

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

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September 2, 2026

SEST 2026, Ciudad Real



Elektrische
Anlagen & Netze,
Digitalisierung &
Energiewirtschaft



Computational
Network Science



Example: Germany



+11%
solar power in 2025

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

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EnWG

mandates control



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- Measurements may be inaccurate
 - No instant synchronization → combine measurements from different points in a (short) time interval
 - Tolerances in measurement devices

- 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

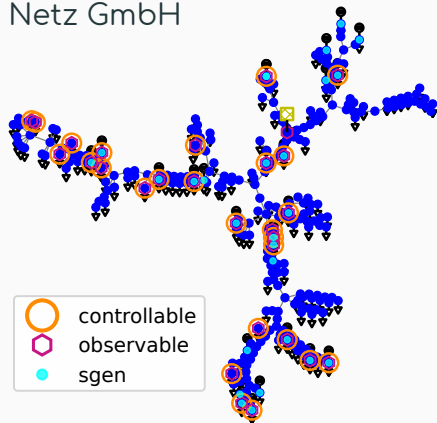
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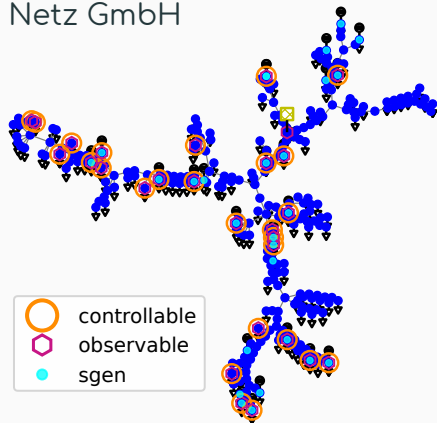
Machine learning: Tune from observation to action (e.g. more / less active)

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

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

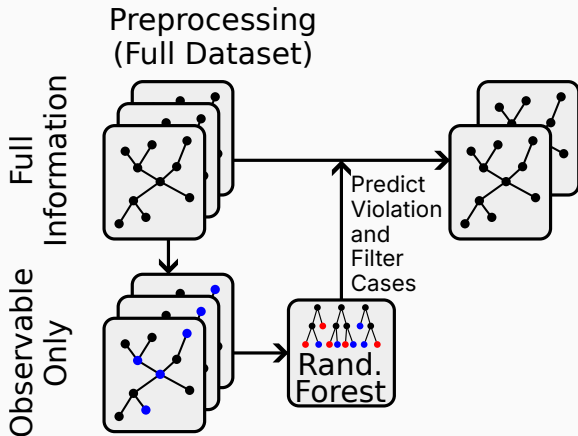


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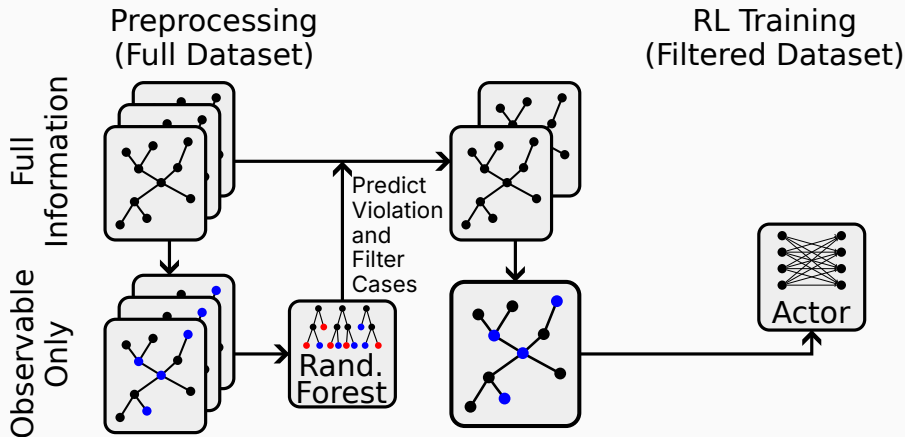


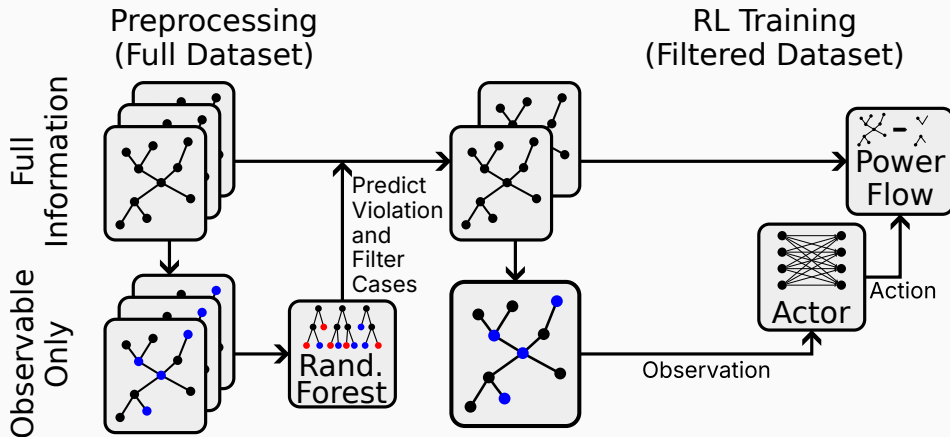
Realistic near-future scenario

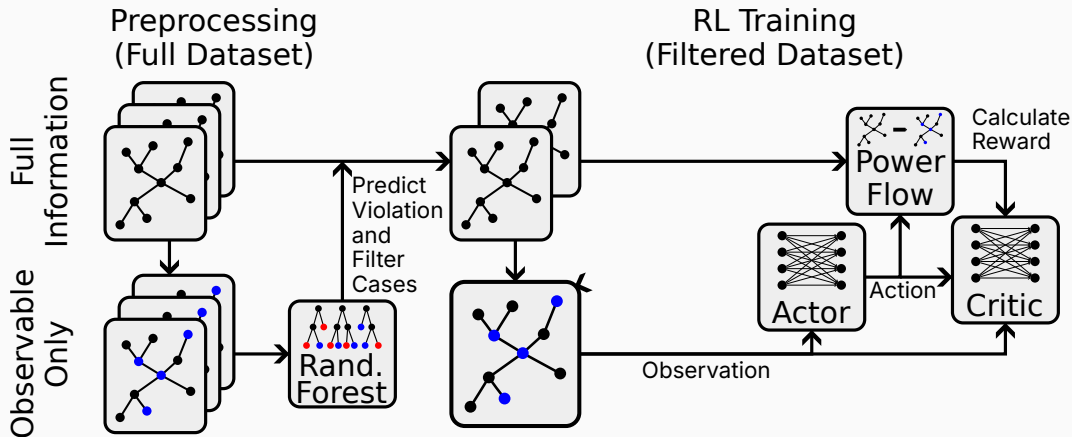
- 10% of buses observable & controllable
- Realistic future demand / generation time series profiles
- Simulated in 15 minute intervals over 1 year
- Optimal Power Flow as idealized baseline (with full observability)

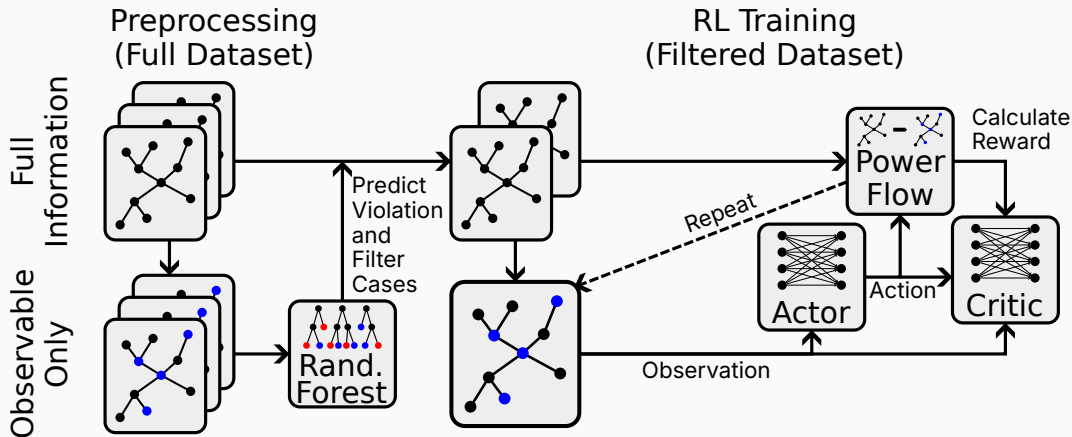


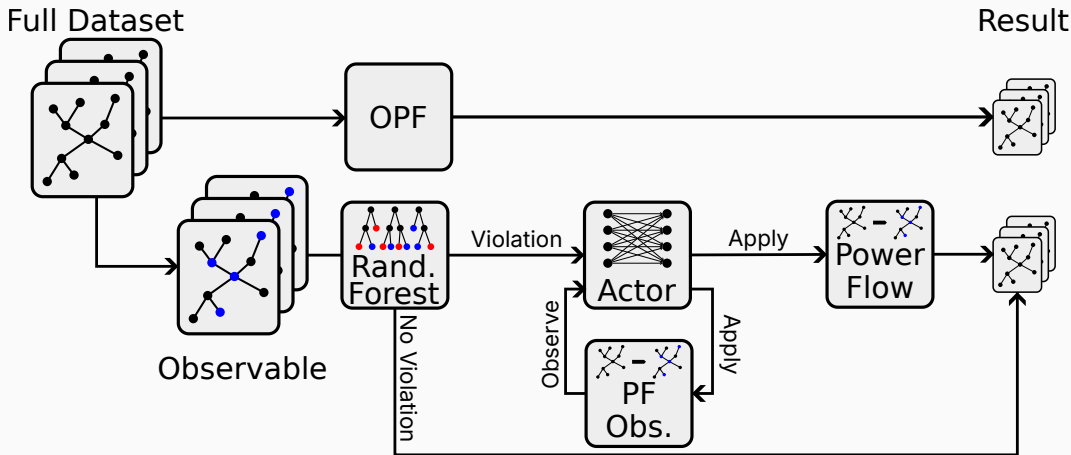
RL Training
(Filtered Dataset)





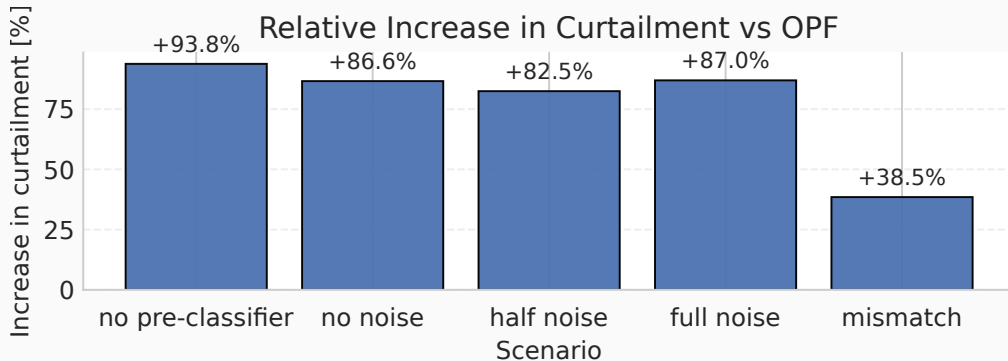




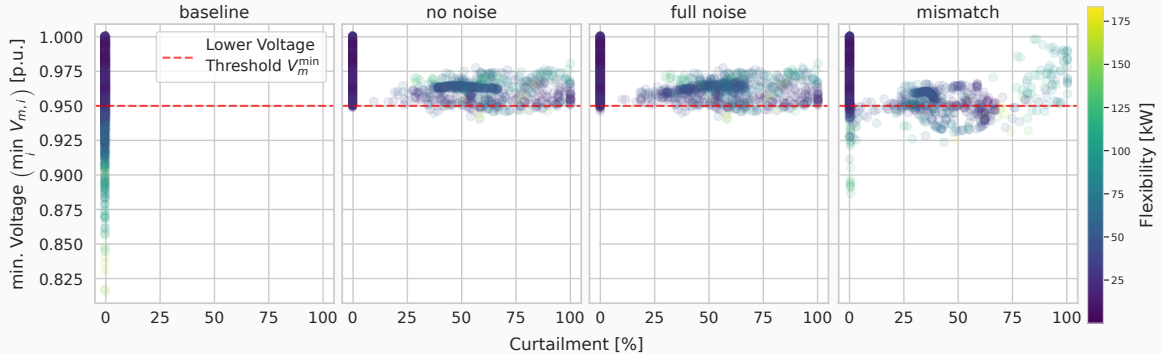


Task: Detect presence of violations from observable measurements

	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: 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%

- 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