

DESTINATION EARTH

ML Demonstrator Energy Systems

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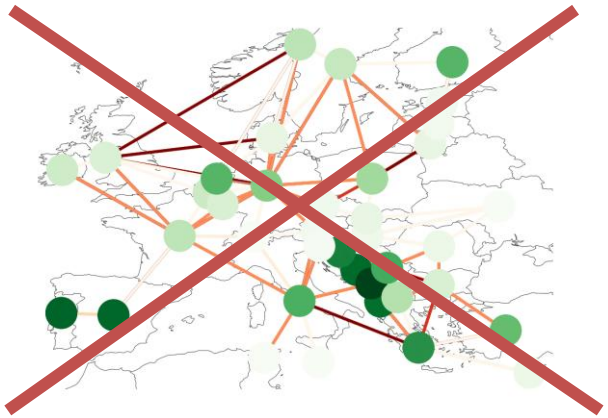
Renewables Grid Initiative

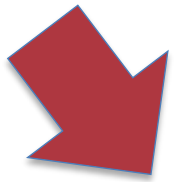
Funded by the European Union Destination Earth implemented by ECMWF esa EUMETSAT

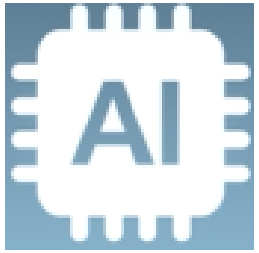


Content

- Background and motivation
- Technical achievements
- Outlook and exploitation







Machine Learning Demonstrator Energy Systems

Improved Climate-Energy Modelling with Machine Learning for Climate-proof Energy Systems

Background and Motivation

- Energy system simulations are in the core of many grid planning and adequacy studies.
- Depending on scope and setup, they can become time- and memory-consuming, and consequently a bottleneck.

Usage scenario

- Users complement their operational grid planning workflows with an additional, **fast and reliable** sensitivity analysis and uncertainty quantification. No need to run expensive simulations for many scenarios!
- Consider uncertainty in policy and grid expansion actions.

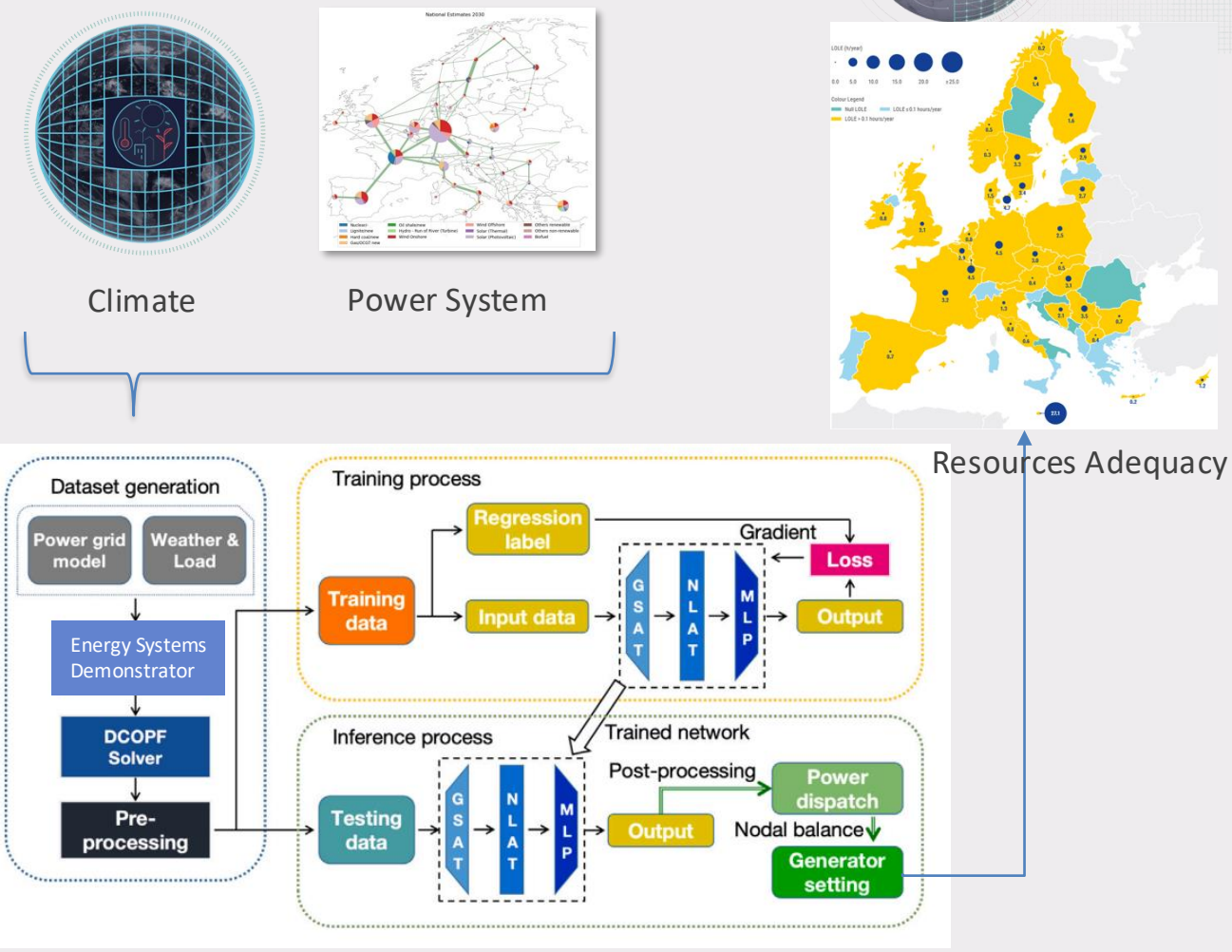
DEVELOPMENTS

Key developments

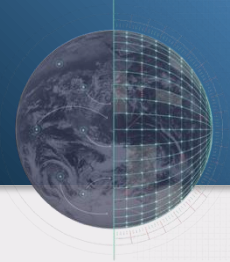
- Physics-Informed Neural Network for Optimal Power Flow predictions
- Data Processing and Management
- Interactive User Dashboard
- Climate Impact on Adequacy Assessments

Data and capacities used

- Standard Databases from TSO community (PECD + PEMMDB)
- DestinE's Energy Systems Demonstrator (simplified open-source implementation of ERAA)
- Climate scenarios from the DestinE's Climate DT
- Copernicus climate-energy Indicators



Physics-Informed Neural Network to convert Climate-Energy Data into actionable insights on Resources Adequacy



Hybrid ML & Optimization model

Obtain complete energy networks (linear problems) with hybrid ML & Optimization

Use AI architectures to predict difficult variables (transmission), then solve a much simpler optimization problem with these inputs

Benefit:

- **Identical output format** as optimization solver → User acceptance as object is identical as currently, existing routines work

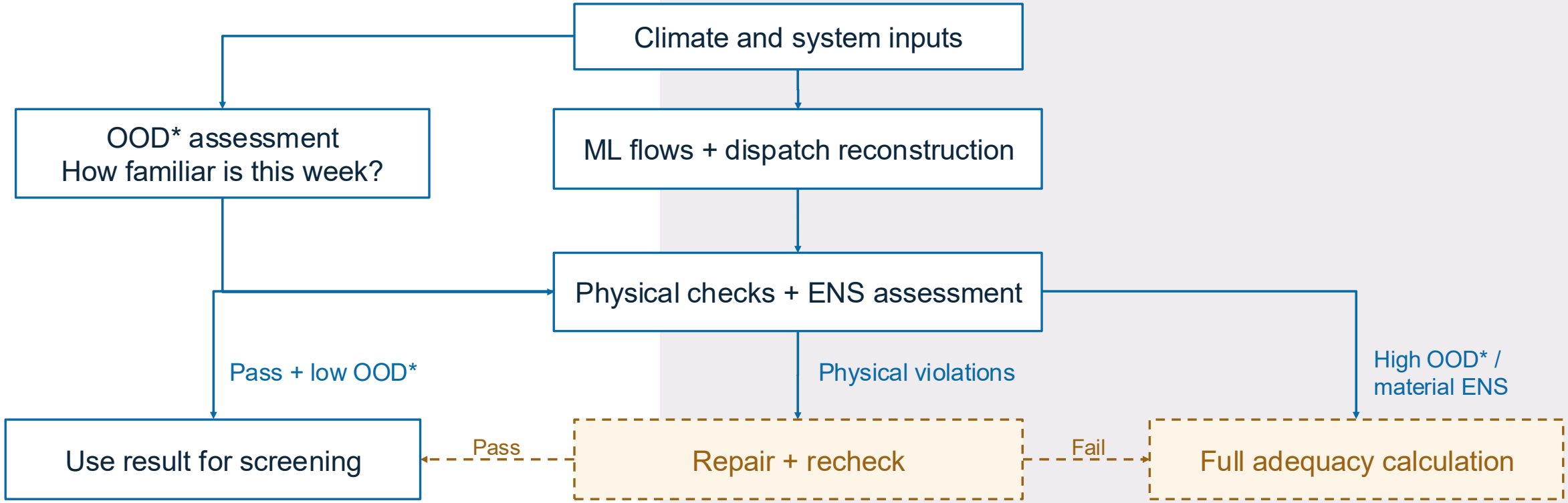
- **More information** from optimization problems (prices, energy not served)

- Better **generalizability**

- A **coherent and feasible solution**

A screening workflow with checks and correction

Fast predictions feed a controlled decision process



* out of distribution

OOD and physics checks provide different information

OOD: familiarity with training conditions

Unusual weeks tend to have larger prediction errors.

Physics: admissible operation

Balance, component limits and storage trajectories need explicit checks for every prediction.

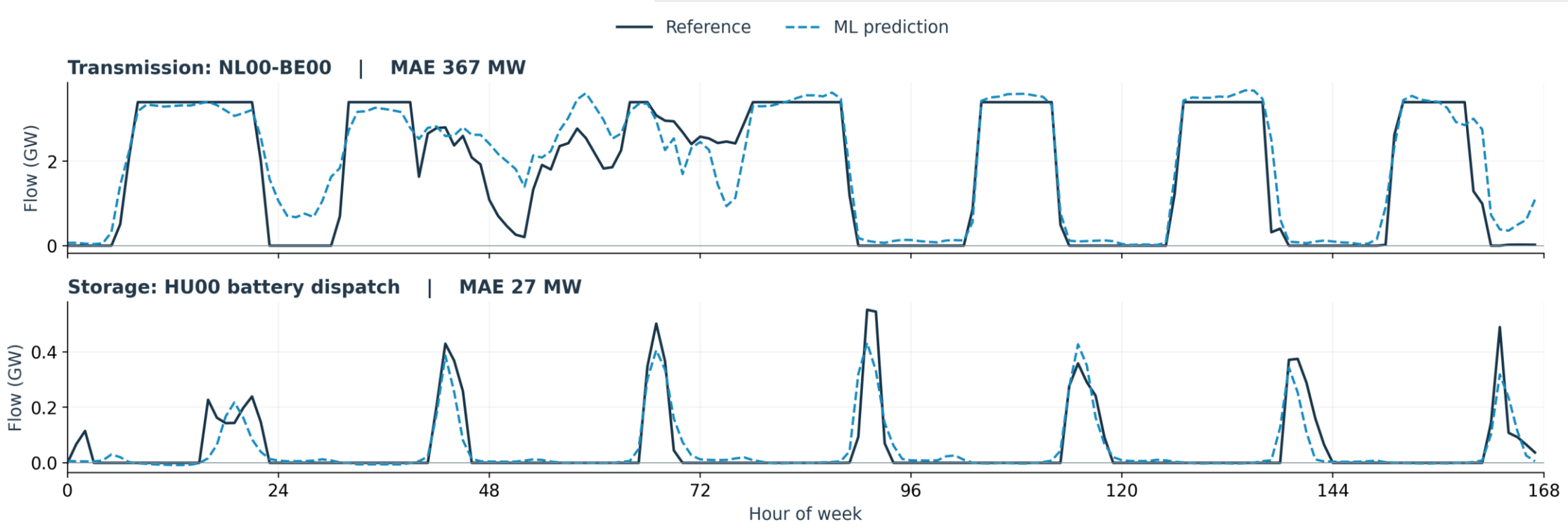
Metric	Correlation with OOD score
Flow prediction error (MAE)	+0.439
Nodal-supply adjustment	+0.433
Transmission violation energy	−0.047

Statistical familiarity alone does not establish physical feasibility.

Earlier diagnostic benchmark: 146 test weeks; separate from the current weather-scenario split.

One validation week: predicted and reference flows

WS24, week 24 · Median-error week with a selected battery example



Selected HU00 battery: R^2 = 0.799 and MAE = 27 MW. Peak deviations remain.

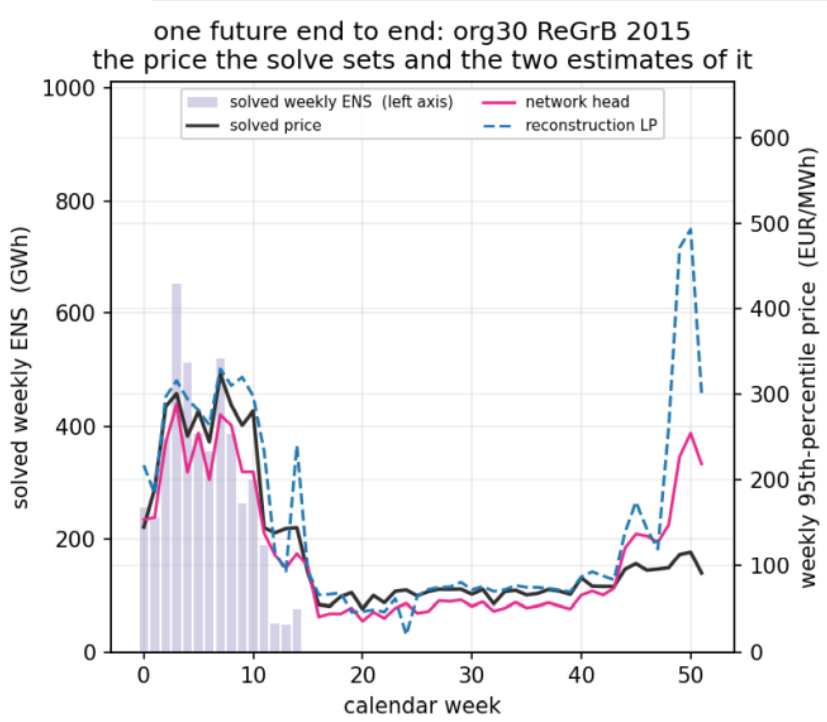
Hybrid ML&Optimization model

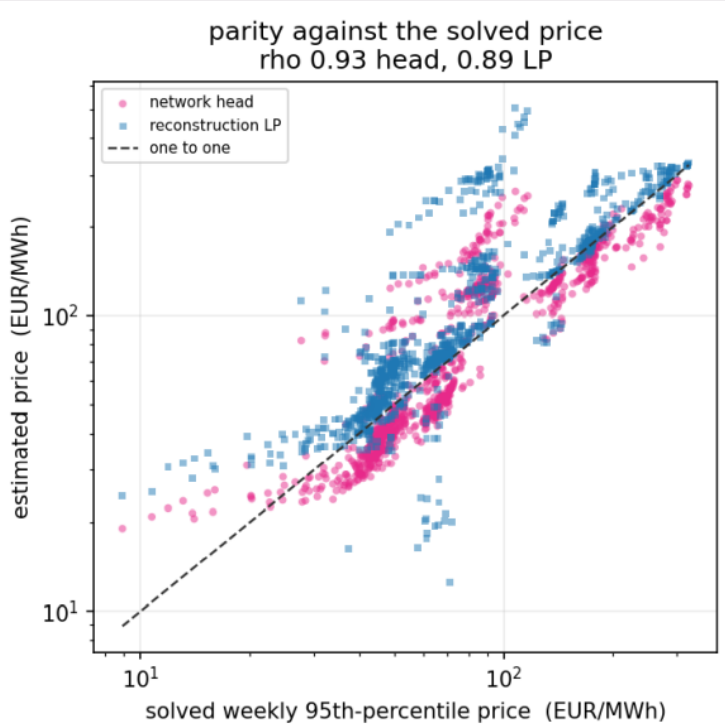
Trained on ERAA, inference on PECD wind onshore scenarios

Ability to estimate extreme prices (95th percentile)

- Direct prediction wo optimization (network head) has better correlation

- On scale and tails reconstruction is more realistic
  - wo optim: 11.6 EUR/MWh
  - w optim: 3.5 EUR/MWh





Hybrid ML&Optimization model

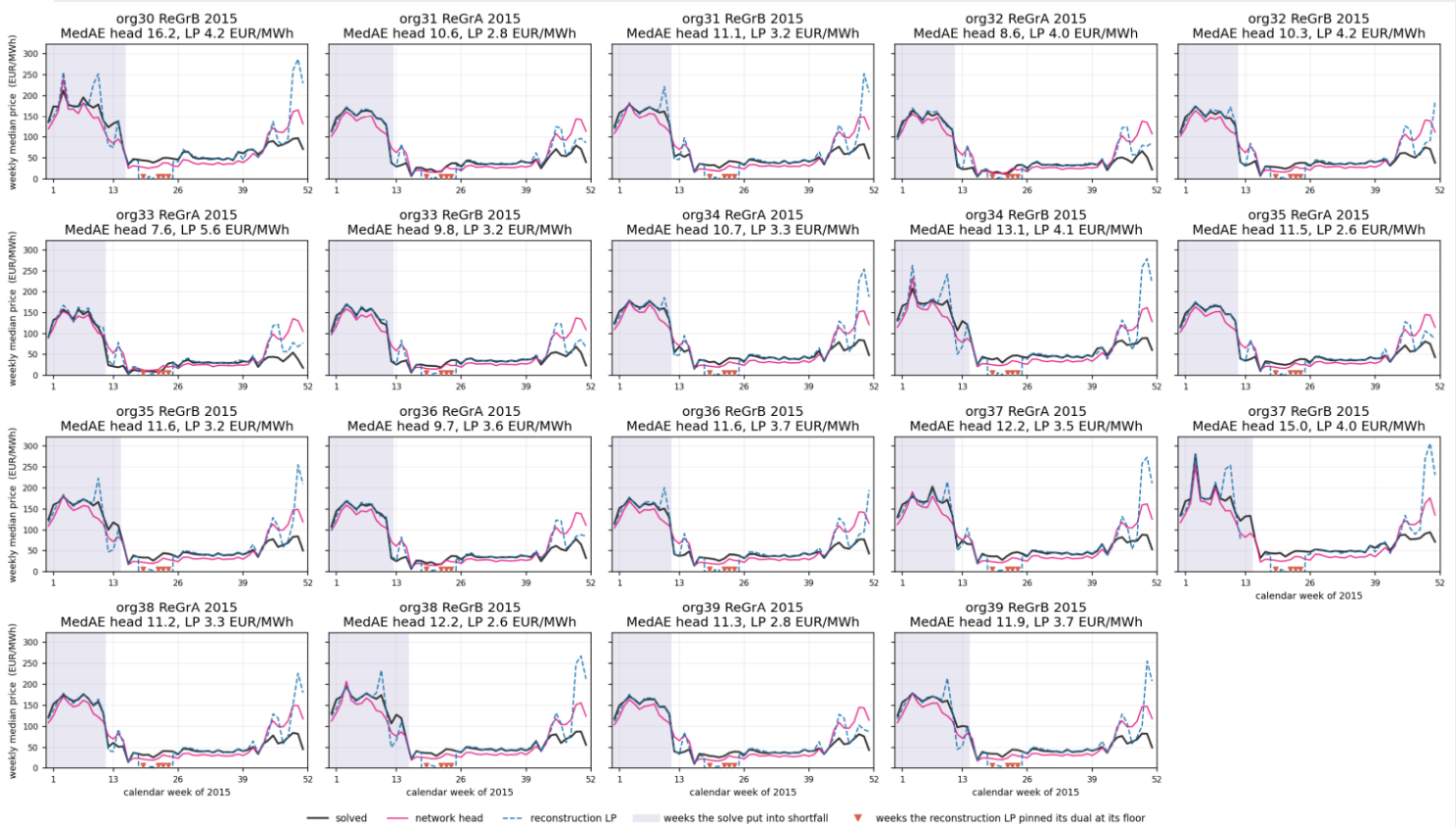
Can the model find the black swans in large datasets?

Situations of high prices can be identified

Reconstruction model is overly pessimistic due to less DOF
→ Desirable for finding critical situations



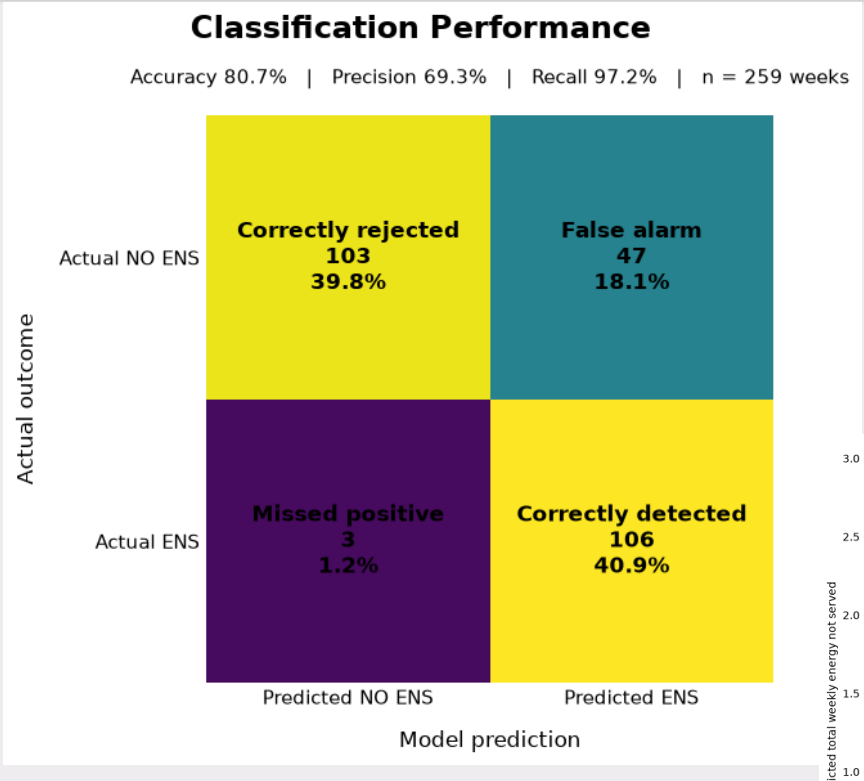
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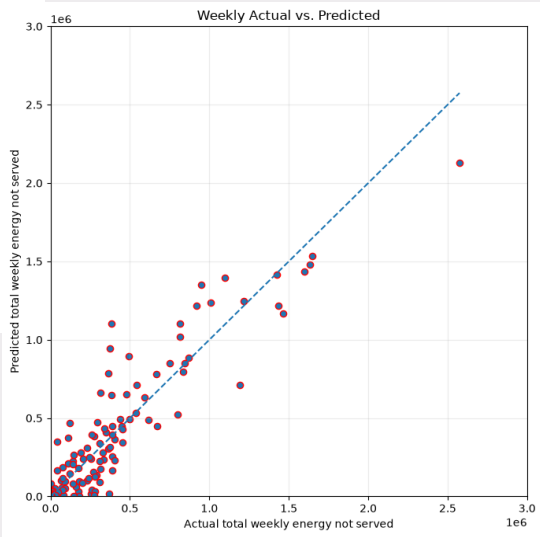
Identifying critical weeks with ML

Find relevant weather years out of millions

- Energy not served is considered as critical weeks
- ENS weeks can be mostly correctly identified from ML model (accuracy=80%)
- Nearly most critical weeks can be identified
  - Recall=97% (TP/(TP+FN))
- Runtime: Around 1s for one week

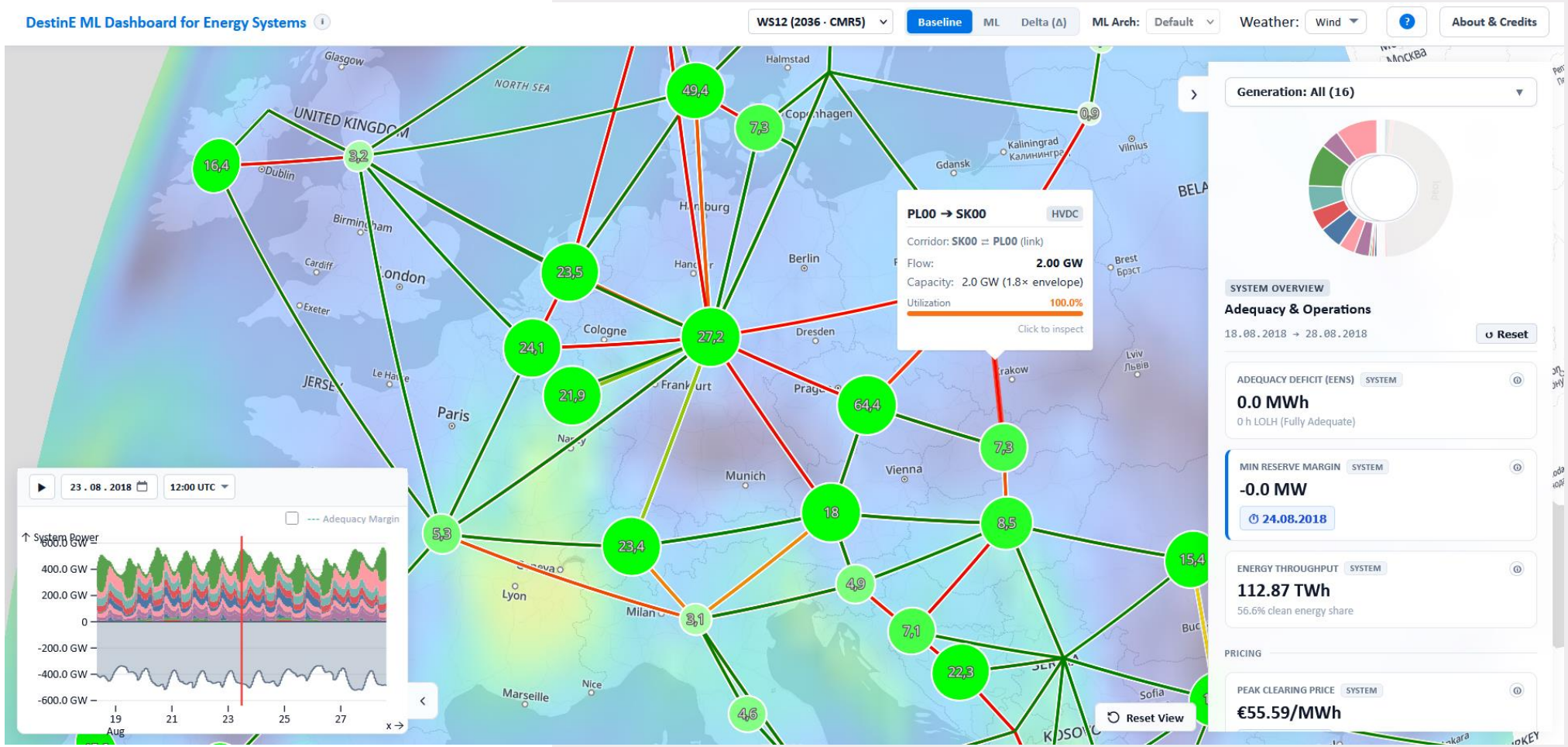


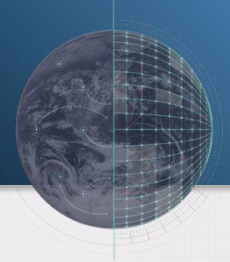
Confusion matrix of classification of weekly ENS>1MWh



Energy not served, one dot is one week (summed over all nodes)

Interactive user dashboard





Summary and Outlook

- A hybrid optimisation/ML workflow has been developed and tested to derive a complete energy system surrogate.
- OOD measure delivers relavant additional information on reliability of ML outputs.
- Critical weeks can reliably be identified from databases.

- Application of ML (and Energy Systems) Demonstrator to support EUCRA-2:
  - Illustrative case studies
  - What-if scenario analysis to identify adaptation measures

- Establishing stakeholder-group for Horizon Europe proposals (industry-focus, solution-oriented)
- Exchanges on implementing concrete use cases with key users

Thank you for your attention