School of Engineering

Civil and Environmental Engineering

Towards Improving the Resilience of Power Systems

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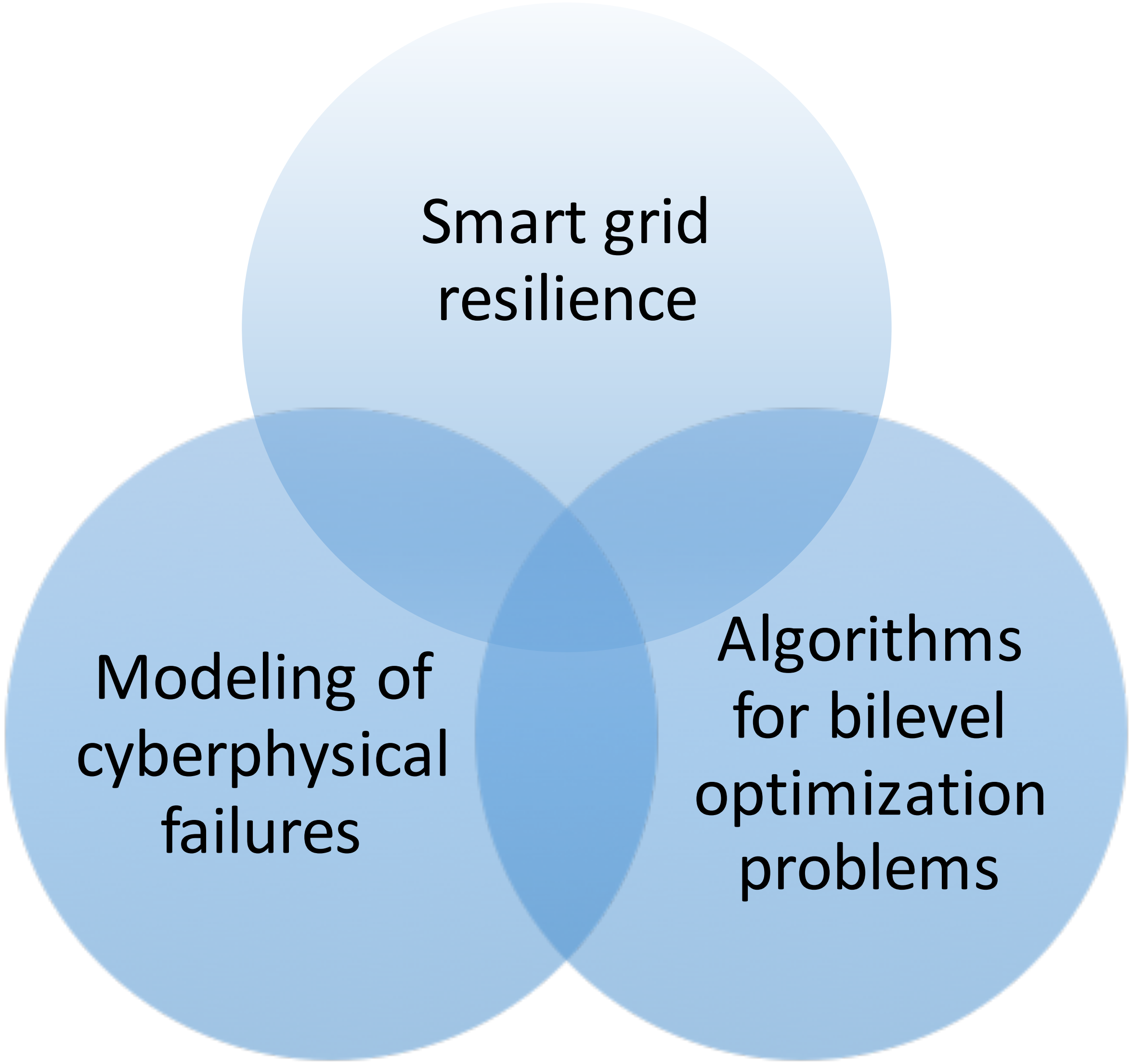
Collaborators: Saurabh Amin, Ian Hiskens

Research Focus



Outline

- Motivation: Resilience-Aware operations
- Attack models and Problem formulation
- Main results

Cyber-Physical disruptions

Hurricane Maria (September 2017)

- Customers facing blackouts for months

Metcalf Substation (April 2013)

- Sniper attack on 17 transformers
- Telecommunication cables cut
- 15 million $ worth of damage
- 100 mn $ for security upgrades

Ukraine attack (Dec ‘15, ‘16)

- First ever blackouts caused by hackers
- Controllers damaged for months

Research challenge

Existing literature considers:

- Physical security of transmission networks
- DC powerflow models

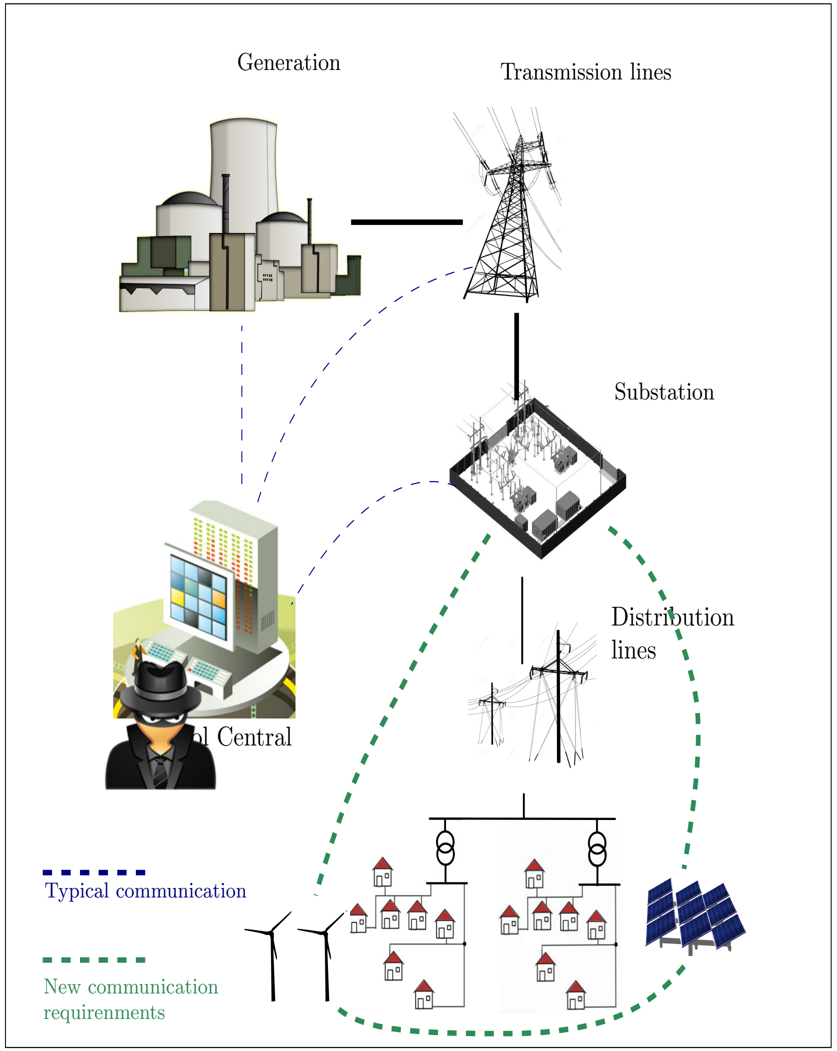
Limited focus on:

- Smart Distribution networks (DNs)
- Optimal attacker/defender strategies based on:
  - Network topology
  - Tradeoffs in resource allocation

My approach combines:

- Physics-based optimal attack
- Semantics-aware software memory attack

Distribution network attack scenarios



- Agent
  - Disgruntled employee
  - External hacker
  - Buggy SCADA implementation
- NESCO Vulnerabilities (EPRI)
  - Mass remote disconnect of smart meters
  - Simultaneous disconnect of DERs
  - Rapid overcharging of electric vehicles
- Impact: **supply-demand disturbances** (sudden or prolonged)

Background: Security-constrained OPF

- Economic Dispatch problem to ensure an operational power system despite contingencies
- Accounts for appropriate corrective actions for the said contingency

Main issues

- Only captures N-k contingencies for small k. Typically k = 1 or 2
- Assumes a priori fixed set of contingencies
- Does not model strategic attacker-induced failures

A. Monticelli, et al. - "Security-Constrained Optimal Power Flow with Post-Contingency Corrective Rescheduling"
J. A. Momoh, et al. - "A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods"

Our formulation: Resilience-Aware OPF

Stage I			Stage II	Stage III	
Minimize	$C_{\text{allocation}}$	$+$	Maximize	Minimize	$C_{\text{post-contingency}}$
Over all allocations			Over all disruptions	Over all responses	

Subject to

- Network constraints
- Component constraints
- Voltage constraints

Resilience-Aware OPF (3-Stages)

Pre-contingency state

Worst-case post-contingency state

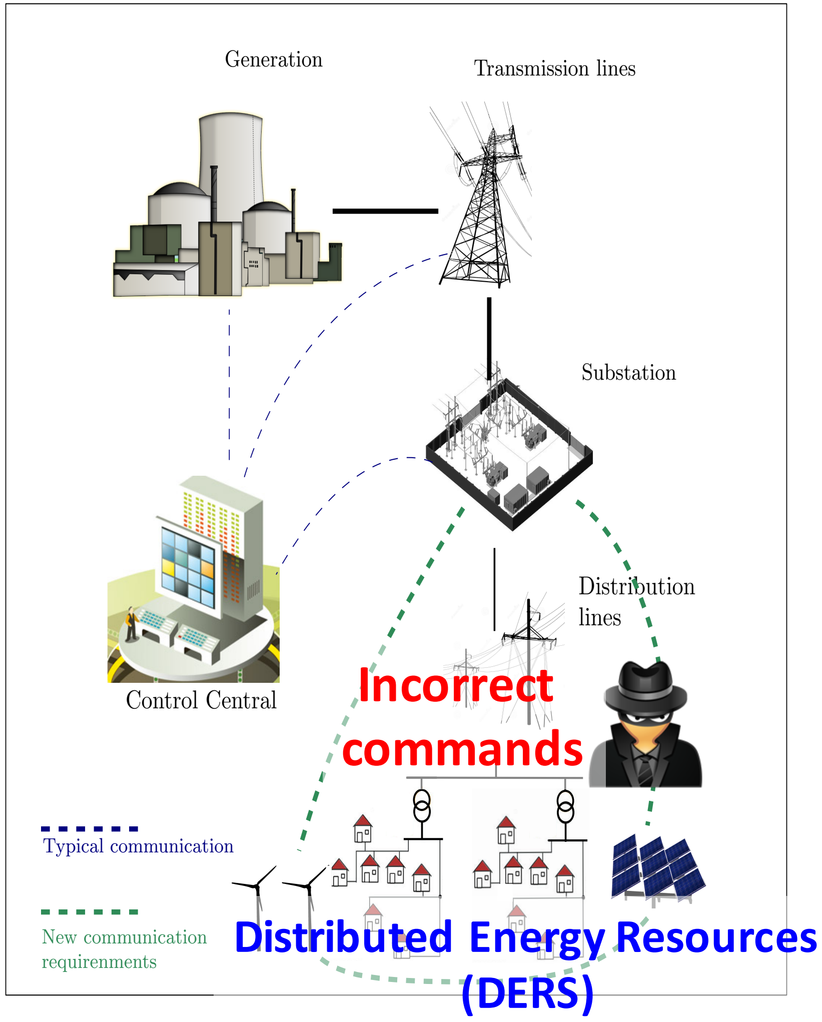
$$\min_{a \in \mathcal{A}} C_{alloc}(a) + \boxed{\max_{d \in \mathcal{D}} \min_{u \in \mathcal{U}} L(a, d, u)}$$

RAOPF
(Stages II and III)

Subject to

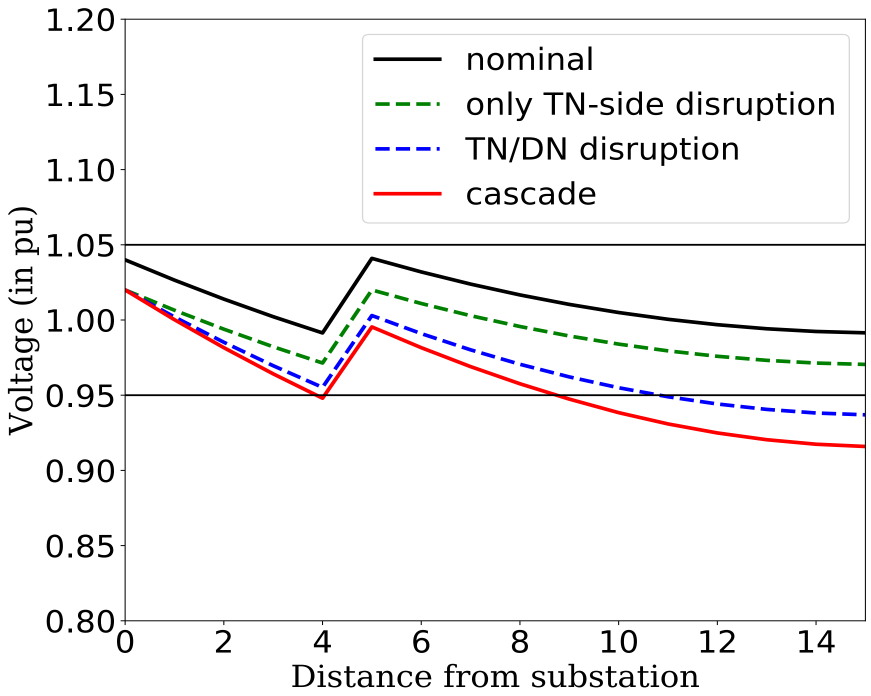
- Network constraints
- Component constraints
- Voltage constraints

A specific attack scenario



Adversary:

- Hack DER SCADA and disrupt DERs
- Create supply-demand disturbance
- Cause frequency and voltage violations
- Induce network failures (cascades)



A 3-regime picture

Grid-connected regime

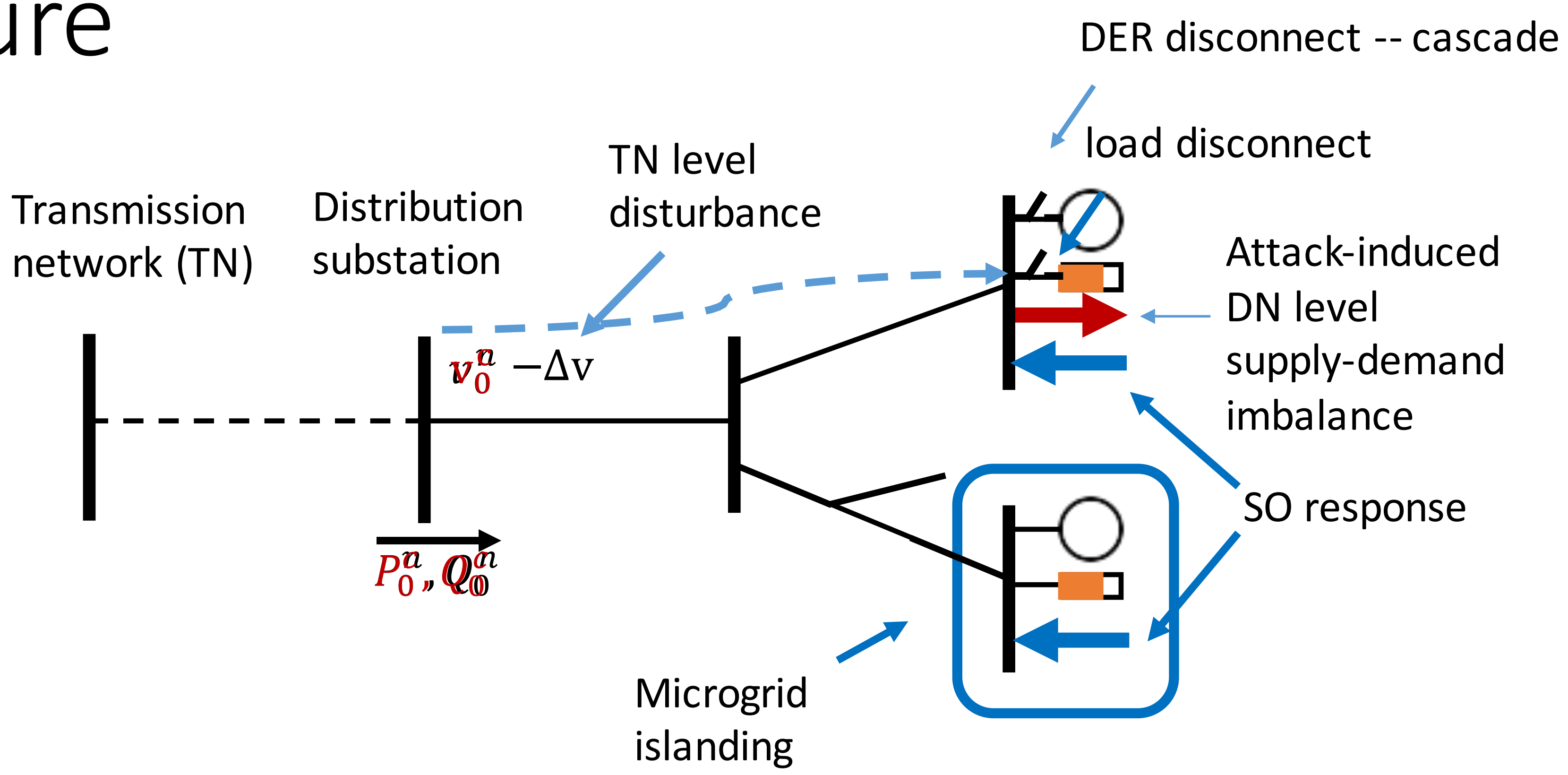
- Can absorb the impact of disturbances

Islanding mode regime

- Larger disturbances may force microgrid islanding

Cascade regime

- High severity voltage excursions, then more DER disconnects (cascades), more load shedding



When TN and DN level disturbances clear, the system can return to its nominal regime

Our approach

Most attacker-defender interactions can be modeled as

- Supply-demand imbalance induced by attacker
- Control (reactive and proactive) by the system operator

- Abstraction: Bilevel (or multilevel) optimization problems

- Supplements simulation based approaches
    - For example, co-simulation of cyber and power simulators

Resilience-aware OPF (Stages II and III)

Stage II - Adversarial node disruptions

a. Which nodes to compromise (δ)?

… can include other attack models

Stage III - Optimal dispatch / response (x^c)

a. Exercise load control or not
b. Disconnects loads/DGs?
c. Maintain voltage regulation

… possible to consider frequency regulation

Goals:

1. Identify critical nodes
2. Determine optimal response

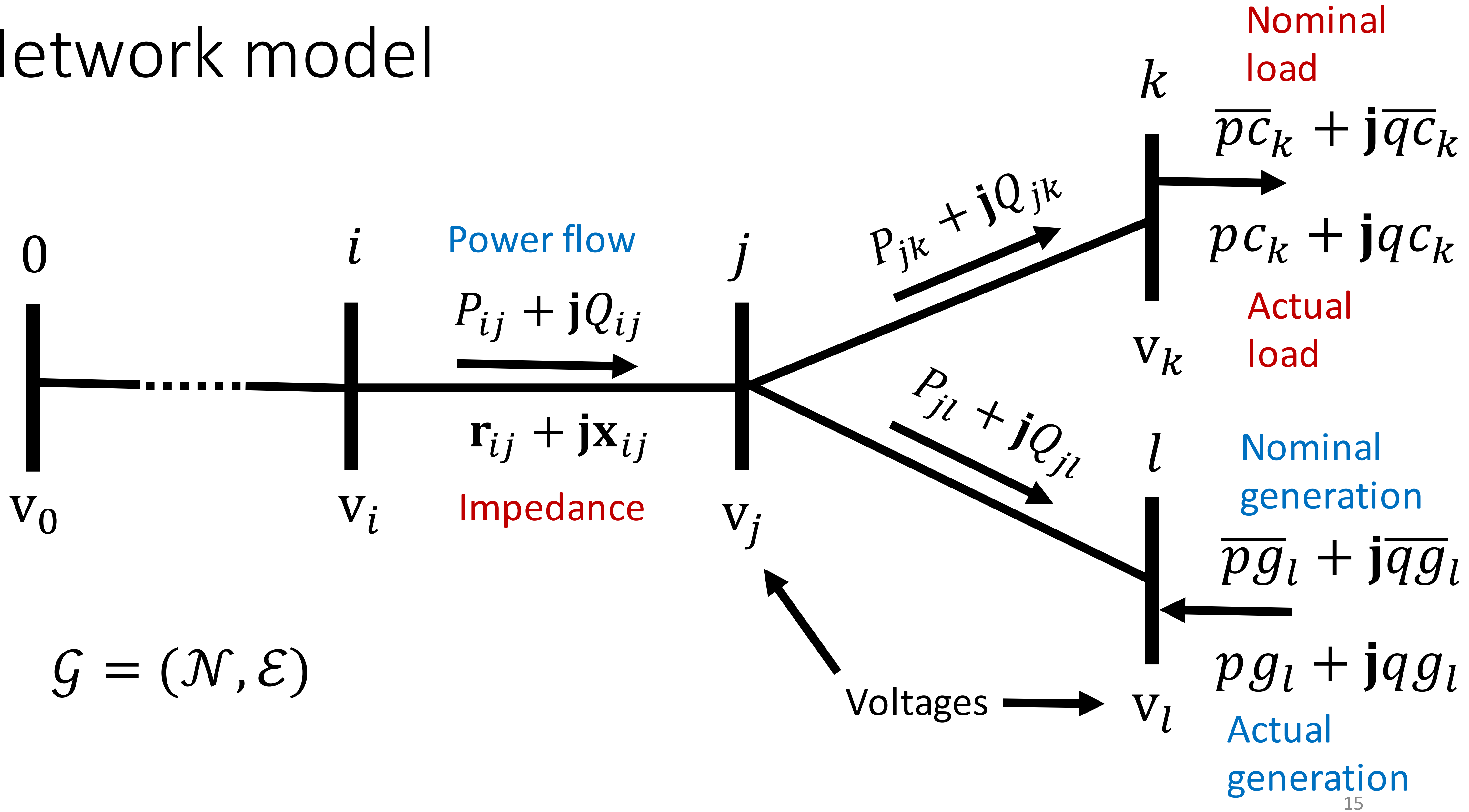
Modeling of Grid-connected/Cascade regimes

$$\max_{d \in \mathcal{D}} \min_{u \in \mathcal{U}} L(d, u)$$

Subject to

- Network constraints
- Component constraints
- Voltage constraints

Network model



$$\mathcal{G} = (\mathcal{N}, \mathcal{E})$$

Defender model in Grid-connected regime

- Defender response: only load control
- $u = \beta$
- $\beta_i \in \left[\underline{\beta_i}, 1\right]$: load control parameter at node i

$$pc_i = \beta_i \, \overline{pc}_i, \qquad qc_i = \beta_i \, \overline{qc}_i$$

Defender response:

How much load control should be exercised?

Losses in Grid-connected regime

$L^{\text{GC regime}}$ = Cost of active power supply + Cost of loss of voltage regulation + Cost of load control

$\mathrm{W_{AC}}P_0$

$\mathrm{W_{VR}}t$

$\sum_{i\in N} \mathrm{W}_{\mathrm{LC},i}(1-\beta_i)$

Where

$$\mathrm{t} \geq \max_{\mathrm{i}\in\mathcal{N}} |\mathrm{v}_0^{\mathrm{nom}} - \mathrm{v}_i|$$

Defender model in Cascade regime

Defender response: load control, connectivity control

$u = (\beta, kg, kc)$

$$kg_i = \begin{cases} 1, \text{if DG } i \text{ is disconnected} \\ 0, \qquad \text{otherwise.} \end{cases}$$

$$kc_i = \begin{cases} 1, \text{if load } i \text{ is disconnected} \\ 0, \qquad \text{otherwise.} \end{cases}$$

Voltage bounds for DG

Connectivity constraints are mixed-integer linear:

- Connected implies no violations
- Violation implies not connected

$$kg_i = 0 \quad \Longrightarrow \quad \mathrm{v}_i \in \left[\underline{\mathrm{vg}}_i, \overline{\mathrm{vg}}_i\right]$$

$$\mathrm{v}_i \notin \left[\underline{\mathrm{vg}}_i, \overline{\mathrm{vg}}_i\right] \quad \Longrightarrow \quad kg_i = 1$$

Defender response:

Which loads and DGs to disconnect?

Similarly for loads!

Losses in Cascade regime

$$L^{\text{CS regime}} \equiv L^{\text{GC regime}} \quad + \quad \text{Cost of load disconnection}$$

$$\sum_{i \in N} \mathrm{W}_{\mathrm{SD},i} k c_i$$

Attacker model

Attacker strategy: $d = (\delta, \Delta\mathrm{v}_0)$

$$\delta_i = \begin{cases} 1, & \text{if node } i \text{ is attacked} \\ 0, & \text{otherwise.} \end{cases}$$

Attacker's resource budget $\sum_i \delta_i \leq \mathrm{k}$

- $\Delta\mathrm{v}_0$: amount by which substation voltage drops
  - Due to physical disturbance or temporary fault in the TN

Attacker strategy:

- Which nodes to compromise?

Effect of attacker actions

- DER disruption makes its output zero.

$$\begin{aligned} kg_i &\geq \delta_i \\ pg_i &= (1 - kg_i)\,\overline{pg_i} \\ qg_i &= (1 - kg_i)\,\overline{qg_i} \end{aligned}$$

- TN-side disturbance impacts substation voltage

$$\mathrm{v}_0 = \mathrm{v}_0^{\mathrm{nom}} - \Delta\mathrm{v}_0$$

Linear power flows

Power conservation

$$P_{ij} = \sum_{k:j \to k} P_{jk} + pc_j - pg_j$$

$$Q_{ij} = \sum_{k:j \to k} Q_{jk} + qc_j - qg_j$$

Voltage drop

$$\mathrm{v}_j = \mathrm{v}_i - 2(\mathbf{r}_{ij} P_{ij} + \mathbf{x}_{ij} Q_{ij})$$

$$\mathrm{v}_0 = \mathrm{v}_0^{\mathrm{nom}} - \Delta \mathrm{v}$$

System state

$$x = (pc, qc, pg, qg, \mathrm{v})$$

Cascade regime

$$\mathcal{L} := \max_{d \in \mathcal{D}} \min_{u \in \mathcal{U}} L^{\text{CS regime}}(d, u)$$

Subject to

- Network constraints
- Component constraints
- Voltage constraints

This is a mixed-integer bilevel linear program: NP-hard!

Islanding regime

$$\max_{d \in \mathcal{D}} \min_{u \in \mathcal{U}} L^{\text{MI regime}}(d, u)$$

Subject to

- Network constraints
- Component constraints
- Voltage constraints

$$L^{\text{MI regime}} \equiv L^{\text{CS regime}} + \text{Cost of islanding}$$

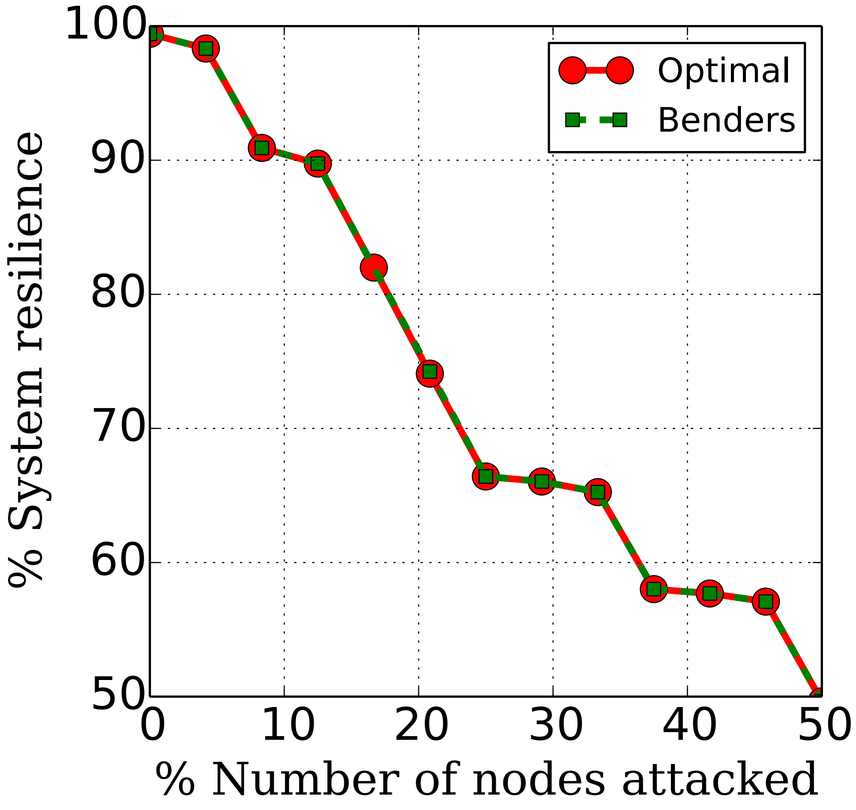
$$\sum_{(i,j)\in\chi} \mathrm{W}_{\mathrm{MG},ij}\, km_{ij}$$

System resilience

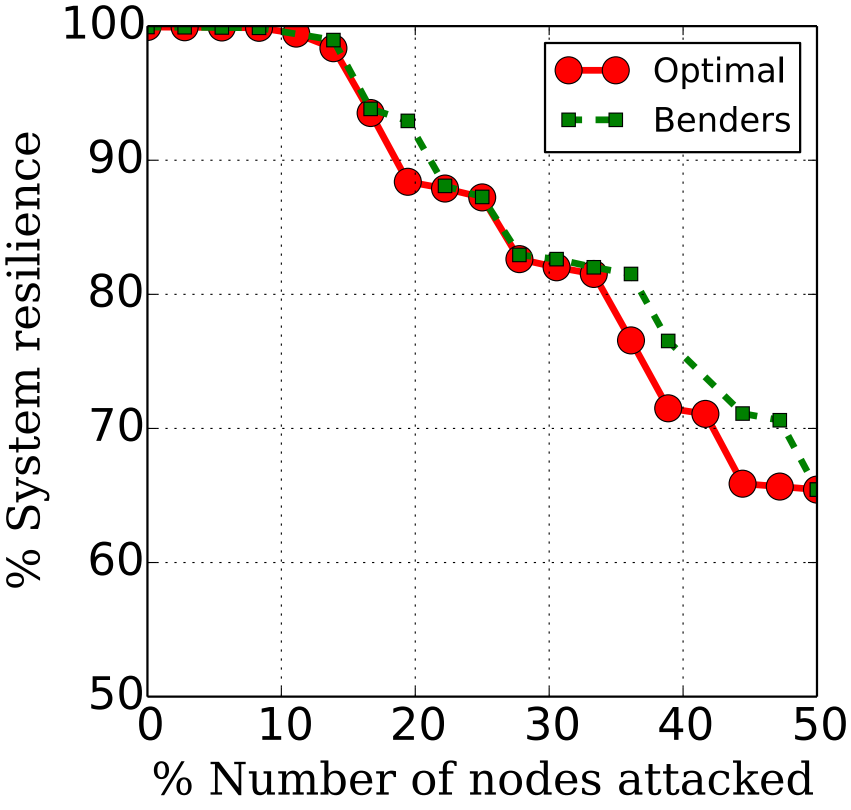
- $\mathcal{L}_{max} = \sum_{i \in N} \mathrm{W}_{\mathrm{SD},i}$: maximum loss
  - Cost of disconnection of all loads

- System resilience
  - Percentage decrease in system performance relative to maximum loss
  - $= 100\left(1 - \frac{\mathcal{L}}{\mathcal{L}_{max}}\right)$

Benders Decomposition vs. Optimal



Grid-connected and
Cascade regime



Grid-connected, cascade,
and Islanding regime

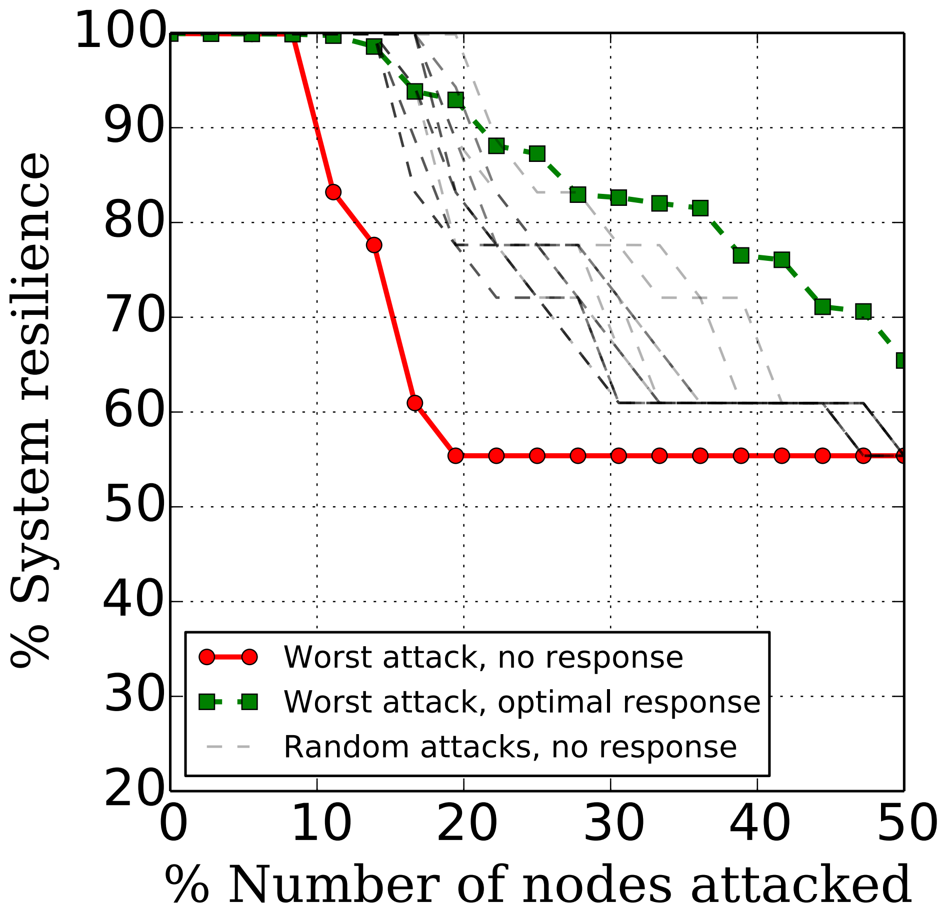
Uncontrolled (multi-round) cascade

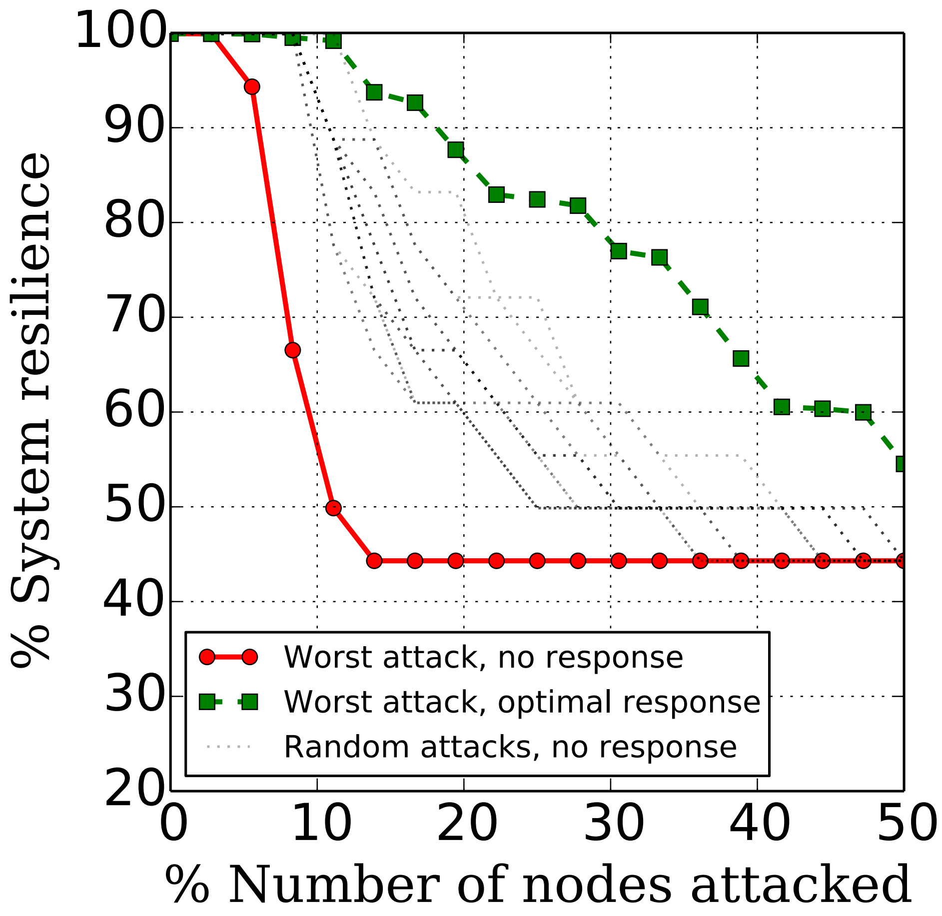
In reality, defender may not be able to instantaneously detect and identify attack, and optimally respond to it

No response cascade algorithm

- Initial contingency
- For r = 1,2,…
  - Compute power flows
  - Determine the nodes that violate the voltage bounds
  - Disconnect the loads or non-controllable DGs accordingly

Uncontrolled vs Cascade regime





N = 36

Performance of Benders Decomposition

Entries are resilience metric of DN (in percentage), number of iterations (written in brackets), time (in seconds), attack cardinality.			
$\mathcal{R}_{\text{target}}$	N = 24	N = 36	N = 118
99	98.75, (3), 0.04, 1	98.96, (11), 0.22, 5	98.52, (27), 1.86, 14
95	91.15, (6), 0.08, 2	93.82, (13), 0.27, 6	94.66, (39), 3.34, 17
90	89.75, (10), 0.16, 3	88.08, (15), 0.34, 8	89.94, (50), 5.44, 26
85	82.41, (11), 0.18, 4	82.93, (17), 0.4, 10	84.96, (69), 9.23, 44
80	74.38, (14), 0.26, 5	76.99, (21), 0.52, 14	79.71, (86), 613.42, 52
75	74.38, (14), 0.26, 5	71.1, (23), 0.59, 16	Failure
65	58.01, (20), 0.41, 9	Failure	
55	49.65, (23), 0.47, 12		
45	Failure		

$$\text{Res}^{\text{Worst-case}} = \left(1 - \frac{L}{L^{max}}\right) 100\ \%$$

Summary (so far)

- Resource allocation and dispatch in electricity DNs
  - under strategic cyber-physical failures
  - Multi-regime defender response

- Benders decomposition approach for solving bilevel MILPs

- Structural results on worst-case attacks and defender response

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Learning of Power Transmission Dynamics from partial PMU observations

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August 30, 2018

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Motivation

- State estimation
  - Optimal resource allocation for improved resiliency
  - Secure and efficient operations
- Dynamic model estimation
  - Detection of faults/attacks
  - Prompt and accurate response
- Data-driven approach

Preliminaries

- Dynamical equation: $x_{t+1} = Ax_t + Fv_t$
- $A \in R^{N \times N}$: dynamic matrix:,
- $x_t \in R^N$: state vector
- $v_t \in \mathrm{R}^N$: Noise vector
- F : Noise-scaling matrix

Assumptions

- Temporal independence of noise vectors
  - v_i and v_j are independent for all $i \neq j$
- Spatial independence of noise vectors
  - F is a diagonal matrix (there is no spatial mixing of noise)

Learning under full observability

Given: observations x_t for $t = 1,2,\cdots,n+1$

Result:

- Maximum likelihood estimator of A [1]

$$\hat{A} = \Sigma_1^{-1}\Sigma_0$$

Where

$$\Sigma_0 = \frac{1}{n}\sum_{t=1}^{n} x_t x_t' \quad \text{and} \quad \Sigma_1 = \frac{1}{n}\sum_{t=1}^{n} x_{t+1} x_t'$$

- Also the solution of least squares regression

[1]A. Lokhov et al. Online Learning of Power Transmission Dynamics

Linear Swing Dynamics model

- Network $(\mathcal{V}, \mathcal{E})$
- $\mathcal{V}$ set of nodes, $N = |\mathcal{V}|$ number of nodes
- $\mathcal{E}$ set of edges

Swing equation

$$M_i \ddot{\theta}_i + D_i\left(\dot{\theta}_i - \omega^0\right) = P_i^{(m)} - P_i^{(e)}$$

- $P_i^{(m)}$: mechanical power input
- -$P_i^{(e)}$: electrical power output

Power system model

Using change of variables

- δ_i : phase deviations from steady state values
- ω_i : relative generator rotor speed relative nominal frequency

$$M_i \, \dot{\omega}_i + D_i \omega_i = - \sum_{(i,j)\in\mathcal{E}} \beta_{ij}\left(\delta_i - \delta_j\right) + \delta P_i$$

$$\begin{bmatrix} \dot{\delta} \\ \dot{\omega} \end{bmatrix} = \underbrace{\begin{bmatrix} 0_{N\times N} & I_{N\times N} \\ -M^{-1}L & -M^{-1}D \end{bmatrix}}_{A_d} \begin{bmatrix} \delta \\ \omega \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & M^{-1} \end{bmatrix} \begin{bmatrix} 0_N \\ \delta P \end{bmatrix}$$

Discrete dynamical model

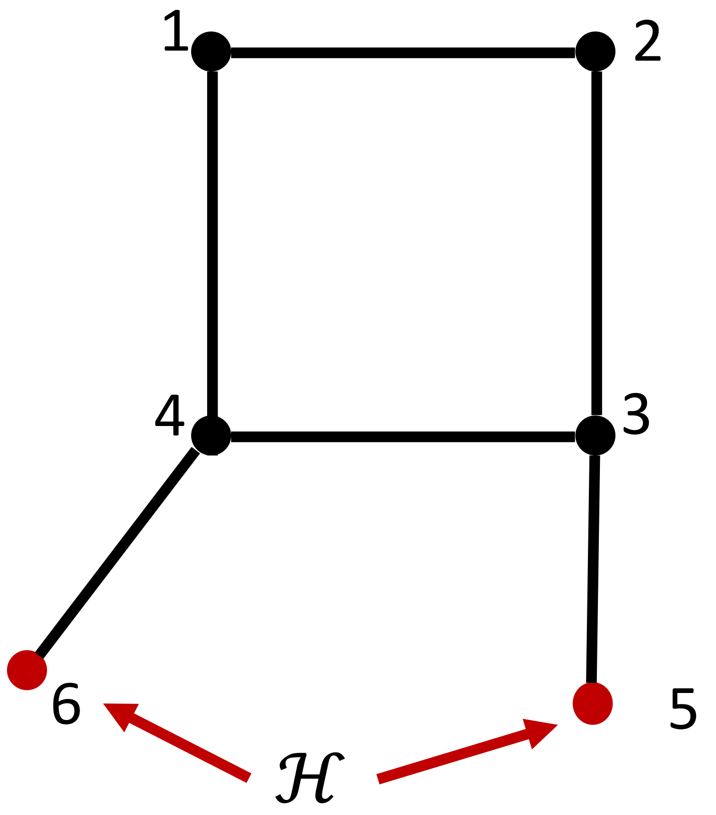
- Using discretization with timestep T
  - $A = (I + A_d T)$

$$\underbrace{\begin{bmatrix} \delta_{t+1} \\ \omega_{t+1} \end{bmatrix}}_{x_{t+1}} = \underbrace{\begin{bmatrix} I_{N\times N} & TI_{N\times N} \\ -TM^{-1}L & I_{N\times \mathrm{N}} - TM^{-1}D \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} \delta \\ \omega \end{bmatrix}}_{x_t} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & TM^{-1} \end{bmatrix}}_{F} \underbrace{\begin{bmatrix} 0_N \\ \delta P \end{bmatrix}}_{v_t}$$

$$x_{t+1} = Ax_t + Fv_t$$

Learning under partial observability

- $\mathcal{H} \subseteq \mathcal{V}$ set of hidden nodes (without PMUs)
- $\mathcal{O} = \mathcal{V} \setminus \mathcal{H}$ set of observable nodes (with PMUs)



Rearrangement of dynamic matrix

$$\begin{bmatrix} \delta_{t+1}^{\mathcal{O}} \\ \omega_{t+1}^{\mathcal{O}} \\ \delta_{t+1}^{\mathcal{H}} \\ \omega_{t+1}^{\mathcal{H}} \end{bmatrix} = \begin{bmatrix} A_{\mathcal{O}\mathcal{O}} & A_{\mathcal{O}\mathcal{H}} \\ A_{\mathcal{H}\mathcal{O}} & A_{\mathcal{H}\mathcal{H}} \end{bmatrix} \begin{bmatrix} \delta_{t}^{\mathcal{O}} \\ \omega_{t}^{\mathcal{O}} \\ \delta_{t}^{\mathcal{H}} \\ \omega_{t}^{\mathcal{H}} \end{bmatrix} + \begin{bmatrix} G & 0 \\ 0 & H \end{bmatrix} \begin{bmatrix} 0 \\ v_t^{\mathcal{O}} \\ 0 \\ v_t^{\mathcal{H}} \end{bmatrix}$$

By change of notation,

$$\begin{bmatrix} y_{t+1} \\ z_{t+1} \end{bmatrix} = \begin{bmatrix} B & C \\ D & E \end{bmatrix} \begin{bmatrix} y_t \\ z_t \end{bmatrix} + \begin{bmatrix} G & 0 \\ 0 & H \end{bmatrix} \begin{bmatrix} u_t \\ w_t \end{bmatrix}$$

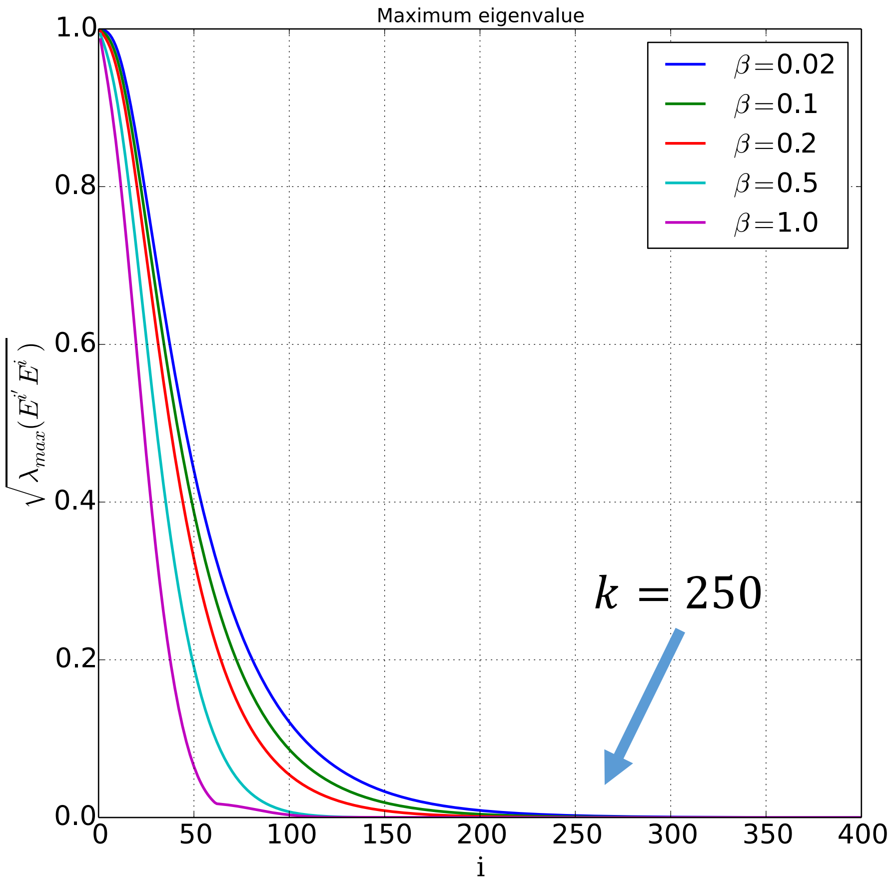
Problem statemement

- Given measurements from observable nodes y_t for $t = 1,2,\cdots,\mathrm{n}$
- Goal: To recover dynamic matrix A
  - Or equivalently, recover sub-matrices B, C, D, E

Some simple observations

- Stable system implies
$$|\lambda_{max}(E)| \le |\lambda_{max}(A)| < 1$$
- Thus, $E^k \approx 0$ for sufficiently large k

- Large susceptance values imply more unstable system



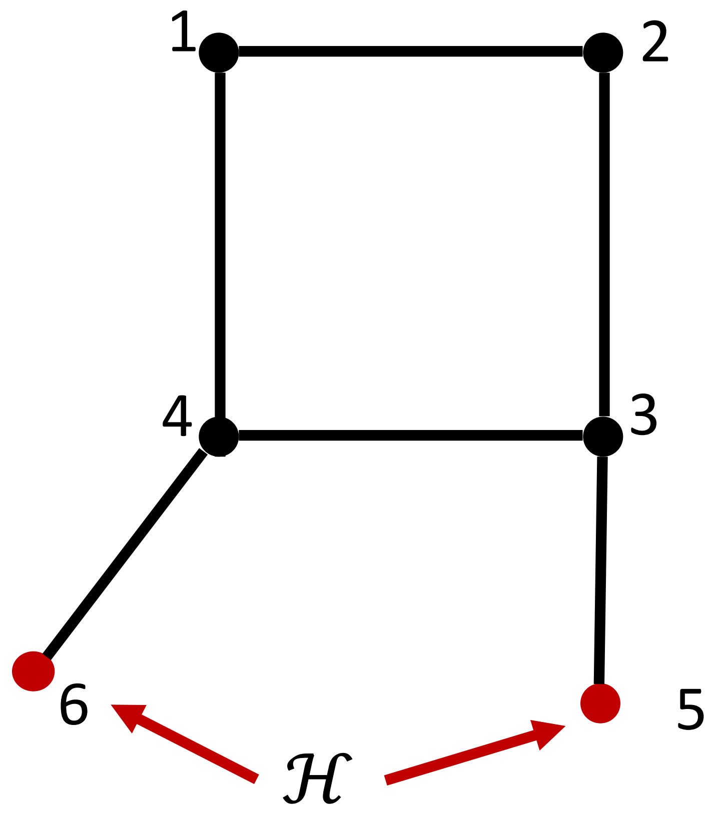
Eliminating hidden node measurements

$$\therefore\ y'_{t+k+1} = [y'_{t+k}\ y'_{t+k-1} \cdots y_t{}'] \begin{bmatrix} B' \\ (CD)' \\ \vdots \\ (CE^{k-1}D)' \end{bmatrix} + \left([G\ CH \cdots CE^{k-1}H] \begin{bmatrix} u_{t+k} \\ w_{t+k-1} \\ \vdots \\ w_t \end{bmatrix} \right)'$$

$$y'_{t+k} = Y'_t X + \eta_t$$

Connectivity restrictions

- Each observable node is connected to at most one hidden node
  - $|\{(o, h) \in \mathcal{E}: h \in \mathcal{H}\}| \leq 1 \; \forall \; o \in \mathcal{O}$
- Each hidden node is connected to exactly one observable node
  - $|\{(o, h) \in \mathcal{E}: o \in \mathcal{O}\}| \leq 1 \; \forall \; h \in \mathcal{H}$



Some simple properties

$$y'_{t+k+1} = [y'_{t+k}\ y'_{t+k-1} \cdots y_t{}'] \begin{bmatrix} B' \\ (CD)' \\ \vdots \\ (CE^{k-1}D)' \end{bmatrix} + \left([G\ CH \cdots CE^{k-1}H] \begin{bmatrix} u_{t+k} \\ w_{t+k-1} \\ \vdots \\ w_t \end{bmatrix} \right)'$$

$$y'_{t+k} = Y'_t X + \eta_t$$

Properties

- G is diagonal by assumption
- Under connectivity restriction, for all $m = 0,1,\cdots,k-1,\quad CE^m H$ is of the form $\begin{bmatrix} 0 & 0 \\ \mathrm{x} & 0 \end{bmatrix}$, where
  - $\mathrm{x} \in R^{\mathcal{O}\times\mathcal{H}}$ with
    - exactly 1 non-zero entry per column, and
    - at most 1 non-zero entry per row.

Implications

For timesteps $t = i, i + k, i + 2k, \cdots$

- The noise vectors η_t satisfy both temporal and spatial independence
- Thus, we can use least squares estimator

$$\begin{bmatrix} y'_{t+k+1} \\ y'_{t+2k+1} \\ \vdots \\ y'_{t+ck+1} \end{bmatrix} = \begin{bmatrix} Y'_t \\ {Y_{t+k}}' \\ \vdots \\ {Y_{t+ck}}' \end{bmatrix} X + \eta_t$$

$$r \approx \mathrm{S X}$$

Least squares estimator

- $\hat{X} = (S'S)^{-1}(S'r)$, or equivalently,

$$\begin{bmatrix} B' \\ (CD)' \\ \vdots \\ (CE^{k-1}D)' \end{bmatrix} = \left(\begin{bmatrix} \Sigma_0 & \Sigma_1 & \cdots & \Sigma_k \\ \Sigma_{-1} & \Sigma_0 & \cdots & \Sigma_{k-1} \\ \vdots & \vdots & & \vdots \\ \Sigma_{-k} & \Sigma_{-k+1} & \cdots & \Sigma_0 \end{bmatrix} \right)^{-1} \left(\begin{bmatrix} \Sigma_k \\ \Sigma_{k-1} \\ \vdots \\ \Sigma_0 \end{bmatrix} \right)$$

Where

$$\Sigma_i = \frac{1}{l - j + 1} \sum_{j=1}^{l} y_{jk+i} \, y'_{jk}$$

- Allows, recovery of B matrix in a straightforward manner.

Recovering submatrices C, E, and D

- Under the connectivity restrictions, C and D are sparse matrices such that $C = \begin{bmatrix} 0 & 0 \\ \mathrm{x} & 0 \end{bmatrix}, D = \begin{bmatrix} 0 & 0 \\ \mathrm{z} & 0 \end{bmatrix}$ and $E^i = \begin{bmatrix} R_{1i} & R_{2i} \\ \mathrm{R}_{3\mathrm{i}} & R_{4i} \end{bmatrix}$
  - $\mathrm{x} \in R^{\mathcal{O}\times\mathcal{H}}$ with exactly 1 non-zero entry per column and at most 1 non-zero entry per row.
  - $\mathrm{z} \in R^{\mathcal{H}\times\mathcal{O}}$ with exactly 1 non-zero entry per row and at most 1 non-zero entry per column.
  - $\mathrm{R}_{ji} \in R^{\mathcal{H}\times\mathcal{H}}$ is a diagonal matrix for j $= 1,2,3,4$ and $i = 1,2,\cdots$

- Hence, given values of CE^1D, CE^2D and CE^3D, are relatively simpler non-linear expressions of entries in C, E and D.

Concluding remarks

Summary

- Connectivity restriction can be leveraged to learn the dynamical model with partial observability.
- These properties may be applicable to other domains

- Identifying properties of non-linear optimization model

Future work

- Relaxing assumptions such as connectivity restriction and using smaller values of k.

Questions?

Thank you

Benders Decomposition approach

- Reformulate **budget-k-max-loss** problem as **target-loss-min-cardinality** problem. Let L_{target} be minimum target loss.

Attacker Master problem

- Initialize with no cuts

$$\min \sum_i \delta_i$$

$$\text{s.t. Bender cuts}$$

$$\delta_i \in \{0,1\}$$

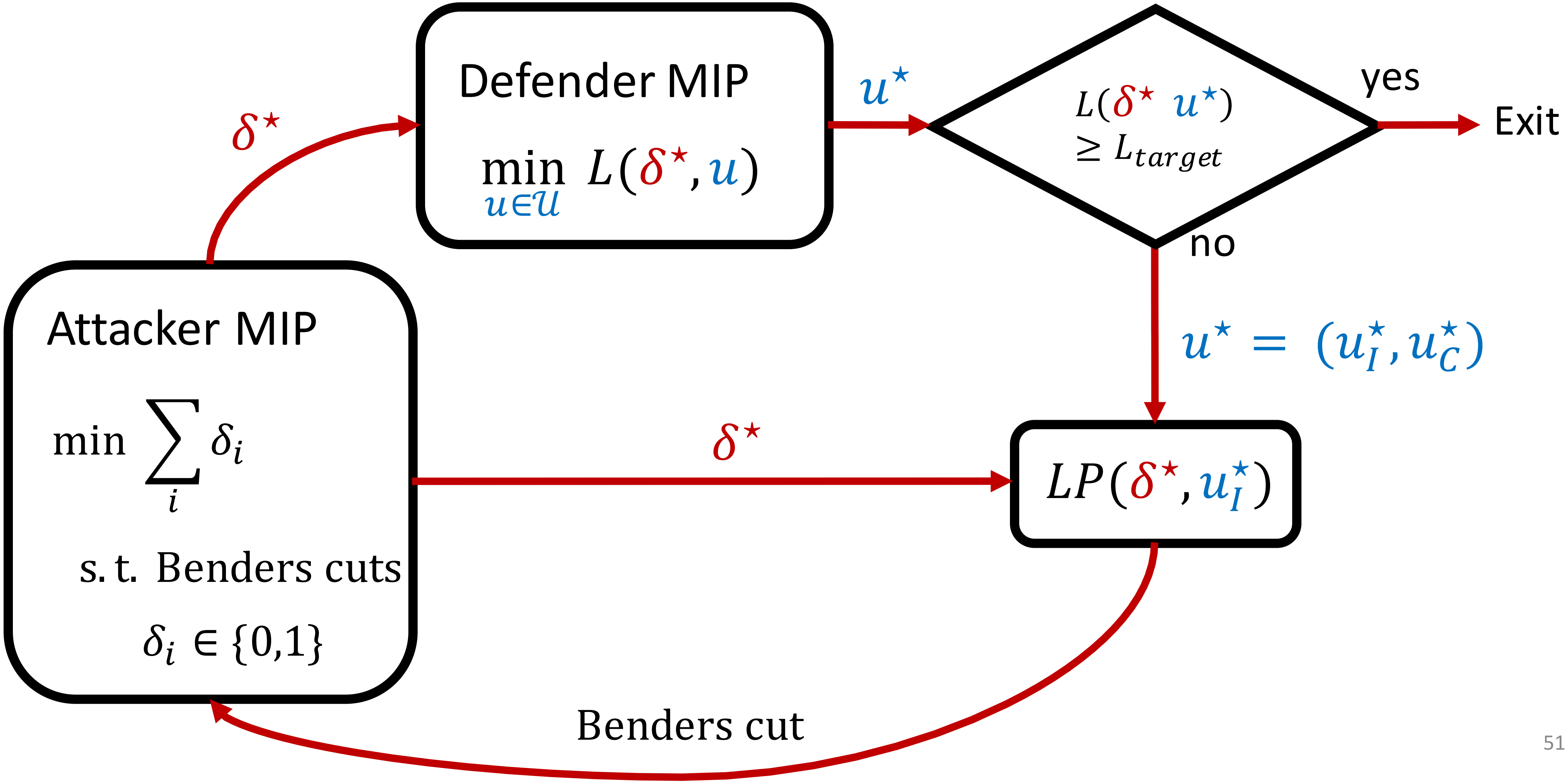
Defender problem (Same as Stage III)

$$\min_{u \in \mathcal{U}} L(\delta, u)$$

s.t.

- Network constraints
- Component constraints
- Voltage bounds

Benders Decomposition approach



Benders Decomposition approach

$$LP(\delta^{iter}, u_I) \equiv \quad \min\ c^T y \quad s.t.\ Ay \geq b + Q\delta^{iter}$$

Fixed attacker strategy for current iteration

Response with fixed integer values

Benders cut

$$\boxed{\lambda^{\star T}(b + Q\delta) \geq L_{target} + \epsilon}$$

Optimal dual vector solution to LP

Right hand side of LP

Small number $\approx 10^{-6}$

Technical Detail

- Bad Benders cuts may arise
  - If no Stage III constraints have non-zero coefficients for both attack variables and continuous inner variables
  - Which indeed is the case in our problem!
  - May perform as badly as brute force!

- Suggestion! Approximate reformulation?
  - Ensure positive coefficients of attack variables in constraints having continuous inner variables
  - Significant computational speed-up
    - Solutions for 118 node network obtained in less than 2 minutes
  - Approximation error produces sub-optimal min-cardinality attacks

Resilience-Aware OPF - Trilevel formulation

pre-contingency state x^o

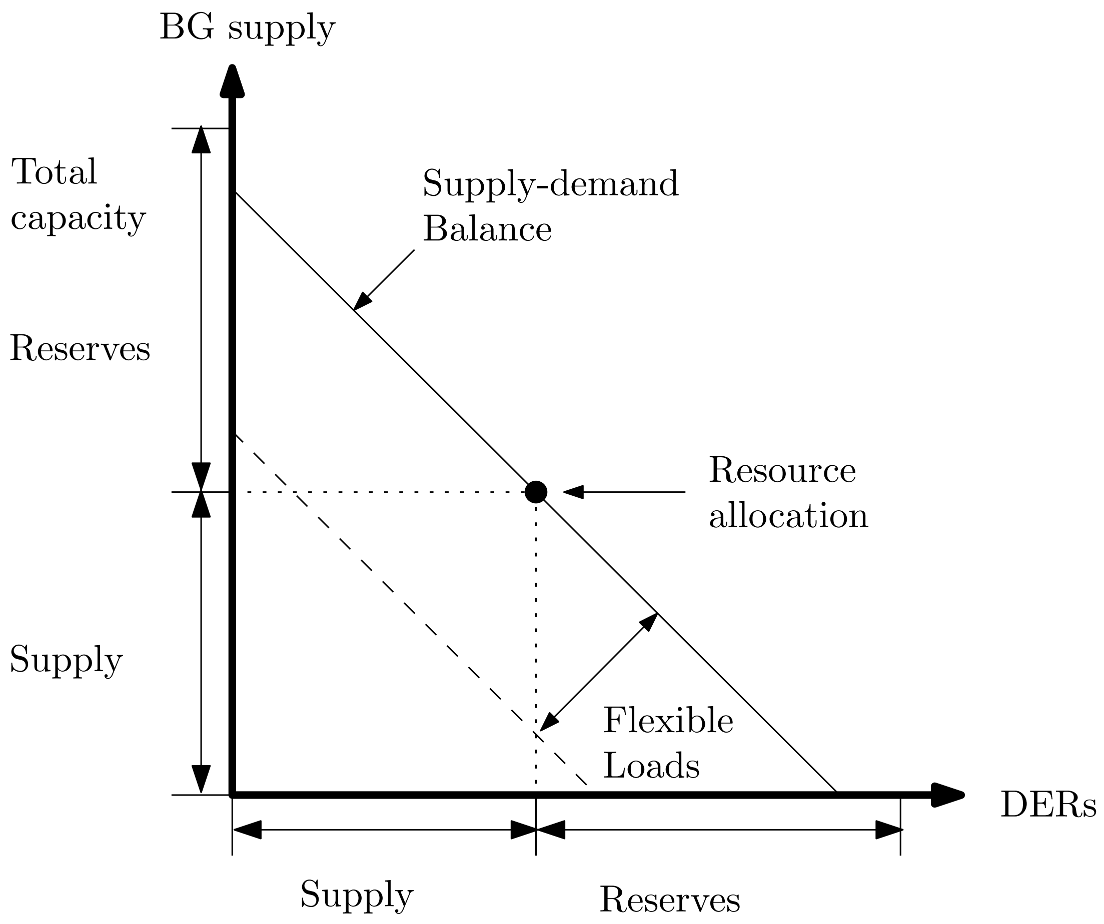
post-contingency state x^c

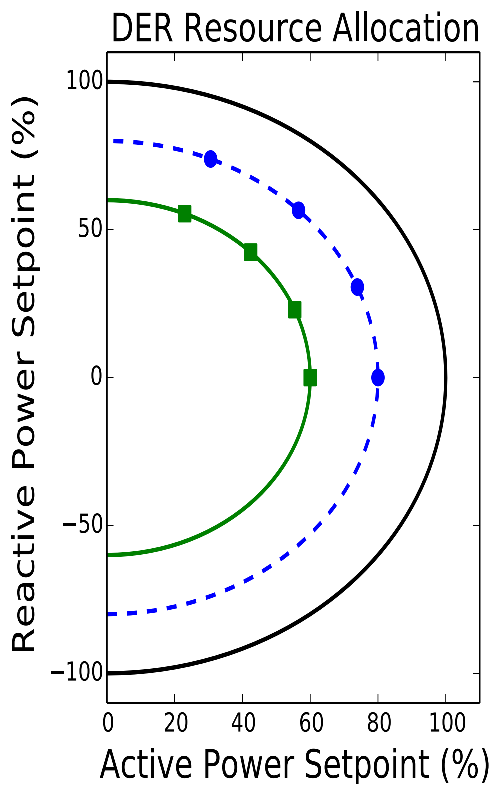
$$\min_{a \in \mathcal{A}} C_{alloc}(a) + \max_{d \in \mathcal{D}} \min_{u \in \mathcal{U}} L(a, d, u)$$

Subject to

- Network constraints
- Component constraints
- Voltage constraints

Resiliency-aware Resource Allocation (Stage I)





Stage I - Allocation of DERs over radial networks

a. Size and location
b. Active and reactive power setpoints (x^n)?

Suppose, some controllable DERs are not vulnerable to attack.

Resiliency-Aware OPF - Trilevel formulation

Frequency deviation model

$$f^{\mathrm{nom}} - f^{c} = -f^{\mathrm{reg}}(P_0^o - P_0^c)$$

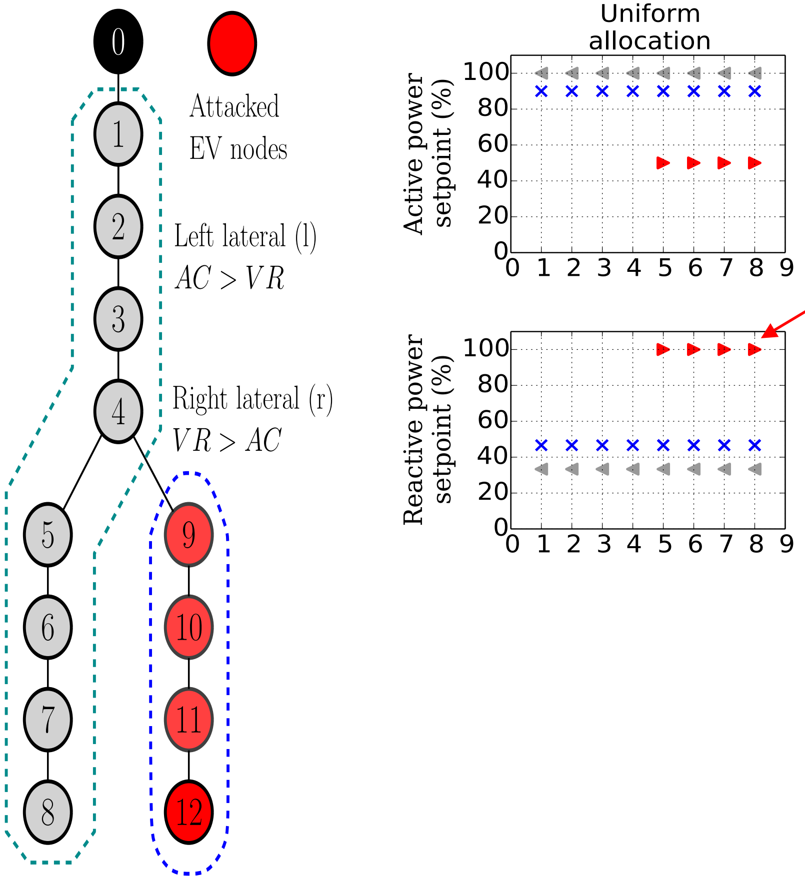
Voltage deviation model

$$\mathrm{v}^{\mathrm{nom}} - \mathrm{v}_0^c = -\mathrm{v}^{\mathrm{reg}}(Q_0^o - Q_0^c)$$

Pre-contingency resource allocation

$$a = (pg^o, qg^o)$$

Defender Response and Allocation: Diversification



- Some DERs contribute to L_{VR} more than L_{AC}, and vice versa
- Diversification holds for "heterogeneous allocation" with downstream DERs with more reactive power
- Post-contingency losses are the same for uniform vs. heterogeneous resource allocations
- Pre-contingency voltage profile is better for heterogeneous resource allocation

Going from LPF to NPF

Lower and upper bound the optimal loss for non-linear power flows with optimal losses computed using linear power flows.

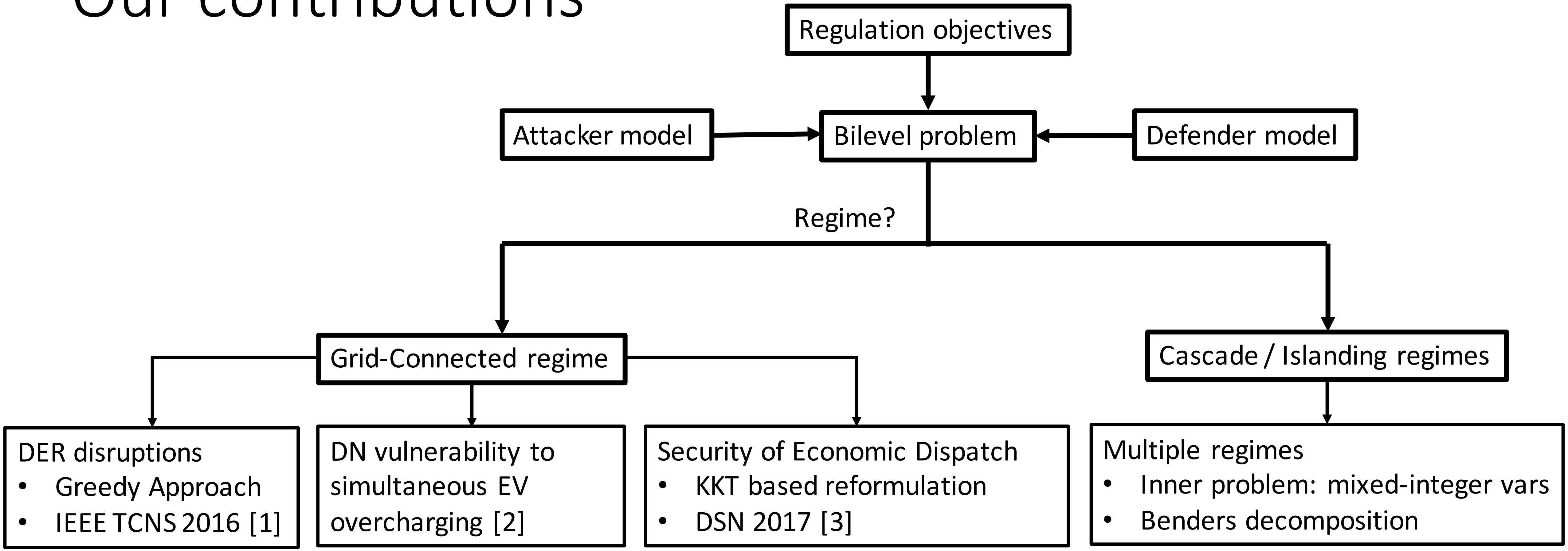
Theorem: Let $\mathcal{L}, \hat{\mathcal{L}}, \text{and } \check{\mathcal{L}}$ denote the optimal losses using NPF, LPF, and ϵ-LPF respectively. Then,

$$\hat{\mathcal{L}} \leq \mathcal{L} \leq \check{\mathcal{L}} + \frac{\underline{\mu} N}{2\underline{\mu} + 4}.$$

Remarks

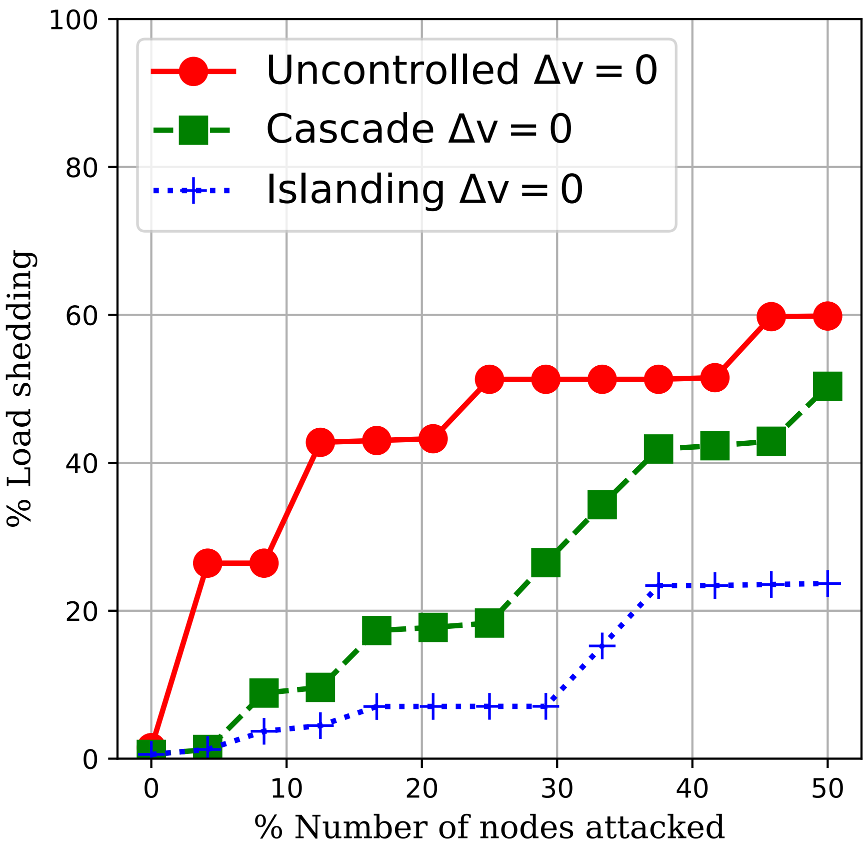
- For $\underline{\mu} = 0.5, N = 37, \frac{\underline{\mu} N}{2\underline{\mu}+4}$ = 3.7. With typical ϵ (max. ratio of line loss to power flows), the gap between the bounds is small (3-5%).

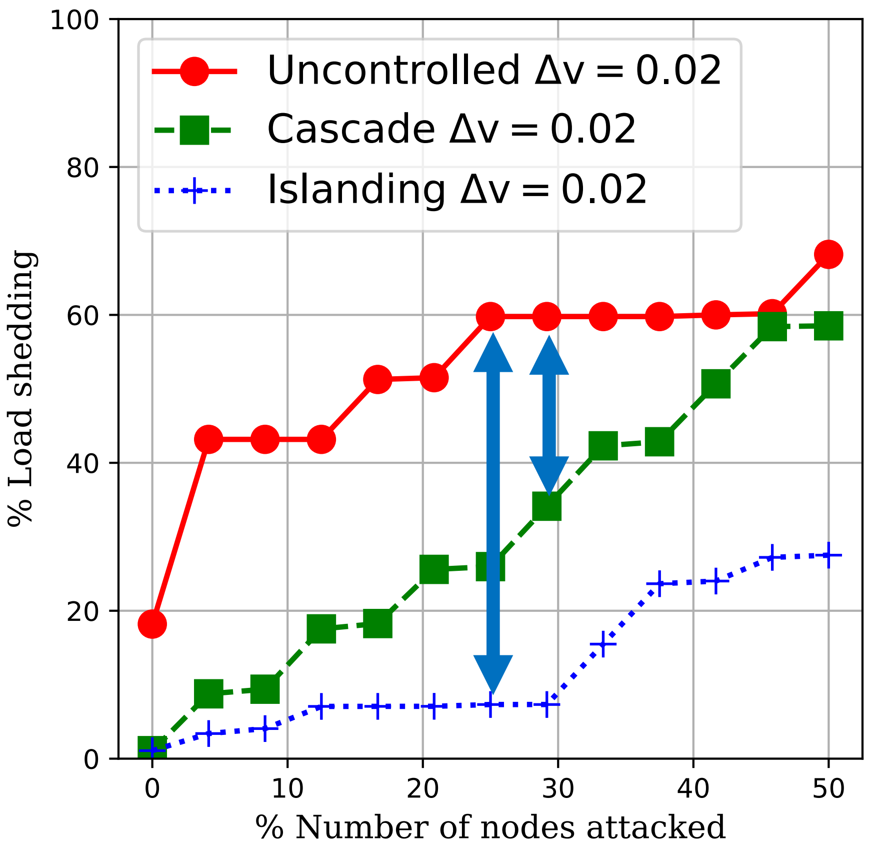
Our contributions



[1] Shelar D. and Amin. S - "Security assessment of electricity distribution networks under DER node compromises”
[2] Shelar D., Amin. S and Hiskens I. – “Towards Resilience-Aware Resource Allocation and Dispatch in Electricity Distribution Networks”
[3] Shelar D., Sun P., Amin. S and Zonouz S. - “Compromising Security of Economic Dispatch software”

Uncontrolled vs Cascade vs Islanding

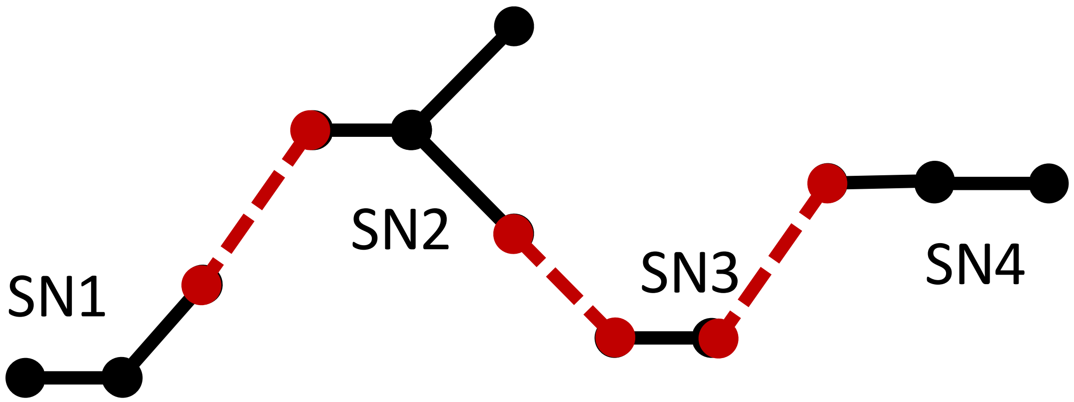




Value of timely
Islanding
disconnections

N = 24

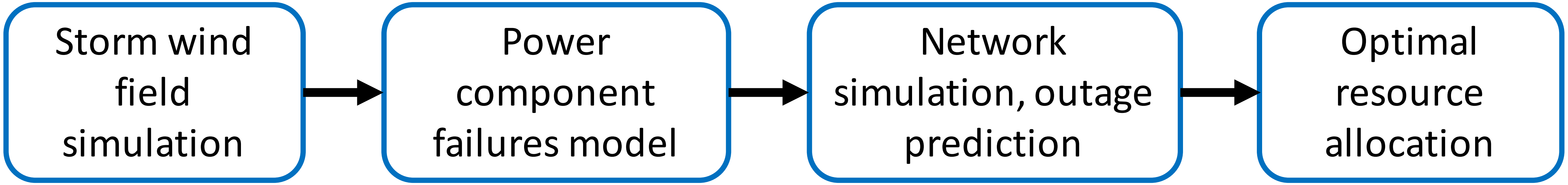
Strategic deployment of portable DERs for post-hurricane power restoration efforts



- A simpler problem
  - Given
    - set of subnetworks
    - repair times of lines
    - inventory of portable DERs with varying capabilities
  - Question
    - What is optimal deployment of portable DERs such that lost demand is minimized?

Portable DERs for power restoration

- More challenging problem
  - What is the optimal deployment of portable DERs before the hurricane to minimize expected lost demand?



Technical detail

Original constraints

$$\begin{array}{lcl} kg_i & \geq & \delta_i \\ pg_i & = & (1-kg_i)\,\overline{pg_i} \\ qg_i & = & (1-kg_i)\,\overline{qg_i} \end{array}$$

LP constraints

$$\begin{array}{lcl} 0 & \geq & 0 \\ 1 & \geq & 0 \\ 1 & \geq & 1 \end{array}$$

Reformulated constraints: Choose $\eta = 10\epsilon$

$$\begin{array}{lcl} kg_i & \geq & \delta_i \\ pg_i & = & (1-(1-\eta)kg_i - \eta\delta_i)\,\overline{pg_i} \\ qg_i & = & (1-(1-\eta)kg_i - \eta\delta_i)\,\overline{qg_i} \end{array}$$

Cases

$\delta_i = 1, kg_i = 1$ ✔

$kg_i = 0, \delta_i = 0$ ✔

$kg_i = 1, \delta_i = 0$?

Going from LPF to NPF

Theorem: Let $\mathcal{L}$, $\hat{\mathcal{L}}$, and $\check{\mathcal{L}}$be optimal solutions to attacker-defender game under NPF, LPF, and ϵ-LPF respectively; and denote the optimal losses by, respectively. Then,

$$\hat{\mathcal{L}} \leq \mathcal{L} \leq \check{\mathcal{L}} + \frac{\underline{\mu} N}{2\underline{\mu} + 4}.$$

Remarks

- Voltages for $\hat{\mathcal{L}}$ $(resp.\ \check{\mathcal{L}})$ upper (resp. lower) bound voltages for $\mathcal{L}$
- Power flows for $\hat{\mathcal{L}}$ $(resp.\ \check{\mathcal{L}})$ lower (resp. upper) bound power flows for $\mathcal{L}$
- For $\underline{\mu} = 0.5, N = 37, \frac{\underline{\mu} N}{2\underline{\mu}+4}$ = 3.7. With typical ϵ (max. ratio of line loss to power flows), the gap between the bounds is small (3-5%).
- Better bounds can be derived

Two simpler problems

$\widehat{\mathcal{L}}$ (LPF model)
$\breve{\mathcal{L}}$ (ϵ-LPF model)

$$\equiv \begin{cases} \max_{\delta} \min_{\phi} L\big(x(\delta,\phi)\big) \\ \text{s.t. constraints,} \\ \text{linear power flow (LPF) or } (\epsilon - \text{LPF}) \end{cases}$$

LPF state: $\hat{x} = \left[\hat{\mathrm{v}}, \hat{\ell},\ sc, sg, \hat{S}\right] \in \widehat{\mathcal{X}}$

$$\hat{S}_{ij} = \textstyle\sum_k \hat{S}_{jk} + s_j + \cancel{z_{ij}\ell_{ij}}$$

$$\hat{\mathrm{v}}_j = \hat{\mathrm{v}}_i - 2\mathbf{Re}\big(\bar{z}_{ij}\hat{S}_{ij}\big) + \cancel{\left|z_{ij}\right|^2 \ell_{ij}}$$

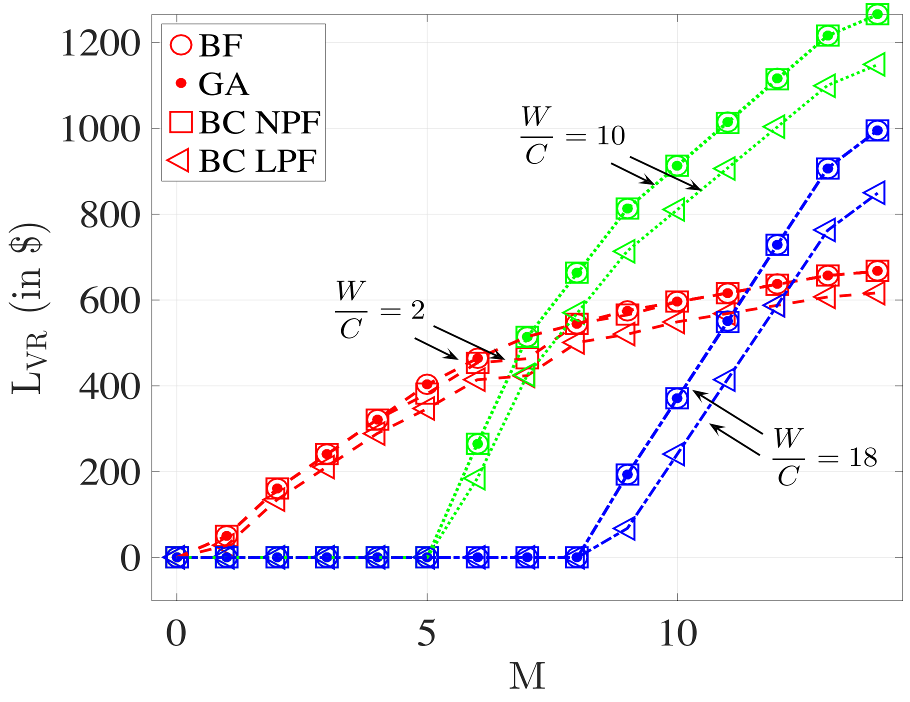
ϵ-LPF state: $\check{x} = \left[\check{\mathrm{v}}, \check{\ell}, sc, sg, \check{S}\right] \in \breve{\mathcal{X}}$

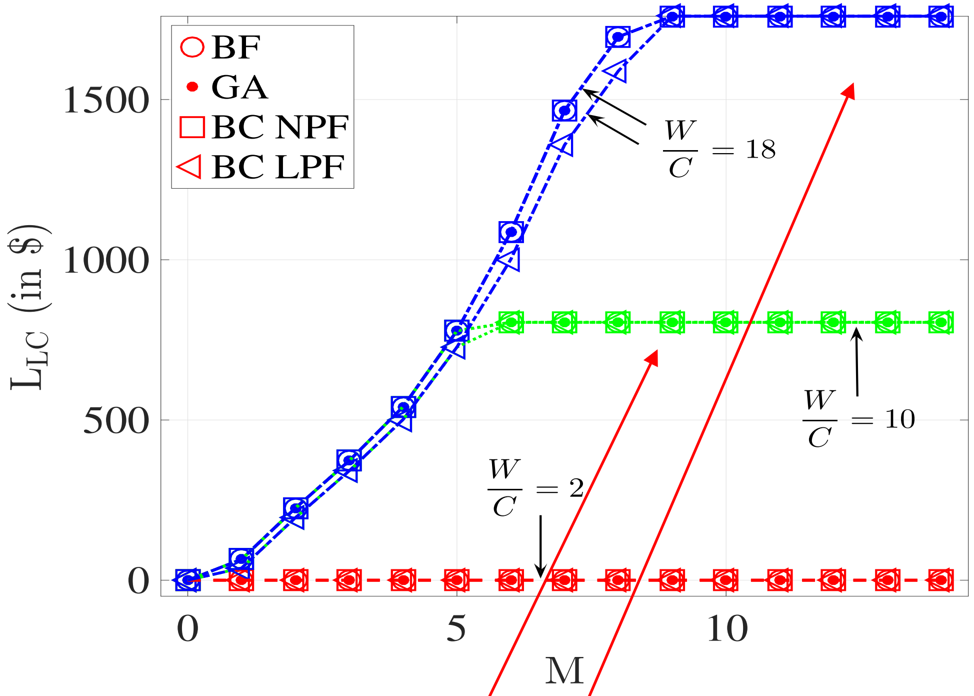
$$\check{S}_{ij} = \textstyle\sum_k \check{S}_{jk} + (1+\epsilon)s_j$$

$$\check{\mathrm{v}}_j = \check{\mathrm{v}}_i - 2\mathbf{Re}\big(\bar{z}_{ij}\hat{S}_{ij}\big)$$

ϵ chosen based on the size of the tree network and the max ratio of line losses to power flows

Structure of attacks





- Downstream nodes are more critical for voltage regulation
- Greedy approach computes “near-optimal” solutions
- Load control is not effective for higher intensity attacks
- Load control reaches higher saturation levels for higher weightage for L_{VR}

Defender model (Cascade regime)

Defender response: $u = (\beta, kg, kc)$

$$kg_i = \begin{cases} 1, \text{if DG } i \text{ is disconnected} \\ 0, \qquad\qquad \text{otherwise.} \end{cases}$$

$$kc_i = \begin{cases} 1, \text{if load } i \text{ is disconnected} \\ 0, \qquad\qquad \text{otherwise.} \end{cases}$$

Connectivity condition:

$$kg_i = 0 \quad \Longrightarrow \quad \mathrm{v}_i \in \left[\underline{\mathrm{vg}}_i, \overline{\mathrm{vg}}_i\right]$$

$$\mathrm{v}_i \notin \left[\underline{\mathrm{vg}}_i, \overline{\mathrm{vg}}_i\right] \quad \Longrightarrow \quad kg_i = 1$$

Voltage bounds for DG

Similarly for loads!

Defender response:

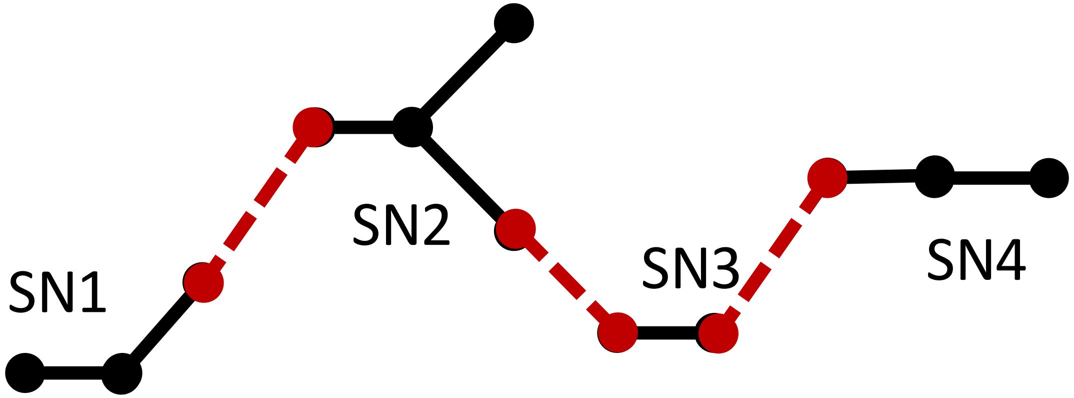
Which loads and DGs to disconnect?

Strategic deployment of portable DERs for post-hurricane power restoration efforts

- Damage to lines result in subnetworks (SNs)

- Usual restoration steps are:
  - Repair the damaged lines
  - Connect to main grid
  - Restore the power supply

- How can portable DERs help?



Literature survey

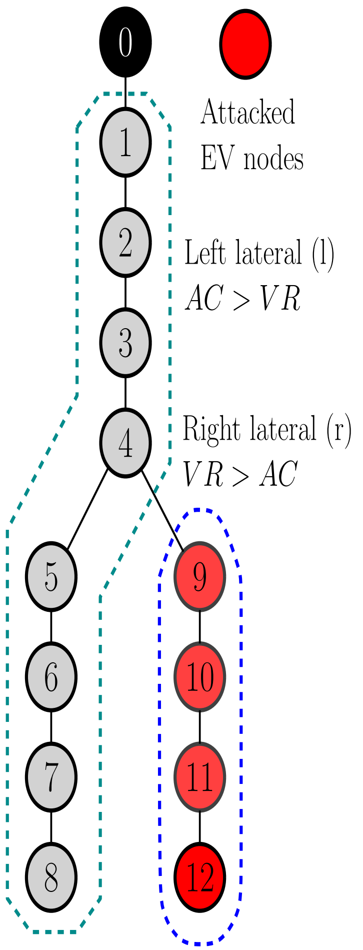
(T1) Interdiction and cascading failure analysis of power grids

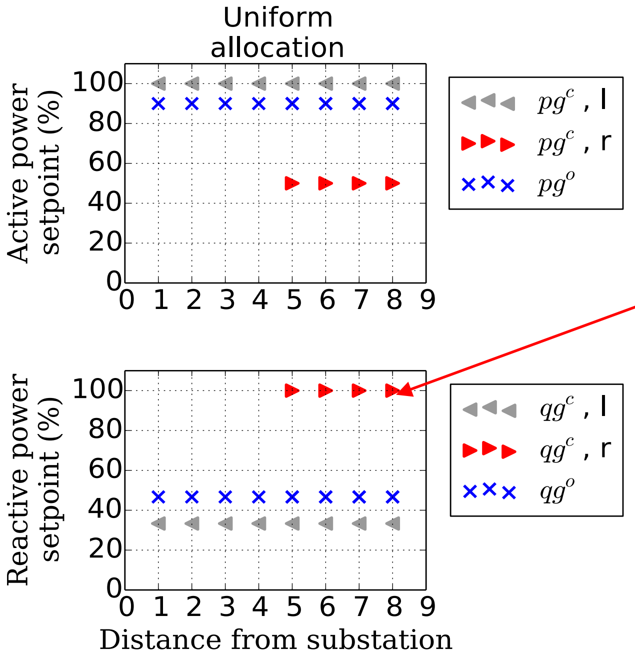
- R. Baldick, K. Wood, D. Bienstock: Network Interdiction, Cascades
- A. Verma, D. Bienstock: N-k vulnerability problem
- D. Papageorgiou, R. Alvarez, et al.: Power network defense
- X. Wu, A. Conejo: Grid Defense Planning

(T2) Data-integrity attacks

- E. Bitar, K. Poolla, A Giani: Data integrity, Observability
- H. Sandberg, K. Johansson: Secure control, networked control
- B. Sinopoli, J. Hespanha: Secure estimation and diagnosis

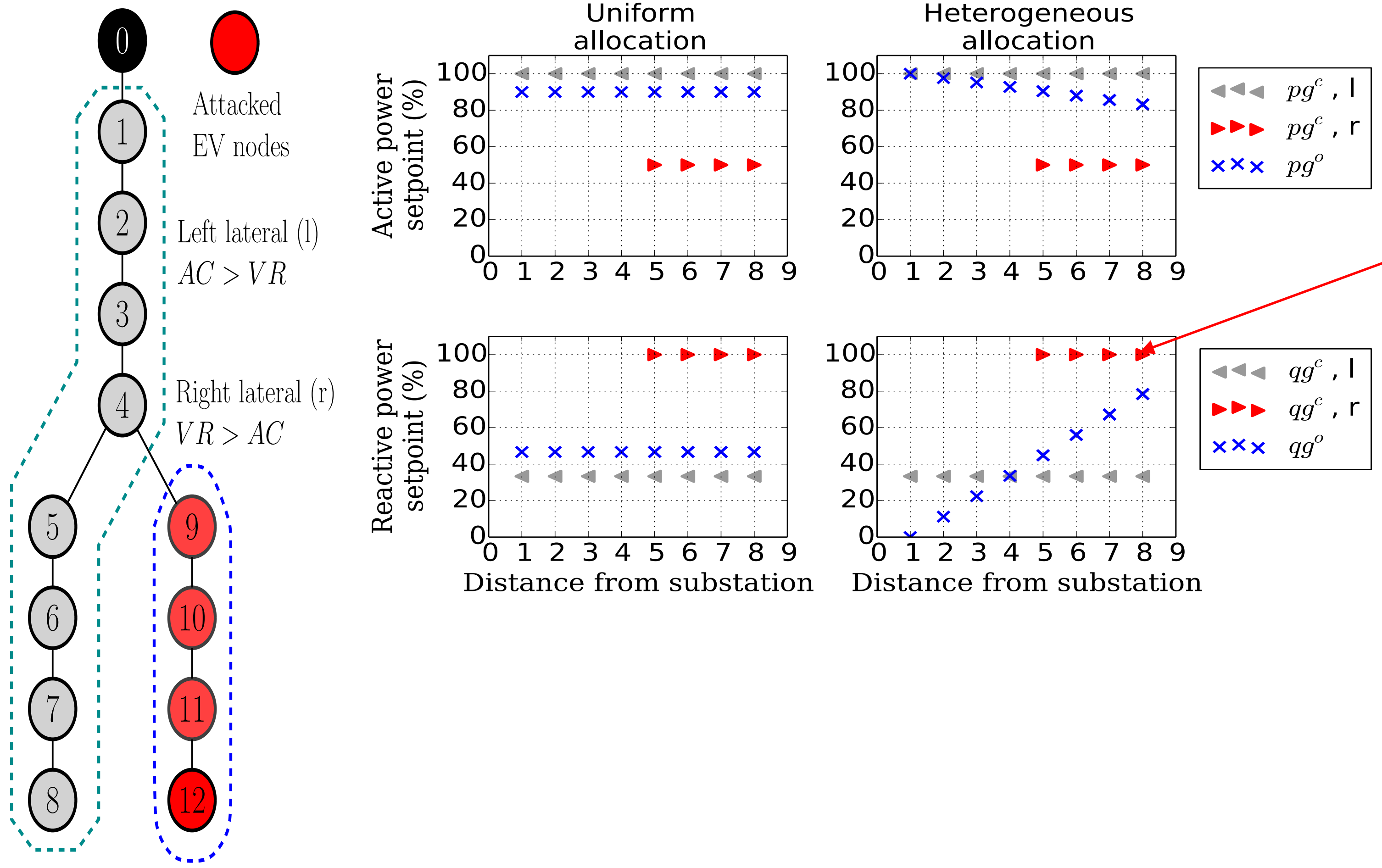
Defender Response and Allocation: Diversification





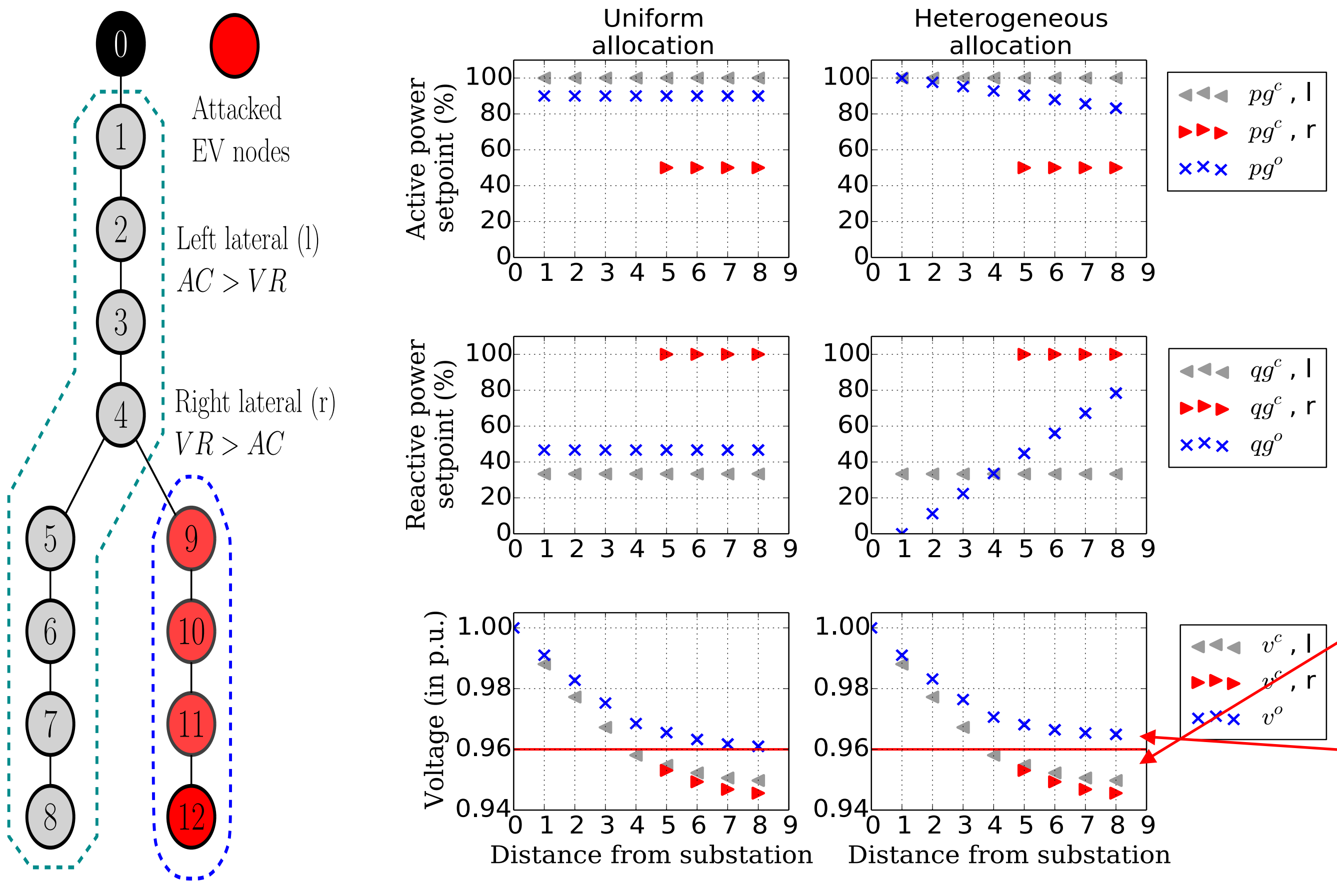
- Some DERs contribute to L_{VR} more than L_{AC}, and vice versa

Defender Response and Allocation: Diversification



- Diversification holds for “heterogeneous allocation” with downstream DERs with more reactive power

Defender Response and Allocation: Diversification

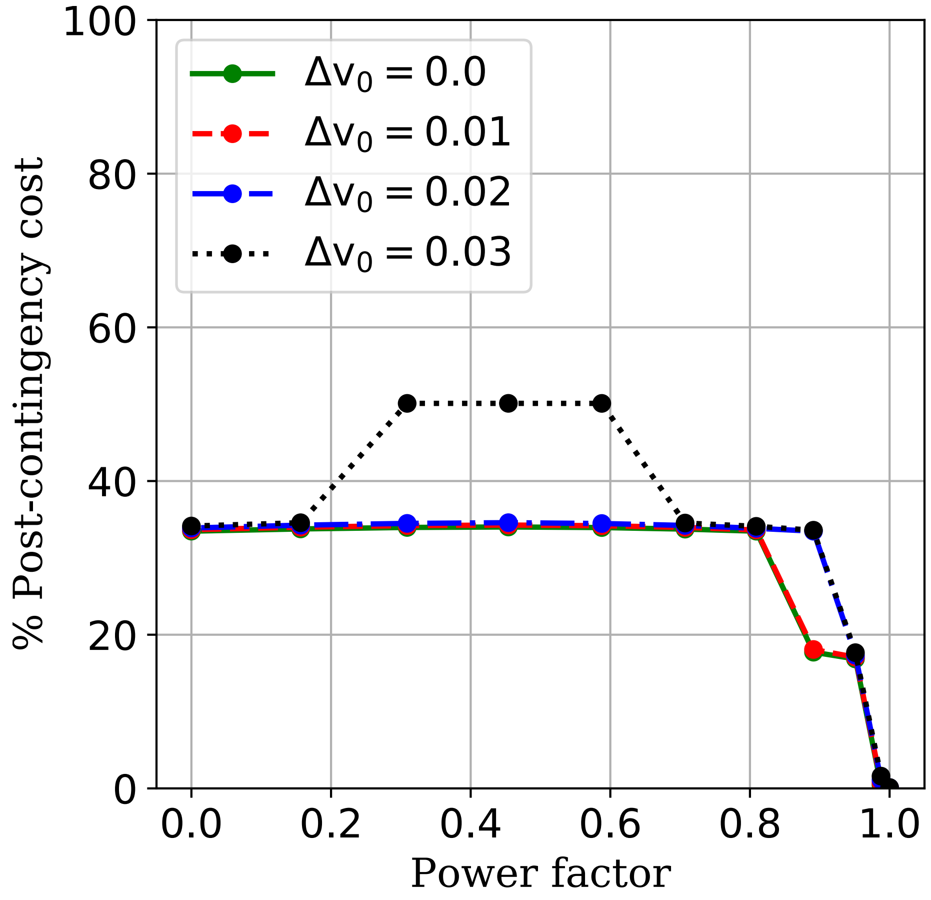


- Post-contingency losses are the same for uniform vs. heterogeneous resource allocations
- Pre-contingency voltage profile is better for heterogeneous resource allocation

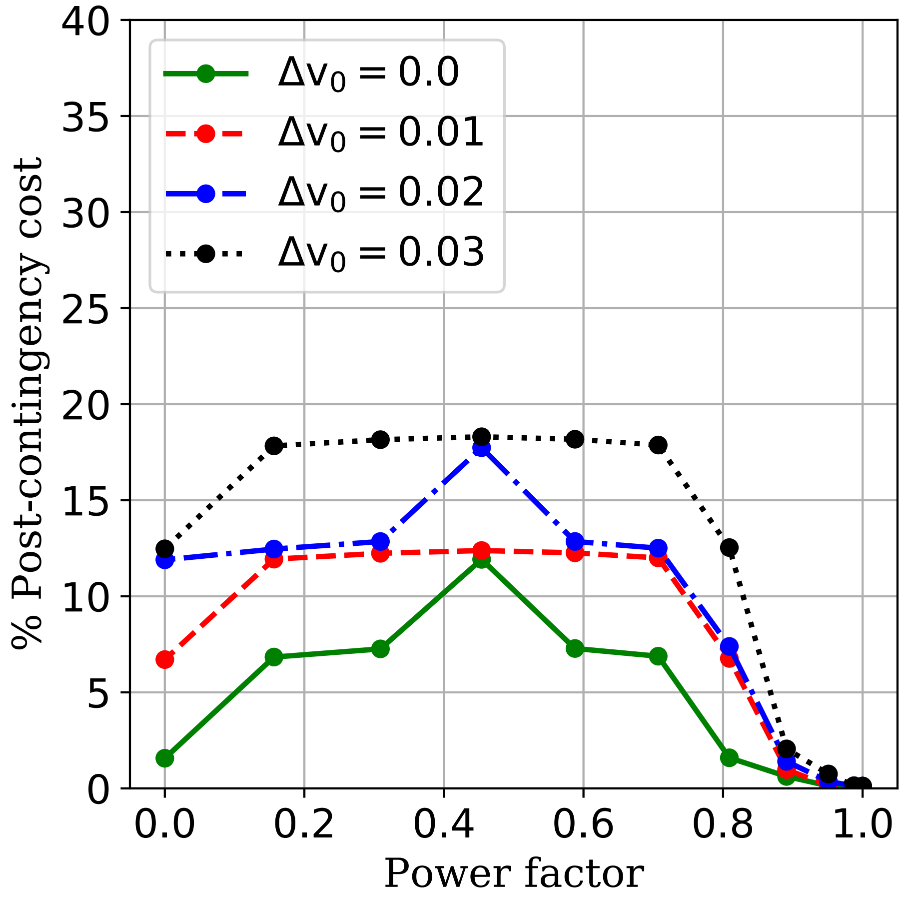
Heterogeneous resource allocation can support more loads than uniform one.

Amin

Effect of power factor on losses



N = 12



N = 36

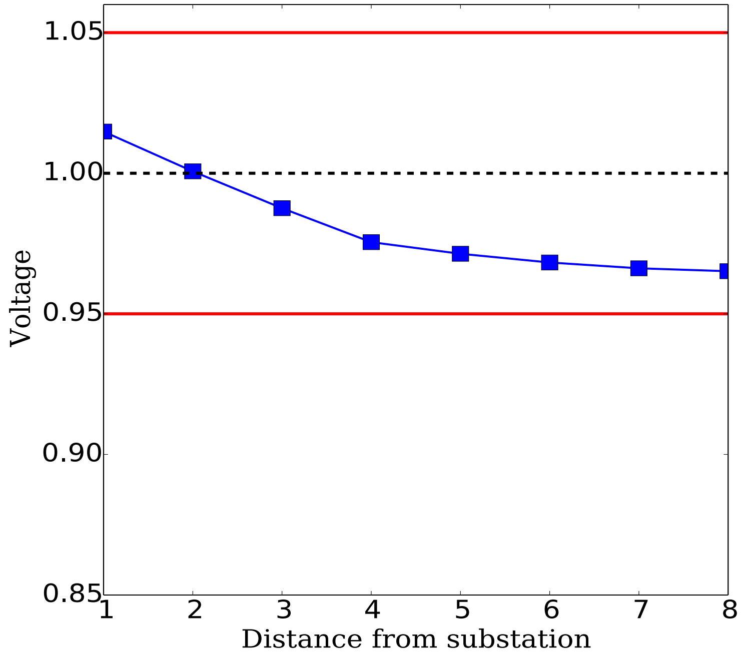
Optimal attacker set-points

Typically,

- Small line losses: in comparison to power flows
- Small impedances: sufficiently small line resistances

Assume for simplicity:

- No reverse power flows: power flows from substation to downstream

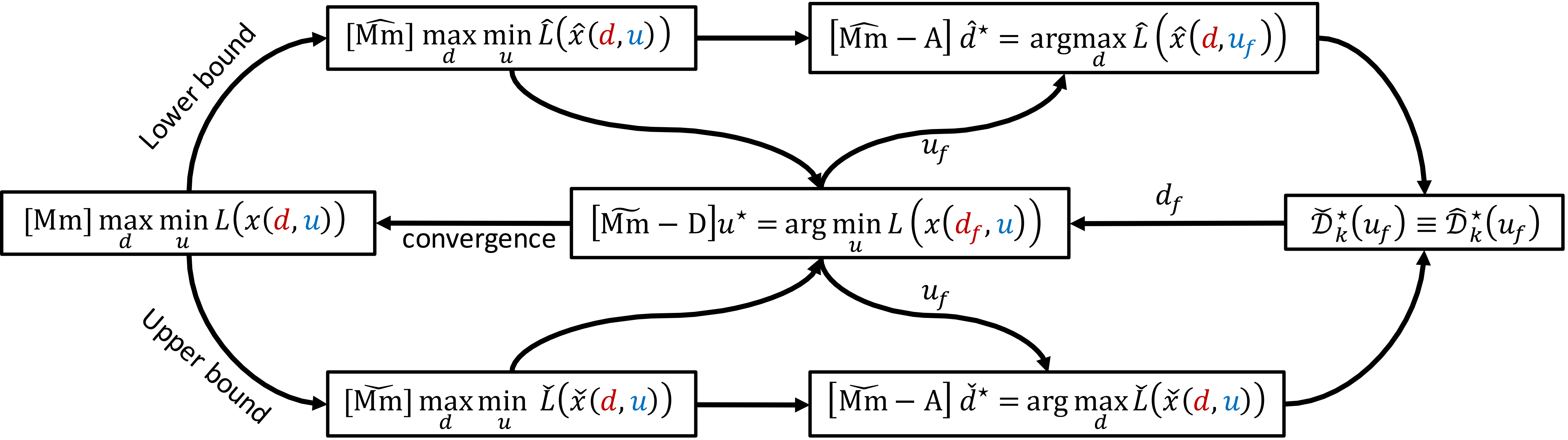


What are optimal attacker set-points?

Proposition: For a defender action ϕ, and given attacker choice of δ, the optimal attacker set-point is given by:

$$pd^{a^\star} = 0, \qquad qd^{a^\star} = -\mathbf{j}\,\overline{\boldsymbol{sg}}_{\boldsymbol{i}}$$

Greedy Approach



For fixed defender action:

- For a fixed attacker action, the ordering of nodes with respect to their voltages remain the same between $\hat{\mathcal{L}}$ and $\check{\mathcal{L}}$
- For any fixed node, the ordering of optimal attacker actions with respect to their impact on this node remains the same between $\hat{\mathcal{L}}$ and $\check{\mathcal{L}}$

Defender model

- Defender response: $u = (pr, qr, \beta)$

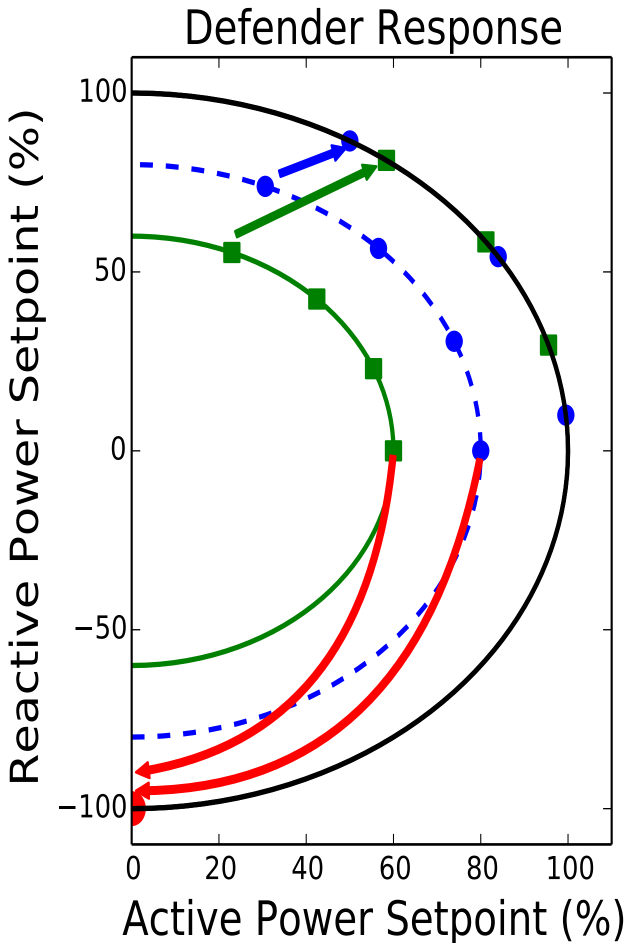
- pr_i, qr_i : active and reactive power output of reserves (controllable DGs) at node i
  - $0 \le pr_i \le \overline{pr}_i, pr_i^2 + qr_i^2 \le \bar{sr}_i^2$

- $\beta_i \in [\underline{\beta_i}, 1]$: load control parameter at node i
  - $pc_i = \beta_i \,\overline{pc}_i, \quad qc_i = \beta_i \,\overline{qc}_i$

Defender response:

How to optimally dispatch reserves?

How much load control should be exercised?



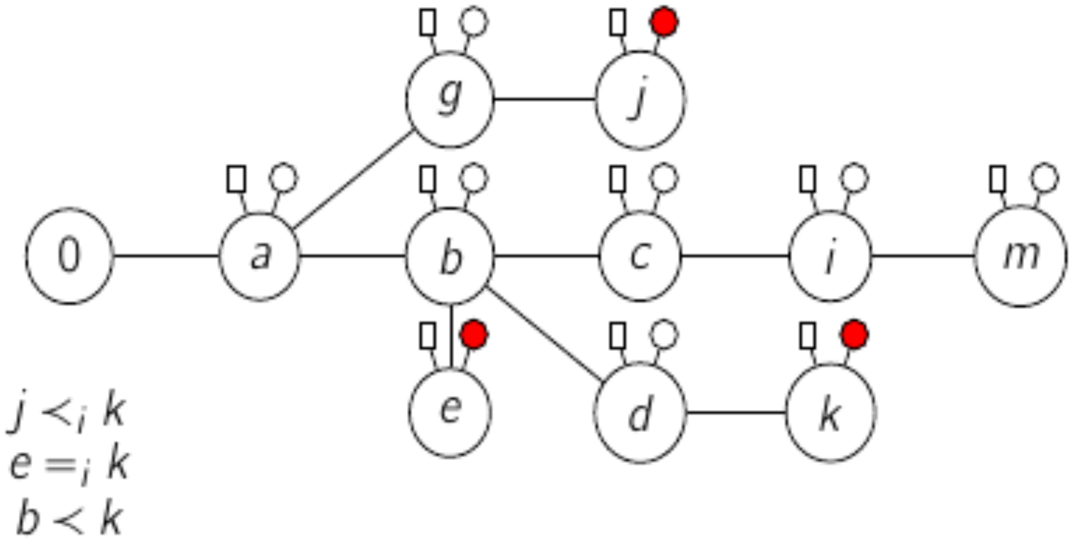
Optimal interdiction plan: fixed defender choices

Proposition

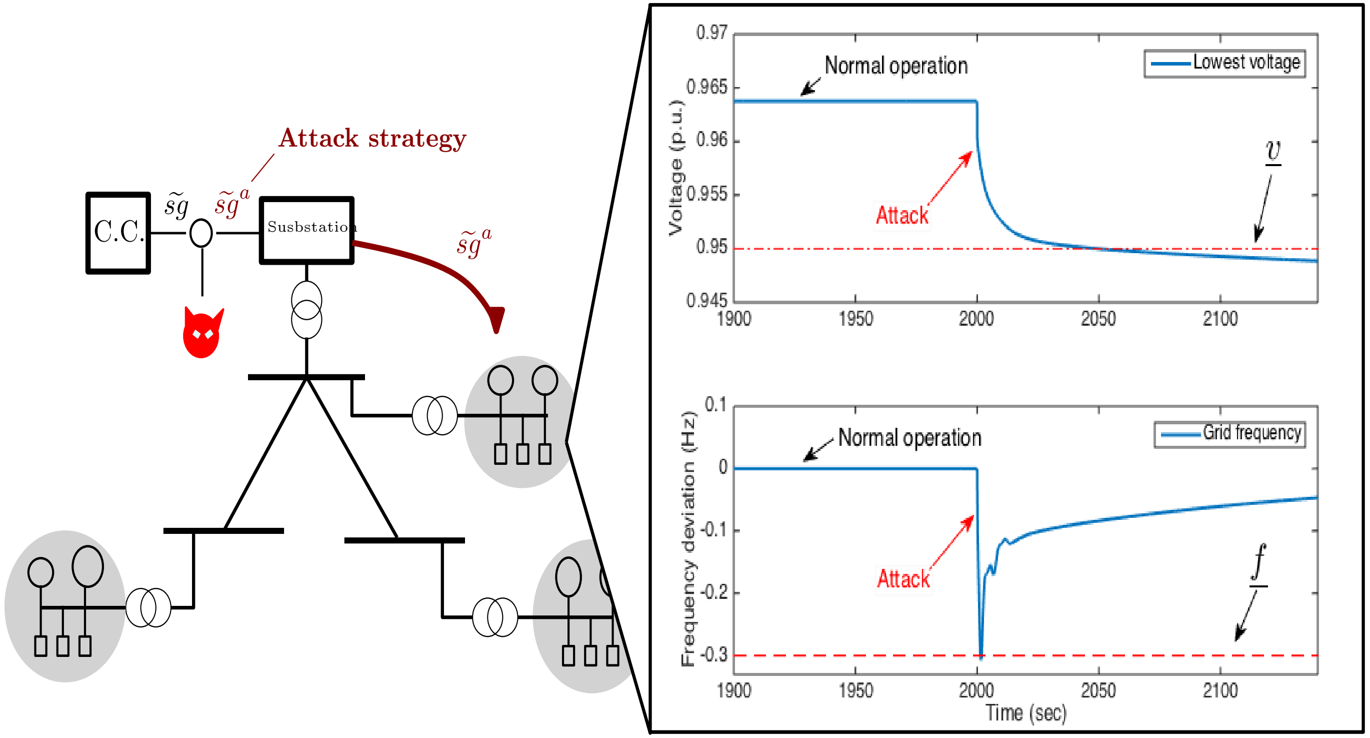
For a tree network, given nodes i (pivot), $j, k \in \mathcal{N}$:

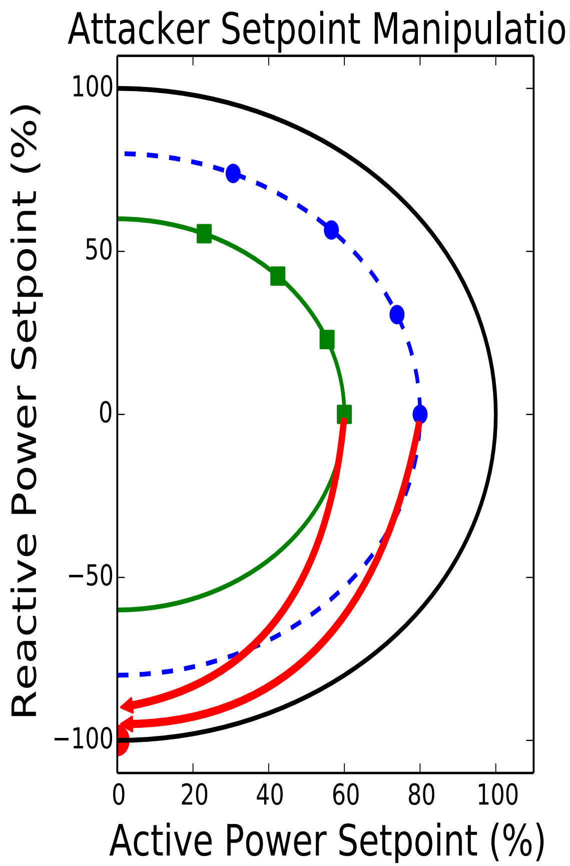
- If DGs at j, k are homogeneous and j is before k w.r.t. i, then DG disruption at k will have smaller effect on ν_i (relative to disruption at j)
- If DGs at j, k are homogeneous and j is at the same level as k w.r.t. i, then DG disruptions at j and k will have the same effect on ν_i

$$\Delta_j(\nu_i) < \Delta_k(\nu_i)$$
$$\Delta_e(\nu_i) \approx \Delta_k(\nu_i)$$



Resiliency-aware Resource Allocation (Stage II)





Stage II - Adversarial node disruptions

a. Which nodes to compromise (δ)?

b. Set-point manipulation (sp^a)?

… can include other attack models

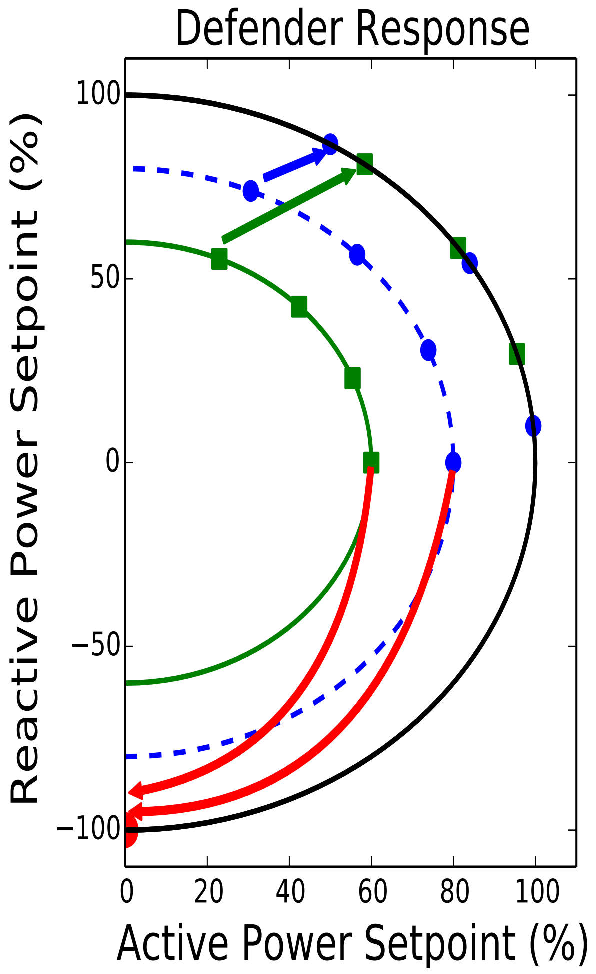
Resiliency-aware Resource Allocation

Stage I - Allocation of DERs over radial networks
a. Size and location
b. Active and reactive power setpoints (x^n)?

Stage II - Adversarial node disruptions
a. Which nodes to compromise (δ)?
b. Set-point manipulation (sp^a)?

Stage III - Optimal dispatch / response (x^c)
a. Maintain voltage
b. Exercise load control or not

Goals:
1. Determine the best resource allocation
2. Identify vulnerable / critical nodes
3. Determine optimal dispatch post-contingency



Resiliency-aware Resource Allocation

Stage II - Adversarial node disruptions

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