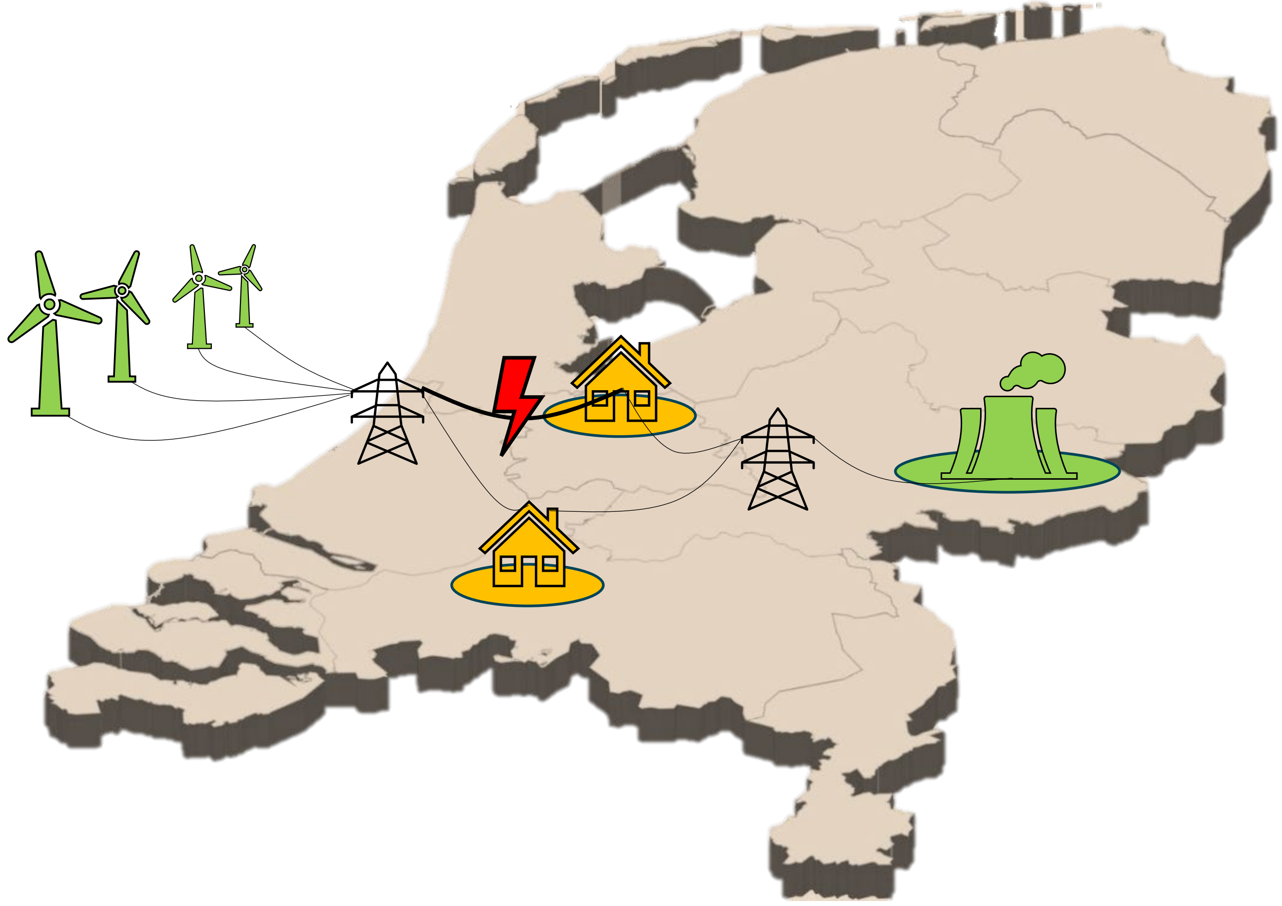
Constraint-Driven Deep Learning for N-k Security Constrained Optimal Power Flow

Bastien Giraud, Ali Rajaei, Jochen L. Cremer



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Acknowledgement

Bastien Giraud

Ali Rajaei

Web: https://www.tudelft.nl/ai/delft-ai-energy-lab

Reference

- Bastien Giraud, Ali Rajaei, Jochen L. Cremer “Constraint-Driven Deep Learning for N-k Security Constrained Optimal Power Flow”, in review *IEEE Power System Computing Conference 2024*

- Code: https://github.com/TU-Delft-AI-Energy-Lab

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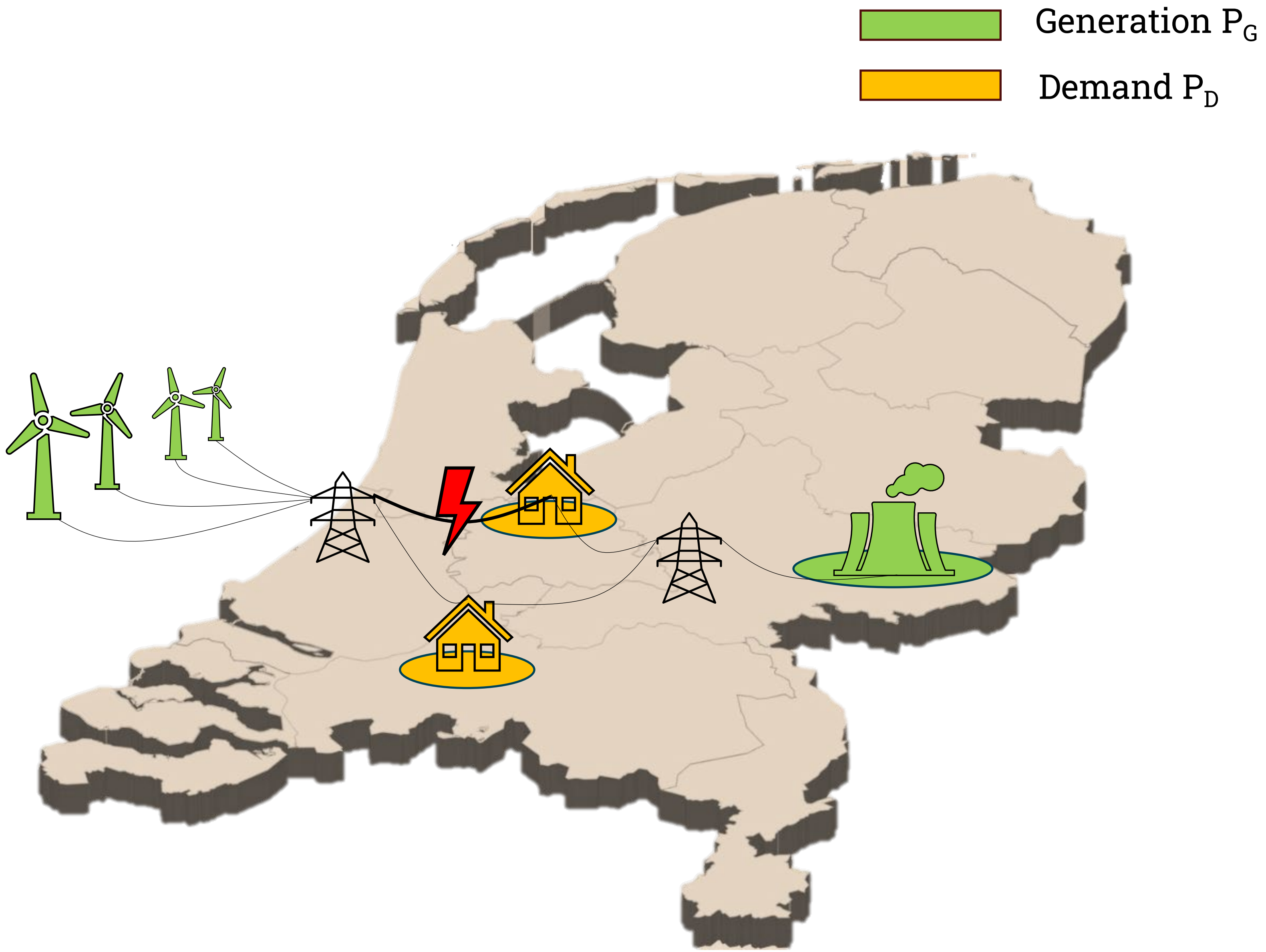
N-1 Security



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Line outage distribution factors

- Line outage distribution factor (LODF)
- Linear sensitivity factor
- Indicates change of flow over line when another line is in outage

$$\boldsymbol{F^c = F^0 + LODF_{N-k} \times F^0}$$

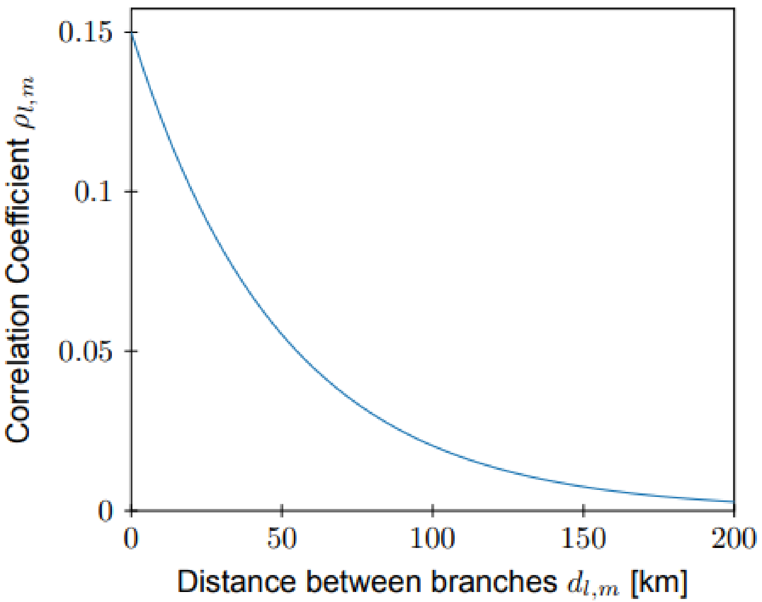
Security constrained optimal power flow (SCOPF)

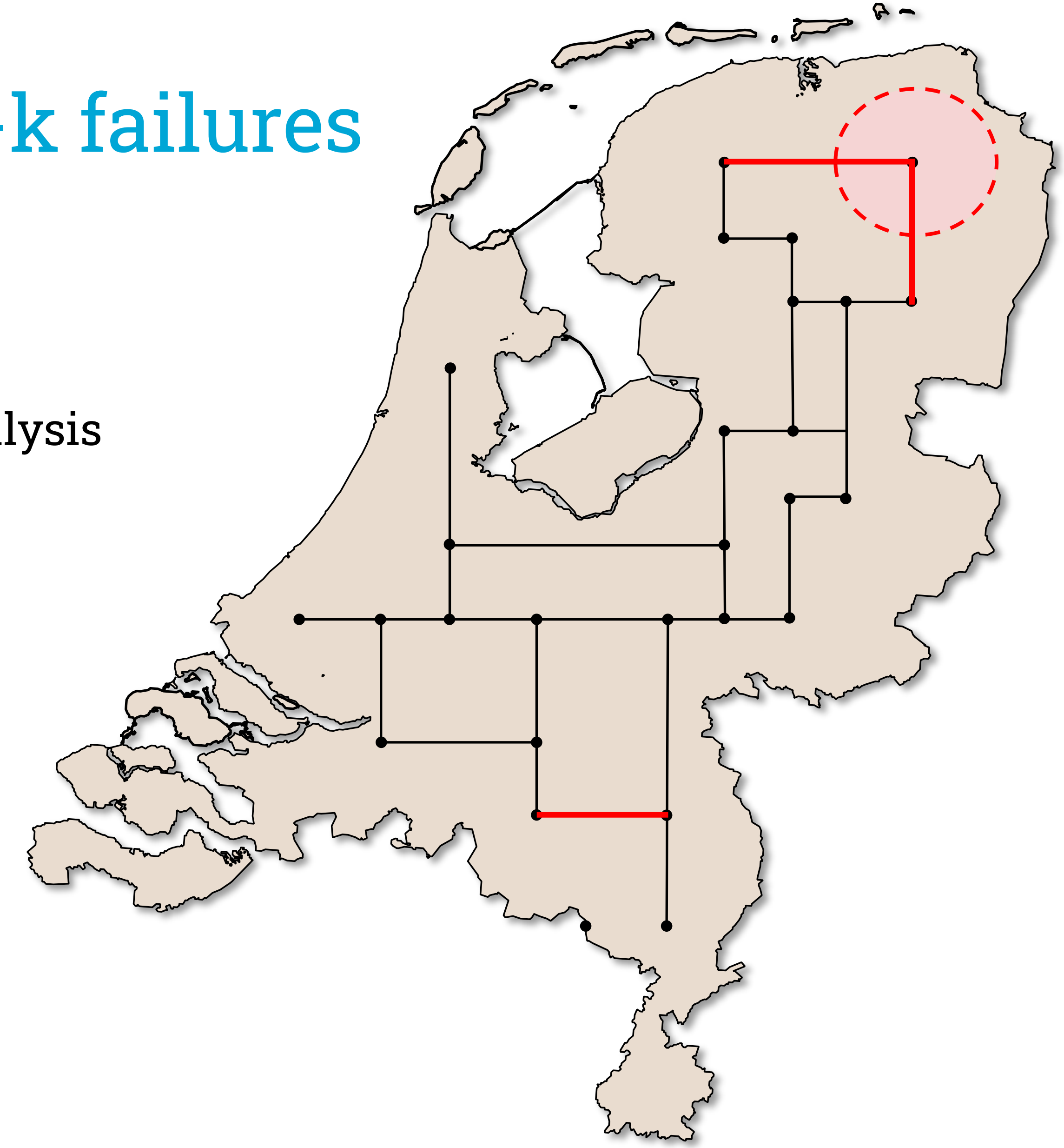
Objective:	minimize cost	$\min_{n \in \Omega^G} \Sigma\, c_n P_{G_n}$
Constraints:	In = out	$\boldsymbol{B} \cdot \boldsymbol{\delta} = \boldsymbol{P_G} - \boldsymbol{P_D}$
	Generator limits	$P_{G_n}^{min} < P_{G_n} < P_{G_n}^{max}\ \forall n \in \Omega^G$
	Line flow limits	$F_l^{min} < F_l < F_l^{max}\ \forall l \in \Omega^L$
Contingency Constraints:	Line flow limits	$F_l^{min} < F_l^c < F_l^{max}\ \forall l \in \Omega^L, \forall c \in \Omega^C$

Solving a large optimization problem can be slow
(Benders, constraint generation)

Probabilistic security for N-k failures

- Compute probabilities of all contingencies
- Spatial correlation between line outages
- Compute joint probabilities using a copula analysis





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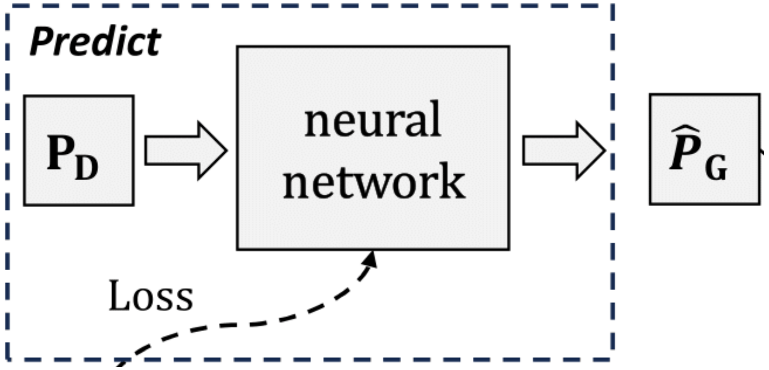
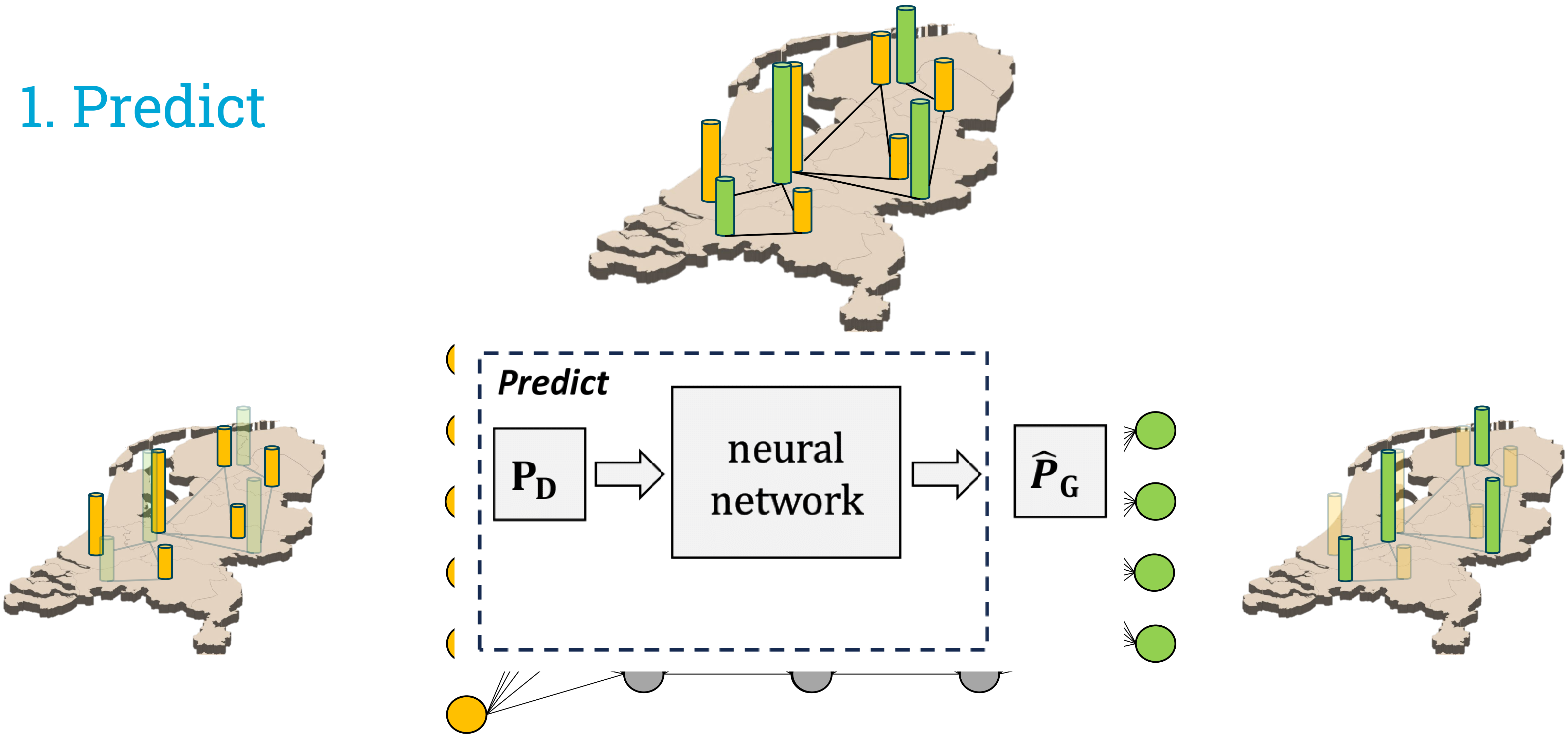
Proposed Constraint-Driven Deep Learning Approach

- Main advantage: constraint-driven so no labeled data needed
- Never actually solve an SCOPF



1. Predict
2. Feasibility Restoration
3. Post-contingency

1. Predict



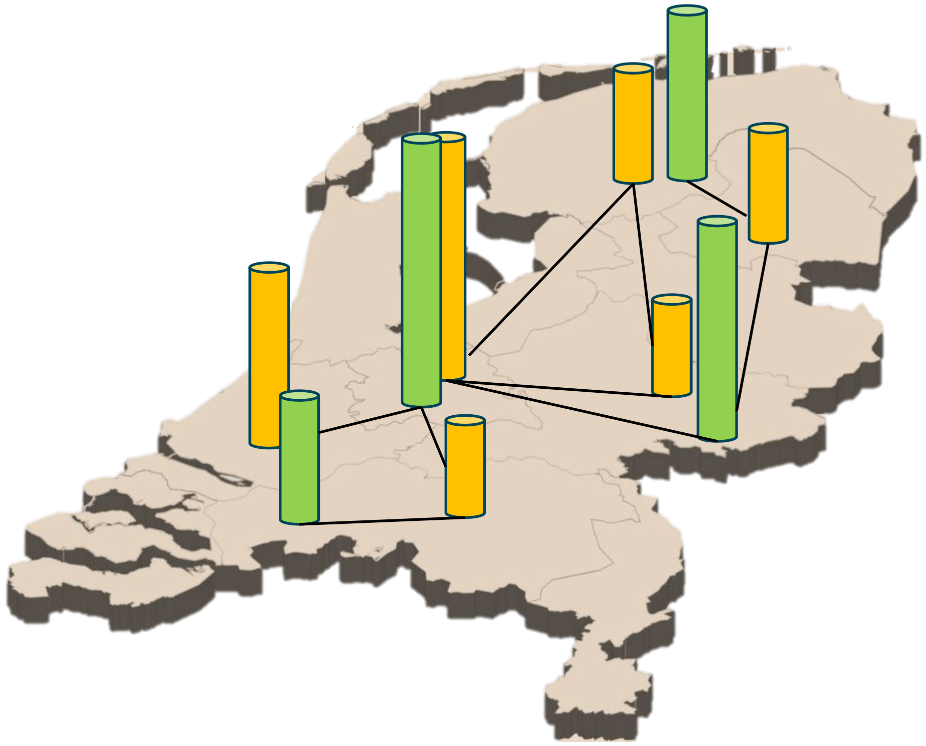
2. Feasibility Restoration

- With $\hat{P}_{G_n}$ compute predicted line flow $\hat{F}_l^0$
- Prediction might be outside physically infeasible

$$g(x): \quad P_{G_n}^{min} < P_{G_n} < P_{G_n}^{max}\ \forall n \in \Omega^G$$

$$F_l^{min} < F_l < F_l^{max}\ \forall l \in \Omega^L$$

$$h(x): \quad \boldsymbol{B} \cdot \boldsymbol{\delta} = \boldsymbol{P_G} - \boldsymbol{P_D}$$

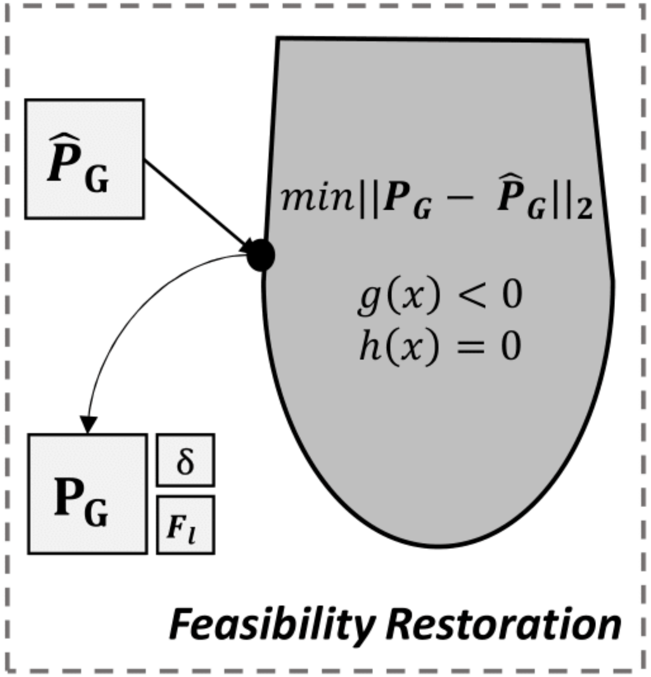


2. Feasibility Restoration

- Map prediction to feasible region
- Minimize distance between prediction and base case feasible region

g(x):	$P_{G_n}^{min} < P_{G_n} < P_{G_n}^{max} \ \forall n \ \in \Omega^G$ $F_l^{min} < F_l < F_l^{max} \ \forall l \ \in \Omega^L$

$h(x)$:	$\boldsymbol{B} \cdot \boldsymbol{\delta} = \boldsymbol{P_G} - \boldsymbol{P_D}$



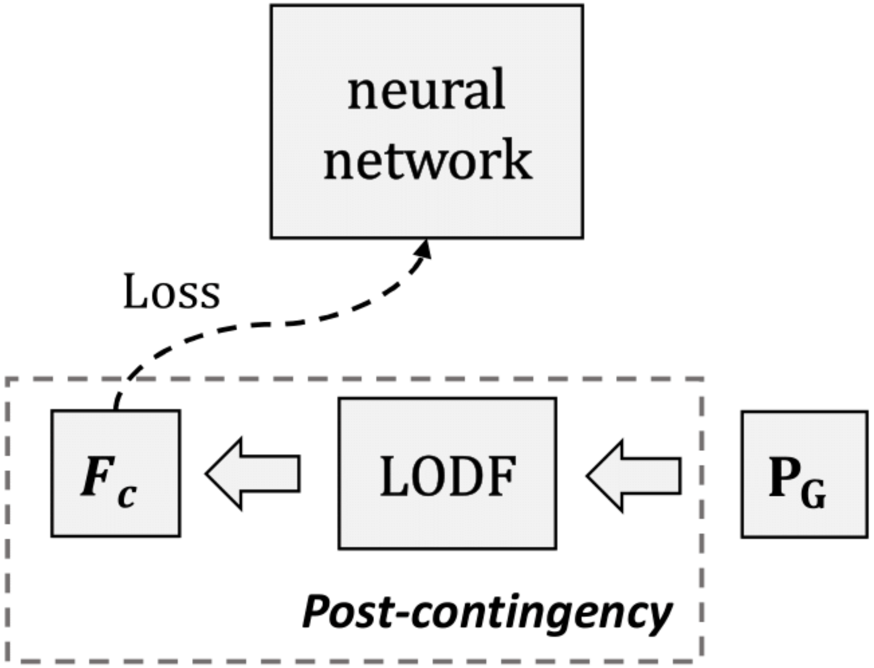
3. Post-Contingency

- Compute post-contingency flows with LODFs

$$\boldsymbol{F^c} = \boldsymbol{F^0} + \boldsymbol{LODF_{N-k}} \times \boldsymbol{F^0}$$

- Check for post-contingency violations

$$F_l^{min} < F_l^c < F_l^{max} \; \forall l \in \Omega^L, \forall c \in \Omega^C$$



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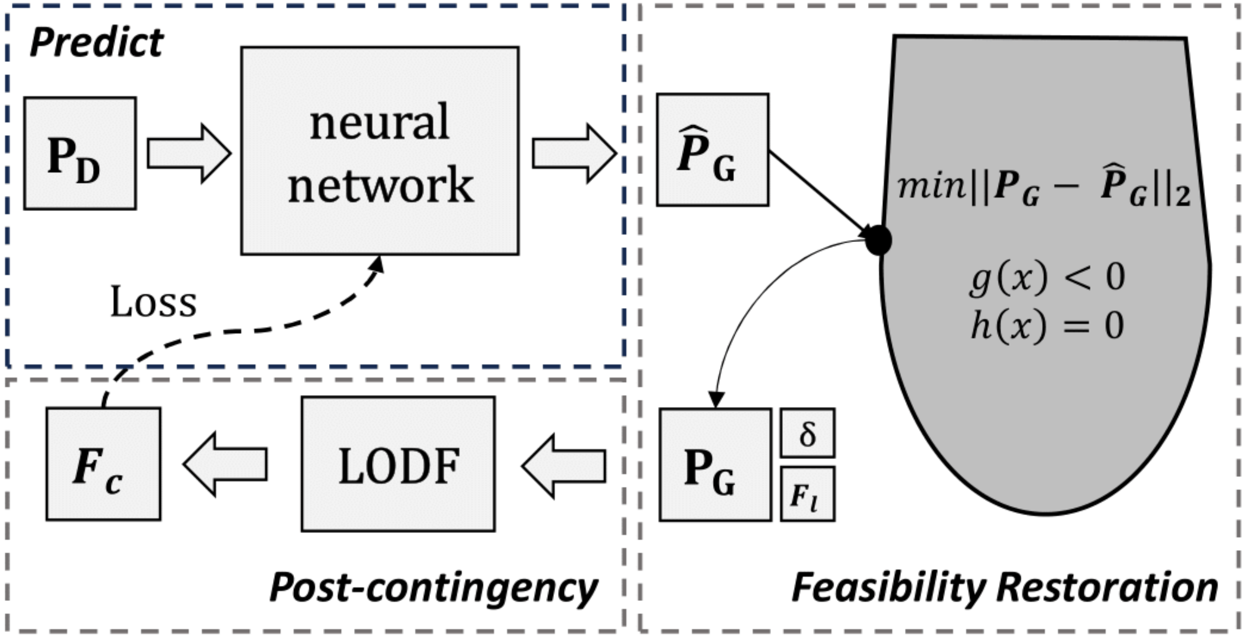
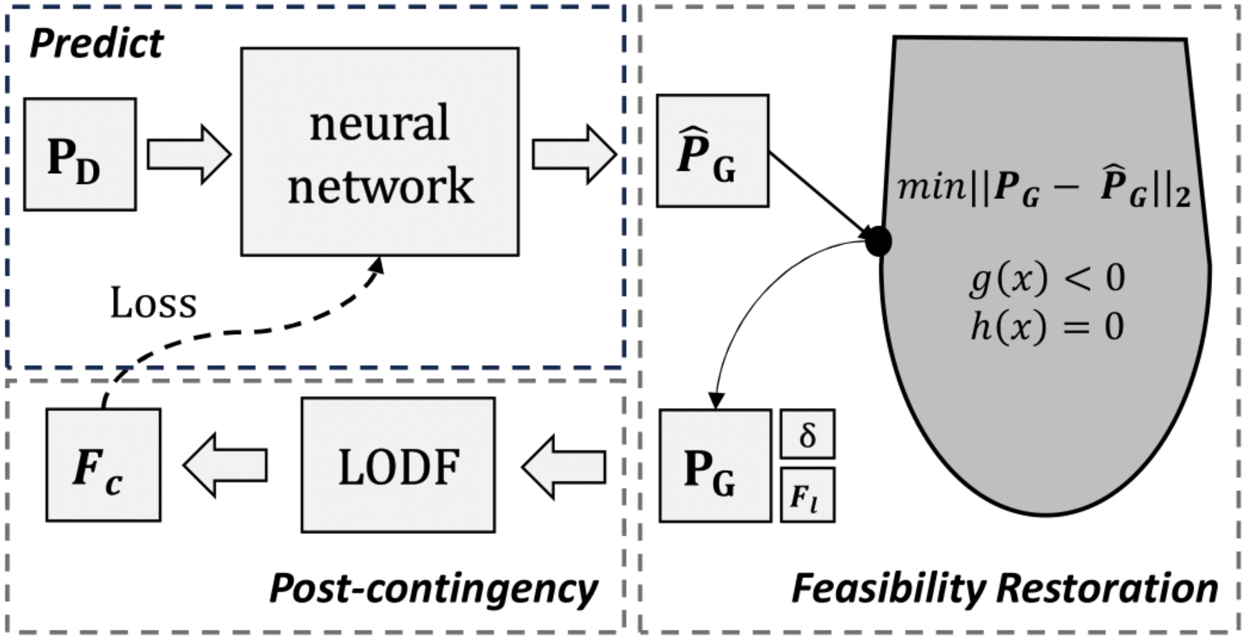
Proposed Constraint-Driven Learning Approach



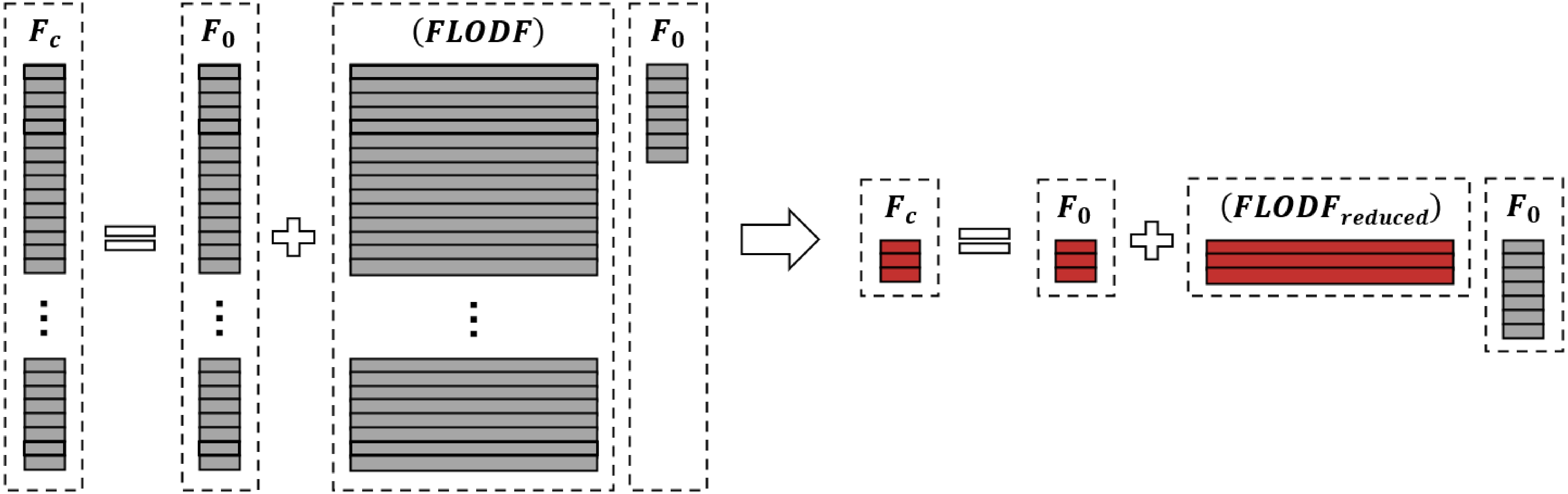
$$Loss = \lambda_c \sum \boldsymbol{P_G} \boldsymbol{c_G} + \lambda_0 \left\| ReLU(|\widehat{\boldsymbol{F}}^{\boldsymbol{0}}| - \boldsymbol{F}^{\boldsymbol{max}}) \right\|_1 + \lambda_1 \| ReLU(|\boldsymbol{F}^{\boldsymbol{c}}| - \boldsymbol{F}^{\boldsymbol{max}}) \|_1 + \lambda_2 \left\| \sum \widehat{\boldsymbol{P}}_{\boldsymbol{G}} - \sum \boldsymbol{P_D} \right\|_1$$

Probabilistic security



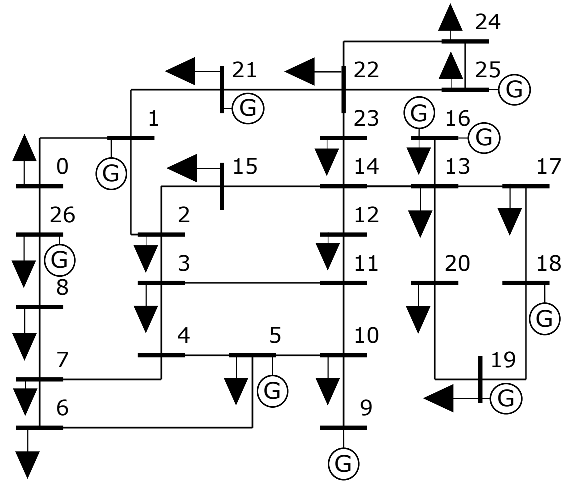
$$Loss = \lambda_c \sum \boldsymbol{P_G c_G} + \lambda_0 \left\| ReLU(|\widehat{\boldsymbol{F}}^{\boldsymbol{0}}| - \boldsymbol{F}^{max}) \right\|_1 + \lambda_1 \| \boldsymbol{\pi}_{N-k} \cdot ReLU(|\boldsymbol{F}^c| - \boldsymbol{F}^{max}) \|_1 + \lambda_2 \left\| \sum \widehat{\boldsymbol{P}}_G - \sum \boldsymbol{P_D} \right\|_1$$

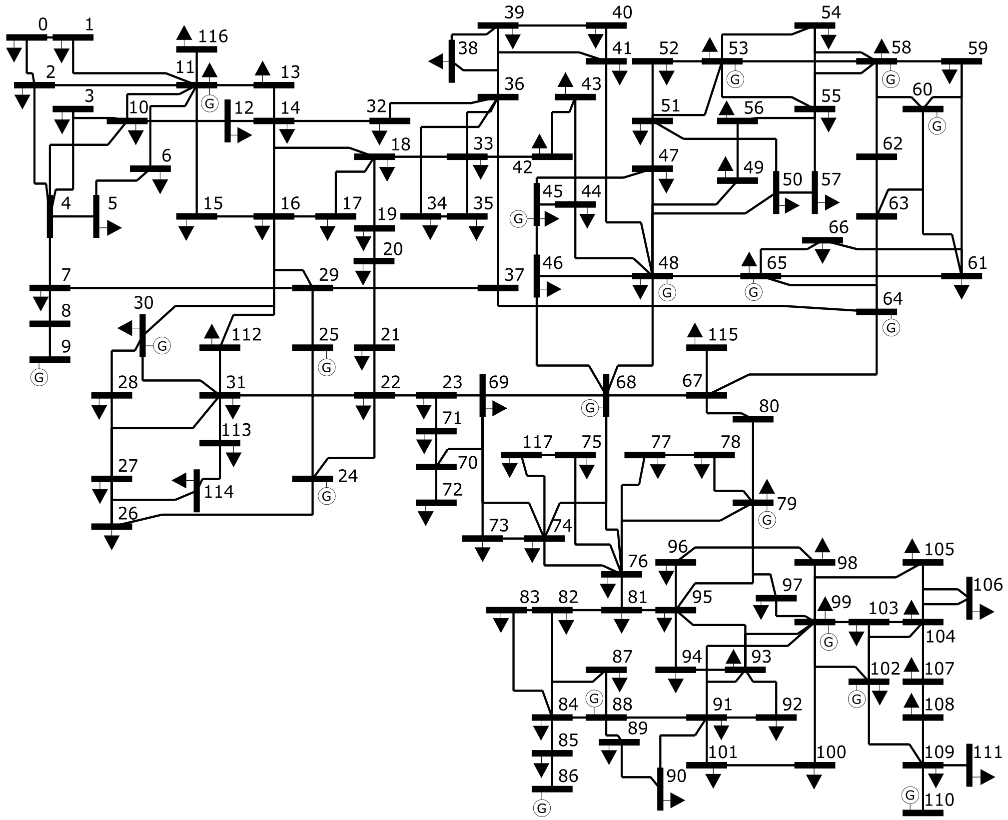
Computational graph to address combinatorical complexity



Case studies

- 39-bus and 118-bus test systems
- k = {1,2,3}
- Baseline: iterative contingency screening with LODFs





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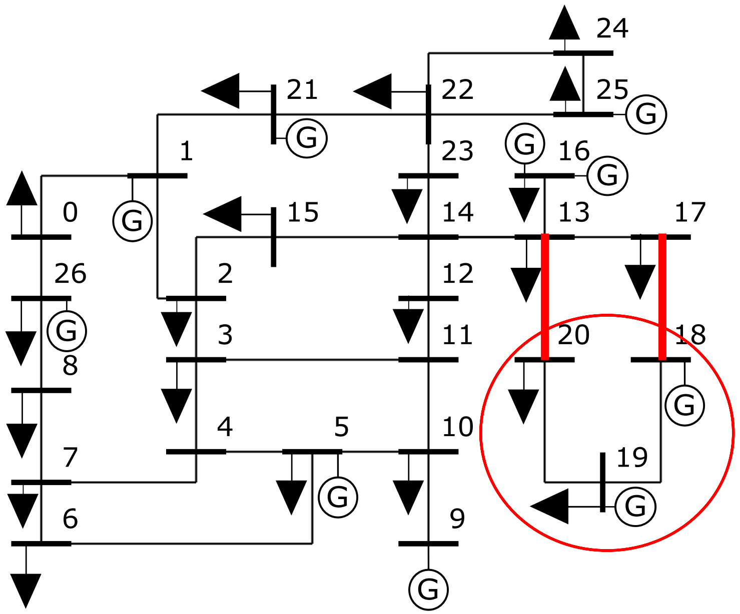
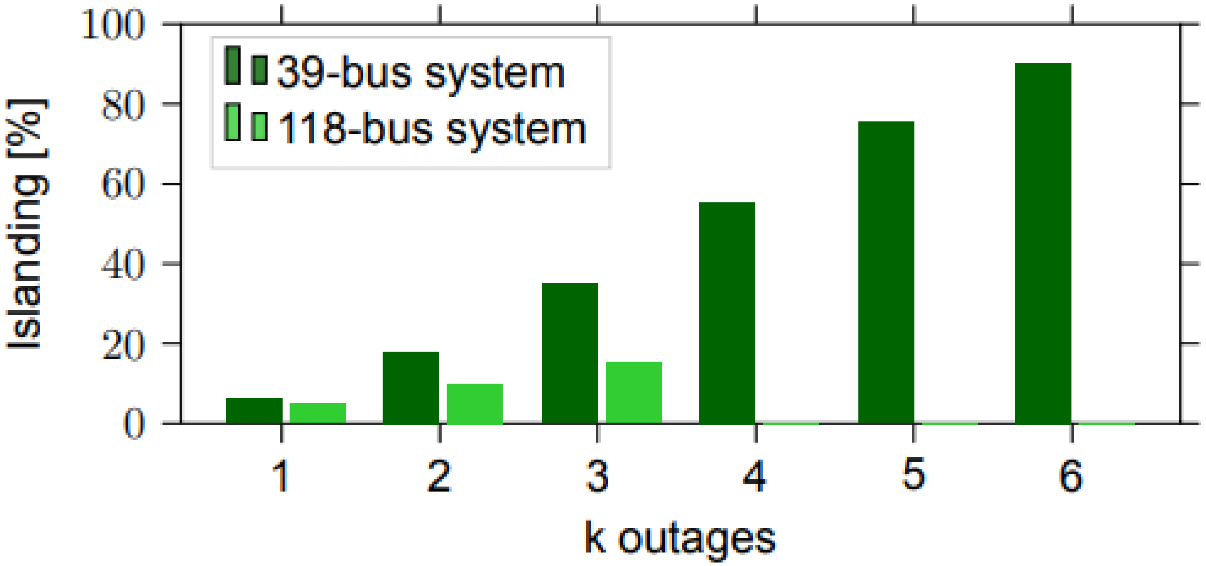
Islanding





Removing islanding cases

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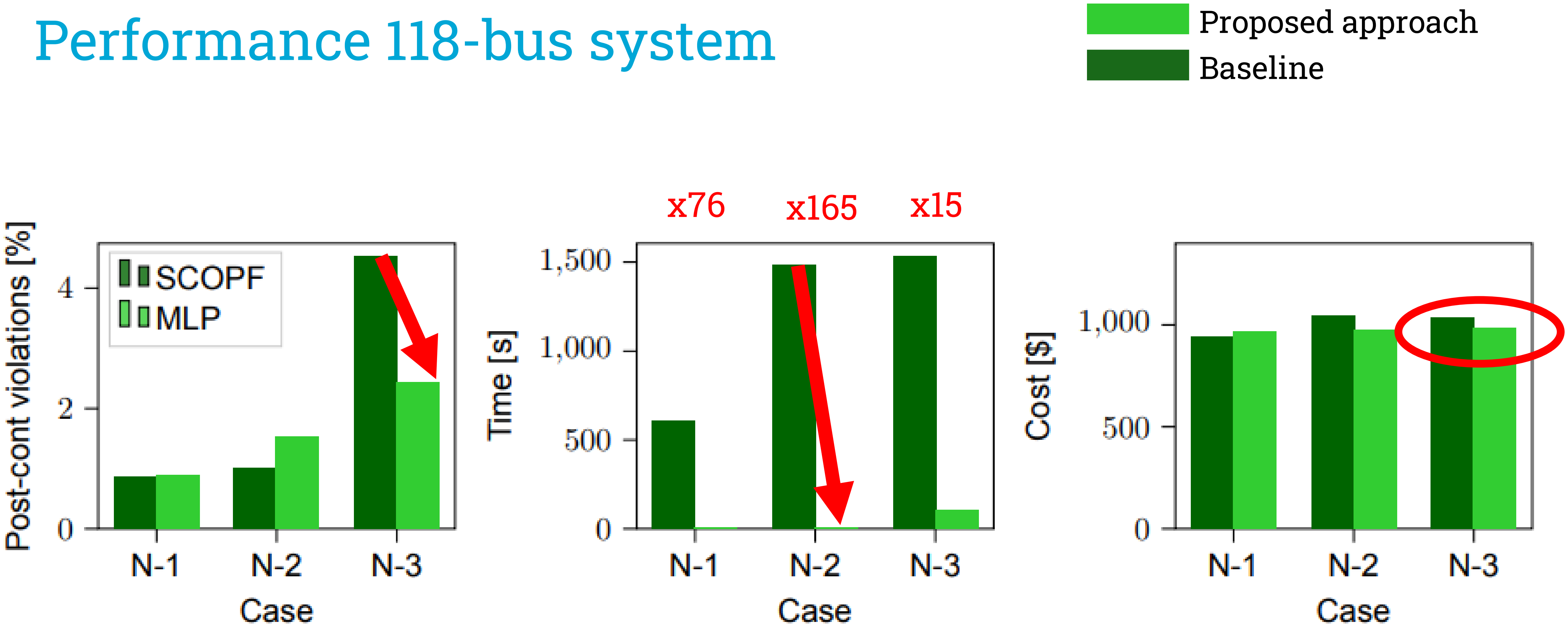
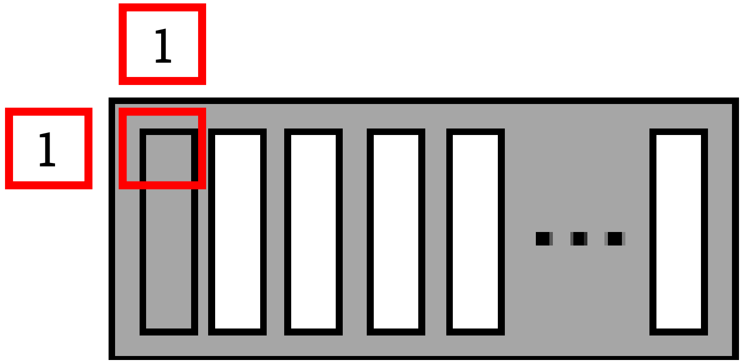
Performance 118-bus system

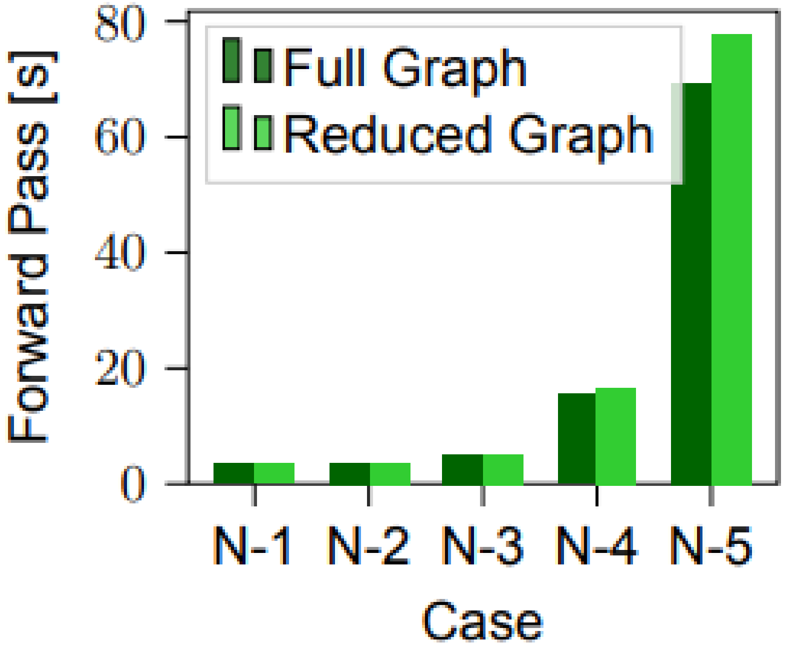


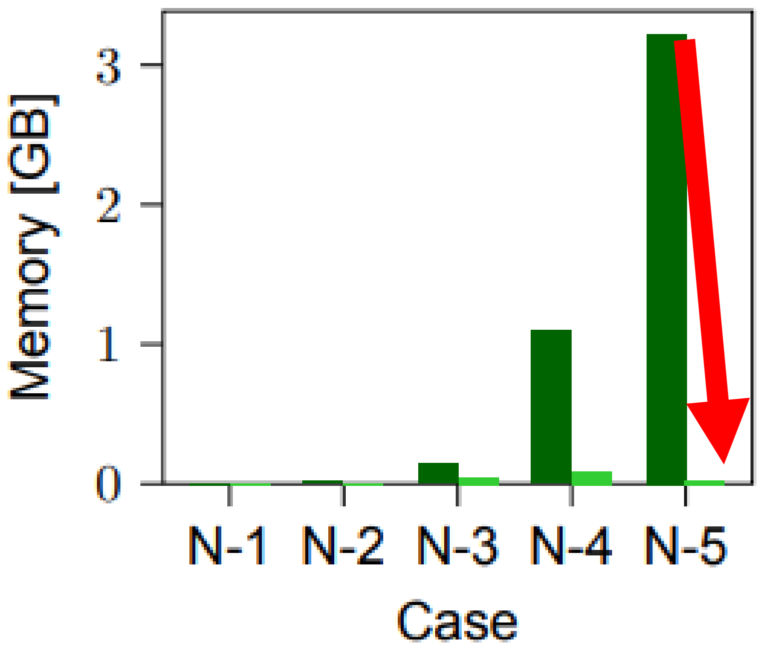
Sparsity

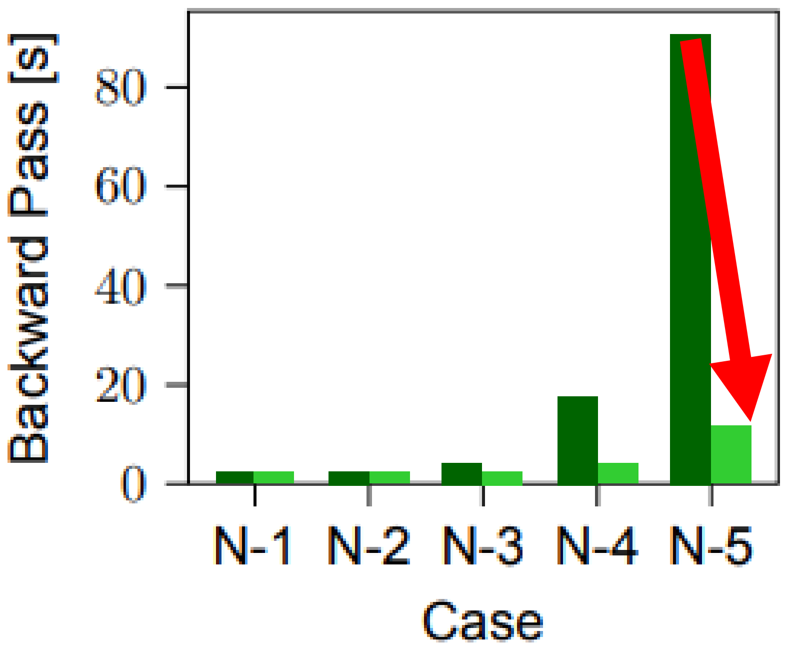


k	1	2	3
39-bus sparsity [%]	98.5	97.6	97.5
118-bus sparsity [%]	99.6	99.3	99.0

Reducing computational graph







Reduction in memory

Reduction in computation time

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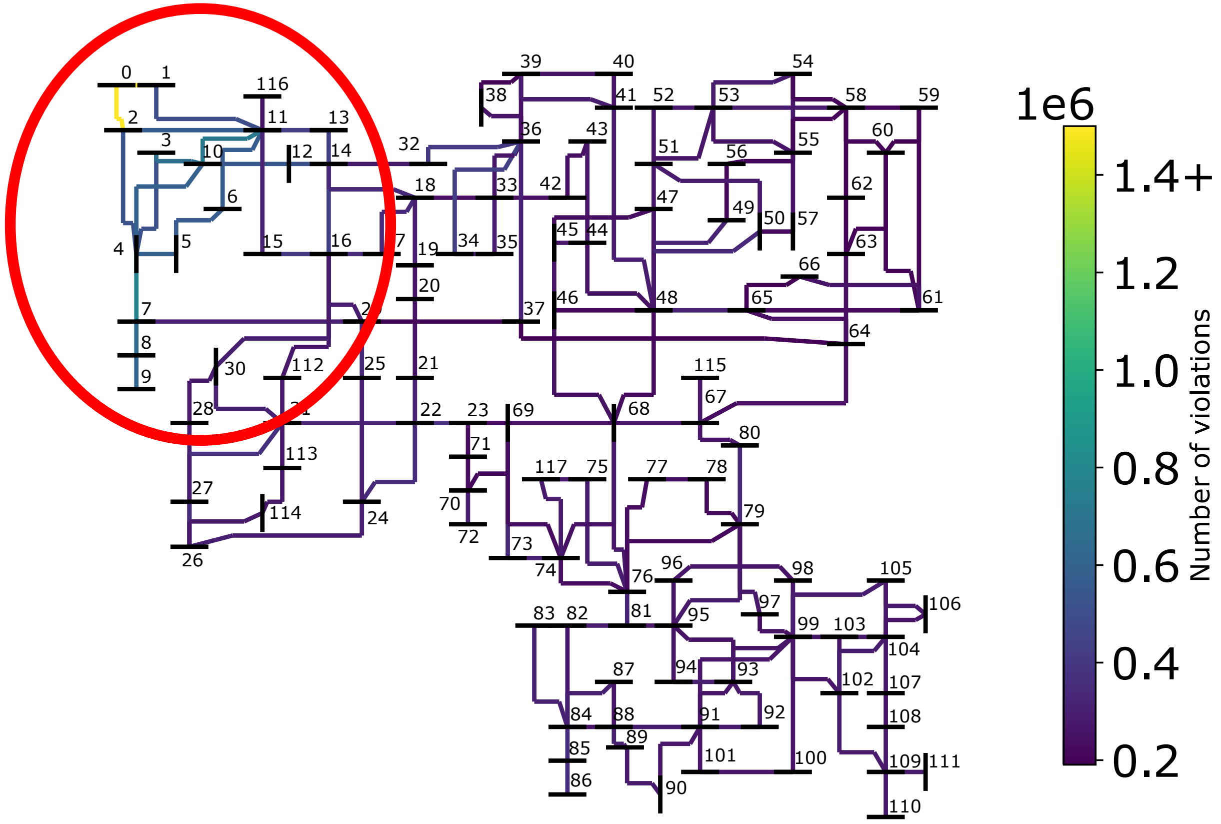
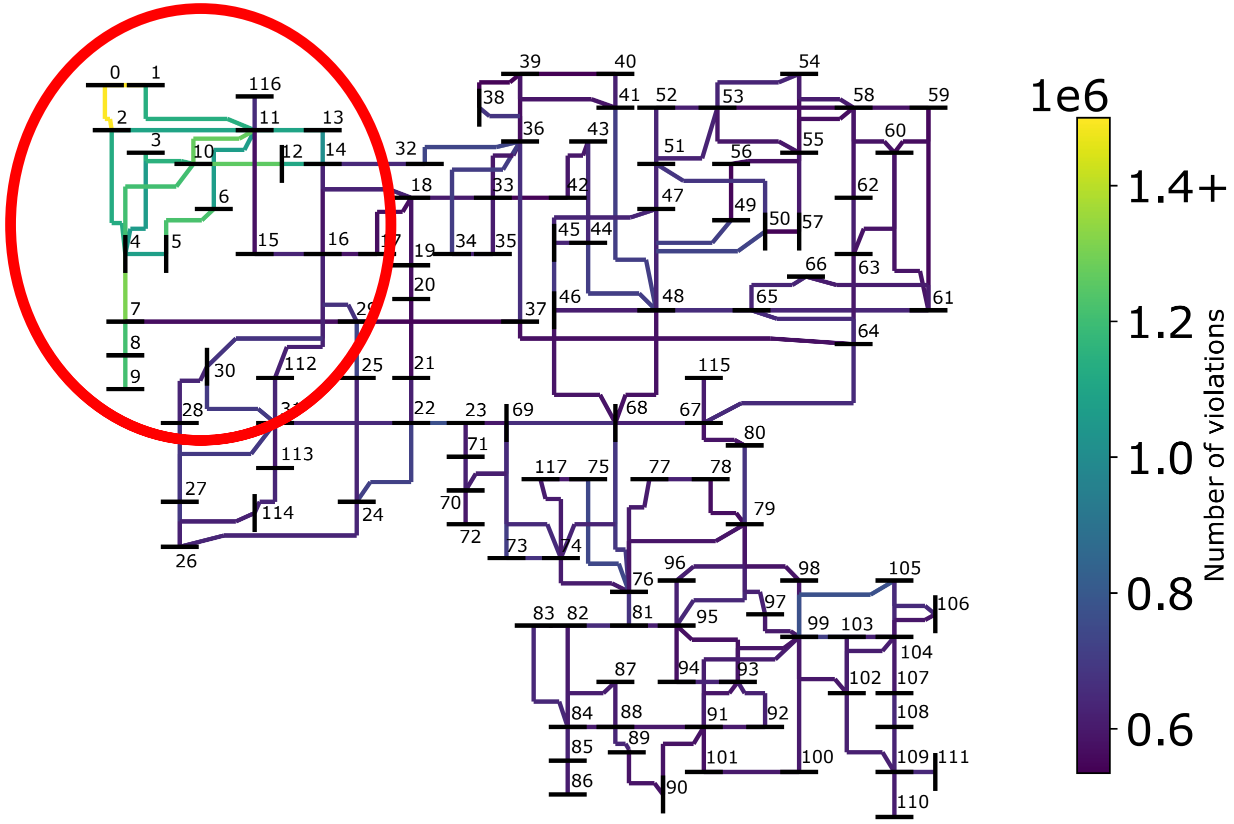
Physical violations of constraints

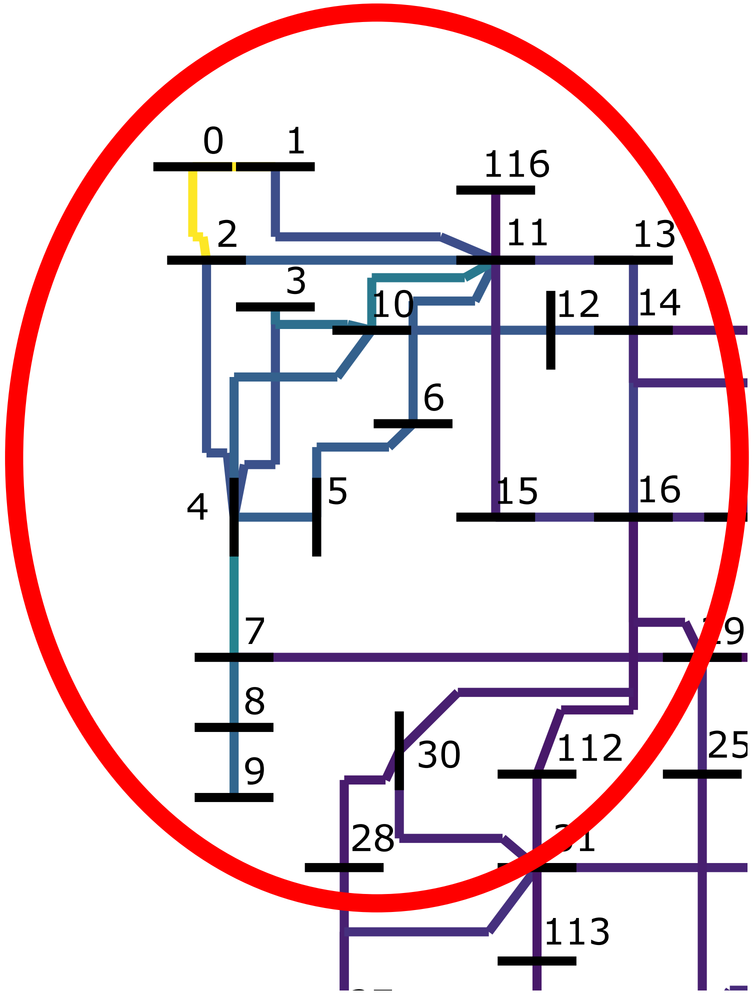
N-3 proposed approach



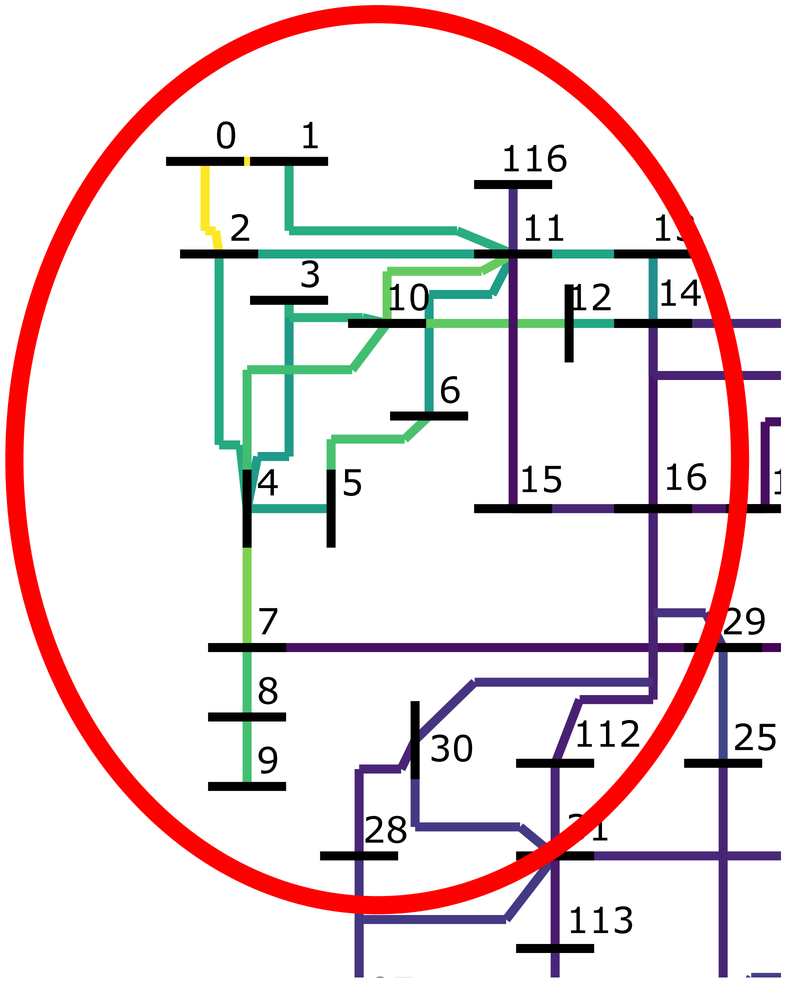
N-3 baseline



N-3 proposed approach

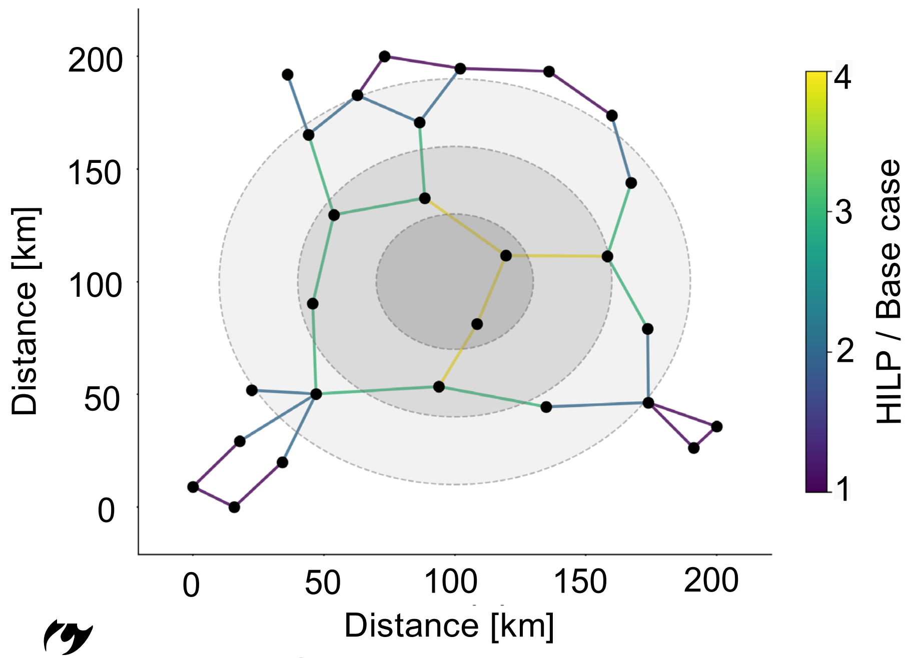


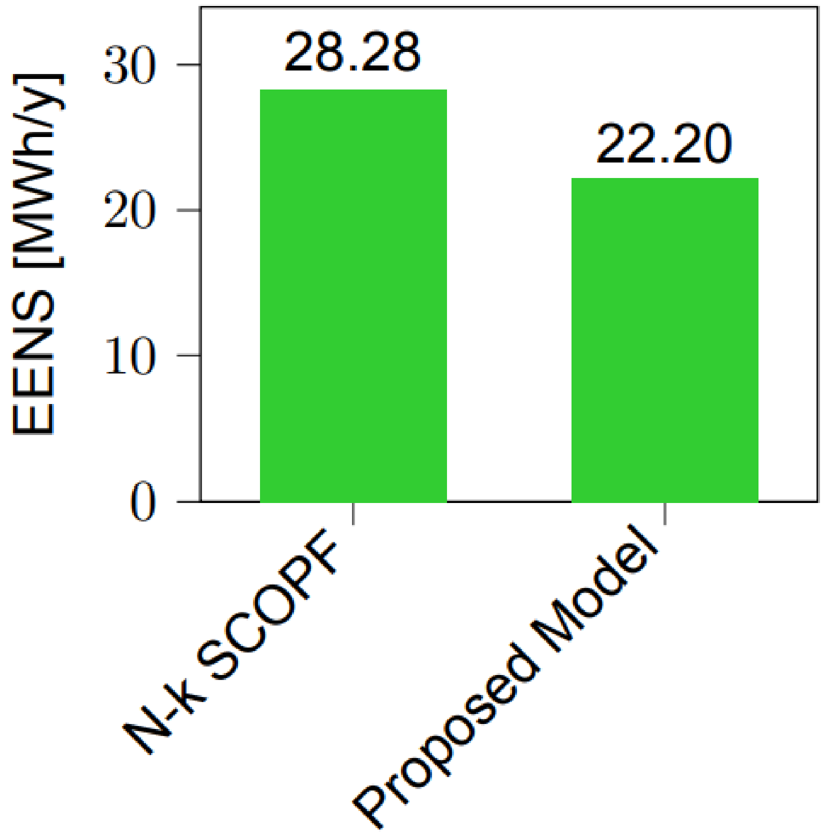
N-3 baseline



Extreme event

- Individual probabilities change due to earthquake
- Recompute joint probabilities
- Recompute Expected Energy not Served (EENS)





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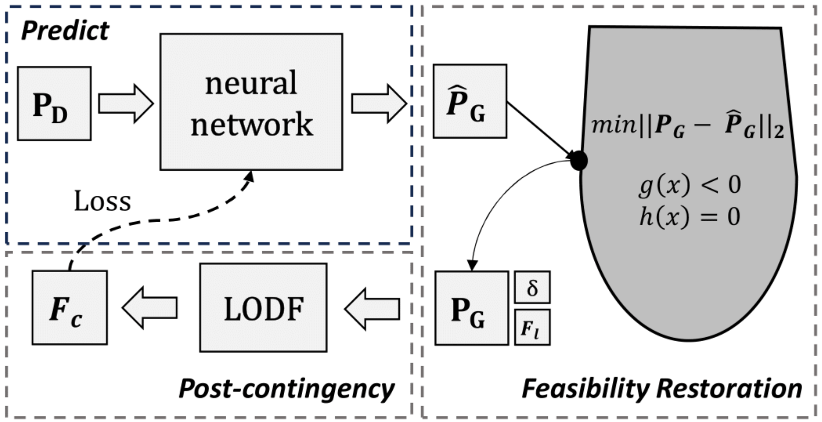
Conclusion

- Successfully identified many violating post-contingency cases up to the 118-bus N-3 case
  - Significant improvement in computational time
  - Small optimality gap in terms of dispatch cost, if not more optimal
- Probabilistic security assessment shows potential for enhanced reliability and resilience
- **Limitations:** only useful for line overloads, no voltages etc can be checked, changing network topology

Future work

- Incorporate other equipment outages, which metrics
- Develop for ACOPF
- Corrective approach
- LODF scalability



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Thank you

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Team

Bastien Giraud

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Reference

- Bastien Giraud, Ali Rajaei, Jochen L. Cremer “Constraint-Driven Deep Learning for N-k Security Constrained Optimal Power Flow”, in review *IEEE Power System Computating Conference 2024*

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