score. (b) Reliability diagram. (c) CRPS.

Figure appendix-I-5: Quality standard metrics comparison on the wind (markers), PV (plain), and load (dashed) tracks.

Part I - Numerical results

Quality results



(a) ROC Wind. (b) ROC PV. (c) ROC load.

Figure appendix-I-6: Wind, PV, and load tracks classifier-based metric.

Part I - Numerical results

Scenarios shape analysis

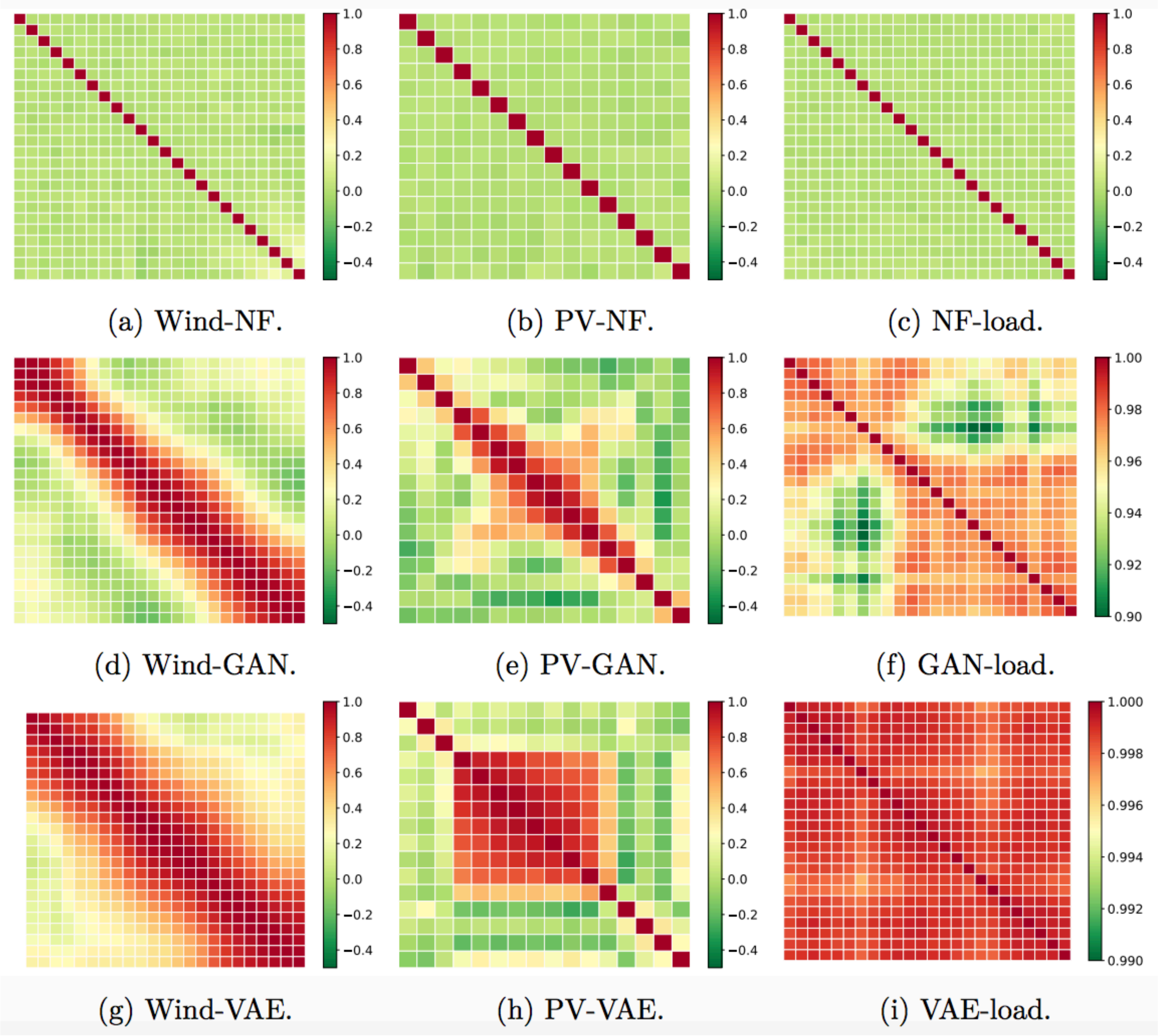


Figure appendix-I-7: Average of the correlation matrices over the testing set.

Part I - Numerical results

Forecast value: energy retailer

Day-ahead scheduling of an **energy retailer**:
- **wind** power generation;
- **PV** generation;
- electrical **consumption**;
- a battery energy storage system (**BESS**).

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

A **stochastic** planner (MILP) is implemented using a **scenario-based** approach.

Part I - Numerical results

Energy retailer: data illustration

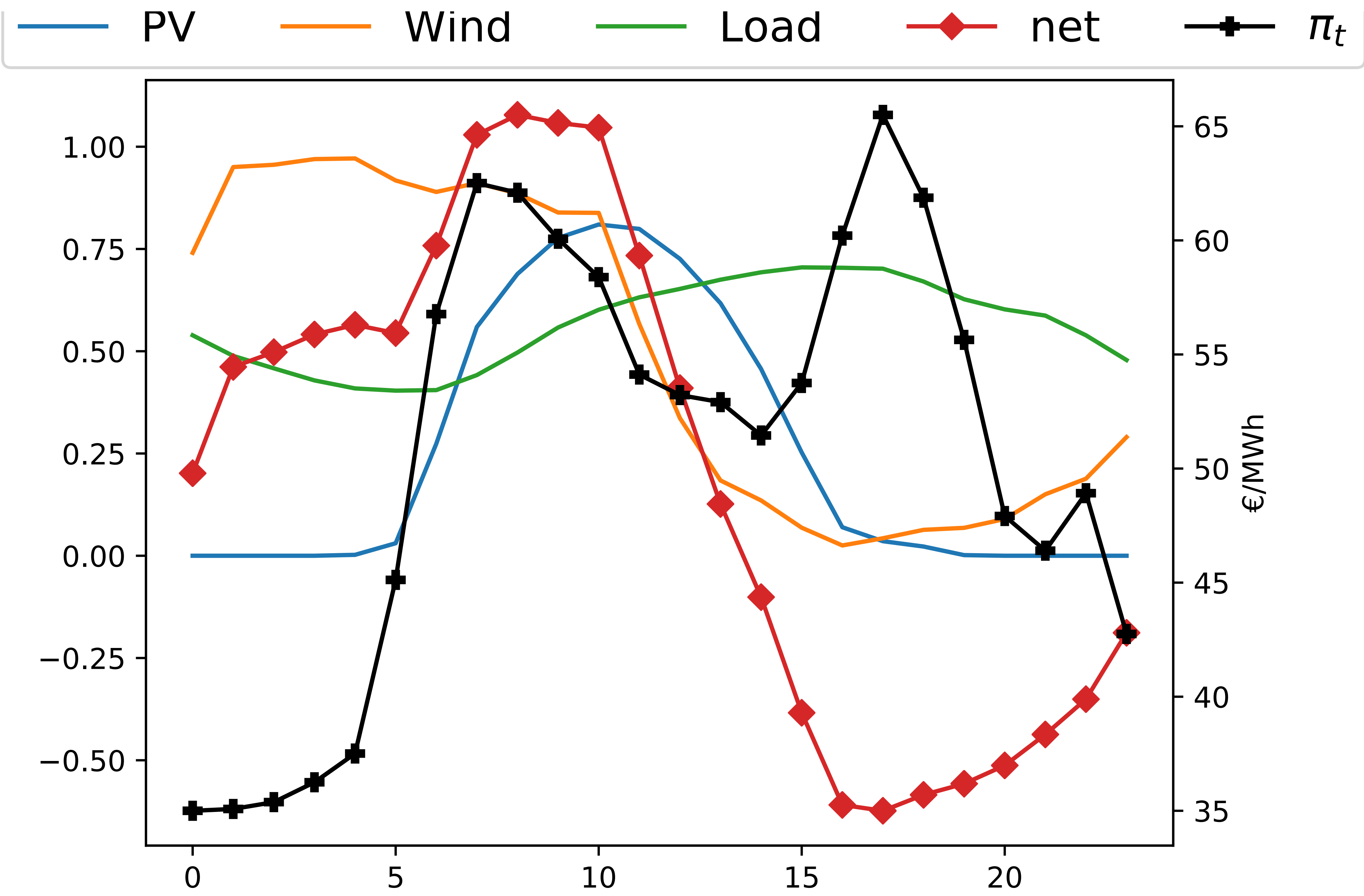


Figure appendix-I-5: Illustration of the observations on a random day of the testing set.

Part I - Numerical results

Energy retailer: implementation details

Energy retailer:
- wind power (10 zones);
- PV generation (3 zones);
- load (1 zone);
- 1 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.

Part I - Numerical results

Energy retailer: numerical settings

BESS min/max capacity = 0/1 kWh

Charging & discharging efficiencies = 95 %

Full charge/discharge in 2 hours

50 PV, wind power, and load **scenarios** per optimization problem

Each simulation day the BESS is fully discharged as the first & last period.

Appendix

Appendix summary

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Part II: day-ahead management of a microgrid using robust optimization

Part II - Problem formulation

Stochastic programming (SP) vs. robust optimization (RO)

Random vector: renewable generation.

1. **Feasibility**

SP: -> solutions feasible **for all** realizations of the random vector.

RO: -> solutions feasible **inside a uncertainty set**.

2. **Optimality**

SP: -> rank random variables J(x, ω) according to their expectations and **pick the biggest** (in a maximization problem).

RO: -> random variables J(x, ω) are ranked by their **worst possible outcome**.

3. **Solution algorithm**

SP: -> a discrete approximation (**scenarios**) of the random vector.

RO: -> definition of an **uncertainty set**.

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

Part II - Problem formulation

SP & RO pros/cons

SP pros:

- **less conservative** than RO & easier to implement than RO;
- Include **risk management** with CVAR.

SP cons:

- problem **size** and **computational requirements** issue;
- challenging to **identify an accurate probability distribution**;
- results are sensitive to the scenario generation technique.

RO pros:

- requires only moderate information about the uncertainty;
- optimal solution that **immunizes against all realizations** of the uncertain data.

RO cons:

- the RO version is not always tractable & more difficult to implement than SP;

Part II - Decomposition techniques

BD & CCG algorithms convergence

1. **Relatively complete recourse assumption**

-> the **SP is feasible** for any engagement plan and generation trajectory (always true in the capacity firming framework).

2. **SP convergence**

-> the **convergence of the relaxed SP is checked** at each iteration of the algorithm by ensuring there is no simultaneous charge and discharge.

3. **Overall convergence**

-> the **overall convergence** of the algorithm toward the optimal solution is **checked**.

Part II - Decomposition techniques

BD & CCG algorithms convergence check

MP^J = MP value at iteration J
SP^J = SP value at iteration J
epsilon = epsilon threshold (0.5 EUR)

When: **|MP^J-SP^J| < epsilon** -> convergence between MP & SP is reached.

-> **Compute MILP^J**: deterministic formulation of the problem computed using the PV worst-case trajectory retrieved from the SP at J.

-> if |MP^J-MILP^J| < epsilon -> ok! :)
-> else |MP^J-MILP^J| < epsilon -> Nok :(-> update big-M's values & restart the algorithm.

Part II - Decomposition techniques

BD warm start

Building an **initial set of cuts** for the BD MP.

-> **sampling PV trajectories** assumed to be close to the worst PV trajectory in the uncertainty set U.

t1 = time period corresponding to the first non null PV 50% quantile
tf = time period corresponding to the last non null PV 50% quantile

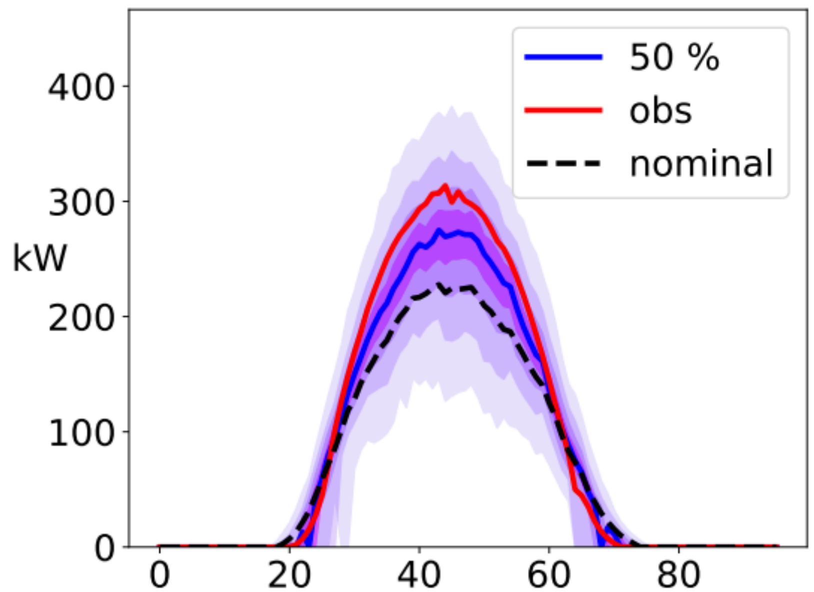
If m = tf - (t1 + Gamma -1) > 0 -> **m trajectories** are sampled:

The trajectory m is built by setting the Gamma values of the PV 50% quantile **to the lower bound** (PV quantile q) for time periods:

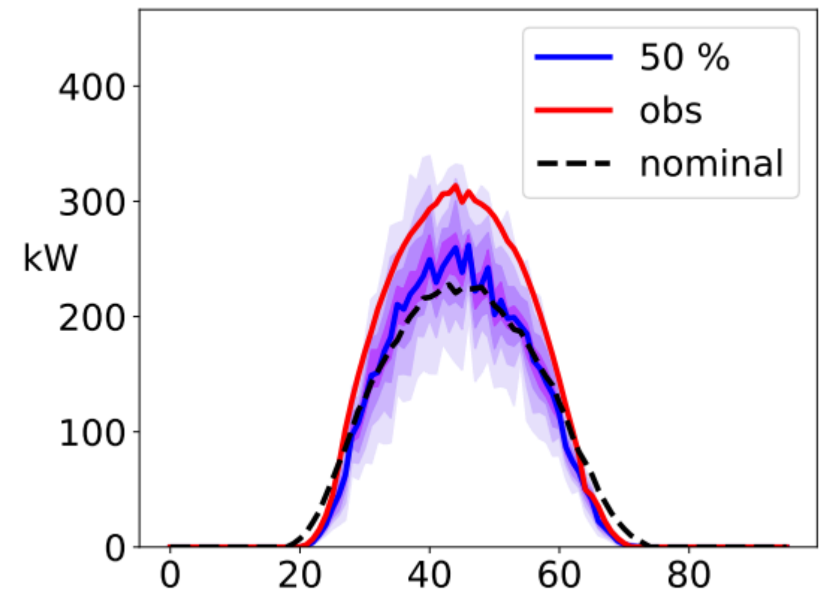
T1 + (m-1) <= t <= t1 + Gamma -1 +(m-1)

Part II - Case study

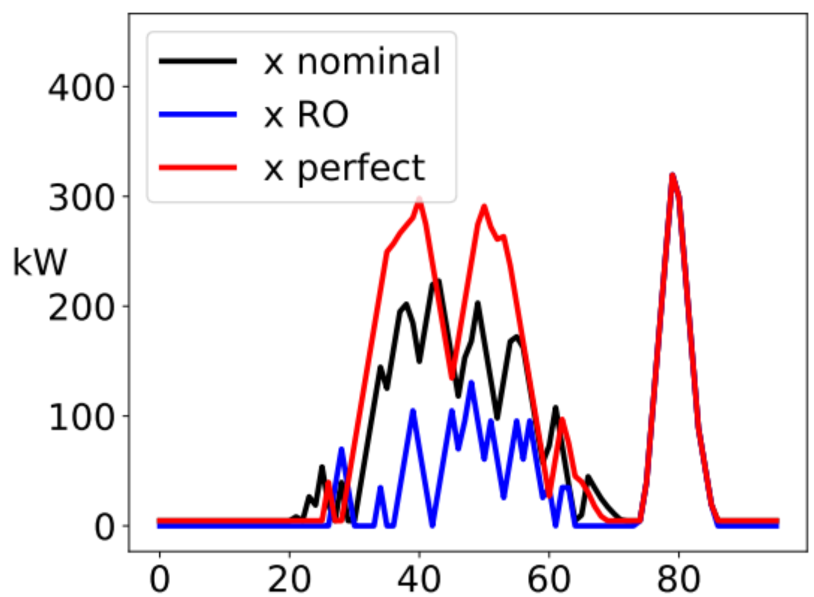
ULiège case study



(a) LSTM PV quantile forecasts.



(b) NFs PV quantile forecasts.



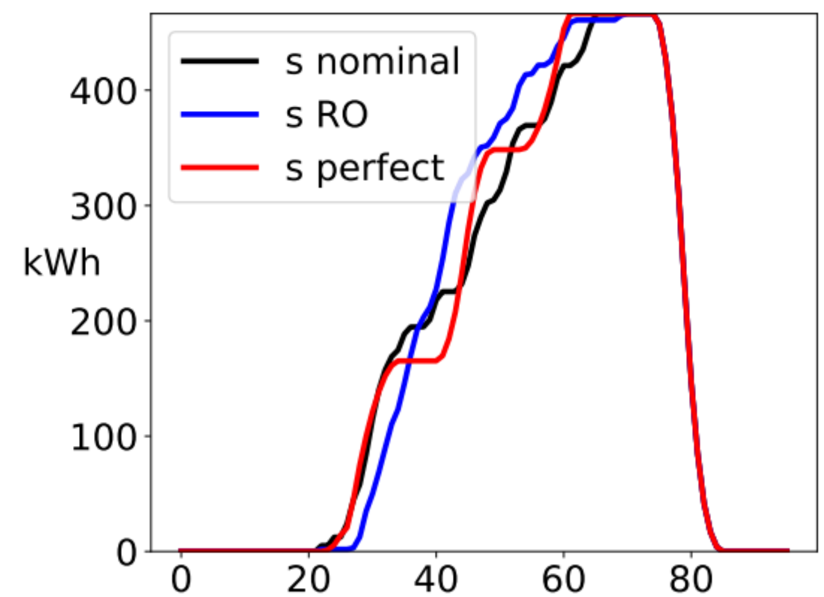


Figure A-II-1: Results illustration on September 14, 2019.

Part II - Case study

Numerical settings

Pc = PV total installed capacity = **466.4** kWp

Planning & controlling periods = **15** minutes

Peak hours are set between **7 & 9 pm** (UTC+0)

Ramping power constraints 7.5%Pc (15%Pc)

Lower/upper bounds on the engagements & net power = 0/466.4 kW

Engagement tolerance = **1%Pc** & penalty factor = 5

BESS min/max state of charge = 0/466.4 kWh

Charging & discharging efficiencies = **95%**

Part II - Case study

Dynamic risk-averse strategy: set of rules

Motivation: the **sharper** the quantile forecast distribution around the median is, the **less risk averse** the strategy should be.

2 parameters are designed:

- PV uncertainty max depth: **d_q** = % distance between PV 10 & 50 % quantiles
- The budget uncertainty depth: **d_Gamma** = % of the total installed capacity

$$u_t^{min} = \begin{cases} \hat{y}_t^{\text{pv},(0.1)} & \text{if } d_t^{50-20/30/40} > d_q d_t^{50-10} \\ \hat{y}_t^{\text{pv},(0.2)} & \text{if } d_t^{50-20/30} > d_q d_t^{50-10} \\ \hat{y}_t^{\text{pv},(0.3)} & \text{if } d_t^{50-20} > d_q d_t^{50-10} \\ \hat{y}_t^{\text{pv},(0.4)} & \text{otherwise} \end{cases} .$$

$$\Gamma = \#\{t : d_t^{50-10} > d_\Gamma P_c\}.$$

BD algorithm with & without warm start

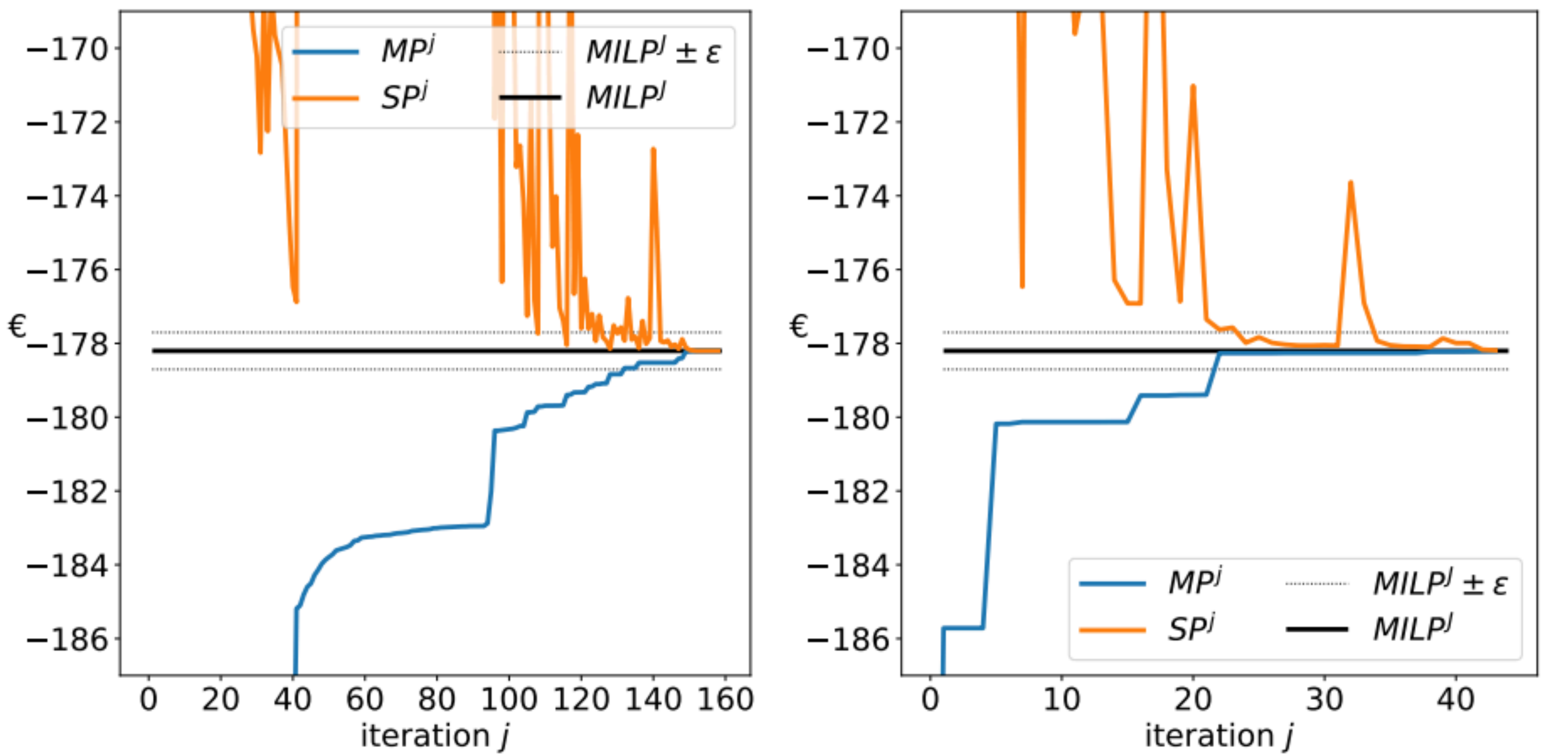


Figure A-II-2: BD convergence without (left) and with (right) warm start on September 14, 2019.

Part II - Case study

BD algorithm warm start computation times statistics

$\{\theta_i\}_{1\leq i\leq I}$	t^{av}	$t^{50\%}$	t^{min}	t^{max}	t^{tot}
False	3.5	2.0	< 0.1	34.1	105.4
True	2.0	0.7	< 0.1	30.4	61.3

Table A-II-1: BD computation times (min) statistics with and without warm start.

-> Reduce the **computation time**

-> Reduce the **number of times the big-M's values** need to be increased before reaching the final convergence criterion with the MILP

Part II - Case study

BD and CCG algorithms comparison

Algorithm	RO-type	$\bar{t}$	$1_{\%}$	J^{max}
BD-NF	static	85.2 (151.9)	$\boxed{0.0}$	72.6
CCG-NF	static	$\boxed{7.5\ (6.0)}$	1.9	$\boxed{73.8}$
BD-NF	dynamic	102.3 (107.3)	$\boxed{0.0}$	72.6
CCG-NF	dynamic	$\boxed{9.2\ (5.5)}$	4.2	$\boxed{75.0}$

Table A-II-1: BD vs CCG statistics.

-> CCG converges in 5-10 iterations vs 50-100 for BD

-> CCG provides better results than BD

-> CCG does not always converge (MILP convergence criterion)