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

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

Two Influence Models
- For link failure
- For load shed

IEEE 30 & 300 test cases
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:

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

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

Total weighted influence from all links:

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

Condition to declare link failure:

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

- Monte Carlo
- Optimization (LSE)
- 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:

$B_{ji}^{11} := \mathbb{P}(l_i[t] = 1 | s_j[t] = 1)$, \hspace{1cm} (4) \hspace{1cm} Monte Carlo
$B_{ji}^{01} := \mathbb{P}(l_i[t] = 1 | s_j[t] = 0)$. \hspace{1cm} (5)

Total weighted influence from all links:

$\tilde{l}_i[t] = \sum_{j=1}^{N_{br}} e_{ij} (B_{ji}^{11} s_j[t] + B_{ji}^{01} (1 - s_j[t]))$, \hspace{1cm} (6) \hspace{1cm} Optimization (LSE)

Condition to declare load shed:

$\tilde{l}_i[t] \geq \delta_i$ \hspace{1cm} Adaptive Thresholding
Results - Prediction Speedup and Accuracy

- Accurate
- Fast
- Reveals structural insight

| 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       |

### 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 |

### Structural insights from learned coefficients

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

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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

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**

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

- load priority
- load shed amount

Network resilience

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

- wind reduction

**Tables**

| Loading level (× base load) | Link Fail Loss | Load Shed Loss |
|----------------------------|----------------|----------------|
| 0.9                         | 10             | 50             |
| 1.0                         | 15             | 60             |
| 1.1                         | 20             | 70             |
| 1.2                         | 25             | 80             |
| 1.3                         | 30             | 90             |
| 1.4                         | 35             | 100            |
| 1.5                         | 40             | 110            |
| 1.6                         | 45             | 120            |
| 1.7                         | 50             | 130            |
| 1.8                         | 55             | 140            |

**Graphs**

- Link Fail Loss under AC Models
- Load Shed Loss under AC Models

**Legend**

- (Exp 1) PF
- (Exp 1) PF: preemptive 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: uniform generation cost, cost-based load shed
Conclusions/Recommendations

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

• Three strategies to minimize loss. Smart scheduling is extremely effective.

• Resilience impact factor to assess the criticality of wind reduction.
The Influence Model as an Advisory Tool

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

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

Thank you!
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