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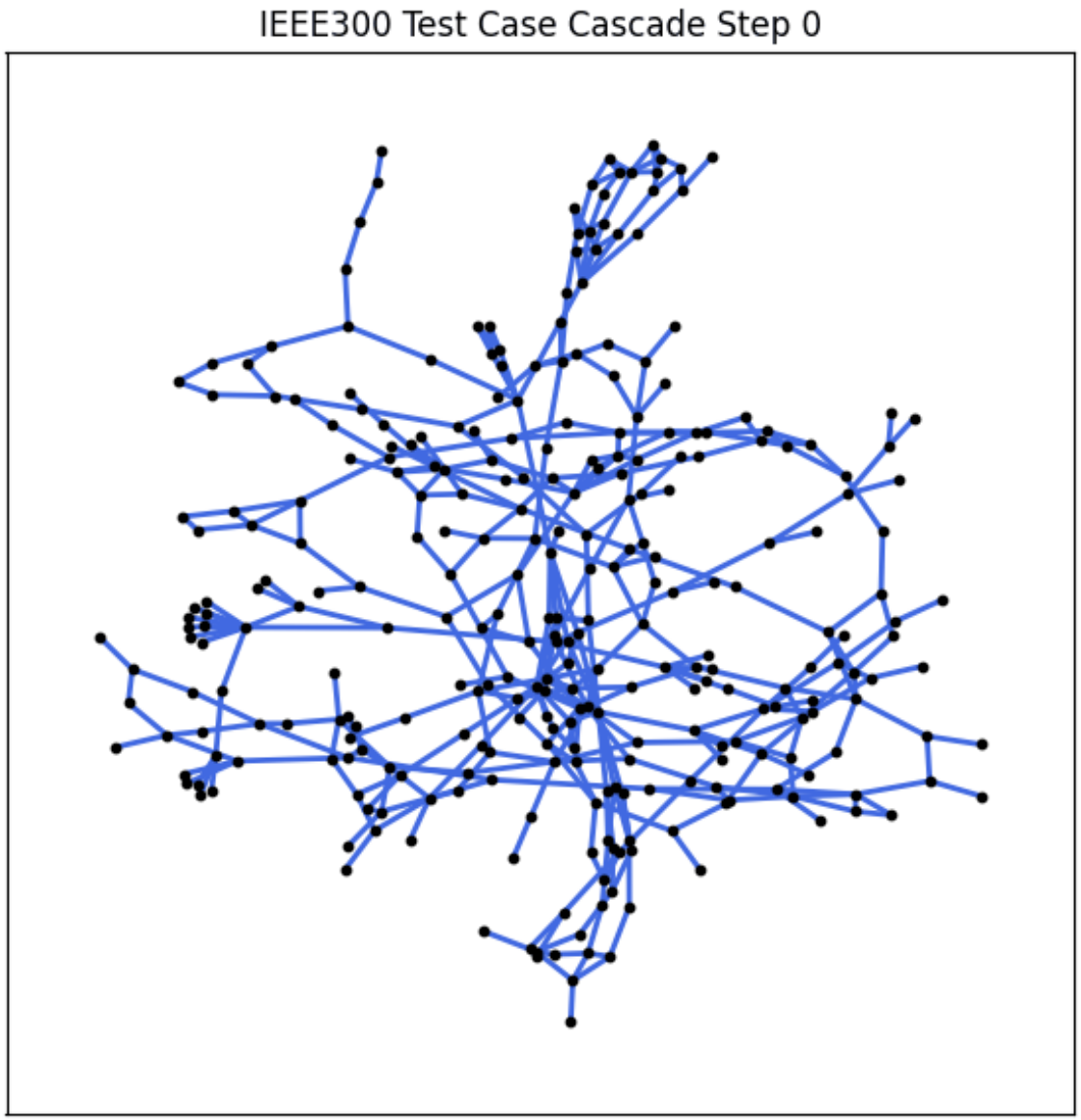

Electric Energy Systems Group

Advisory Tool for Managing Failure Cascades in Systems with Wind Power

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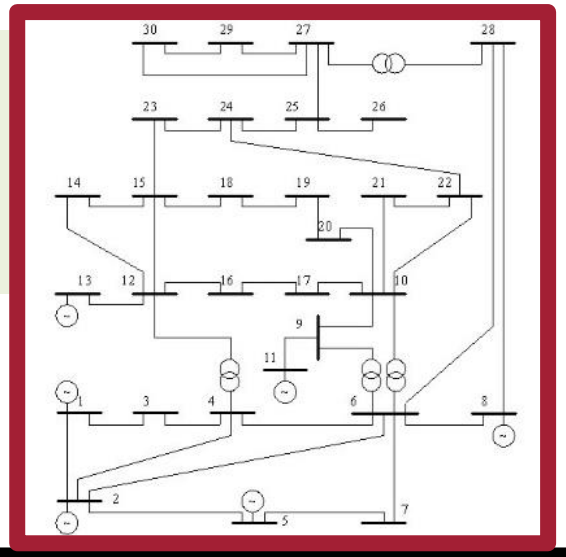
Background

- Today: utilities are N-1 or N-2 robust
- No method to study imminent possibility of failure cascades for intermittent resources
- Wind: less predictable, higher congestion risk
- Our contribution:
  - Predict cascade failures as they evolve
  - Advise system operators on corrective actions

Two Influence Models
- For link failure
- For load shed

IEEE 30 & 300 test cases



Our approach

- Offline: **data-enabled learning** using synthetic data.
- Online: Markovian **Influence Model** predictions and advisory that are **reliable**, **applicable**, and **efficient.**

Corrective actions, ran with both **DC** and **AC** models

1. No action
2. Generation re-dispatch:
   a) Serves load in full
   b) Minimizes generation cost
3. **Smart scheduling**: generation re-dispatch that
   a) Preserves all links
   b) Allows load shed
   c) Minimize load shed cost

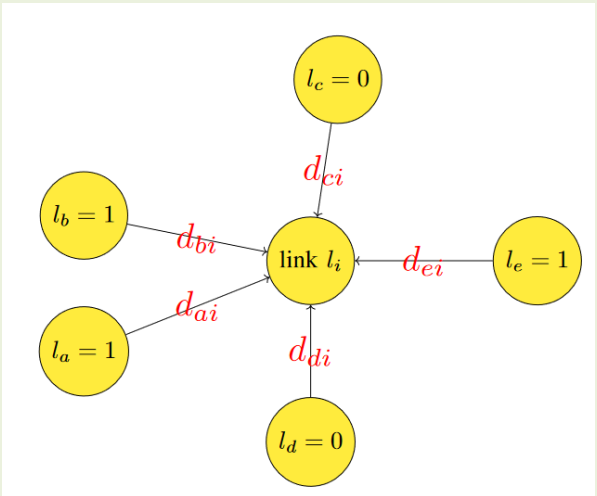
Our Approach

The Influence Model

Link Failure Prediction

Decide the status of link i by :

- Status of link j (for all j)
- Influence factor d_{ji} that characterizes the importance level (for all links j)
- Scenario specific threshold for link j



Pairwise influences from one link to another:

$$A_{ji}^{11} := \mathbb{P}(s_i[t+1] = 1 | s_j[t] = 1), \quad (1)$$
$$A_{ji}^{01} := \mathbb{P}(s_i[t+1] = 1 | s_j[t] = 0). \quad (2)$$

Monte Carlo

Total weighted influence from all links:

$$\widetilde{s}_i[t+1] = \sum_{j=1}^{N_{br}} d_{ji} \left(A_{ji}^{11} s_j[t] + A_{ji}^{01} (1 - s_j[t]) \right), \quad (3)$$

Optimization (LSE)

Condition to declare link failure:

$$\widetilde{s}_i[t+1] \geq \epsilon_i$$

Adaptive Thresholding

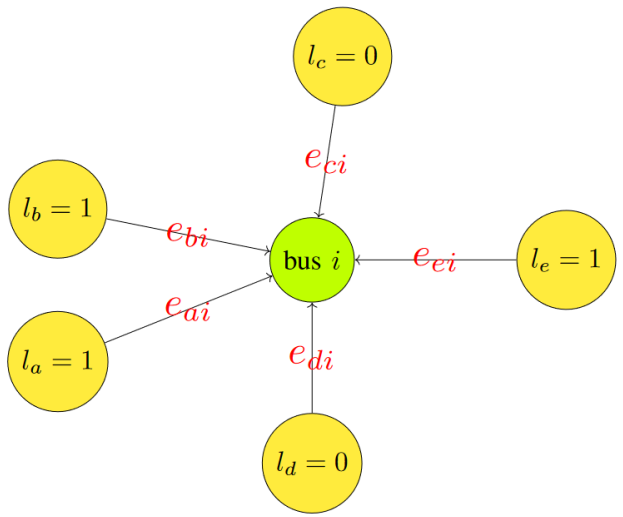
Our Approach

The Influence Model

Load Shed Prediction

Decide the status of load i by :

- Status of link j (for all j)
- Influence factor e_{ji} that characterizes the importance level (for all links j)
- Scenario specific threshold for load i



Pairwise influences from one link to a bus:

$$B_{ji}^{11} := \mathbb{P}(l_i[t] = 1 | s_j[t] = 1), \quad (4)$$

$$B_{ji}^{01} := \mathbb{P}(l_i[t] = 1 | s_j[t] = 0). \quad (5)$$

Monte Carlo

Total weighted influence from all links:

$$\widetilde{l}_i[t] = \sum_{j=1}^{N_{br}} e_{ij} \left(B_{ji}^{11} s_j[t] + B_{ji}^{01} (1 - s_j[t]) \right), \quad (6)$$

Optimization (LSE)

Condition to declare load shed:

$$\widetilde{l}_i[t] \geq \delta_i$$

Adaptive Thresholding

Results - Prediction Speedup and Accuracy

- Accurate
- Fast
- Reveals structural insight

Link failure prediction error

	IM	Rand.	Unif.
exp1	0.038	0.188	0.109
exp2	0.019	0.093	0.049
exp3	0.000	0.094	0.049

Load Shed prediction error

	IM	Rand.	Unif.
exp1	0.214	0.318	0.255
exp2	0.043	0.082	0.043
exp3	0.014	0.026	0.014

Computation Time Improvement (in seconds)

Corrective Action	Simulation	Training	Prediction
No action	170	612	15.40
Re-dispatch for full service	183	306	10.05
Re-dispatch for lowest load shed cost	246	333	6.76

Structural insights from learned coefficients

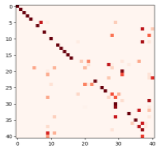


Fig. 11: D matrix for DC PF, 1.6× loading

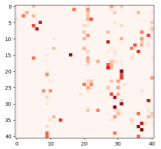


Fig. 12: D matrix for AC PF, 1.6× loading

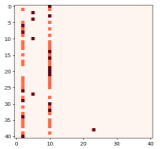


Fig. 13: D matrix for DCOPF, 1× loading

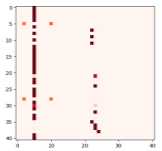


Fig. 14: D matrix for ACOPF, 1× loading

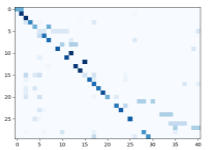


Fig. 15: E matrix for DC PF, 1.6× loading

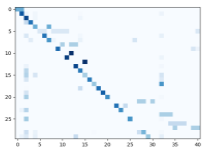


Fig. 16: E matrix for AC PF, 1.6× loading

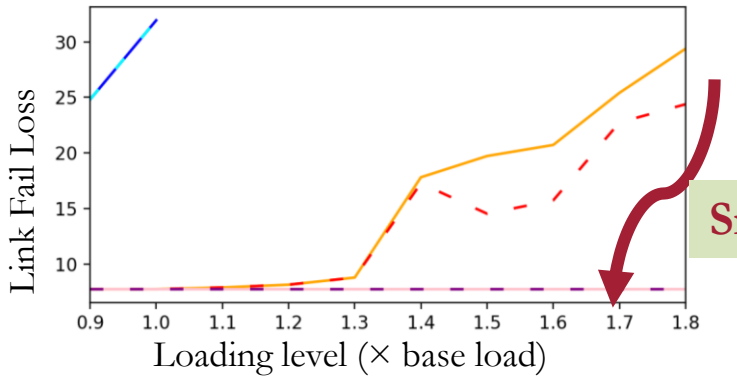
Fig. 17: D, E matrix structures.

- Most influences are localized.
- Influences are sparse under low loading levels.
- **Some links cause large-scale damage.**
- **Some links and buses are particularly vulnerable.**

X. Wu, D. Wu and E. Modiano, "Predicting Failure Cascades in Large Scale Power Systems via the Influence Model Framework," in *IEEE Transactions on Power Systems*, Sept. 2021.

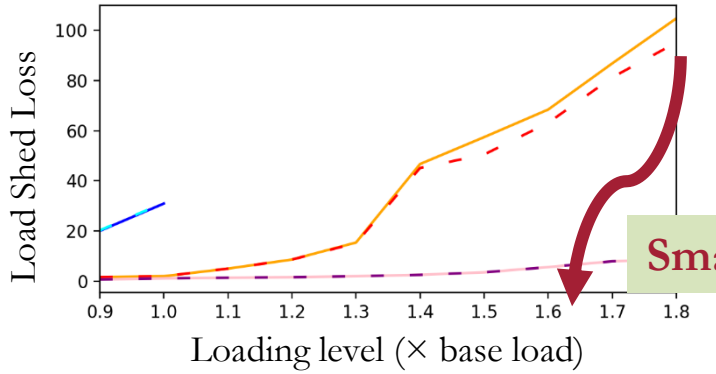
Results – Online Advisory

Link Fail Loss under AC Models



Smart scheduling

Load Shed Loss under AC Models



Smart scheduling

(Exp 1) PF
(Exp 1) PF: preemptivel load shed
(Exp 2) OPF: actual generation cost uniform scale load shed
(Exp 2) OPF: uniform generation cost, uniform scale load shed
(Exp 3) OPF: actual generation cost, cost-based load shed
(Exp 3) OPF: unifrom generation cost, cost-based load shed

Metrics to evaluate corrective actions

Grid-centric

$$G(p) = \sum_{b=1}^{N_{br}} C(b) \cdot e^{-0.2t_b}$$

load priority

early failure penalty

User-centric

$$L(p) = \sum_{l=1}^{N} \sum_{t=1}^{T_k - 1} C(l) \cdot LS_l(t) e^{-0.2t}$$

load priority

load shed amount

Network resilience

$$R(p, \Delta w) = R^G(p, \Delta w) + R^L(p, \Delta w),$$

wind reduction

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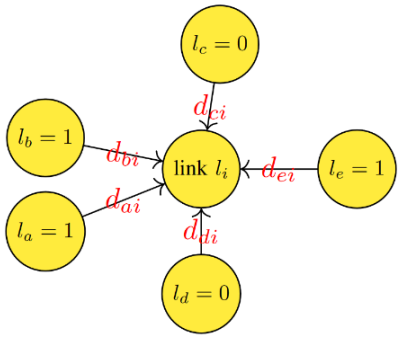
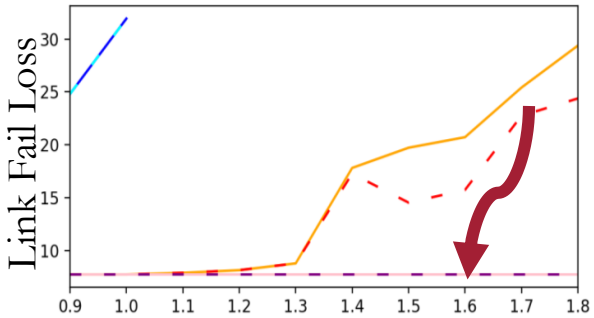
Conclusions/Recommendations

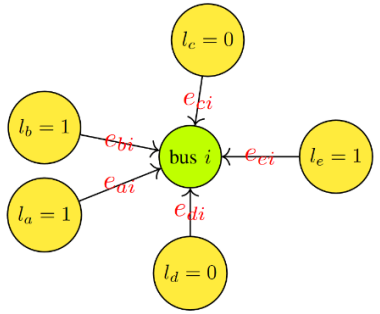
- Markovian Influence Model
  - Online prediction of link failure and load shed during a wind reduction-induced cascade.
  - Speed and accuracy.



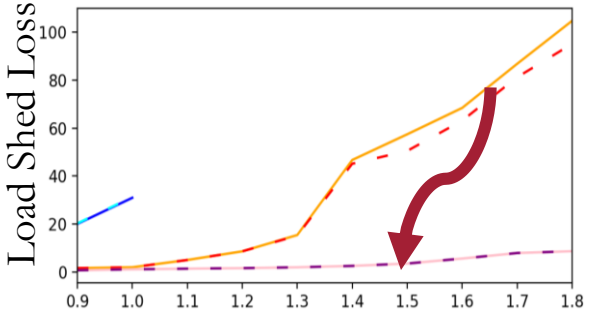
Link Fail Loss under AC Models



- Three strategies to minimize loss. Smart scheduling is extremely effective.
- Resilience impact factor to assess the criticality of wind reduction.



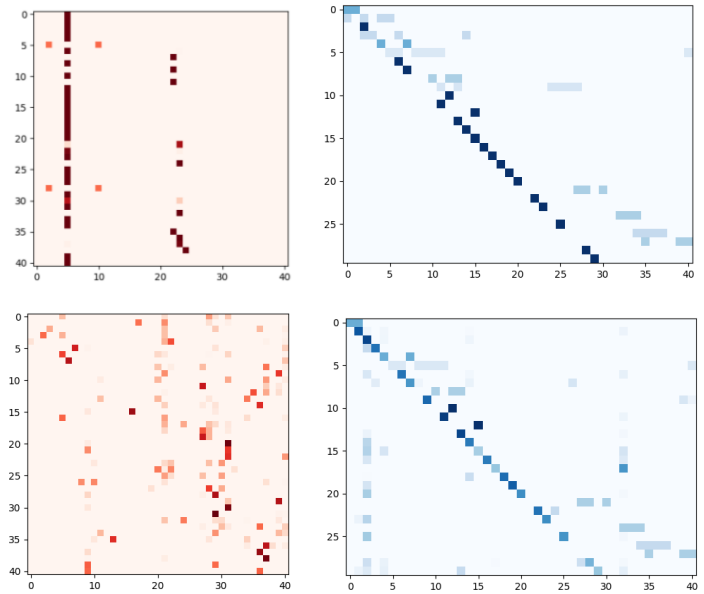
Load Shed Loss under AC Models



The Influence Model as an Advisory Tool

- Find the most critical links and loads
- Inform best way to shed load

Data-driven solution are tremendously effective in predicting and managing uncertainties for utilities.



Thank you!

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