Robustness of Reinforcement Learning-Based Congestion Management in Low-Voltage Grids

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IAEW Elektrische Anlagen & Netze, Digitalisierung & Energiewirtschaft

0100001 0101 Computational Network Science

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Motivation: Increasing Renewables & EVs

Example: Germany

+11%
solar power in 2025

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EnWG
mandates control

59.6%
(PH)EVs (new cars, 2025)

Motivation: Challenges

- Limited observability: Smart meter adoption takes time, only certain consumers / producers have to be connected by law
- Model mismatch: Uncertainty in the impedance of cables
  - Imprecise / inaccurate documentation (installed at a time where exact cable parameters were not required)
  - Aging infrastructure: Heating-cooling cycles, repairs, other construction work can affect exact electrical properties
- Measurements may be inaccurate
  - No instant synchronization $\rightarrow$ combine measurements from different points in a (short) time interval
  - Tolerances in measurement devices

Possible Solutions

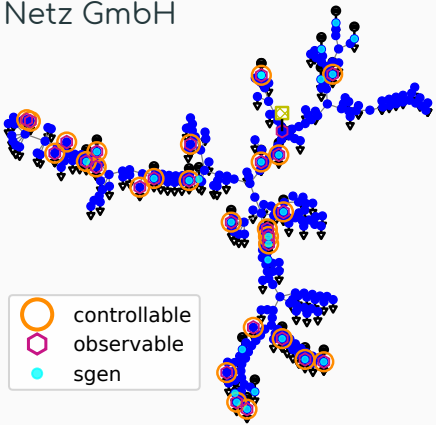
- State Estimation + Optimal power flow (OPF)
  - State Estimation returns one result based on pseudo-measurements
  - OPF is exact and compounds errors, difficult to tune trade-off
- Neural Networks for State Estimation: Works well, but same categorical problems for control

Machine learning: Tune from observation to action (e.g. more / less active)

General approach: *Wolf, Hinrikus, et al. "End-to-End Reinforcement Learning of Curative Curtailment with Partial Measurement Availability." IEEE, 2024.*

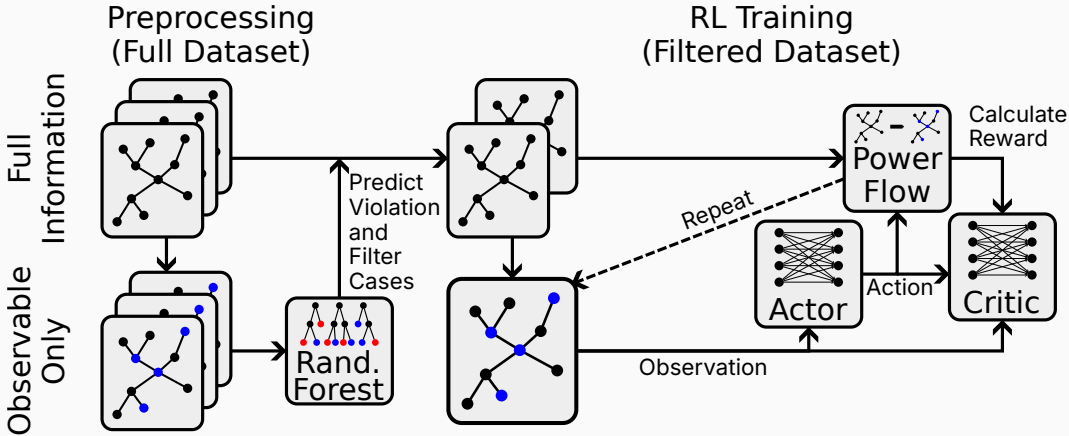
Generating Near-Future Scenarios

Real-world electricity grid, provided by Schleswig-Holstein Netz GmbH

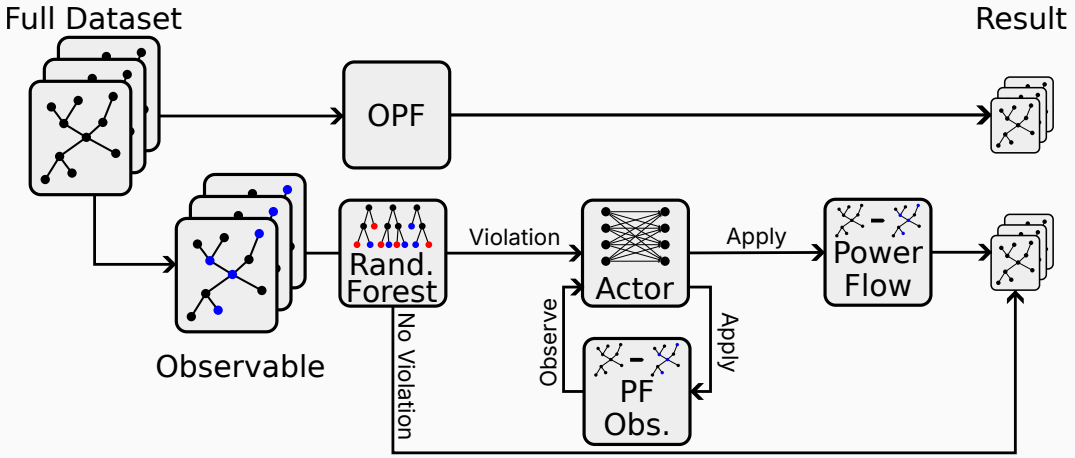


Realistic near-future scenario

- 10% of buses observable & controllable
- Realistic future demand / generation time series profiles
- Simulated in 15 minute intervals over 1 year
- Optimal Power Flow as idealized baseline (with full observability)


Preprocessing
(Full Dataset)
RL Training
(Filtered Dataset)
Full Information
Observable Only
Predict Violation and Filter Cases
Rand. Forest
Power Flow
Calculate Reward
Repeat
Actor
Action
Critic
Observation

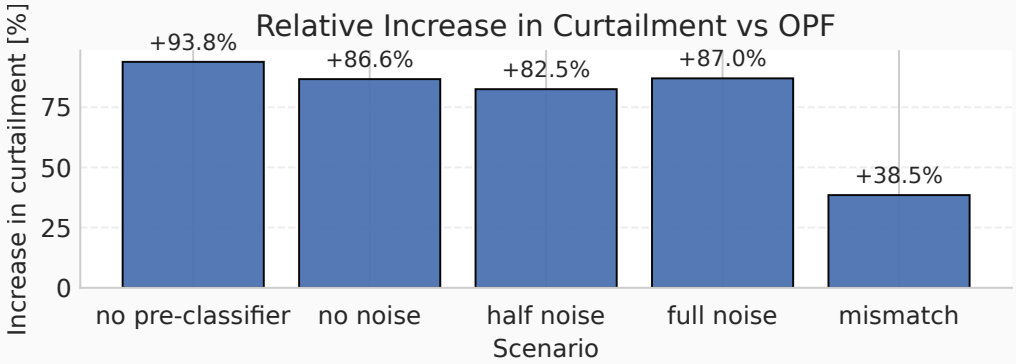
Evaluation Setup



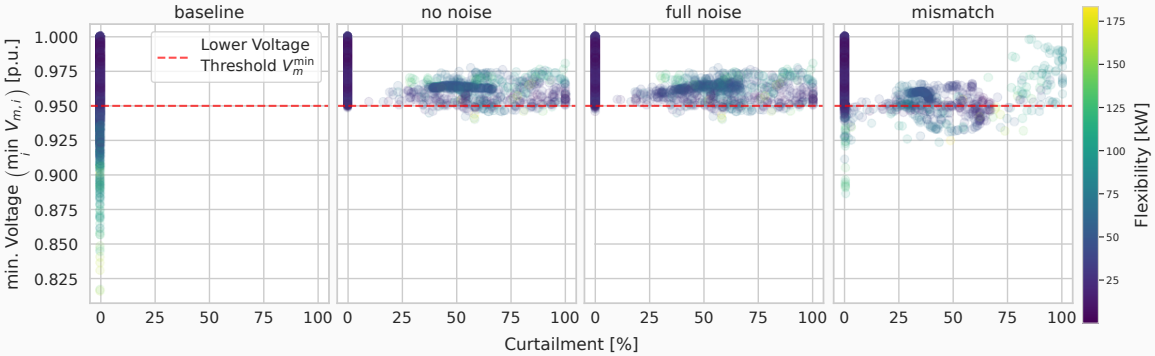
Task: Detect presence of violations from observable measurements

	No Noise	Half Noise	Full Noise	Mismatch
False Pos	7	20	49	4
False Pos (%)	0.2 %	0.6 %	1.4 %	0.1 %
False Neg	4	10	15	119
False Neg (%)	0.3 %	0.7 %	1.2 %	9.2 %

Results: Curtailment



Results: Minimum Voltage



	Baseline	No noise	Full noise	Mismatch
No. of violated cases	726	60	70	301
Mean reduction in violation	0.0%	98.9%	98.8%	79.6%

Conclusion

- RL-Approach quite robust to (zero-mean) measurement noise
- Grid parameter mismatch is a bigger challenge
- Random Forest classifier reduced overactivity significantly
- Random Forest also speeds up training (only train on violated cases)

Future Work on Robustness:

- Changing load profiles (out of distribution)
- Incorrect / uncertain topology

arXiv:
2607.16004