Probabilistic uncertainty forecasting in electricity system models in 31 European countries

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FACULTÉ DES SCIENCES

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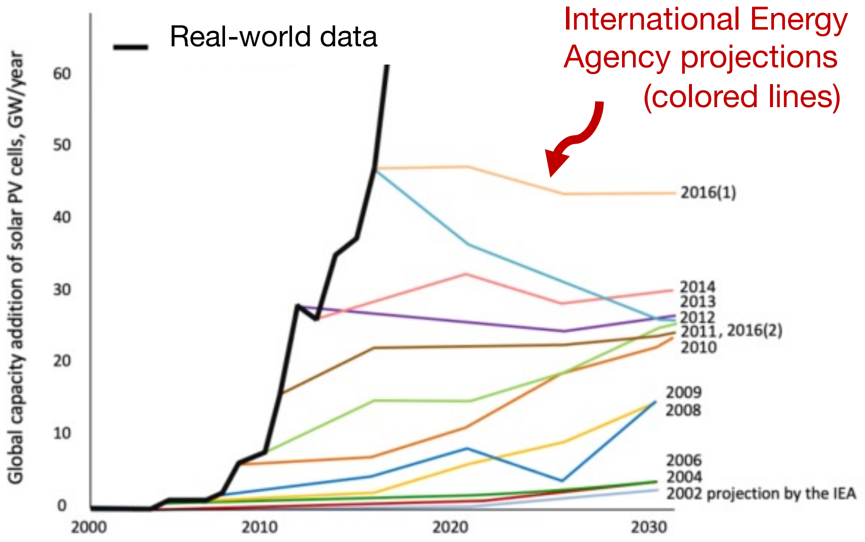
The need for improving uncertainty analysis in long-range transition

RES

- Energy projections have shown noticeable and repeated deviations from the real-world transitions.
- We need a better uncertainty analysis



Source: redrawn from the data of Hoekstra (2017)

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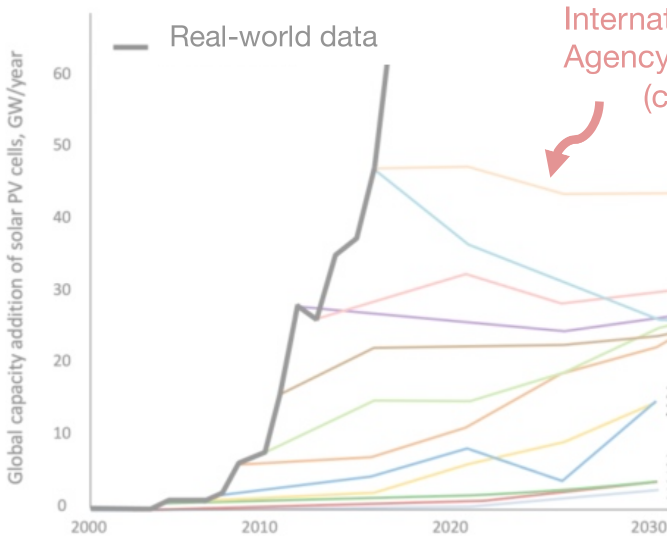

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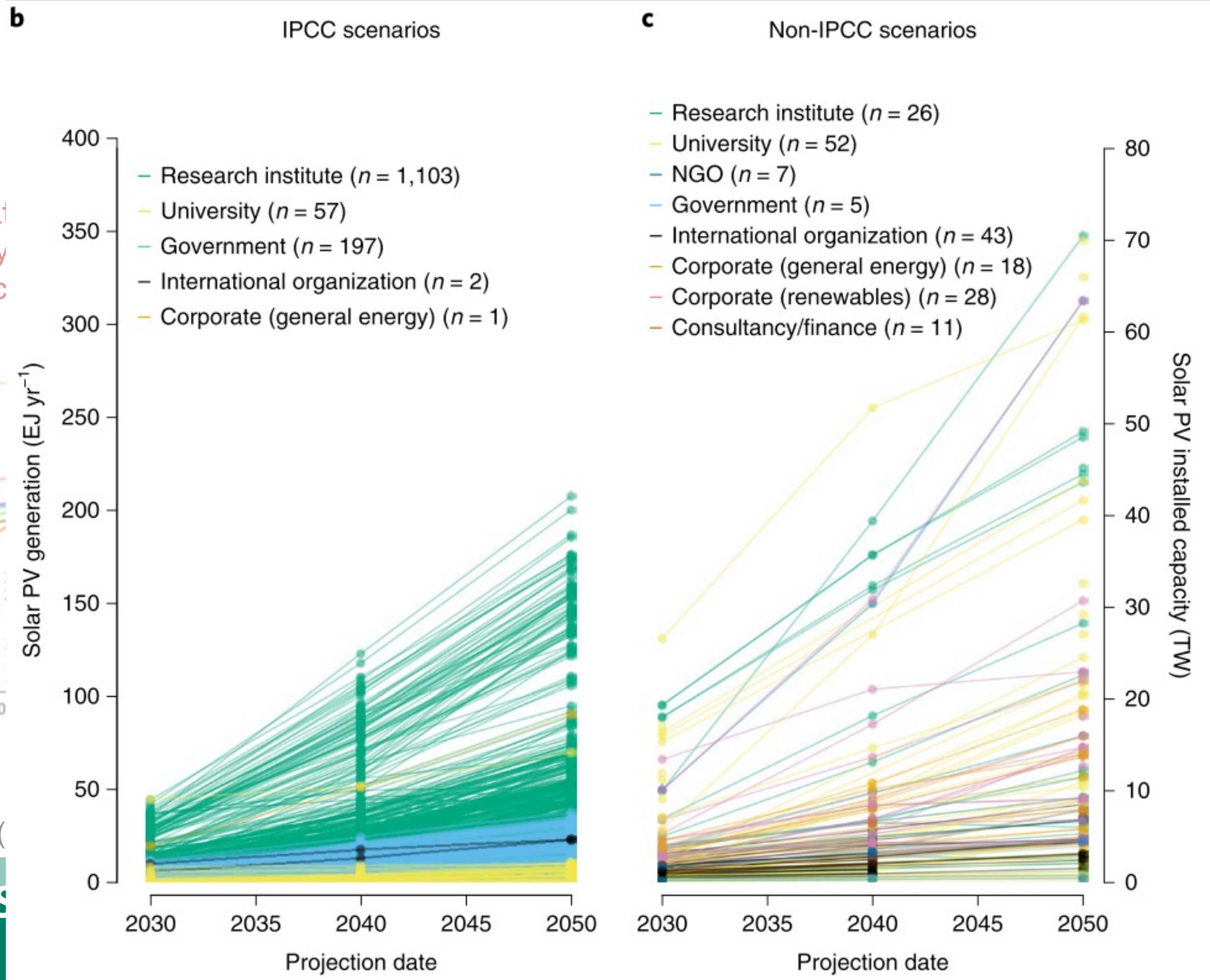

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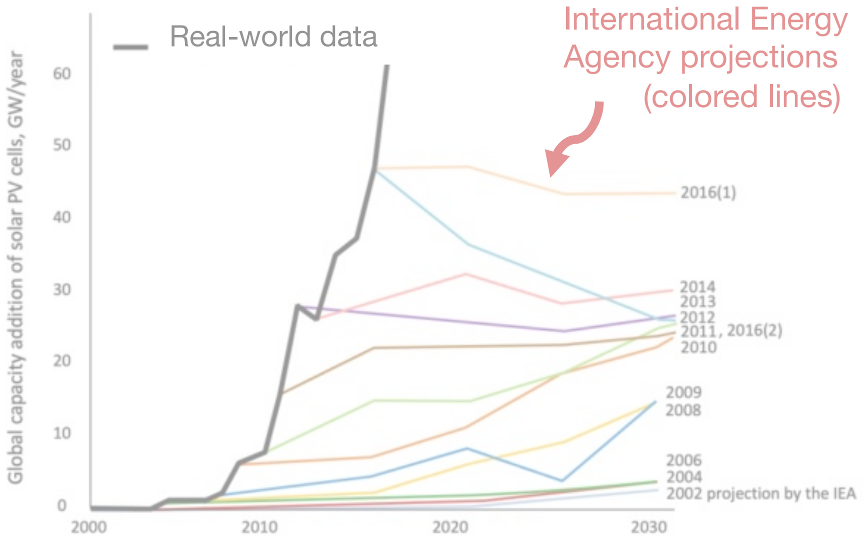
- Projections could be probabilistic to sharpen uncertainty analysis, but there have been few demonstrations



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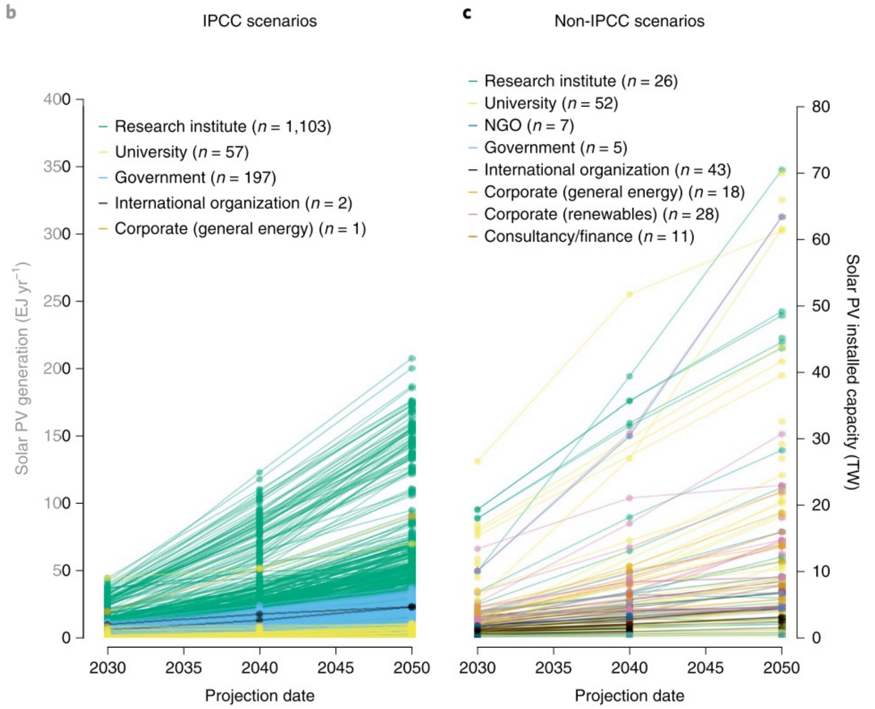
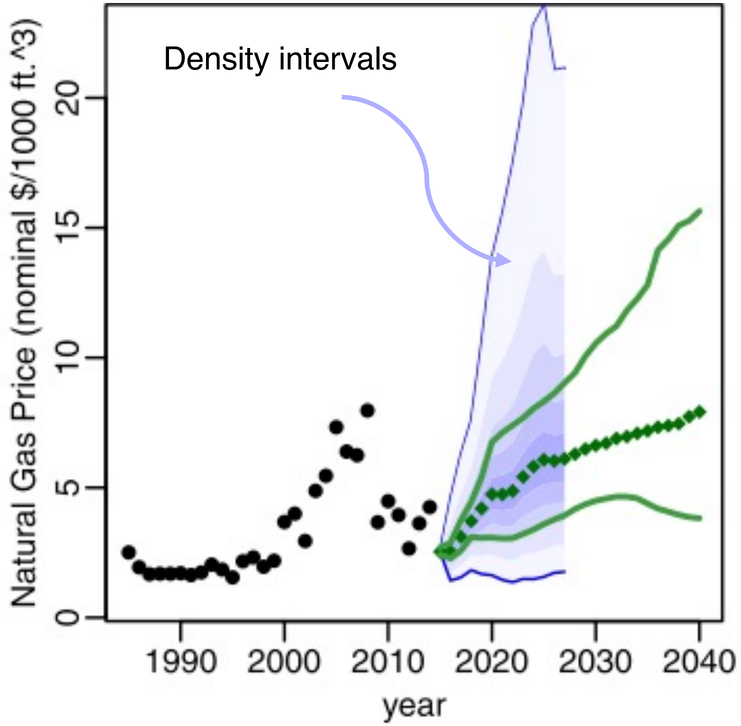


(Jaxa-Rozen & Trutnevyte, Nature and Climate Change, 2021)

Density forecasts for natural gas prices



(Kaack et al., PNAS, 2017)

Probabilistic uncertainty forecasting by hindcasting

- Empirical research on probabilistic uncertainty forecasting largely focused on a single country:
  - Novel probabilistic forecasting methods have been pioneered for the case of the US energy projections with Energy Information Administration (EIA) model (Kaack et al., 2017)
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- Obstacles remain in terms of how to integrate the probabilistic forecasting in energy models rather than to apply probabilistic ranges post-hoc on the modelled projections.
  - Probabilistic cost forecasting methods have been used to estimate future renewable technology costs and explore how technology cost uncertainty propagates through to system costs (Way et al., 2022)
  - Barely any study has focused on the probabilistic uncertainty forecasting of all the model outputs

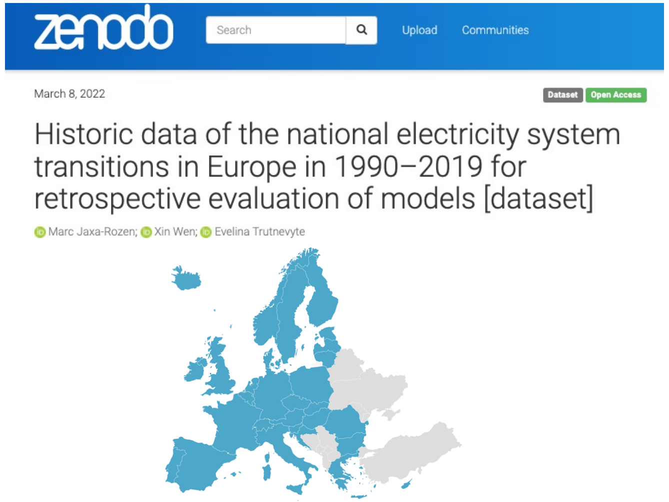
Objective

By investigating past deviations between our D-EXPANSE* model and real-world transition, we aim for probabilistic density forecasting using D-EXPANSE in 31 European countries.

- How to integrate the probabilistic uncertainty forecasting in national-level electricity system modeling for multiple countries?
- For each model output, what are the most suitable methods for generating probabilistic projections?
- How does the future uncertainty look in national electricity system transitions based on the empirical uncertainty?

* **D-EXPANSE :** Dynamic version of EXploration of PAtterns in Near-optimal energy ScEnarios (Trutnevyte, 2016; Wen et al. 2022)

Method overview: Hindcasting based uncertainty forecasting



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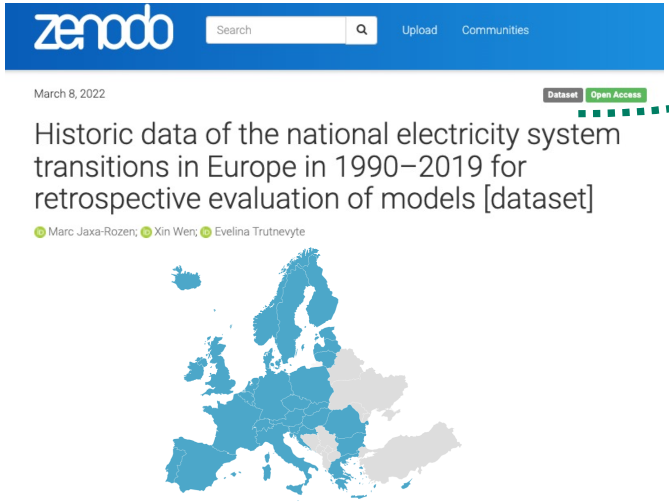

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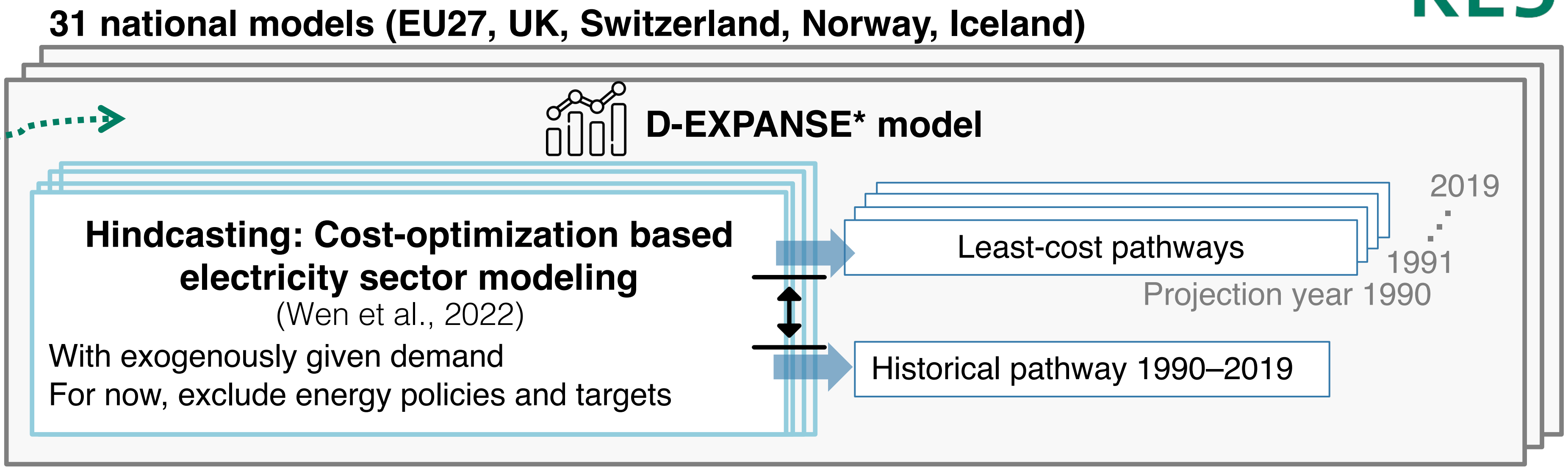

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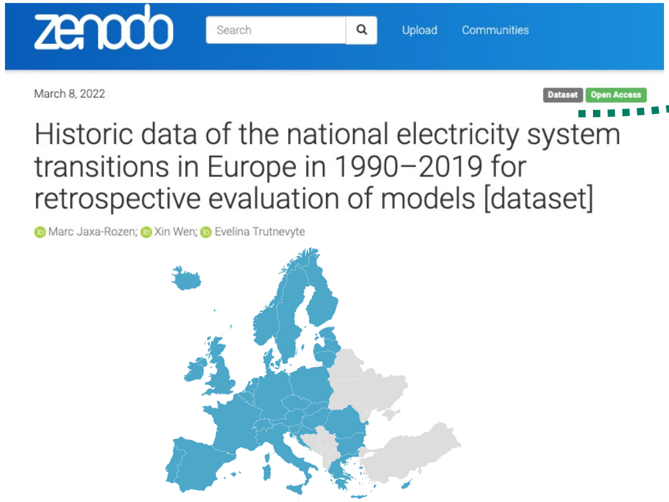

(Jaxa-Rozen et al., 2022)

31 national models (EU27, UK, Switzerland, Norway, Iceland)

D-EXPANSE* model

Hindcasting: Cost-optimization based electricity sector modeling
(Wen et al., 2022)
With exogenously given demand
For now, exclude energy policies and targets

Least-cost pathways
2019
1991
Projection year 1990

Historical pathway 1990–2019

Uncertainty forecasting model

Deviations of projections in different projection years
2019
1991
Projection year 1990

Multiple density forecasting methods based on
- out-of-sample testing
- different types of projection errors
- three assumptions on error distributions

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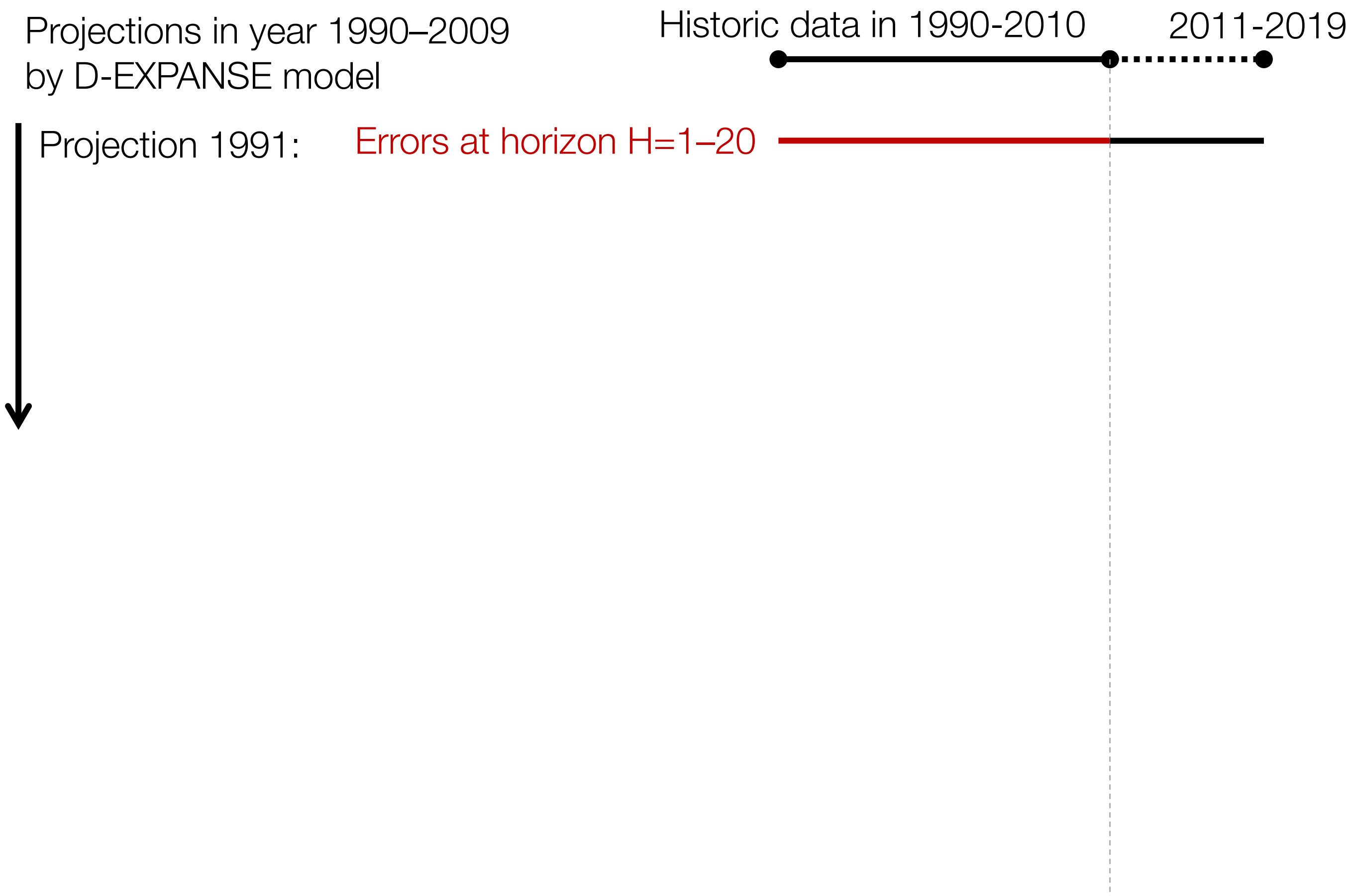
Methods [step 1/4]: Empirical probabilistic forecasting input data generation

- ❑ **Step 1: Generate training set and validation set.**

The model is trained with different ranges of consecutive training years and validation years

Example: training years 1990–2010, validation 2011–2019



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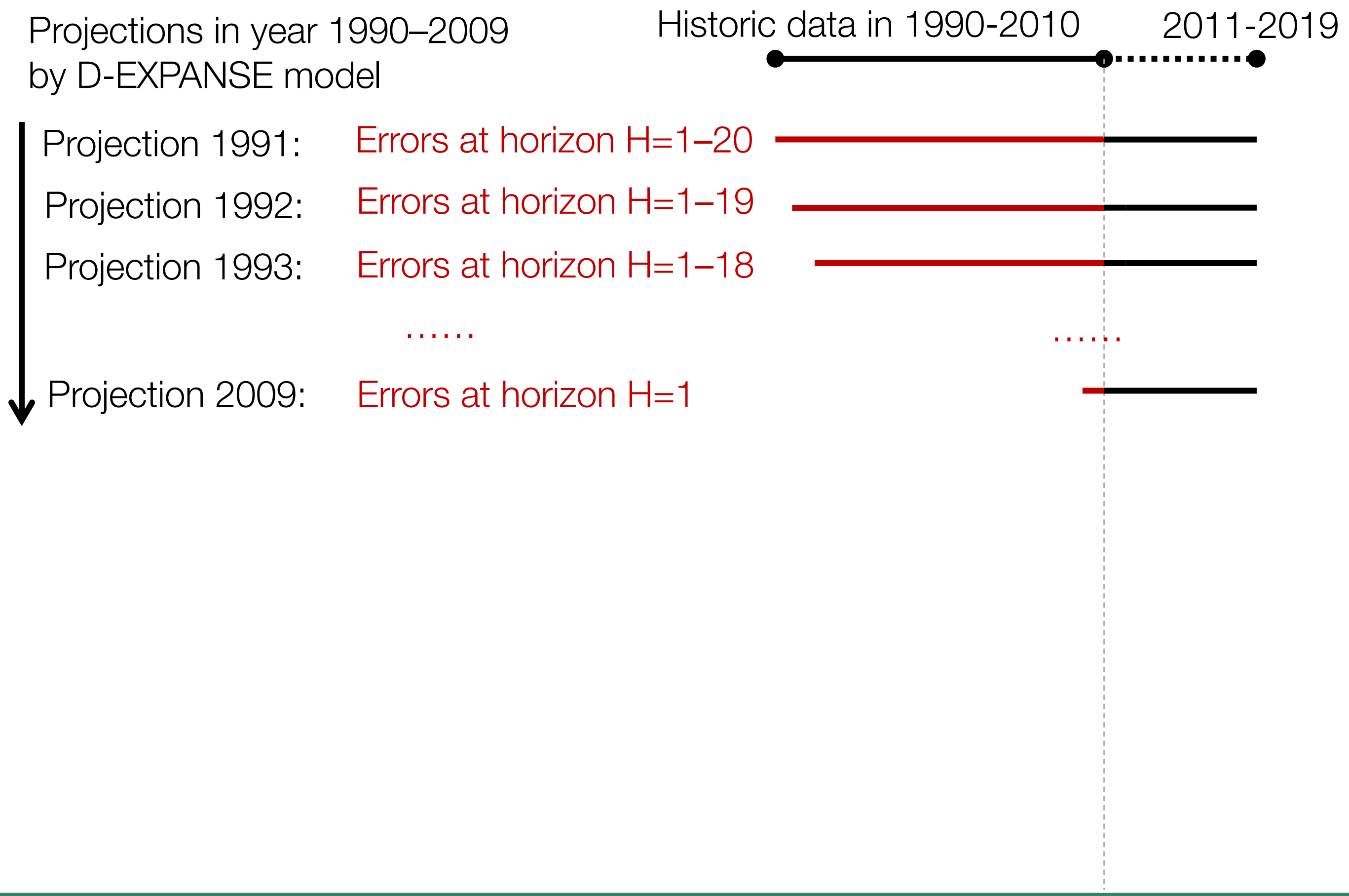

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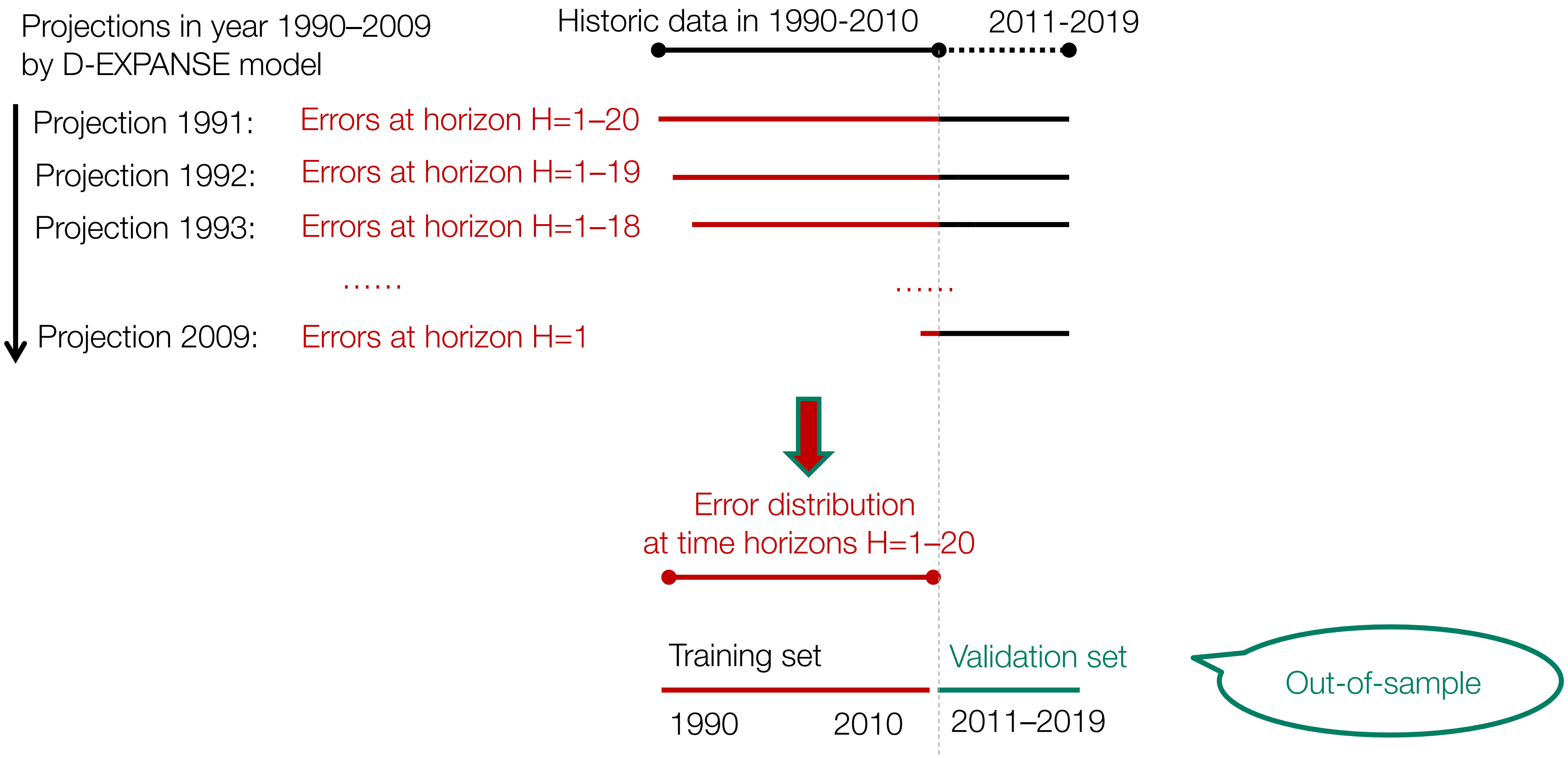
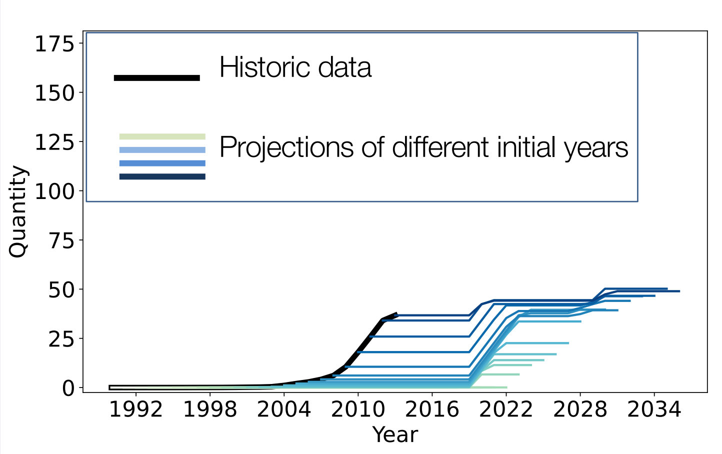


Methods [step 2/4]: Multiple empirical probabilistic forecasting methods

Step 2: Uncertainty forecasting model

Installed capacity for solar PV in Germany



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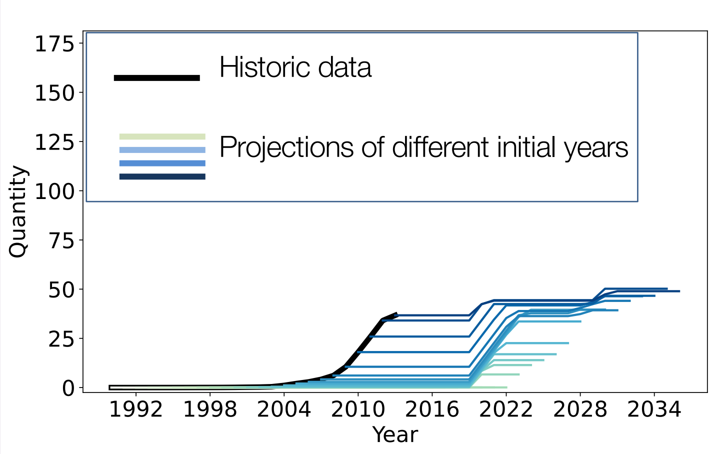

Multiple probabilistic density forecasting methods based on:

- Out-of-sample testing
- Different projection error types
  - Mean error (ME)
  - Mean logarithmic error (MLE)
  - Mean percentage error (MPE)
- Three probabilistic density assumptions
  - Nonparametric
  - Parametric (Gaussian distribution assumption)
  - Chebyshev's inequality (Gardner, 1988) (Armstrong & Collopy, 2001)

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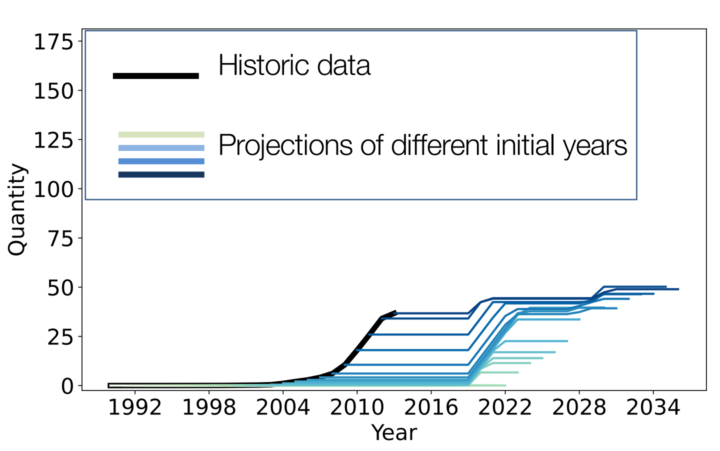

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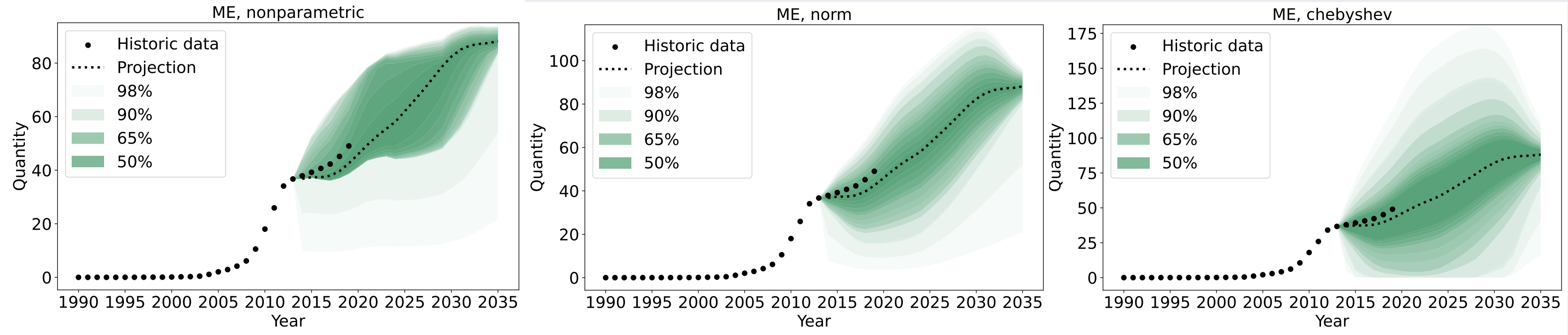

Methods [step 3/4 and 4/4]: Model evaluation and future projection

- **Step 3: Evaluate different probabilistic forecasting methods** by continuous ranked probability score (CRPS) (Kaack et al., 2017), or weighted interval score (WIS) (Bracher et al., 2021)
  - The scores can be decomposed into sharpness and calibration:
    - Sharpness: narrow probability density intervals are preferred
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- **Step 4: Future projection with probabilistic density forecasting**

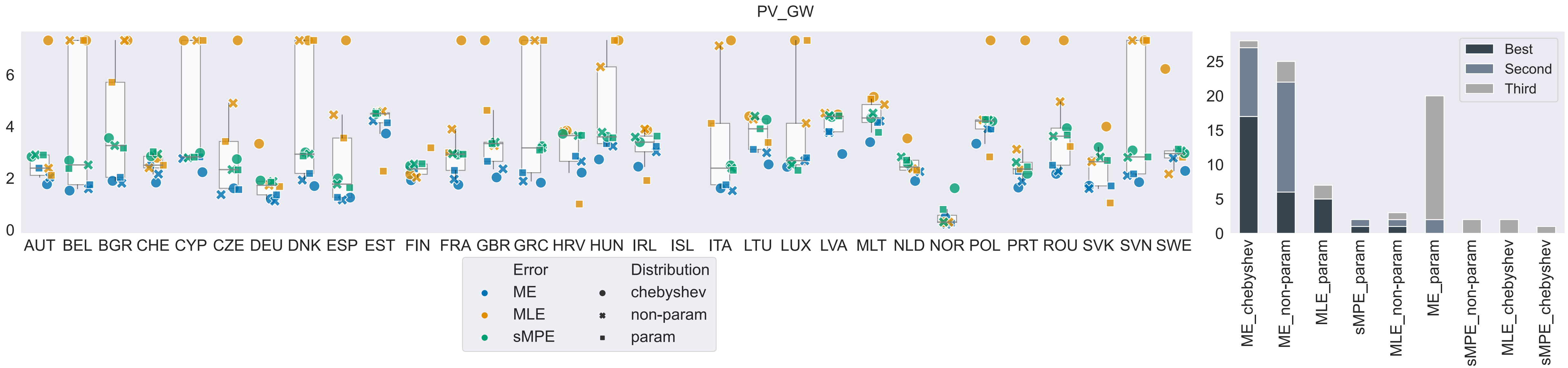
Historic data 1990 – 2019

Projection – 2035

Projection: from the modeled EXPANSE scenario
Probabilistic forecasting: based on the forecasting errors

Preliminary results: Probabilisitc density forecasting methods evaluation

Weighted interval scores (WIS) of the installed capacity for solar PV



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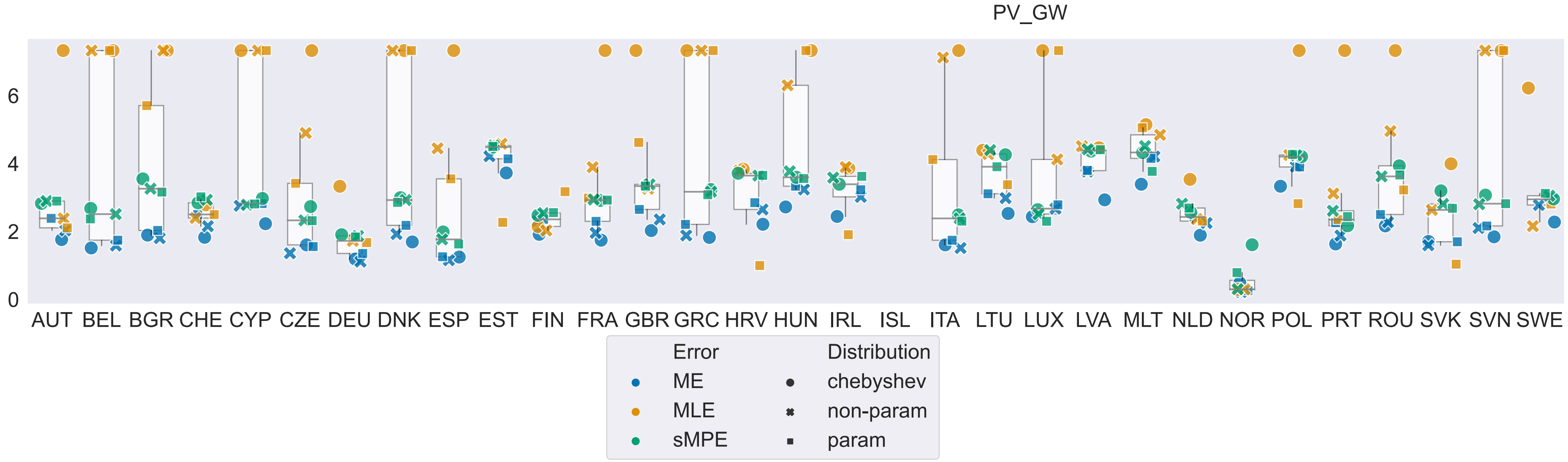
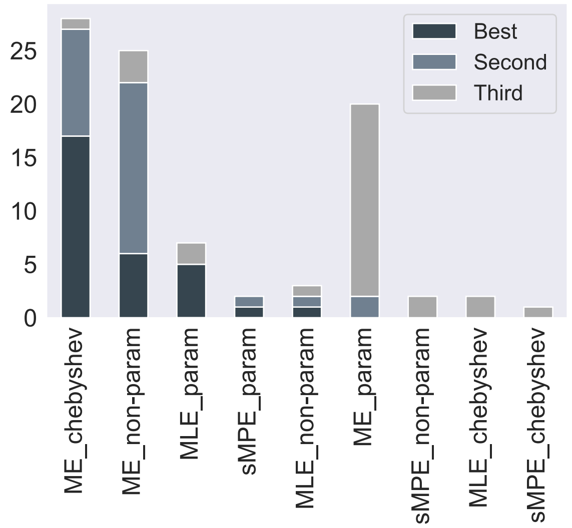
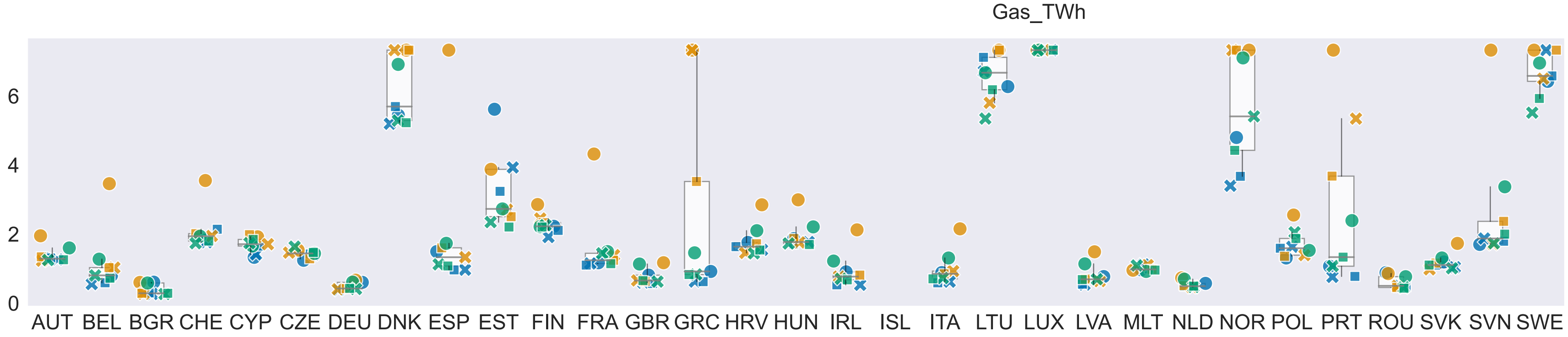
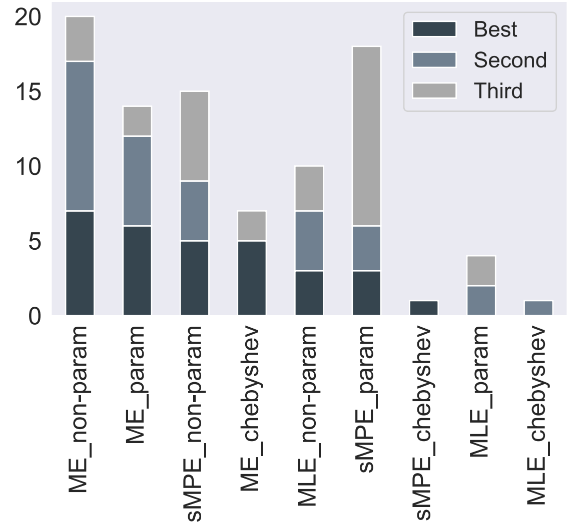


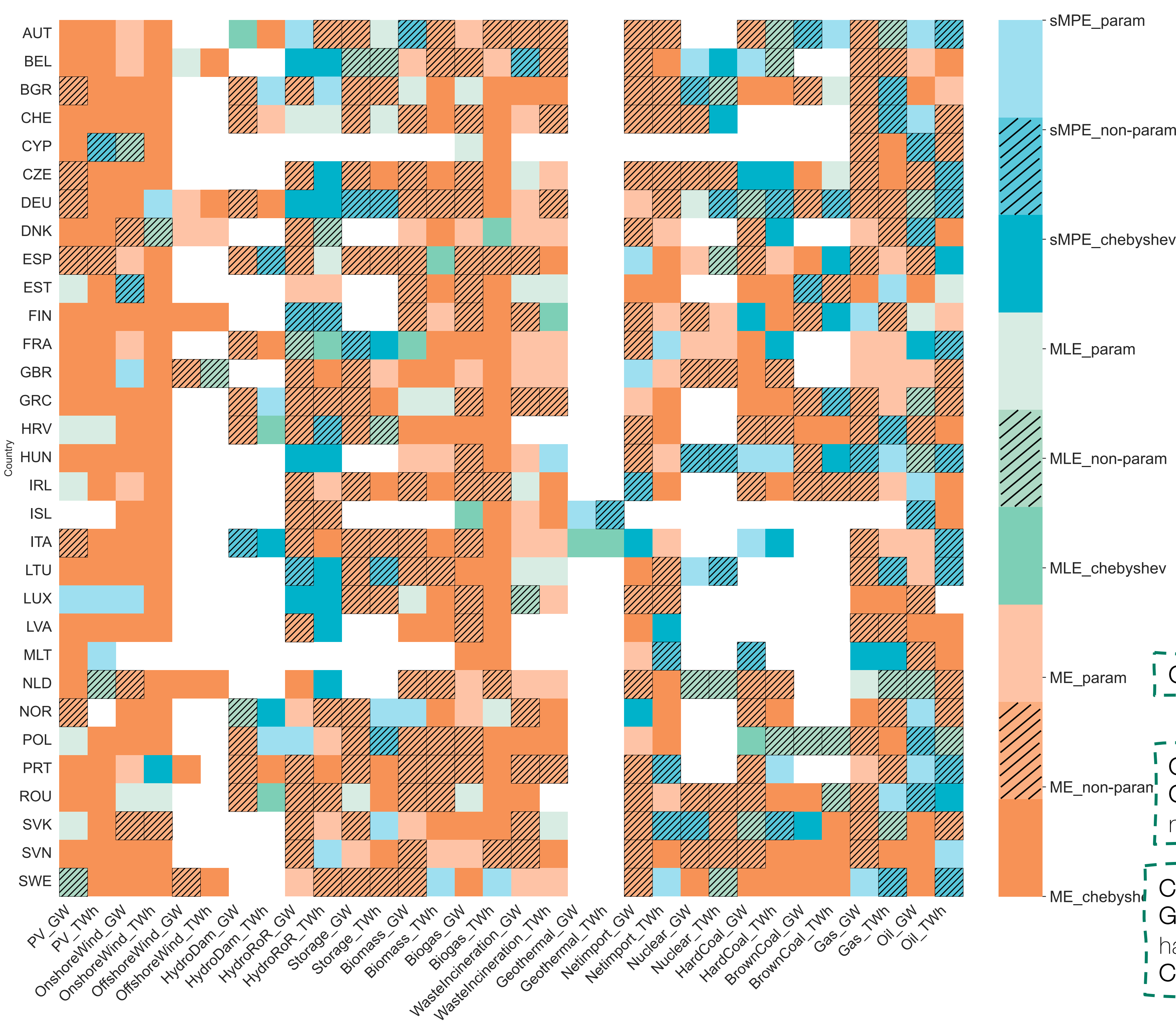


WIS of the annual electricity generation for gas





Preliminary results: Probabilisitc density forecasting methods evaluation in 31 European countries



Capacity: Geothermal

Generation: Geothermal, oil

Generation: Run-of-river hydropower (RoR)

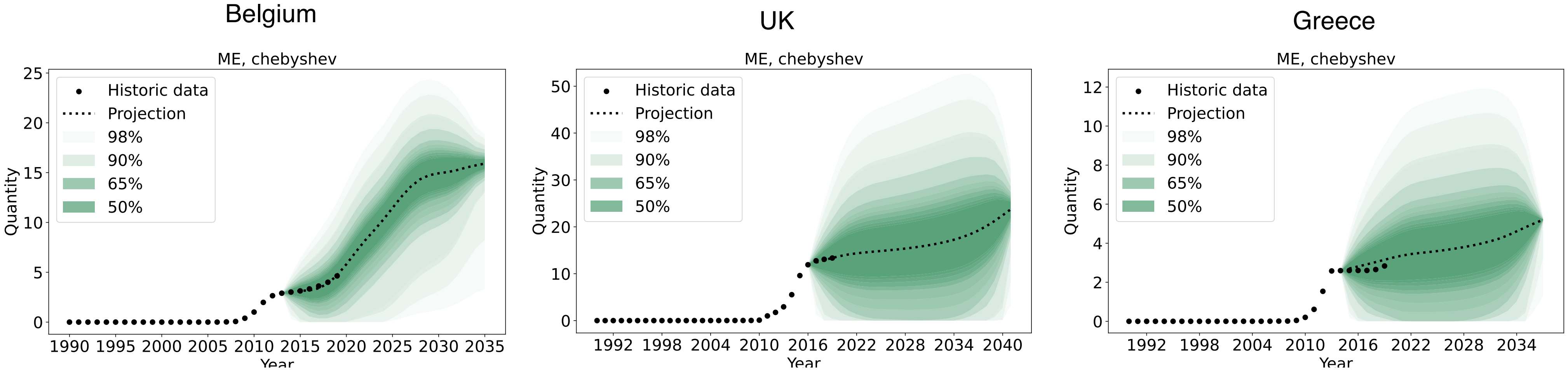
Capacity and generation: Waste incineration

Capacity and generation: gas, nuclear
Capacity: Hydro dam, RoR, storage, biomass, biogas, net import, hard coal, brown coal

Capacity and generation: PV, Onshore wind, offshore wind
Generation: Hydro dam, storage, Biomass, biogas, net import, hard coal, brown coal
Capacity: Oil

Preliminary results: Forecasting for the future (no policy scenario)

(a) Installed capacity for PV with method ME, Chebyshev



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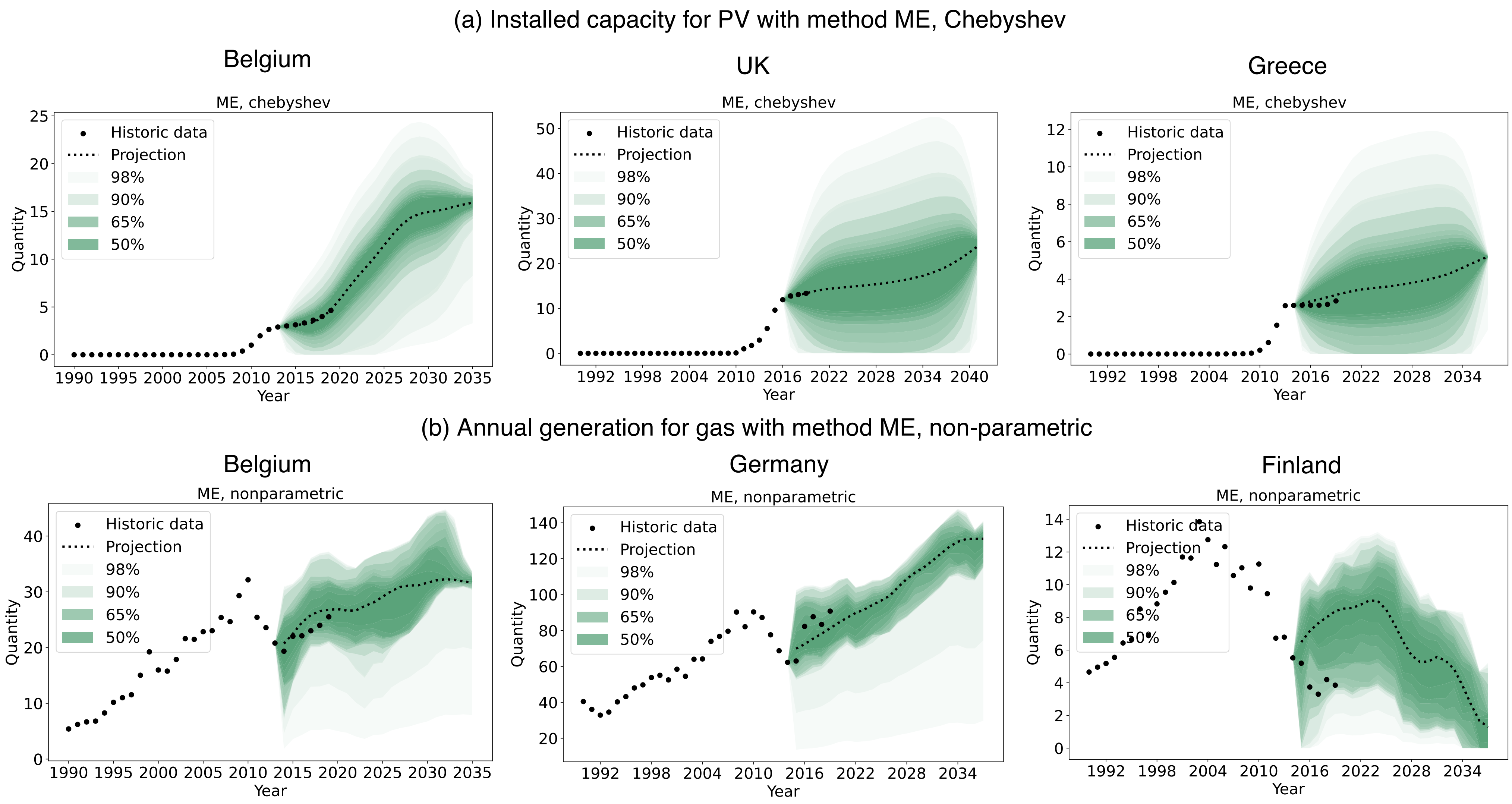

Conclusions

- Empirical probabilistic density forecasting in the national electricity system models can help forecast the uncertainty around the model projections, leading to probabilistic projections
- The evaluation of the probabilistic uncertainty forecasting methods is needed to ensure the most suitable choices of methods for different model outputs
- For renewable technologies and fossil fuel-based technologies, different density forecasting methods should be tested and employed in each country, based on their out-of-sample performance

Next steps

- Refine the method used, such as synthesizing different probabilistic projection methods by weighting
- Integrating methods to reduce the limitation of number of samples for longer projection horizon

Thank you for your attention!

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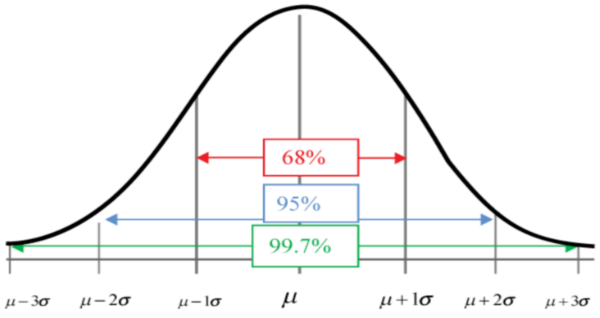
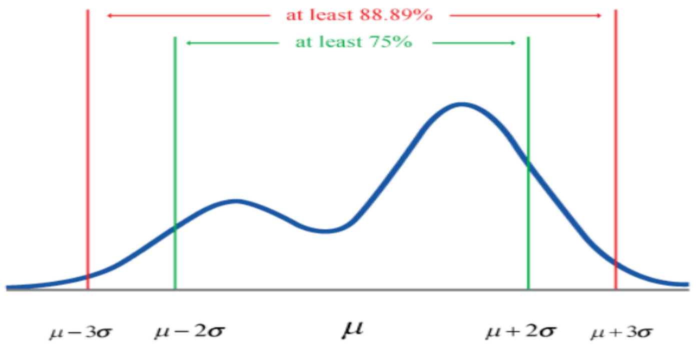
Density forecast methods

Probabilistic density assumption	Parametric	Based on error type
Non-parametric	No	Mean error (ME) Mean logarithmic error (MLE) Symmetric mean percentage error (sMPE)
Gaussian (assume a normal distribution) 	Yes	
Chebyshev's inequality (for any distribution) 	Yes	