Washington State University

Distribution System Resilience: Modeling and Optimization

Anamika Dubey
Assistant Professor (EECS)
Washington State University, Pullman
(anamika.dubey@wsu.edu)

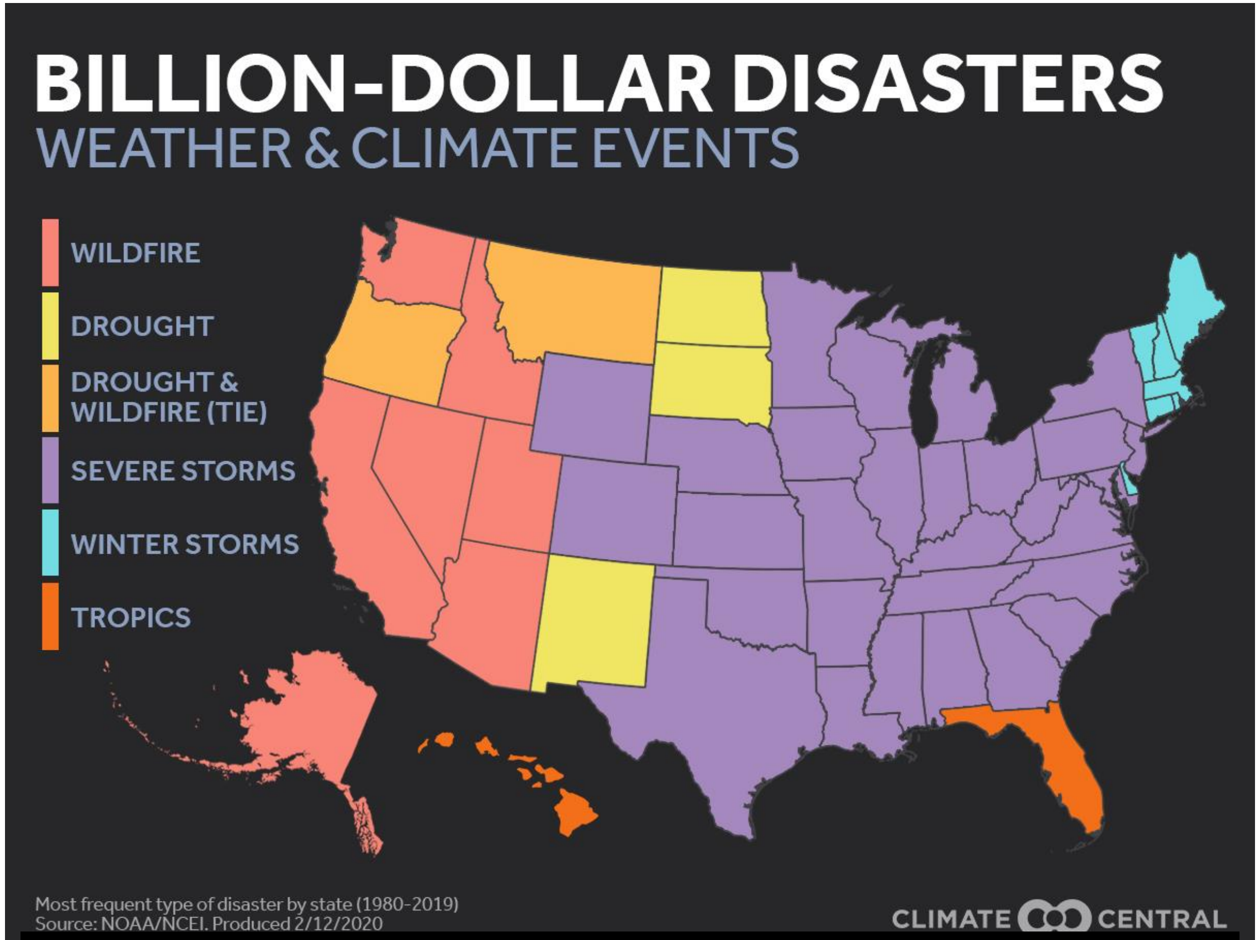
PSERC Webinar
September 21, 2021

NSF Career Award #1944142

Outline

- Motivation
- Resilient power distribution systems
- Model and Quantify Resilience
- Risk-averse optimization for resilience
- Ongoing work and future directions

Motivation



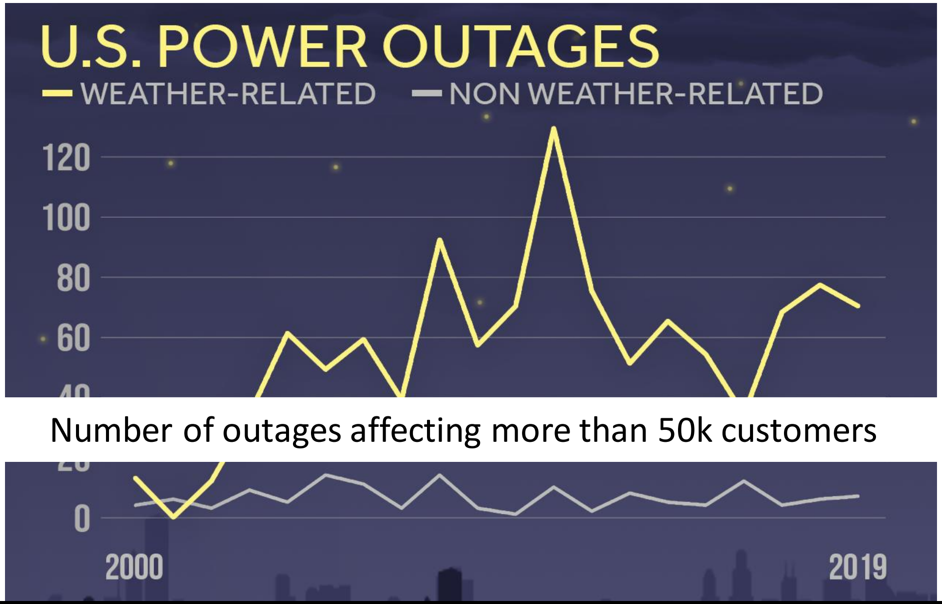
Billion-Dollar Disasters by Decade | Climate Matters (climatecentral.org)

Dramatic increase of extreme events related outages

- In the United States, extreme weather caused nearly 70 percent more power outages from 2010-2019 than the previous decade.
- Weather-related power outages cost Americans $20-55 billion annually [1].
- Utility customers experienced 1.33 billion outage hours in 2020, up 73% from roughly 770 million in 2019, according to PowerOutage.US, an aggregator of utility blackout data.

Executive Office of the President, Economic Benefits of Increasing Electric Grid Resilience to Weather Outages, (August 2013)

Motivation



Number of outages affecting more than 50k customers

[Billion-Dollar Disasters by Decade | Climate Matters (climatecentral.org)]

Region	2000-2009 Weather Related Outages	2010-2019 Weather Related Outages	Change %
Northeast	127	329	159%
Southwest	24	51	113%
Southern Great Plains	42	88	110%
Northwest	17	32	88%
Southeast	209	282	35%
Midwest	131	203	55%
HI & PR	6	3	-50%
Northern Great Plains	2	2	0%

https://medialibrary.climatecentral.org/resources/power-outages

Severe power outages caused by extreme weather events: (Most Recent)

- 2019 California power shutoffs: 3 million customers
- Texas Power Crisis (2021): 5 million customers (at its peak)
- Hurricane Ida (2021): 1.2 million customers

Increasing frequency of Extreme Weather Events:

- 1980 to 2020 - average 7.1 events/year,
- 2016 to 2020 - average 16.2 events/year

Increasing average annual cost of disasters.

Resilience: Power Distribution Systems

Outages due to damage: Transformers, utility poles, overhead distribution lines are all vulnerable to severe weather, particularly high winds, heavy rain, ice, snow.

Outages due to public safety power shutoffs: Extreme weather events (wildfire risk, increased demand due to heatwave or cold front) stressing the supply system, PSPS disrupting the power supply to millions of customers.

Avista prepares for dry conditions, planned outages during Inland Northwest heat wave

June 25, 2021

Washington firefighters rein in 20,000 acre wildfire as state dodges mass power outages

By Tim Gruver | The Center Square Jun 29, 2021

Bloomberg Green

Open the Data Dash >

Green

A Wildfire Is Pushing California Toward the Brink of Blackouts

By Lynn Doan and Naureen S Malik

July 10, 2021, 6:31 PM PDT *Updated on July 11, 2021, 6:18 PM PDT*

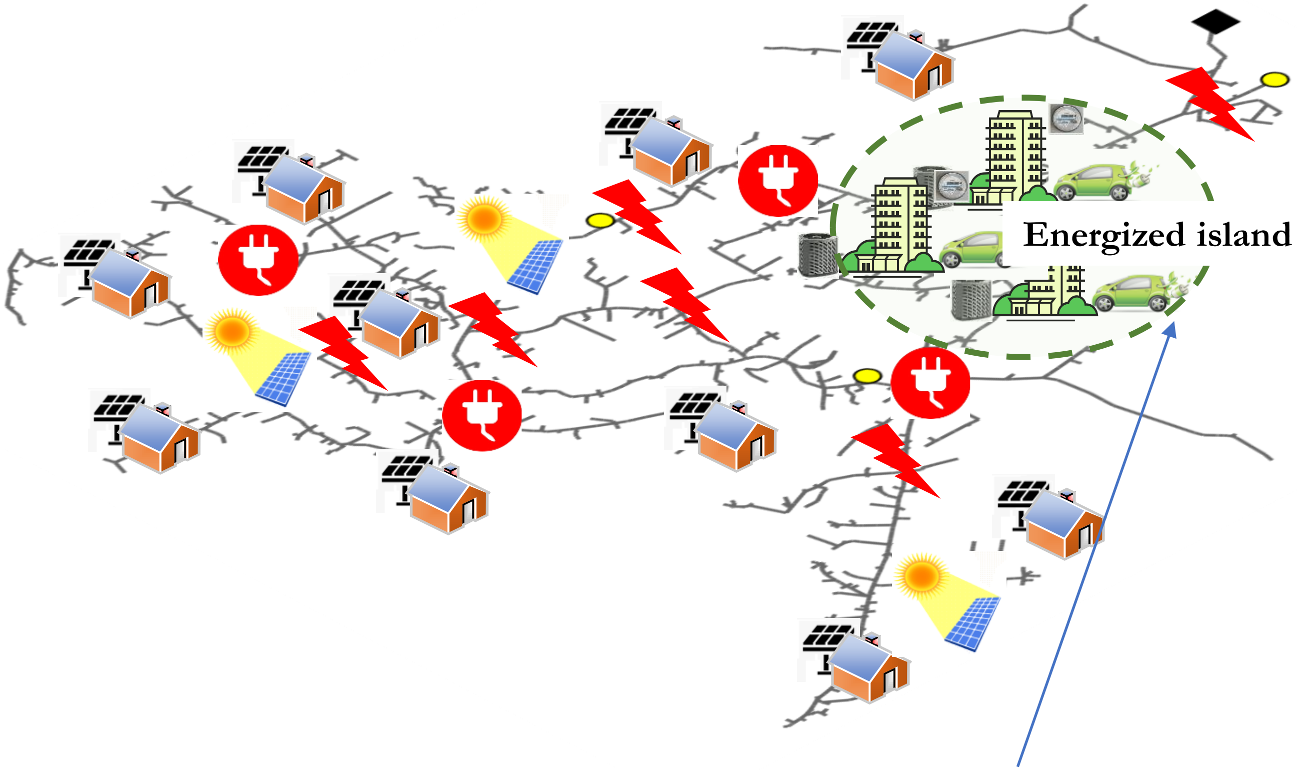
Need an expedited incorporation of resilience in the aging and stressed power distribution systems

Resilient Distribution Systems

How to keep the lights on?

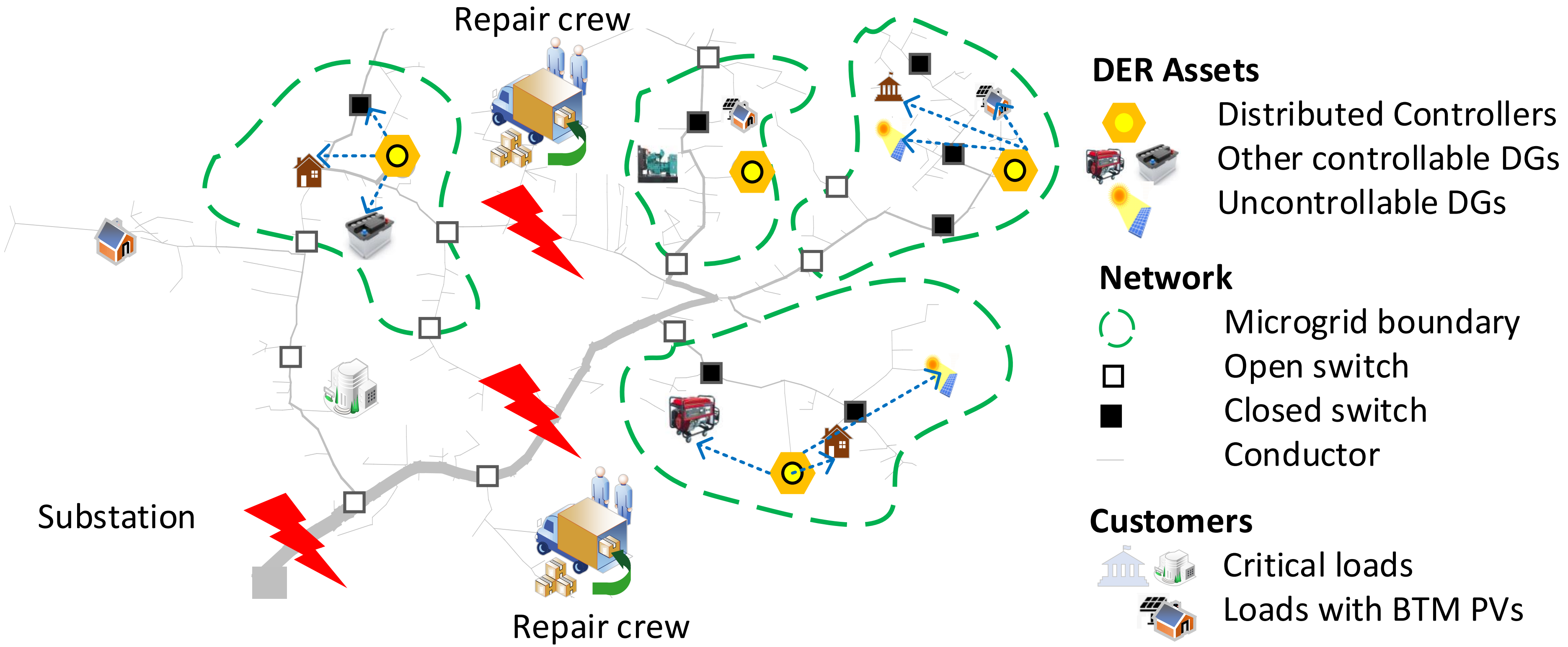
- Grid hardening: vegetation management, undergrounding lines
- Smart grid investments – added sensors, communication, decision-support systems
- Non-traditional ways of operating grid:
    - Networked microgrids
    - Demand-side flexibility to better manage rare contingencies
    - Planned rolling/rotating blackouts

An Example of Improving Resilience to Extreme Event



Intentional Islanding using Local Generation Resources to support intentional islands.

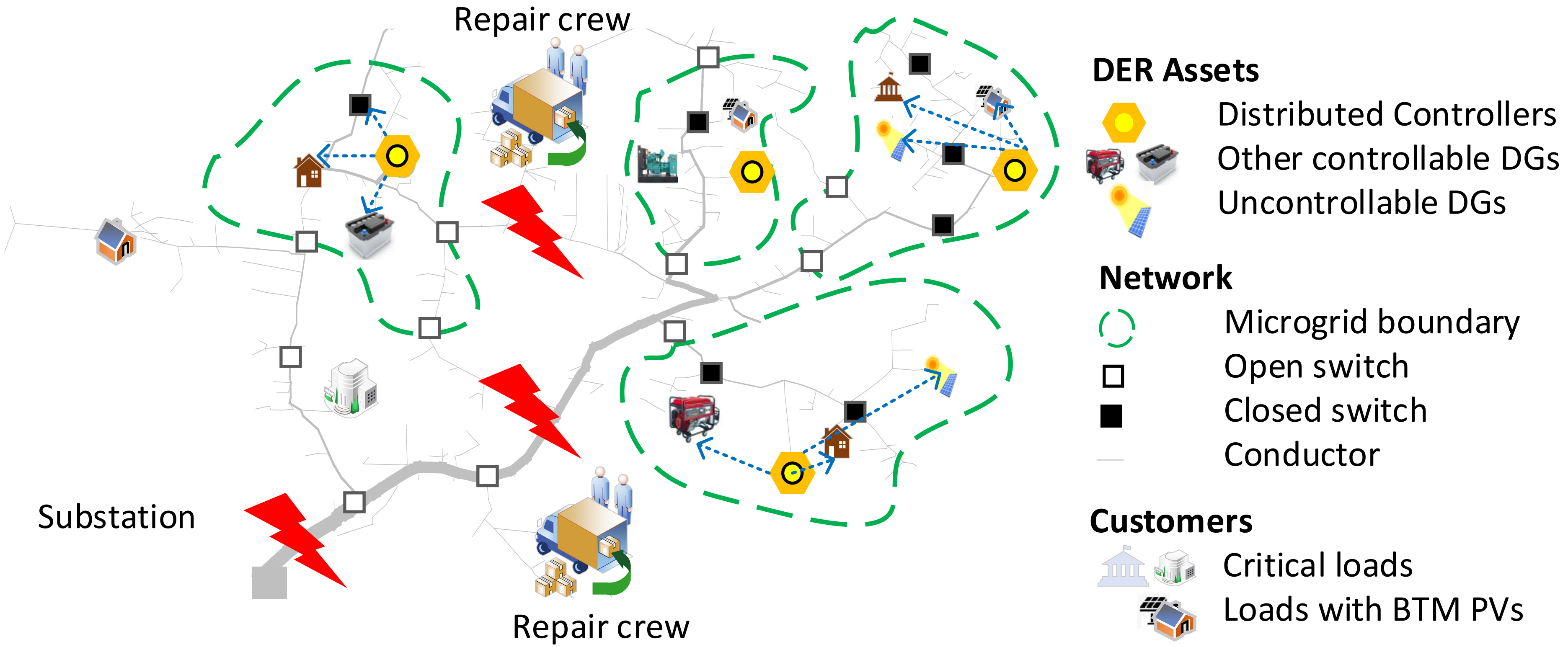
What is needed? – Plan and Operate for Resilience



Long-term planning:

- Where and what lines/poles to harden?
- Where to place new devices for added flexibility: tie switches, DGs, storage?
- How prioritize different long-term planning activities?

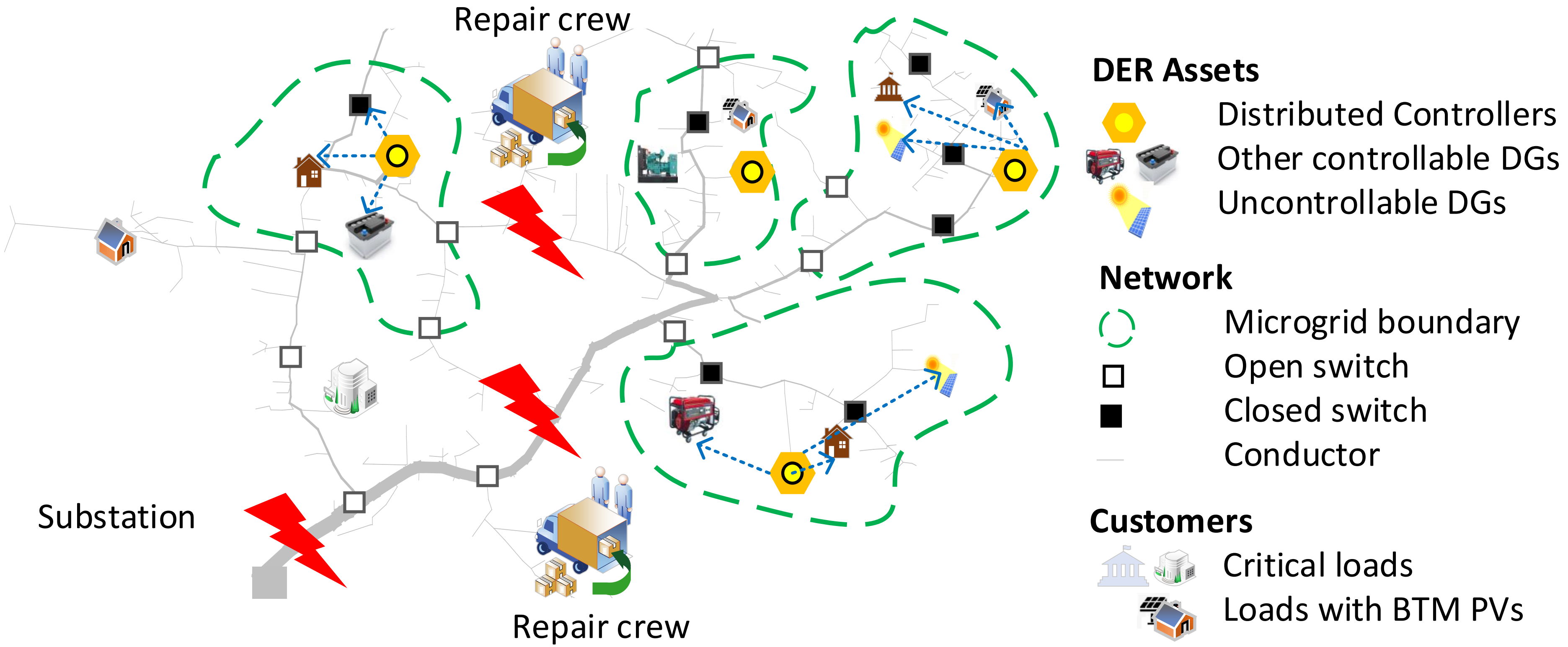
What is needed? – Plan and Operate for Resilience



Operational planning (preparation for upcoming event):

- Planned rolling/rotating blackouts, proactive islanding, plan mobile energy resources
- Plan disaster recovery – dispatch crew, line and poles
- Need to capture time-varying impacts of an upcoming event.

What is needed? – Plan and Operate for Resilience



- These solutions cost a lot and planning for rare events need to justify the cost
- These solutions need to reflect the value they provide in mitigating the risks imposed by the High Impact Low Probability (HILP) events

Distribution System Resilience Modeling and Optimization

A framework for planning distribution systems for resilience

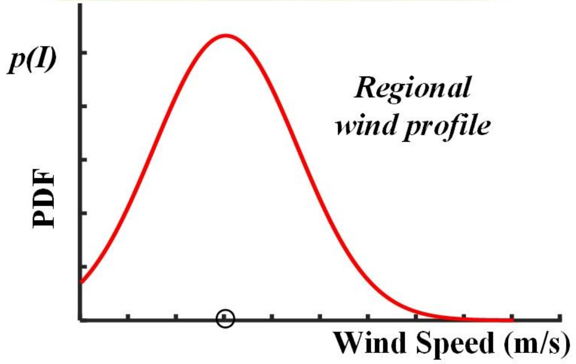
- Non-traditional ways of operating grid
- Attention to HILP events
- Modeling and Computational Challenges

Distribution grid planning in response to HILP Events:

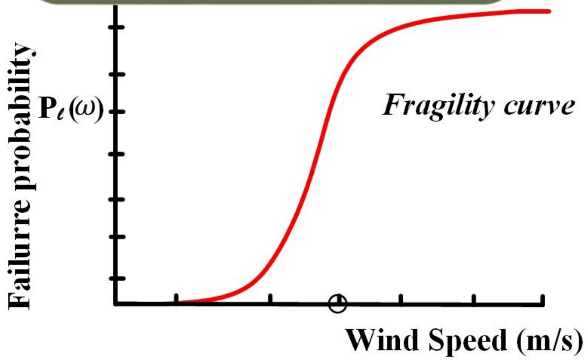
- **Infrastructural Risk modeling: Characterize the impacts of HILP events on the power grid infrastructure**
- **Risk-averse optimization models for Long-term and Operational planning: Add operational flexibility to the grid to improve their response during HILP events**

Overall Approach - HILP Events and Resilience (Power Distribution Systems)

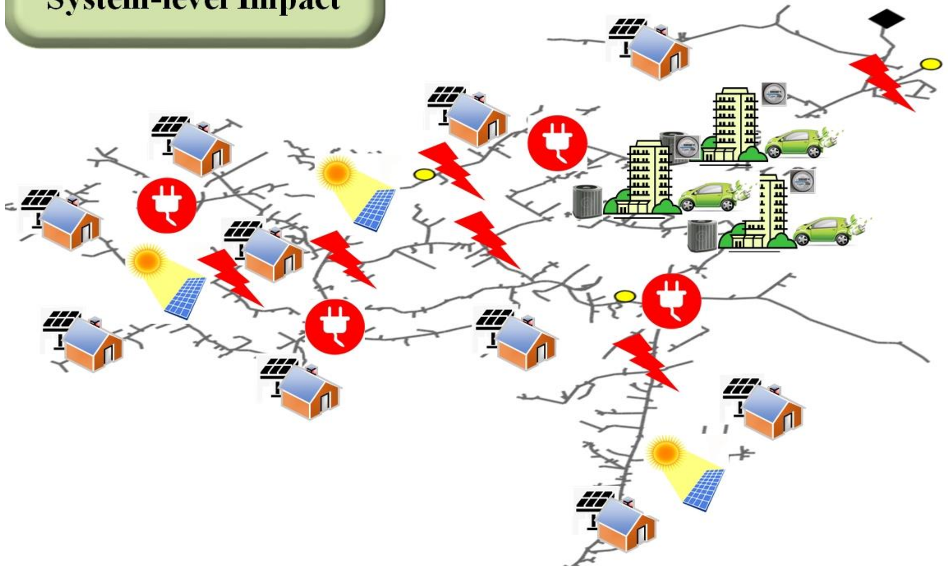
Event modeling



Component-level fragility

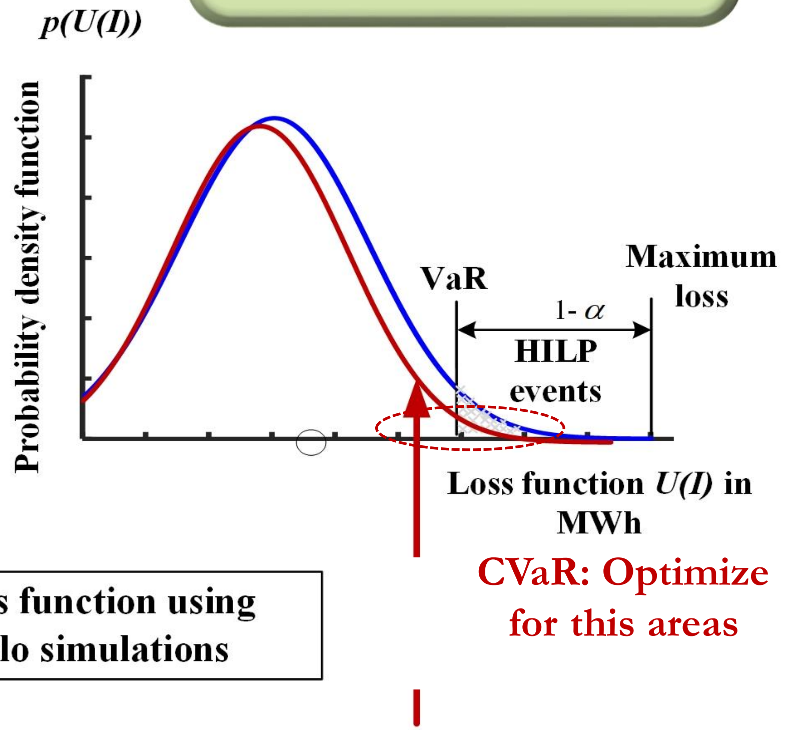


System-level Impact



- One possible system damage scenario
- How to quantify the impacts or highest loses?
- Probabilistic risk-measure

Probabilistic Loss Function



PDF for Loss function using Monte-Carlo simulations

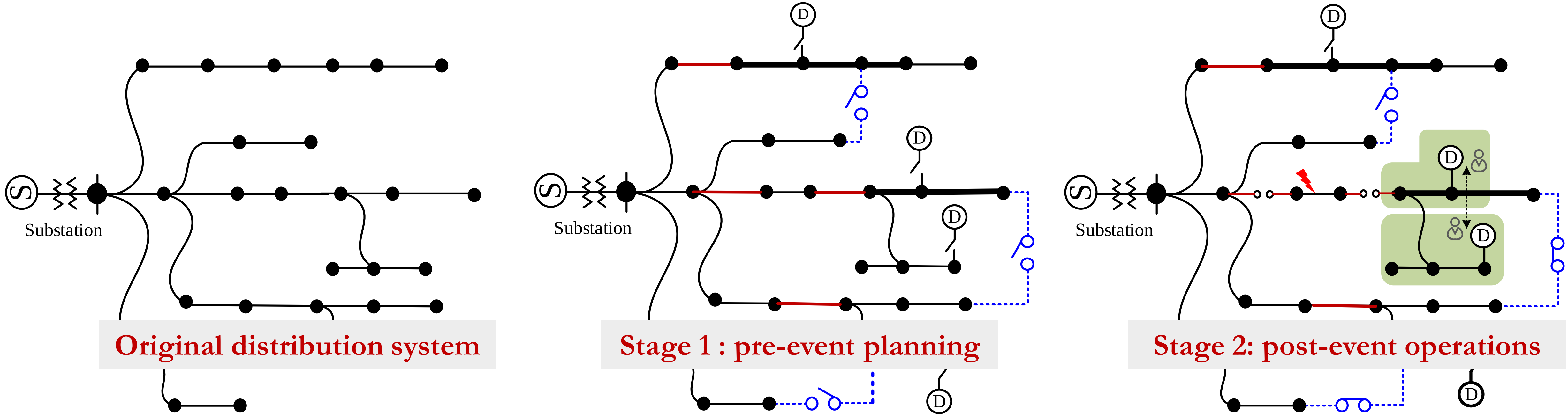
Possible remedial schemes (non-traditional ways of grid operation)

Resilience Planning: Two-stage Stochastic Program

Optimize CVaR metric - Resilience planning of power distribution system

A two-stage stochastic optimization formulation

- **Stage 1 (pre-event) planning decisions - line hardening, DG placement, etc. (Sampling and impact assessment via simulation framework)**
- **Stage 2 (post-event) operational decisions - DG-assisted restoration, intentional islanding (solve optimal coordination problem)**



Model and Quantify

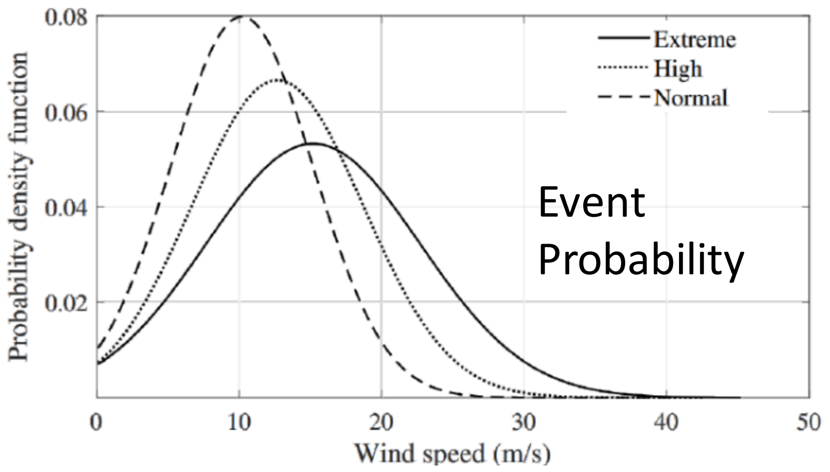
How to characterize High-impact and Low-probability (HILP) events for their impacts on the power grid infrastructure?

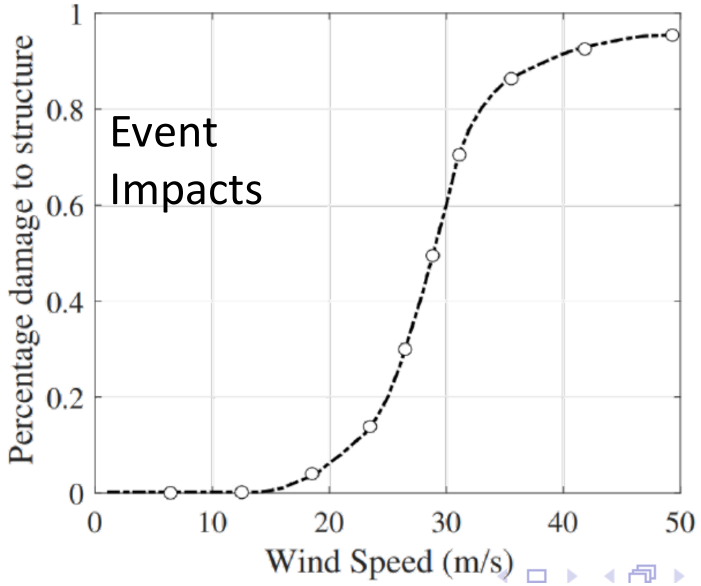
Risk-based Resilience Quantification

How to characterize High-impact and Low-probability (HILP) events for their impacts on physical infrastructure?

Modeling the spatio-temporal risks of an extreme event on the resilience of the critical infrastructure systems;

- Risk-based metric for quantifying the impacts of HILP events.
- Relating the impacts with the planning measures to reduce the risks of HILP events
- Mechanism to identify trade-offs among planning measures by evaluating their impacts on risks posed by HILP events.





- Shiva Poudel, Anamika Dubey, and Anjan Bose, “Risk-based Probabilistic Quantification of Power Distribution System Operational Resilience,” IEEE Systems Journal on Aug 2019.
- Shuva Paul, Shiva Poudel, A. Dubey, “Planning for Resilient Power Distribution Systems using Risk-Based Quantification and Q-Learning,” accepted, IEEE PES GM 2021.

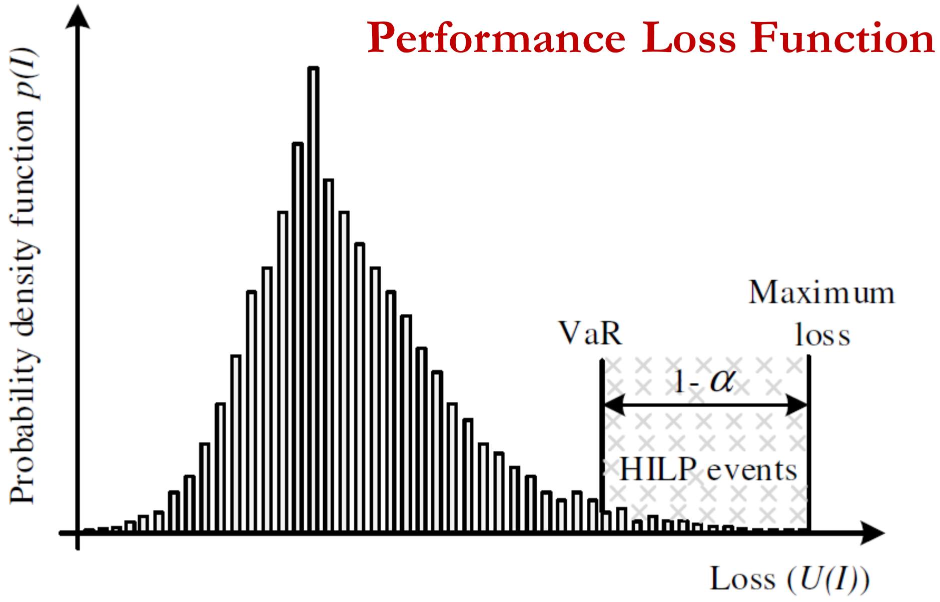
Risk-based Resilience Quantification

Define two risk-based resilience metrics

1. Value-at-risk (VaR_α): maximum loss expected over a given time period for a specified degree of confidence, α.

$$\psi(\zeta) = \int_{U(I)\leq\zeta} p(I)dI$$

$$VaR_\alpha = \min\{\zeta \in \mathbb{R} : \psi(\zeta) \geq \alpha\}$$



2. Conditional value-at-risk ($CVaR_\alpha$): expected system loss (MWh) due to the top $(1-\alpha)\%$ of highest impact events.
   - measures the resilience of the system as impacted by HILP events.

$$CVaR_\alpha = (1-\alpha)^{-1} \int_{U(I)\geq VaR_\alpha} U(I)\ p(I)\ dI.$$

R. T. Rockafellar and S. Uryasev,"Optimization of conditional value-at-risk" Journal of Risk 2 (2000), 493-517

N. Noyan, Risk-averse two-stage stochastic programming with an application to disaster management, Computers & Operations Research, vol. 39, no. 3, pg. 541-559, Mar. 2012

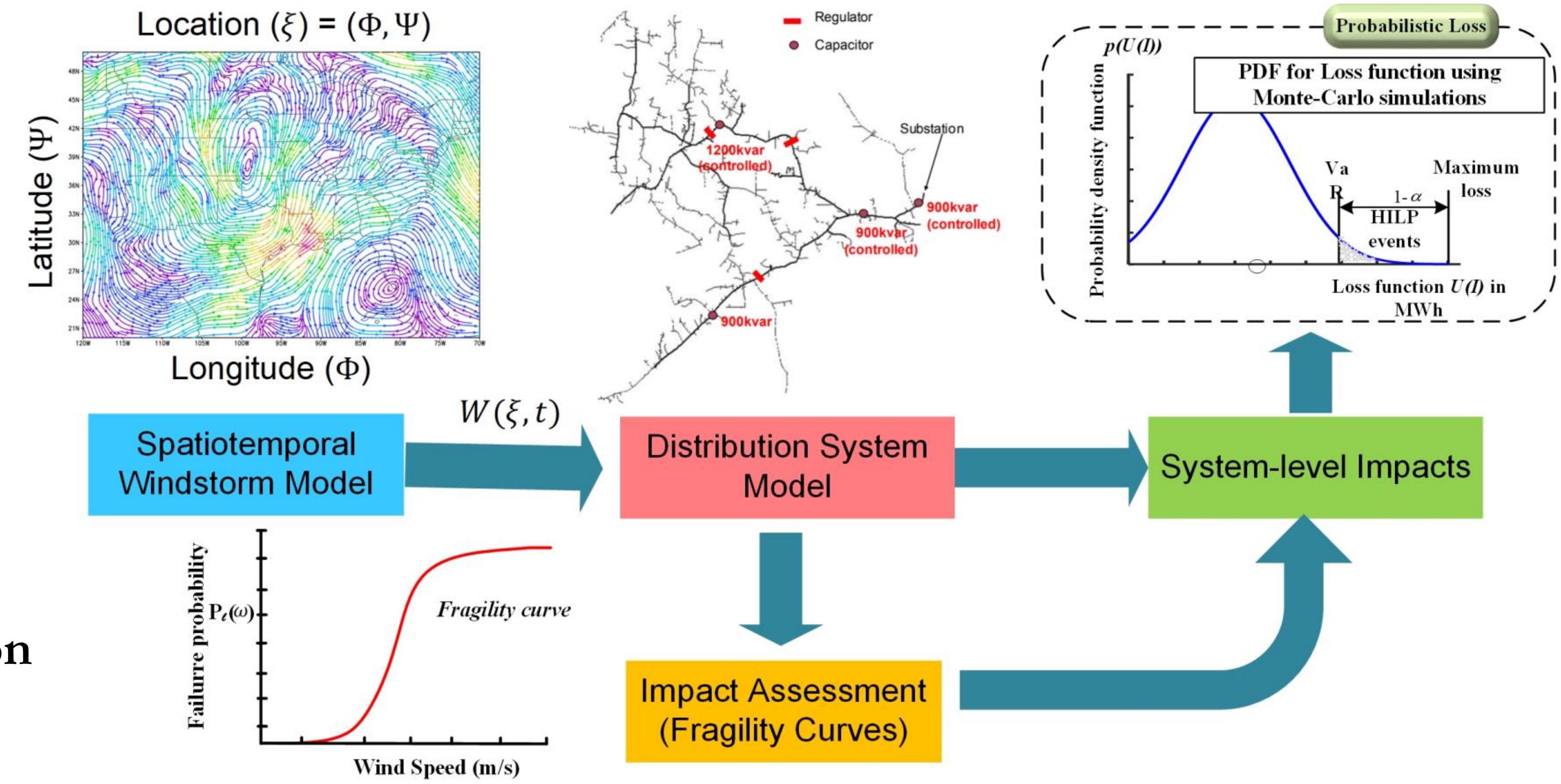
Quantifying Resilience: Risk Modeling

A simulation-based approach

Data generation

- Opensource data for event modeling
- Hypothetical fragility curves
- Monte-Carlo simulations

Probabilistic quantification of the impacts (risks)



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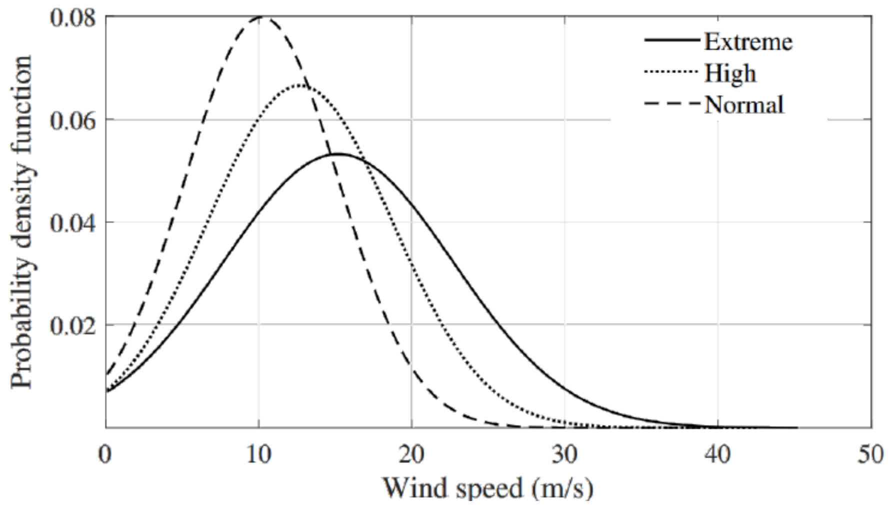
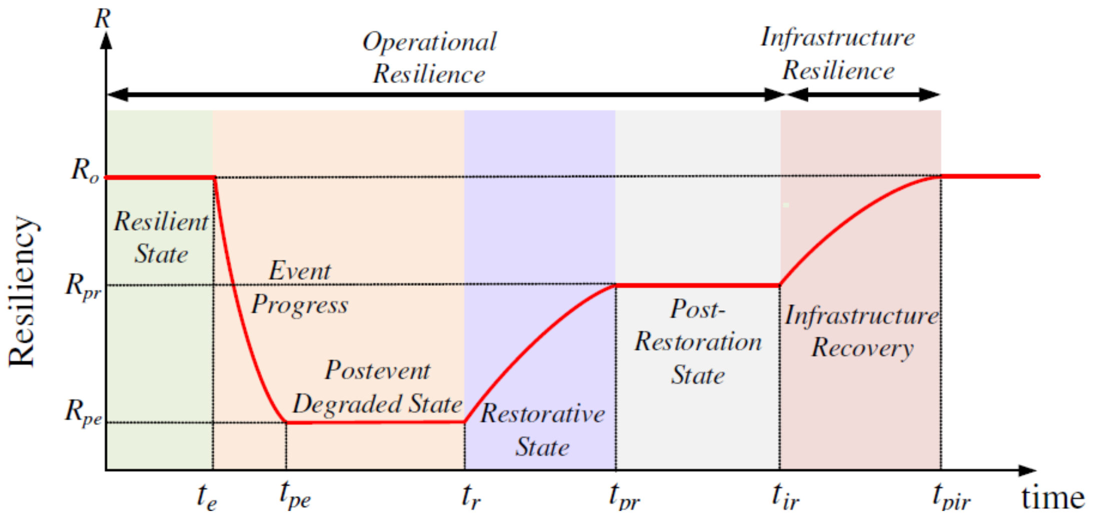
Probabilistic Event and System Performance loss

- An event is characterized by two parameters:
  - intensity of the event, I, modeled as a random variable and
  - the probability of its occurrence, $p(I)$
- System performance loss when impacted by an event I, $U(I)$
  - function of loss, $L(I)$ and time of the event, $t(I)$
  - $U(I) = f\left[L(I),\ t(I)\right];\ in\ MWh$





M. Panteli and P. Mancarella, “The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience,” IEEE Power Energy Mag., vol. 13, no. 3, pp. 58–66, May/Jun. 2015

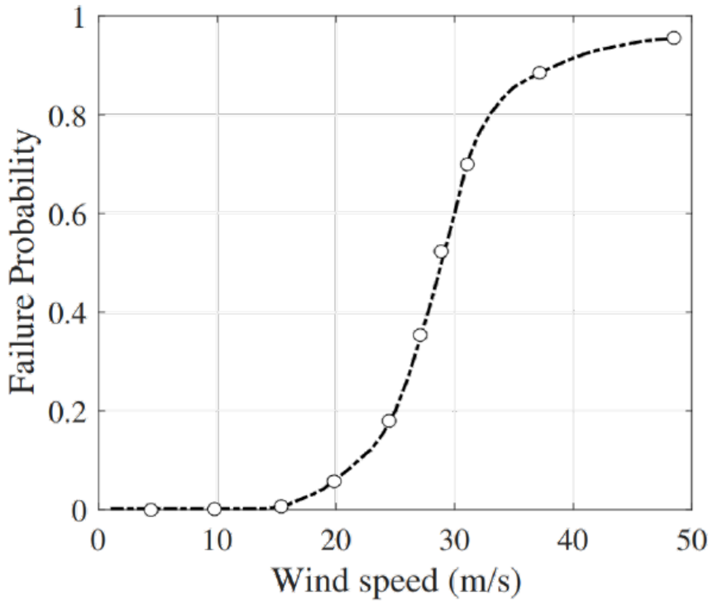
Component Level Impact Model

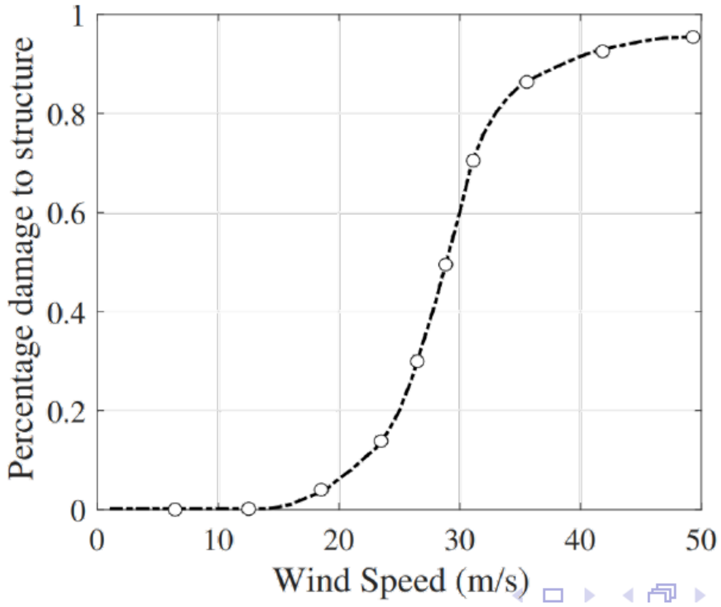
- Probabilistic component-level fragility curve
- Generate component damage scenarios

$$P_l(\omega) = \begin{cases} P_l^n, & \text{if } \omega < \omega_{critical} \\ P_l(\omega), & \text{if } \omega_{critical} < \omega < \omega_{collapse} \\ 1, & \text{if } \omega > \omega_{collapse} \end{cases}$$

$$F_l^c(\omega) = \begin{cases} 0, & \text{if } P_l(\omega) < r_k \\ 1, & \text{if } P_l(\omega) > r_k \end{cases}$$

where, $r_k \sim \mathcal{U}(0,1)$

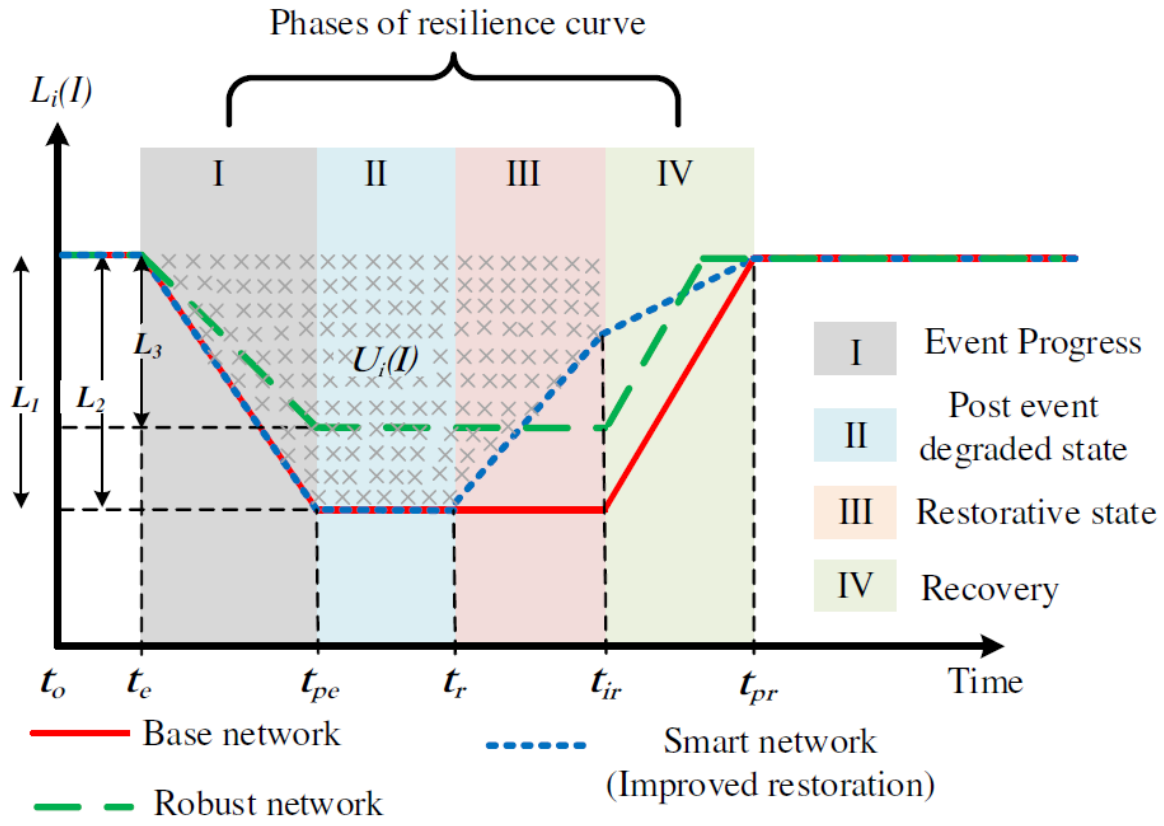




System-level Impact Model

- System performance: A simplified resilience curve

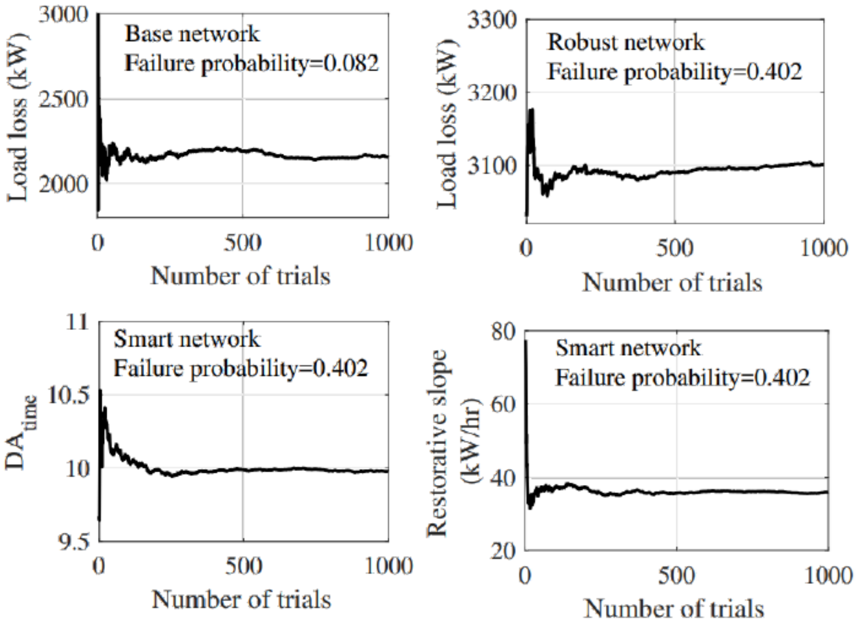
- Initial system loss
  - Phase I ($t_{pe} - t_e$)
- Damage assessment
  - Phase II ($t_r - t_{pe}$)
- Restoration and active islanding scheme
  - Phase III ($t_{ir} - t_r$)

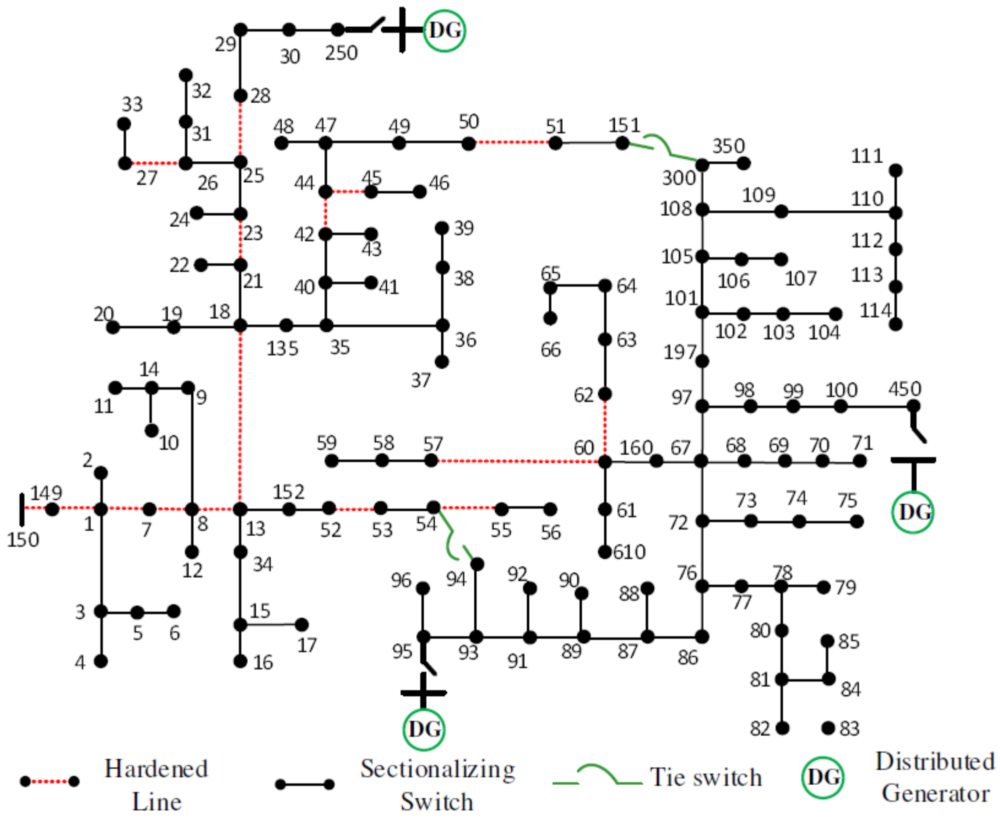


- Calculate system performance loss: **Area under the curve**

Simulated Results

- IEEE 123-bus test feeder
- Smart network: tie switches and DGs
- Robust network: hardening of lines
- Monte-Carlo simulations: 1000 trials





	DG-95	DG-250	DG-450
kW capacity	272.35	160.65	180.21
kVaR capacity	105.6	85.62	98.56

Results

- **The approach can incorporate planning measures in place to reduce the risks of HILP events**
- **Used for Resilience oriented design of power distribution system: example case of optimal line hardening Q-learning framework based on risk metrics**

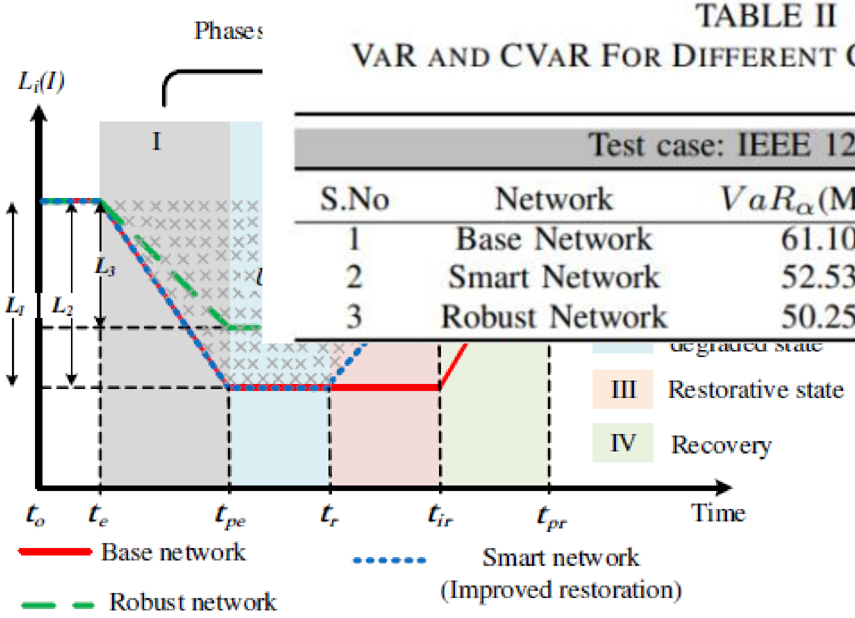


TABLE II
VaR AND CVaR FOR DIFFERENT CASES WITH $\alpha = 95\%$

Test case: IEEE 123-bus			
S.No	Network	VaR_α(MWh)	$CVaR_\alpha$(MWh)
1	Base Network	61.10	68.22
2	Smart Network	52.53	56.73
3	Robust Network	50.25	57.52

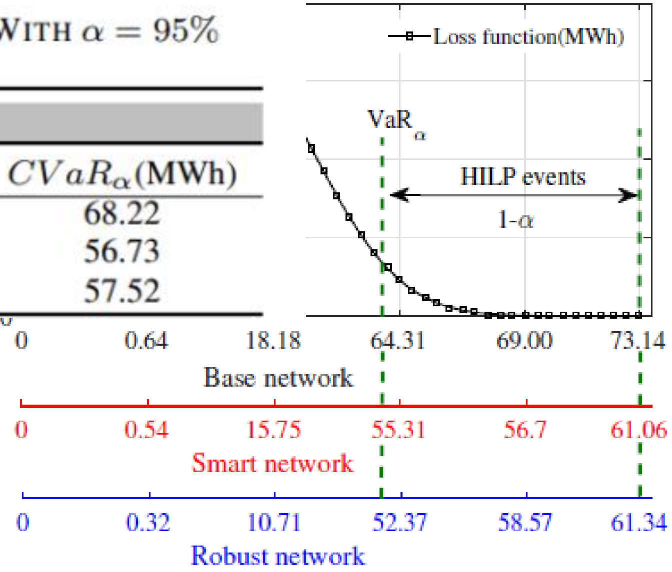
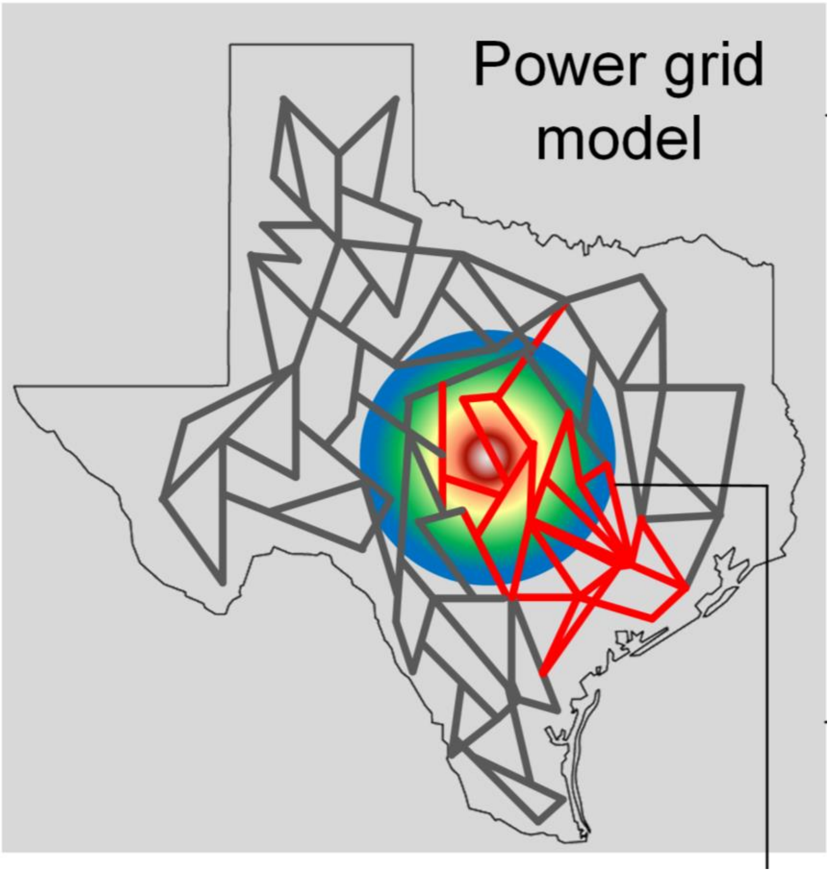


Figure 3: (a) Approximated resilience curve for an event. The different colored lines correspond to effects of proactive planning: (1) Base network - does not include any proactive planning measure; (2) Smart network - includes DERs to support intentional islands; (3) Robust network - includes hardening of the distribution lines. (b) System performance loss (in MWh) during extreme wind for base, smart, and robust network.

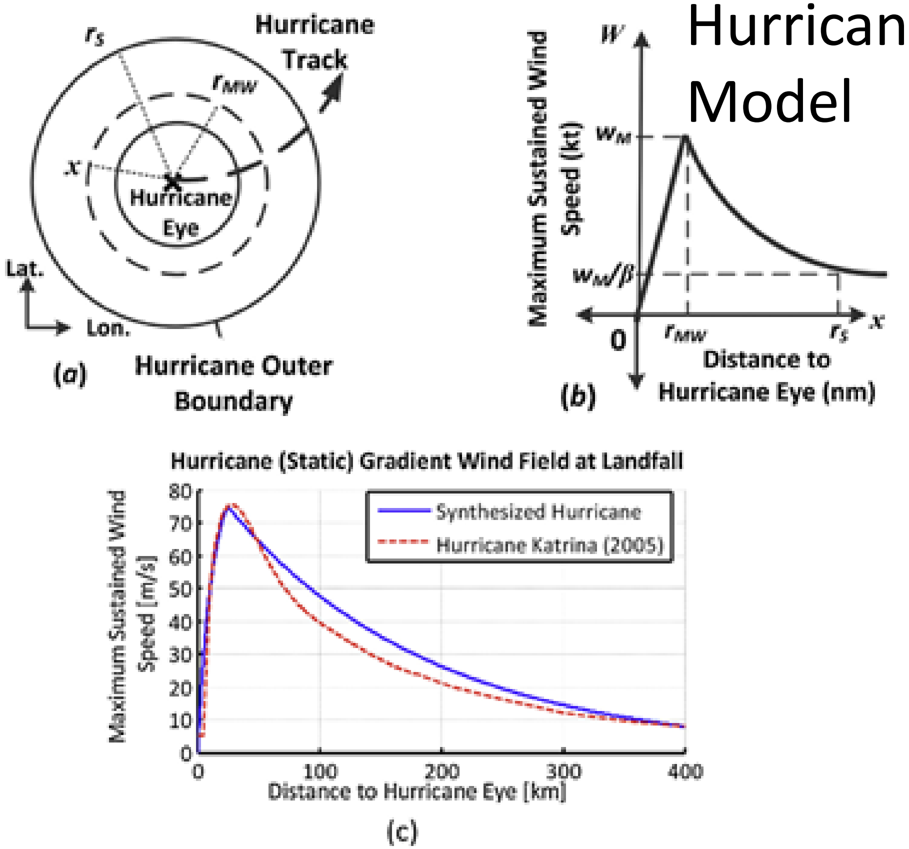
Shiva Poudel, Anamika Dubey, and Anjan Bose, “Risk-based Probabilistic Quantification of Power Distribution System Operational Resilience,” IEEE Systems Journal, Aug 2019.

Resilience Metric at the Bulk Grid Level

Large geographic area, need to capture time-varying effects of the extreme event, use the time-varying impact model for operational planning over multiple time-period



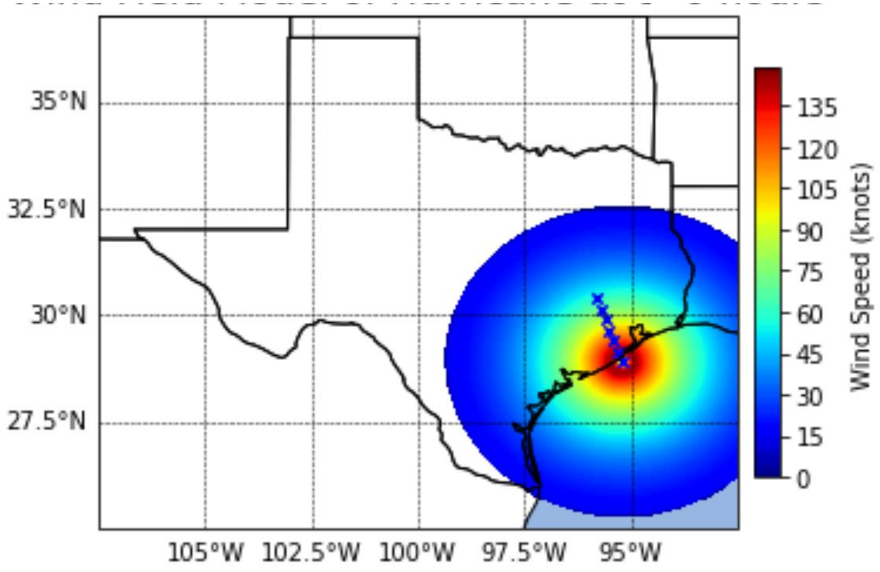
Hurricane Model

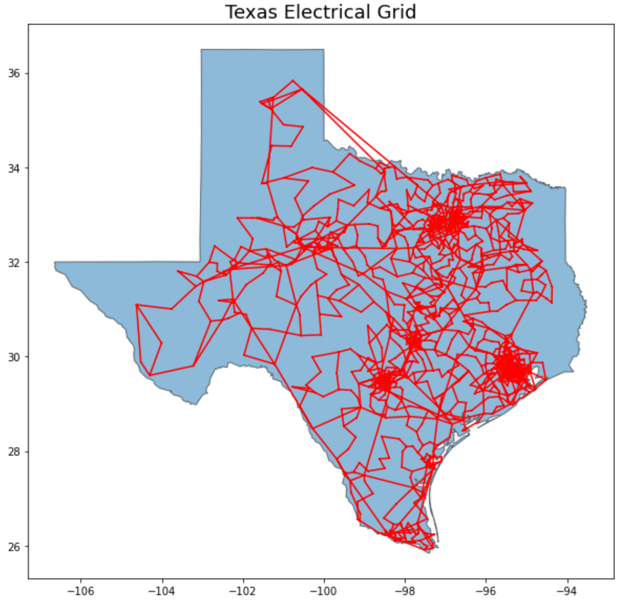


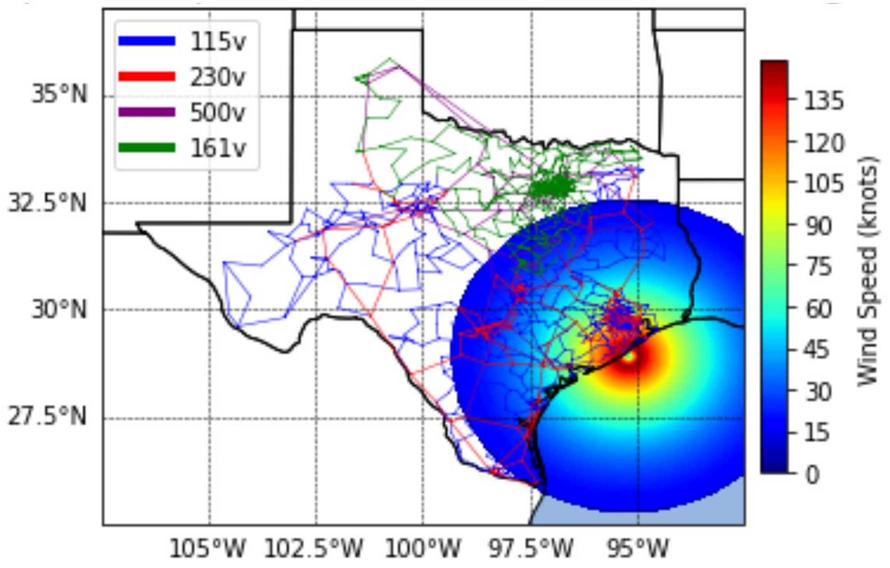
P. Javanbakht, S. Mohagheghi, “A risk-averse security-constrained optimal power flow for a power grid subject to hurricanes”, Electric Power Systems Research, Nov. 2014

Resilience Metric at the Bulk Grid Level: Simulation

- **Hurricane Model - Hurricane parameters from real data: National Oceanic and Atmospheric Administration[1], parameters are randomly sampled to generate a single scenario of Hurricane[2]**
- **Power System Model - Texas 2000 bus synthetic model is used as a test case[3] to evaluate system-level impacts**
- **Time-varying probabilistic systems loss is calculated as hurricane eye moves in consecutive time steps**



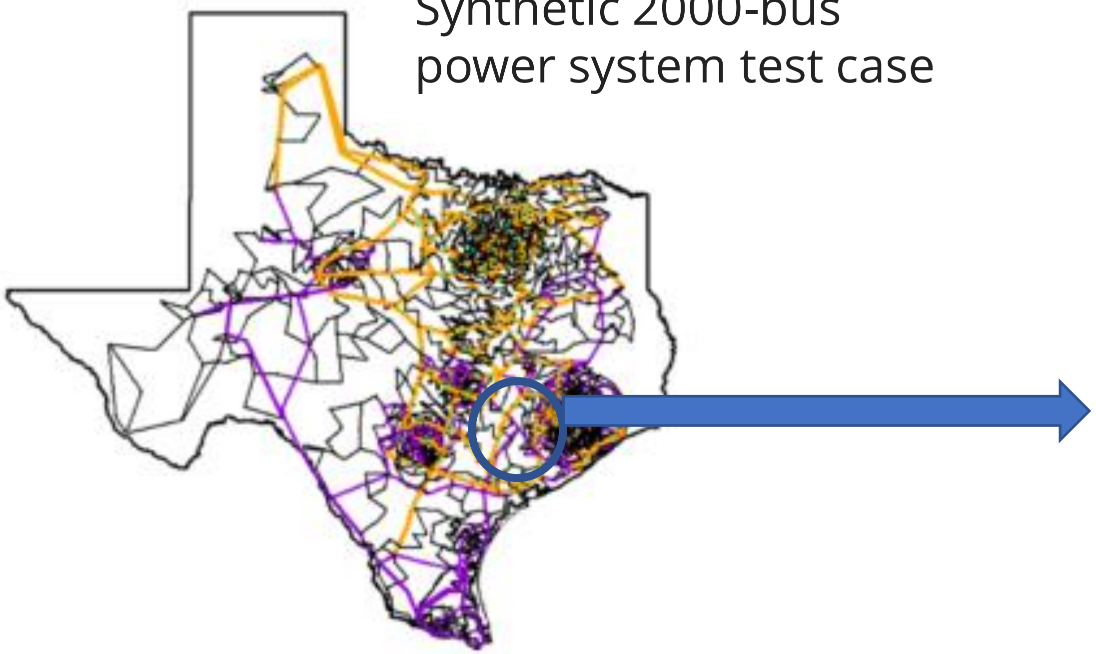




1. http://www.aoml.noaa.gov/hrd/data sub/us history.html
2. P. Javanbakht, S. Mohagheghi, “A risk-averse security-constrained optimal power flow for a power grid subject to hurricanes”, Electric Power Systems Research, Nov. 2014
3. A. B. Birchfield, T. Xu, K. M. Gegner, K. S. Shetye and T. J. Overbye, "Grid Structural Characteristics as Validation Criteria for Synthetic Networks," in IEEE Transactions on Power Systems, vol. 32, no. 4, pp. 3258-3265, July 2017

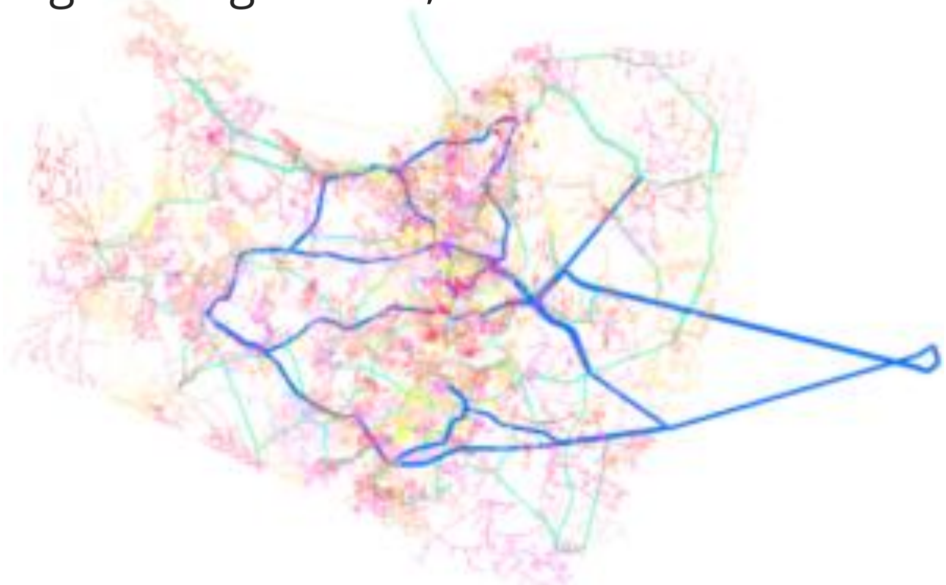
Impact Modeling and Resilience Metric for T&D System

- **Co-simulation methods to evaluate the impacts of extreme events on T&D systems**
- **Minimum exchange of data between bulk grid and distribution system operators, only need to know what lines/buses may be impacted and with what probability**
- **Currently, working on integrating synthetic Tx2000 bus and synthetic Austin distribution feeder available at** [Electric Grid Test Case Repository (tamu.edu)]



Synthetic 2000-bus
power system test case

307,236 end-use customers with 160
high-voltage buses, 448 feeders



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Risk-averse Optimization

How to economically add operational flexibility to the grid to improve their response during extreme weather events?

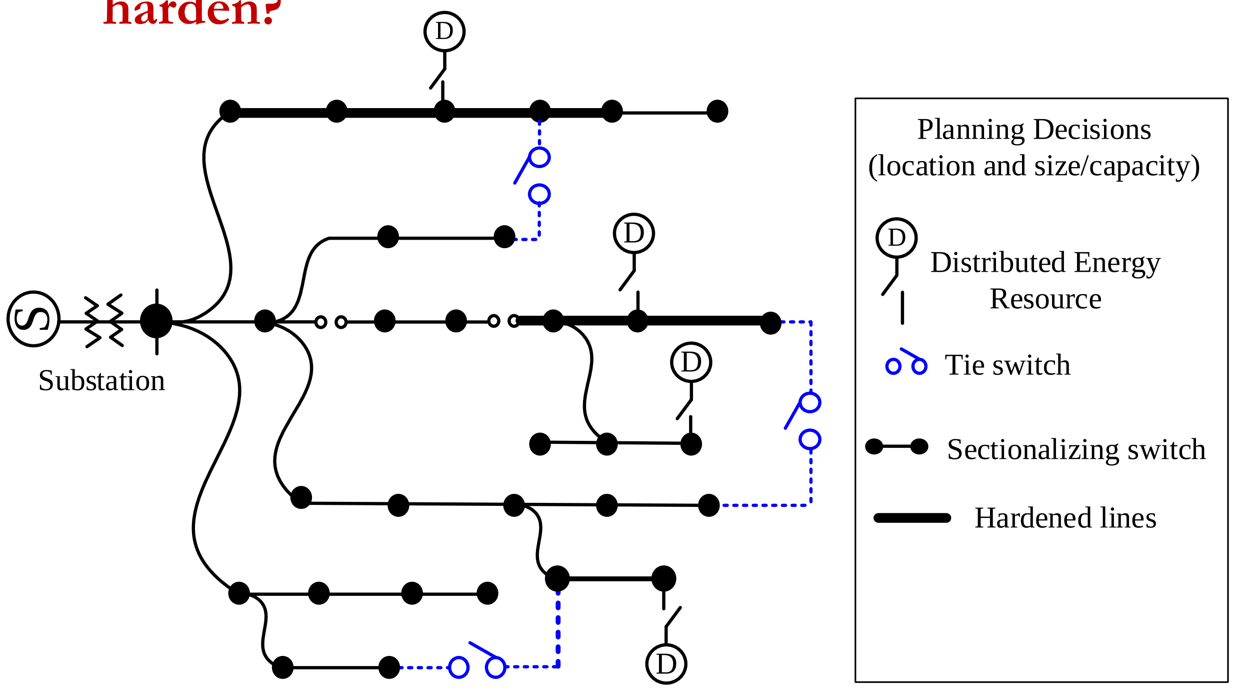
Resilience Planning

How to economically add operational flexibility to the grid to improve their response during extreme weather events?

Our contributions:

- Risk-averse framework for resource planning to manage disruptions in critical infrastructure system
- Long-term planning solutions to identify the locations for system upgrades for improved resilience
- A CVaR-based formulation to minimize the highest impacts of low-probability events
- Tradeoff among planning measures - backup resources vs. Line hardening

Example: Where to place DGs, which lines to harden?



Stochastic Optimization

- A framework for modeling any optimization problem that involves uncertainty
- Two-stage Stochastic Program: A large number of potential scenarios,
  - Stage I: Make some advance decisions (plan ahead),
  - Stage II: Observe the actual input scenario, Take recourse actions in response to the realization of the random variables and the first stage decisions

Stage 1 (pre-event)(x: first-stage decision variables) - should not depend on future observation

$$\min c^T x + \mathbb{E}[Q(x,\xi)]$$

subject to,

$$Ax \geq b$$

$$\mathbb{E}[Q(x,\xi)] = \sum_{s=1}^{S} p_s Q(x,\xi_s)$$

$$\xrightarrow{x(fixed)}$$

Stage 2 (post-event) after realizing scenario, we take recourse decisions, y (second stage decision variables)

$$Q(x,\xi) = \min q^T y$$

subject to,

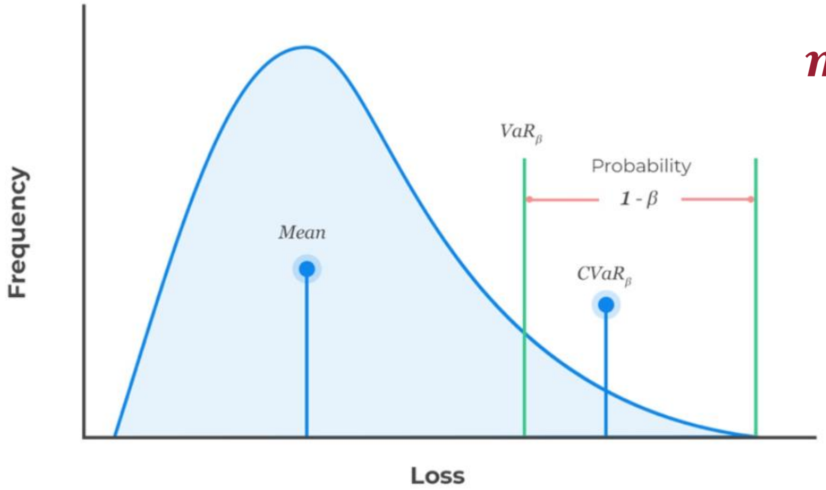
$$Tx + Wy \leq h$$

Schultz, R., Tiedemann, S. Conditional Value-at-Risk in Stochastic Programs with Mixed-Integer Recourse. Math. Program. 105, 365–386 (2006).

Risk-averse Optimization

Conditional value at risk in the objective :

- **a tradeoff parameter λ can differentiate the risk-neutral vs risk-averse objective**



$$\min_{x} \mathbf{c}^T\mathbf{x} + \boxed{(1-\lambda)\mathbb{E}_\rho \mathbf{Q}(\xi, x) + \lambda \mathbf{CVaR}_\alpha(\mathbf{Q}(\xi, x))} \longrightarrow$$

tradeoff for risk-neutral vs risk-averse

where,

$$CVaR_\alpha(\mathrm{Z}) = \inf_{\eta \in \mathbb{R}} \left\{ \eta + \frac{1}{1-\alpha} \mathbb{E}(\max([Z-\eta], 0) \right\}$$

where, η = value-at-risk

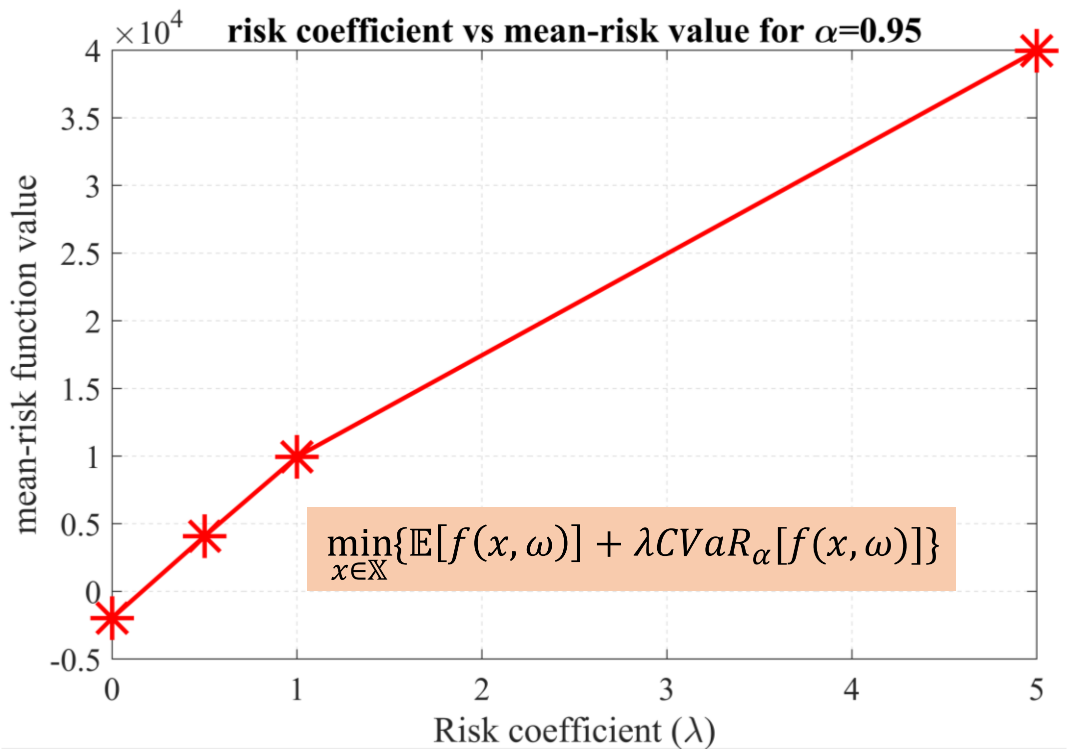
Mean-risk function with $CVaR_\alpha$ as risk measure: $\min_{x \in \mathbb{X}} \{\mathbb{E}[f(x,\omega)] + \lambda CVaR_\alpha[f(x,\omega)]\}$

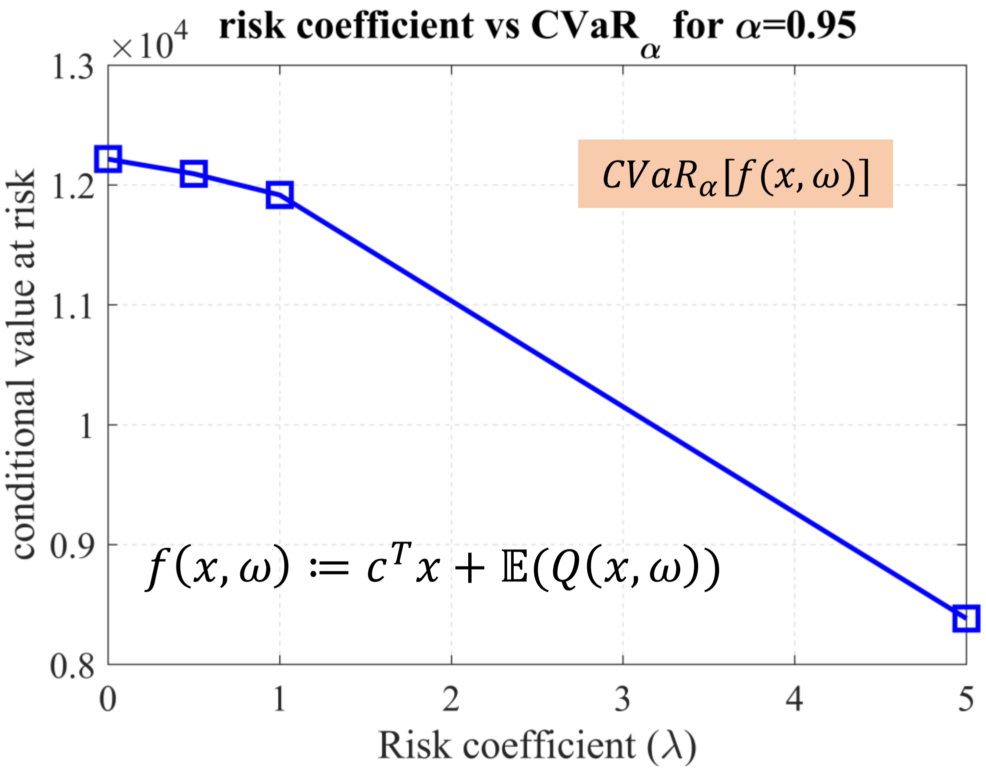
where, λ is the non-negative trade-off coefficient known as the risk coefficient

Risk-averse vs Risk-neutral

- **Higher the value of $\boldsymbol{\lambda}$, higher is the inclination towards risk aversion**
- **due to changing trade-off between expectation and $\boldsymbol{CVaR_\alpha}$, higher $\boldsymbol{\lambda}$ gives higher expected total cost and hence lower $\boldsymbol{CVaR_\alpha}$**

$$f(x,\omega) := c^T x + \mathbb{E}(Q(x,\omega))$$



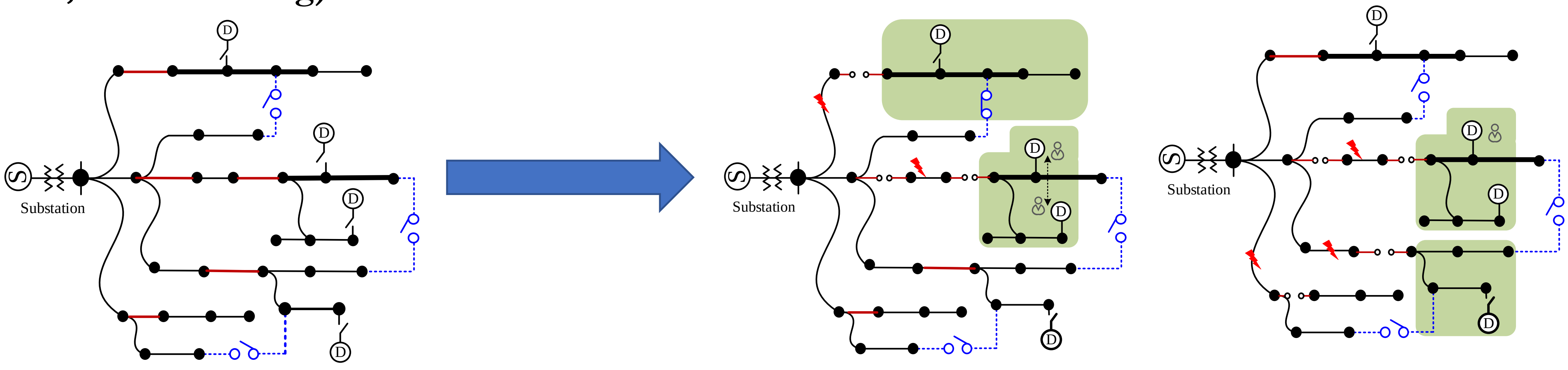


Two-Stage Risk-averse Stochastic Program - Distribution System Planning

Overall problem: Identify optimal locations for feeder upgrades given the PDF of weather event, component fragility curves and load criticality to minimize CVaR.

Stage 1 (Decision Variables) – location and sizes of planning decisions (DGs, switches, line hardening)

Stage 2 (Decision Variables) – How to restore the network for a give realization of outages/fault?



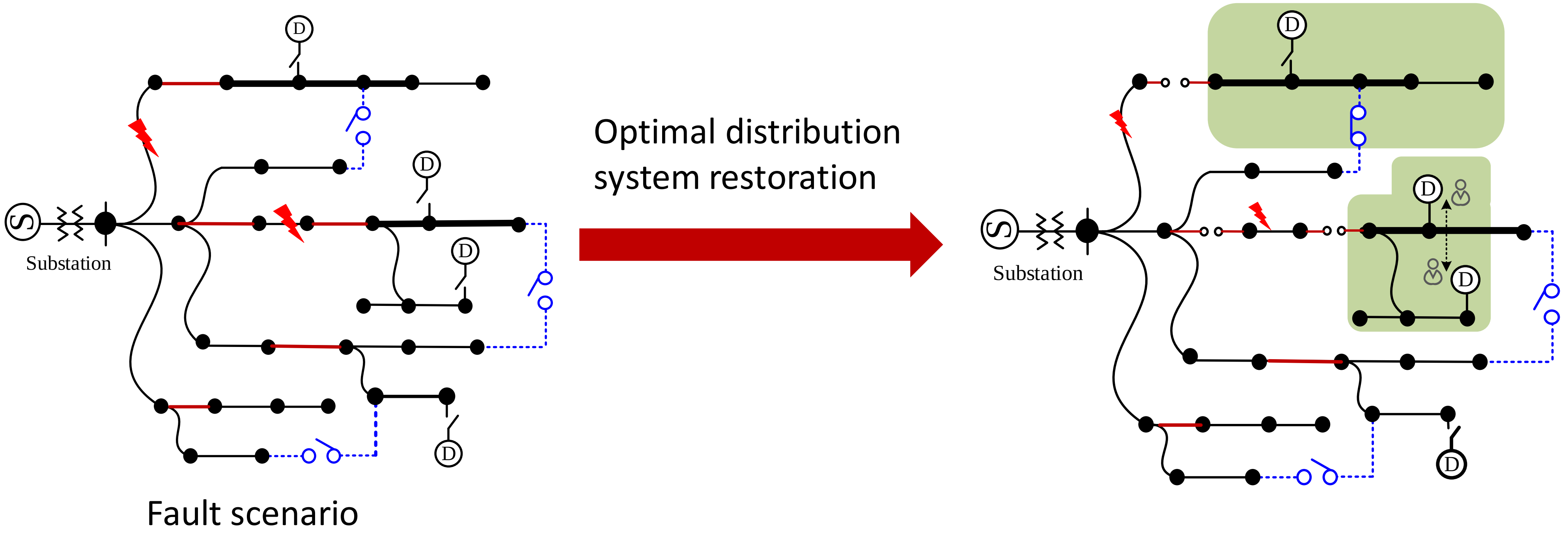
Need to be optimal for possible realization of fault scenarios

Fault scenario 1

Fault scenario 2

Stage 2 Problem (Inner loop Optimization Problems)

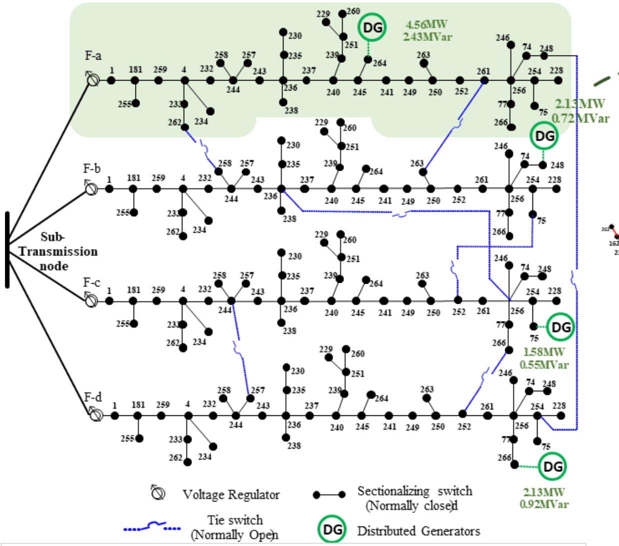
- Inner loop optimization problems
  - Optimal power flow problems
  - Require optimal coordination of all assets for a given realization of extreme weather event.
  - Require solving difficult nonlinear optimization problem at the distribution level for feeder restoration

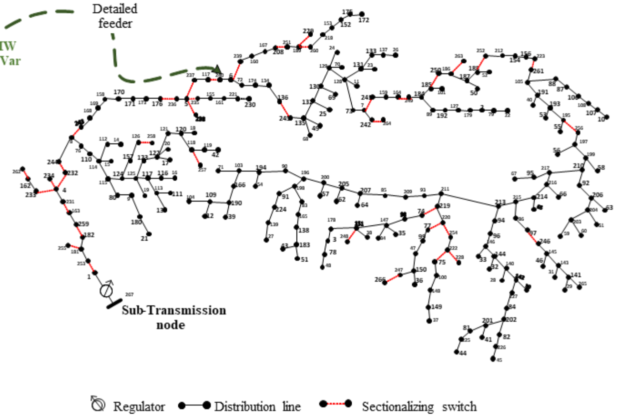


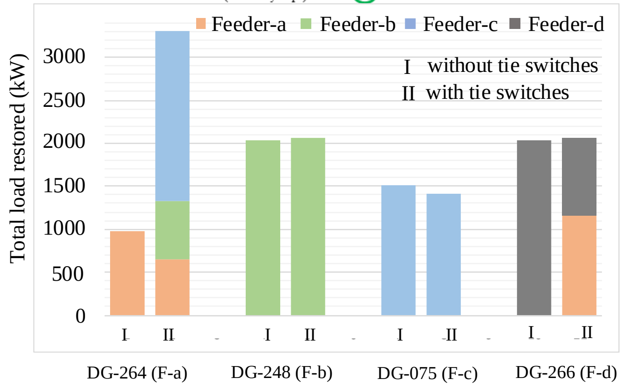
Optimal Coordination (of controllable assets) for a given Realization of Extreme Event

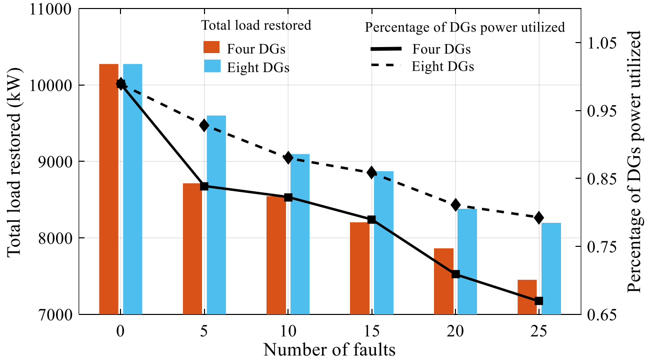
Inner loop Optimization Problem (solved for each scenario)

- DG-assisted resilient restoration grid-forming and grid-following technologies to support critical load via intentional islanding
  - Mixed-integer linear programming formulations
  - Use of mobile energy resources along with other DGs









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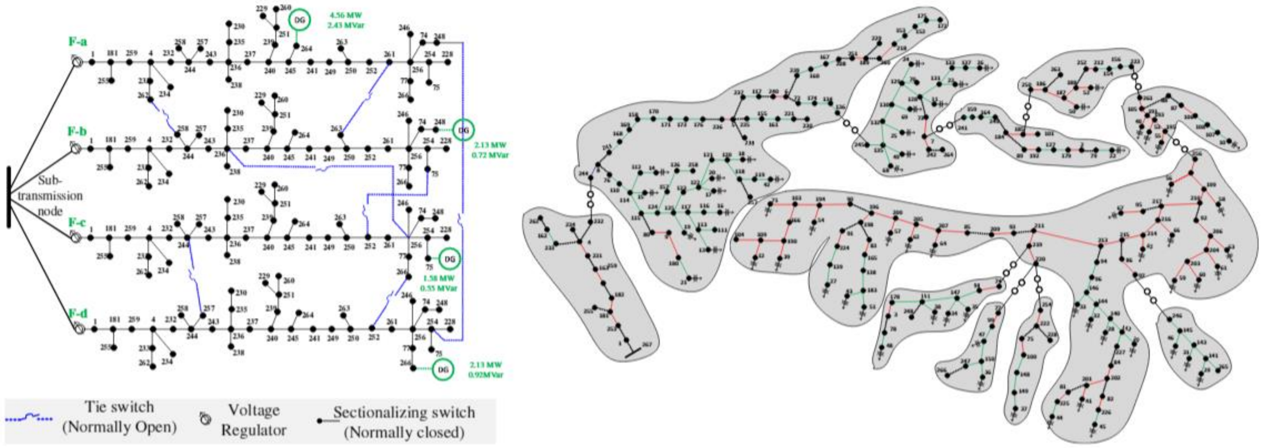
2. S. Poudel, A. Dubey, P. Sharma, and K. P. Schneider, “Advanced FLISR with Intentional Islanding Operations in an ADMS Environment Using GridAPPS-D,” IEEE Access, May 2020.
3. S Poudel, A Dubey, and K P. Schneider, “A Generalized Framework for Service Restoration in a Resilient Power Distribution System,” IEEE Systems Journal, Aug 2020.
4. S Poudel and A Dubey, “A Two-Stage Framework for Service Restoration of Power Distribution Systems,” IET Smart Grid, Jan 2021.

Optimal Coordination (of controllable assets) for a given Realization of Extreme Event

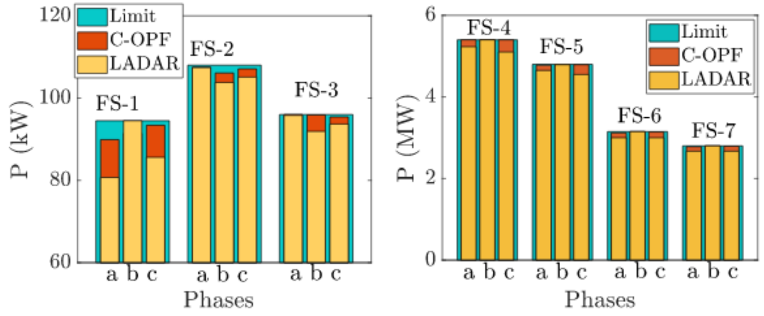
Inner loop Optimization Problem (solved for each scenario)

- Self-organizing Islands - Distributed solutions to restoration via use of microgrids and networked microgrids
  - Laminar architecture for distributed applications
  - Distributed computing algorithms for fast consensus
  - Stability of islanded systems



(a) Modified 4 feeder PNNL R3-12_47-2 test system

(b) Area Decomposition of Single Feeder (TS-2)



(a) TS-1

(b) TS-2

Figure 8: Comparison of C-OPF and LADAR in Each Phase

1. R. Sadnan and A. Dubey, “Distributed Optimization using Reduced Network Equivalents for Radial Power Distribution Systems,” IEEE Transactions on Power Systems, Jan 2021
2. R. Sadnan, N. Gray, A. Dubey, and A. Bose, “Distributed Optimization for Power Distribution Systems with Cyber-Physical Co-simulation,” IEEE PES GM 2021.
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Resilient Restoration: GridAPPS-D Platform

*GridAPPS-D – open-source advanced distribution management platform (real-time operational environment)

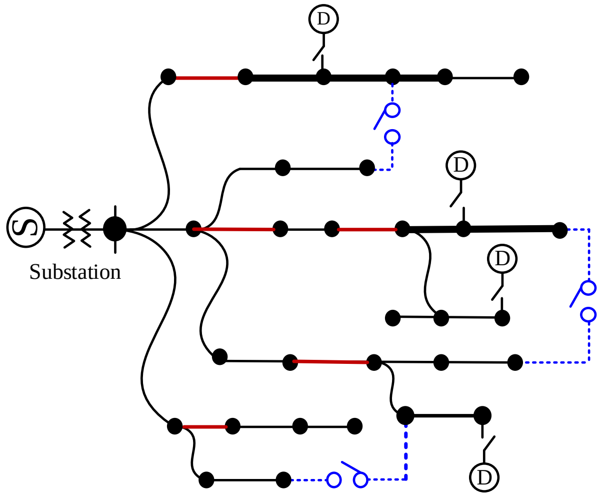
Application to restore power system using distributed generators (deployed: https://gridappsd-restoration.readthedocs.io/en/latest/**)**

S. Poudel, A. Dubey, P. Sharma, and Kevin P. Schneider, "Advanced FLISR with Intentional Islanding Operations in an ADMS Environment Using GridAPPS-D," IEEE Access, May 2020

Two-Stage Risk-averse Stochastic Program - Distribution System Planning

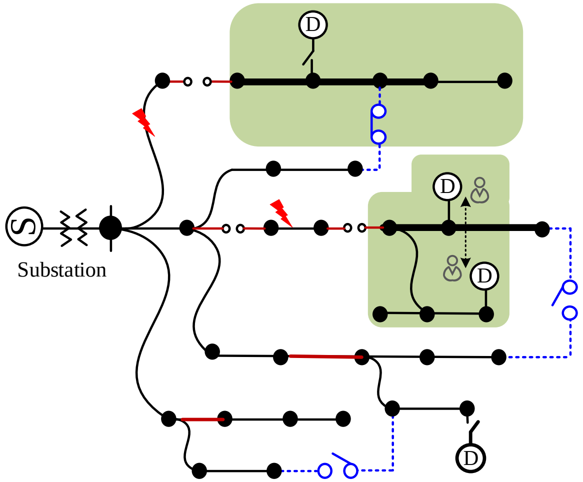
Overall problem: Identify optimal locations for feeder upgrades given the PDF of weather event, component fragility curves and load criticality to minimize CVaR.

Stage 1 (Decision Variables) – location and sizes of planning decisions (DGs, switches, line hardening)

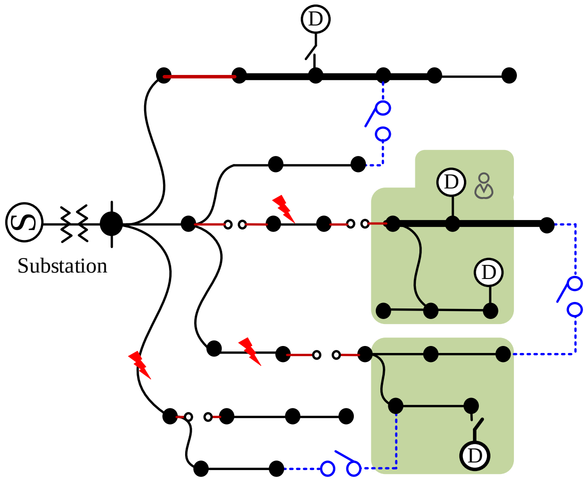


Need to be optimal for possible realization of fault scenarios

Stage 2 (Decision Variables) – How to restore the network for a give realization of outages/fault



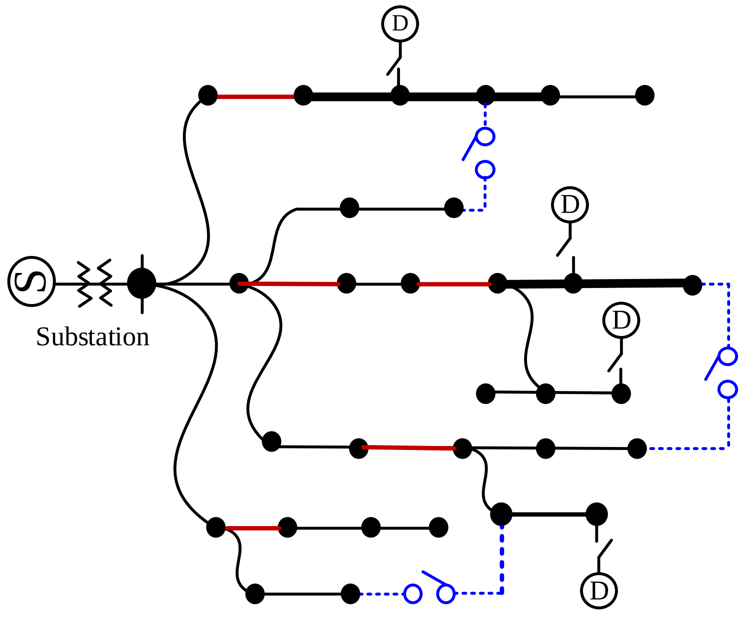
Fault scenario 1



Fault scenario 2

Two-Stage Risk-averse Stochastic Program for Distribution System Planning (First Stage)

Stage 1 (Decision Variables) – location and sizes of planning decisions (DGs, switches, line hardening)



Need to be optimal for possible realization of fault scenarios

Stochastic optimization with mixed-integer recourse

$$\min \sum_{i \in \mathcal{V}} c^T \delta_i + (1-\lambda)\mathbb{E}(\mathcal{Q}(\delta, \mathcal{E}_\xi)) + \lambda CVaR_\alpha(\mathcal{Q}(\delta, \mathcal{E}_\xi))$$

where,

$$\delta_i = \delta_i^{DG} \times \beta_i$$

$$\mathbb{E}(\mathcal{Q}(\delta, \mathcal{E}_\xi)) = \sum_{\xi \in \mathcal{E}_\xi} p_\xi \mathcal{Q}(\delta, \xi)$$

$$CVaR(\mathcal{Q}(\delta, \mathcal{E}_\xi)) = \eta + \frac{1}{1-\alpha} \sum_{\xi \in \mathcal{E}_\xi} p^\xi \nu^\xi$$

Subject to:

$$0 \leq \delta_i \leq \delta_{max}$$

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

$$\eta \in \mathbb{R}$$

Two-Stage Risk-averse Stochastic Program for Distribution System Planning (Second Stage)

Stage 2 (Decision Variables) – How to optimally restore the network for a give realization of outages/fault

For each scenario

Objective function:

- Maximize the amount of load restored
- Minimize the cost of switching

Constraints

- Connectivity constraints
  - Switch and load decision
  - Radial operation
- Operational constraints
  - Power flow and voltage constraints
  - Network operating constraints
  - DG limit constraints

Mixed-integer linear program

Maximize:

$$\sum_{i\in\mathcal{V}_S}\sum_{\phi\in\{a,b,c\}} s_i\, w_i P_{Li}^{\phi}. \tag{4}$$

Subject to:

$$s_i \le v_i, \quad \forall i \in \mathcal{V}_S \tag{5a}$$

$$s_i = v_i, \quad \forall i \in \mathcal{V}_{area}\backslash\mathcal{V}_S. \tag{5b}$$

$$\sum_{e:(i,j)\in\mathcal{E}} \boldsymbol{P}_e = s_j\, \boldsymbol{P}_{Lj} + \sum_{e:(j,i)\in\mathcal{E}} \boldsymbol{P}_e \tag{6a}$$

$$\sum_{e:(i,j)\in\mathcal{E}} \boldsymbol{Q}_e = s_j\, \boldsymbol{Q}_{Lj} + \sum_{e:(j,i)\in\mathcal{E}} \boldsymbol{Q}_e \tag{6b}$$

$$\boldsymbol{U}_i - \boldsymbol{U}_j = 2(\tilde{\mathbf{r}}_e\boldsymbol{P}_e + \tilde{\mathbf{x}}_e\boldsymbol{Q}_e), \quad \forall e \in \mathcal{E}_{area}\backslash(\mathcal{E}_S\cup\mathcal{E}_R) \tag{6c}$$

$$V_j^{\phi} = a_{\phi}V_i^{\phi}, \tag{7a}$$

$$\boldsymbol{U}_j = A^{\phi}\boldsymbol{U}_i, \quad \forall e:(i,j)\in\mathcal{E}_R. \tag{7b}$$

$$q_{cap,i}^{\phi} = u_{cap,i}^{\phi} q_{cap,i}^{rated,\phi} U_i^{\phi}. \tag{8}$$

$$v_i\boldsymbol{U}^{min} \le \boldsymbol{U}_i \le v_i\boldsymbol{U}^{max}, \quad \forall i \in \mathcal{V}_{area}. \tag{9}$$

$$(\boldsymbol{P}_e)^2 + (\boldsymbol{Q}_e)^2 \le \left(\boldsymbol{S}_e^{rated}\right)^2 \quad \forall e \in \mathcal{E}_{area}\backslash\mathcal{E}_S. \tag{10}$$

$$\begin{aligned} -\sqrt{3}\,(\boldsymbol{P}_e + \boldsymbol{S}_e) \le \boldsymbol{Q}_e \le -\sqrt{3}\,(\boldsymbol{P}_e - \boldsymbol{S}_e), \\ -\sqrt{3}/2\,\boldsymbol{S}_e \le \boldsymbol{Q}_e \le \sqrt{3}/2\,\boldsymbol{S}_e, \\ \sqrt{3}\,(\boldsymbol{P}_e - \boldsymbol{S}_e) \le \boldsymbol{Q}_e \le \sqrt{3}\,(\boldsymbol{P}_e + \boldsymbol{S}_e), \quad \forall e \in \mathcal{E}_{area}\backslash\mathcal{E}_S. \end{aligned} \tag{11}$$

$$\mathbf{P}_e \le \mathbf{P}_e^{max}, \forall e \in \mathcal{E}_{fed}. \tag{12}$$

Two-stage Problem Formulation in Extensive form

$$g(x,y,\eta,\nu) \coloneqq \min_{x\in\mathbb{X}}(1+\lambda)\sum_{i=1}^{n} c^T\delta_i + \sum_{s=1}^{N} p_s \sum_{i\in V}\sum_{\phi\in\{a,b,c\}} w_{i,s}s_{i,s}P_{Li,s}^{\phi} + \lambda\left(\eta + \frac{1}{1-\alpha}\sum_{i=1}^{N} p_i \nu_i\right)$$

$$g(x,y,\eta,\nu) \coloneqq \min_{x\in\mathbb{X}}(1+\lambda)\sum_{i=1}^{n} c^T\delta_i + \lambda\eta + \sum_{s=1}^{N} p_s \sum_{i\in V}\sum_{\phi\in\{a,b,c\}} w_{i,s}s_{i,s}P_{Li,s}^{\phi} + \lambda\left(\frac{1}{1-\alpha}\sum_{s=1}^{N} p_s \nu_s\right)$$

Restored Load

$$\left(demand - \left[\sum_{i\in V}\sum_{\phi\in\{a,b,c\}} w_{i,s}s_{i,s}P_{Li,s}^{\phi}\right]\right)$$

Overall Loss

Subject to,

$$\nu_i \geq \left(demand - \left[\sum_{i\in V}\sum_{\phi\in\{a,b,c\}} w_{i,s}s_{i,s}P_{Li,s}^{\phi}\right]\right) - \eta, \qquad \forall i = 1,2,\dots,N$$

$$\eta \in \mathbb{R}, \nu_i \geq 0, \qquad \forall i = 1,2,\dots,N$$

$$x, y \in \mathbb{Z}_+ \times \mathbb{R}_+$$

total prioritized load restored in scenario s after solving the optimal restoration problem for the scenario s (inner loop optimization)

Solving the two-stage problem: Methods and tools

All methods convert stochastic problem to a deterministic problem

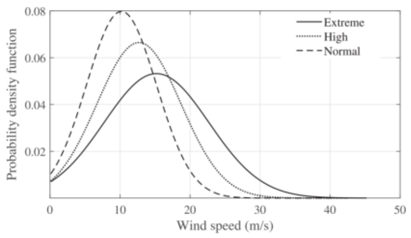
- Sampling-based approaches: Extensive form, create multiple copies of second stage problem, solve a large single-stage deterministic optimization problem, most accurate, scenario selection is crucial

- Progressive hedging: relax non anticipativity constraint, primal and dual of convex stochastic problems, equivalent to alternating direction method of multipliers (ADMM), fast algorithm → parallelizable

- Stochastic Dual Dynamic Programming: Great in a multi-stage setting, stage-wise decomposition of the problem

Solution Approach

[1]Sampling and system-level impacts



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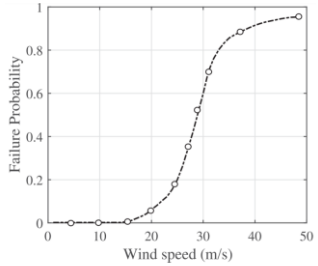
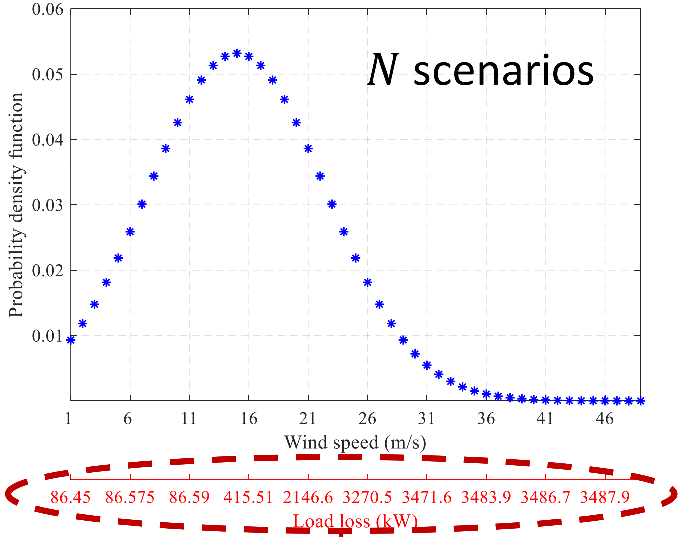
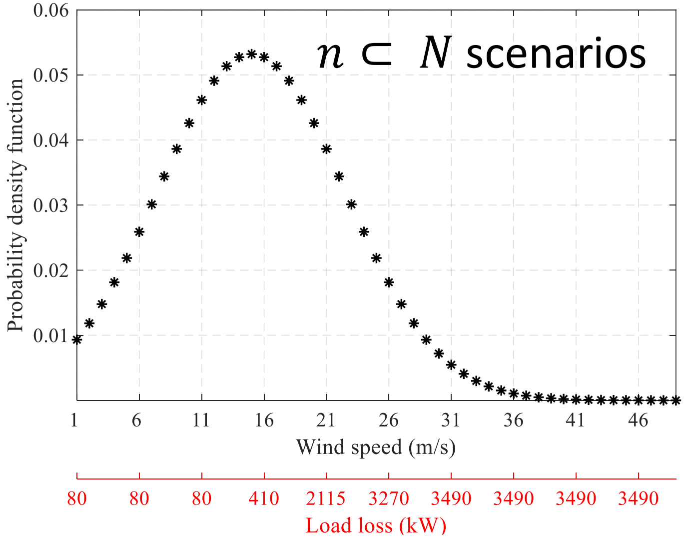


Monte-Carlo
Simulation

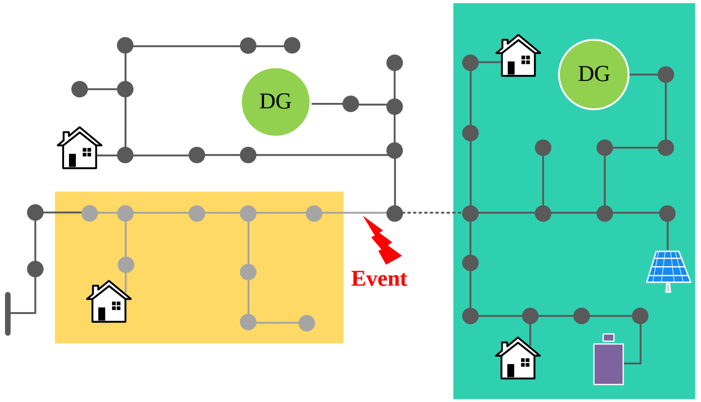


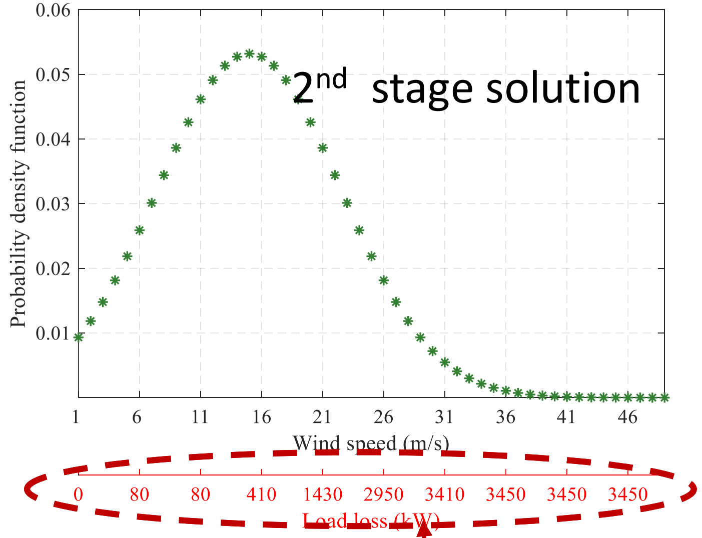
[2]Scenario selection

- Choose representative scenarios based on probabilistic loss function
- Appropriately represents low probability events compared to uniform sampling

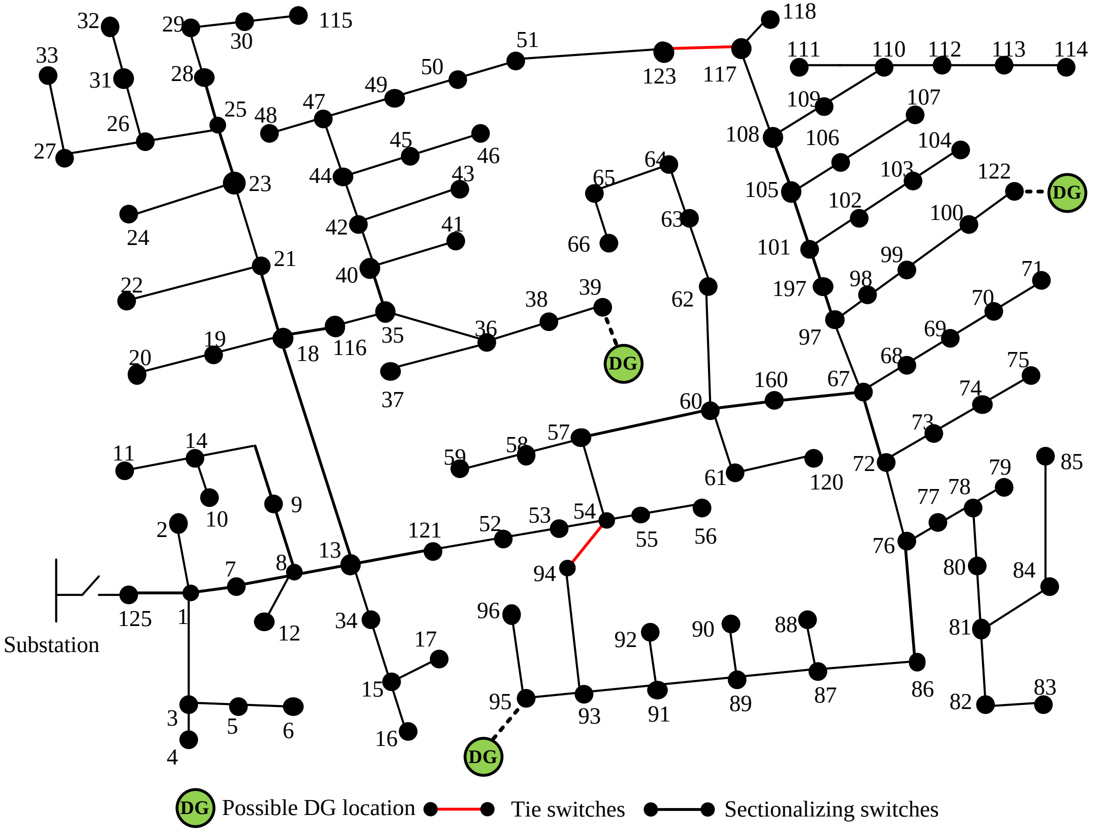


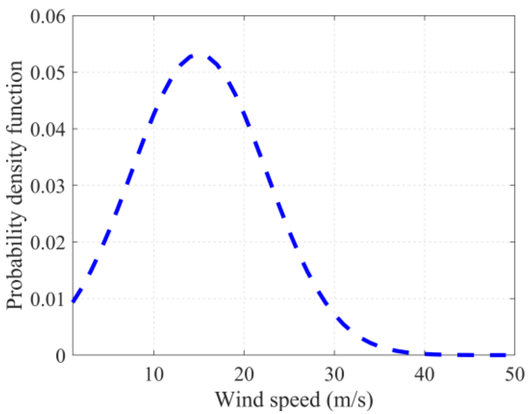
[3]Two-stage stochastic optimization

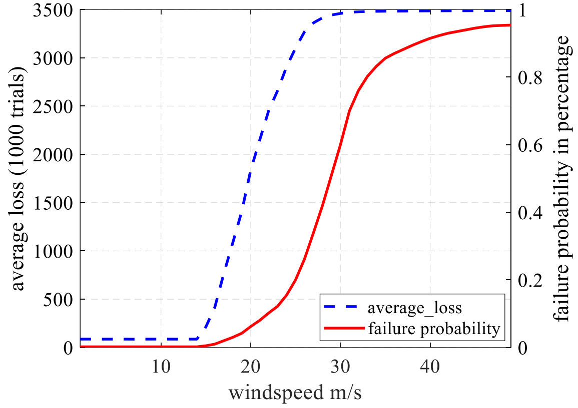




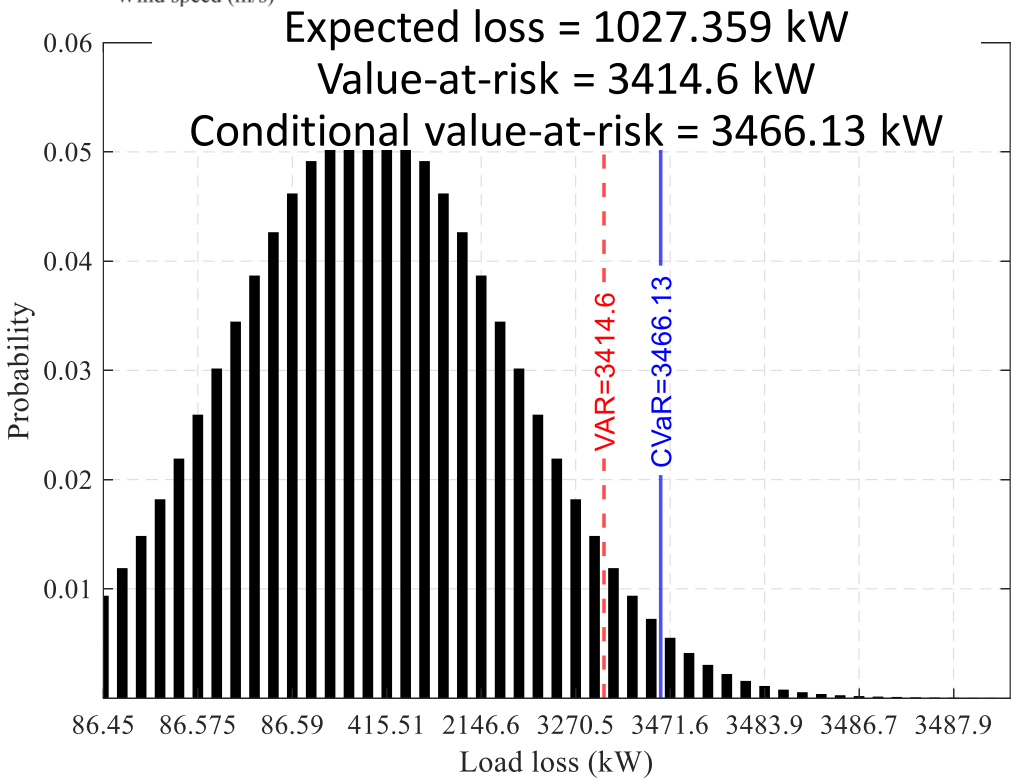
Preliminary Results: Planning Decision Tradeoffs







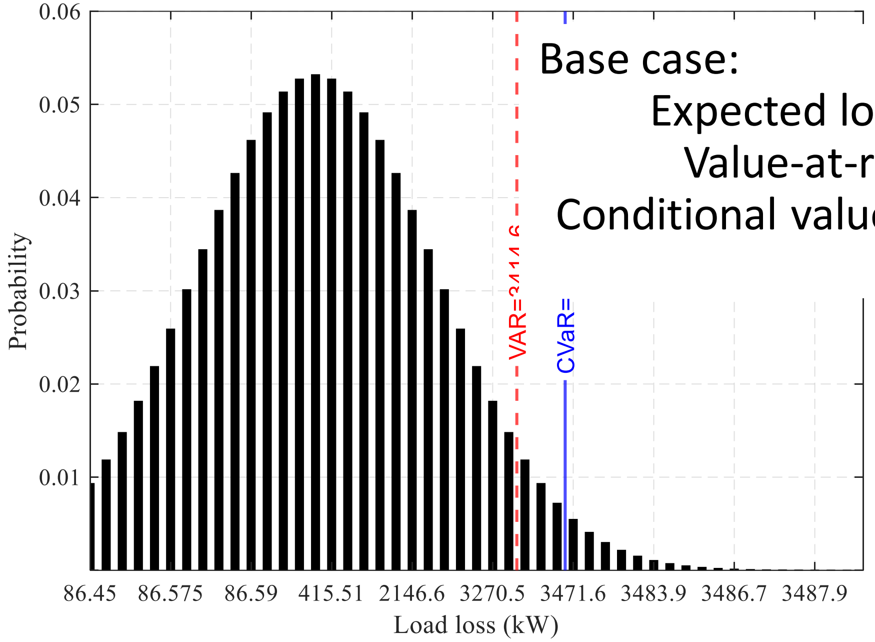
Base case, No DGs



Test cases (Planning tradeoffs for risk-averse vs risk-neutral cases):

1. Increase in number of DGs for different risk factor, λ
2. Increase in total size of DGs for different risk factor, λ

Preliminary Results: Planning Decision Tradeoffs



Base case:
Expected loss = 1027.359 kW
Value-at-risk = 3414.6 kW
Conditional value-at-risk = 3466.13 kW

After placing DGs: Sum of DG size = 900 kW

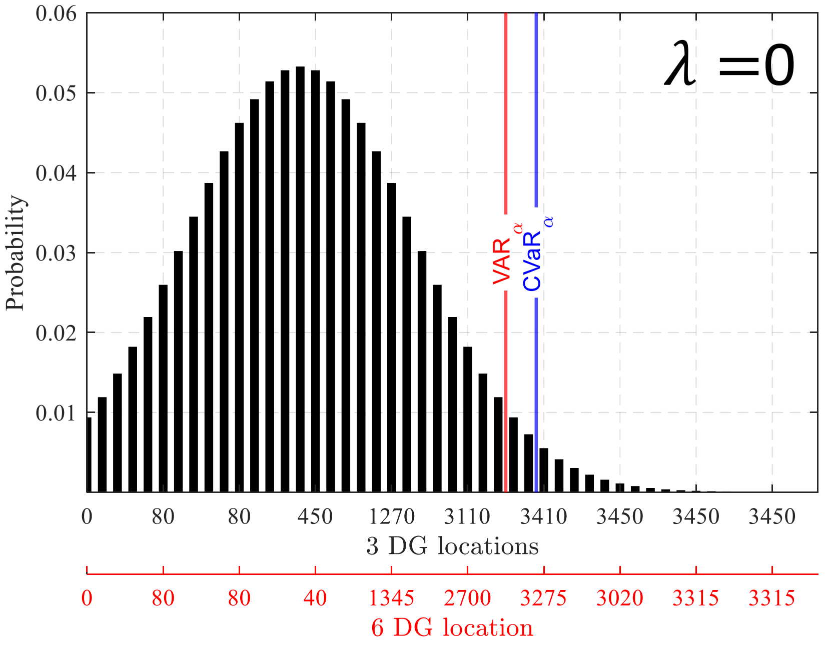
- total possible loss = 3490 kW
- the number of scenarios that have loss above 3000 kW were recorded
  - no restoration = 27027
  - risk neutral ($\lambda = 0$) = 23570
  - mean-risk ($\lambda = 0.5$) = 23494
  - risk-averse ($\lambda = 1$) = 23270

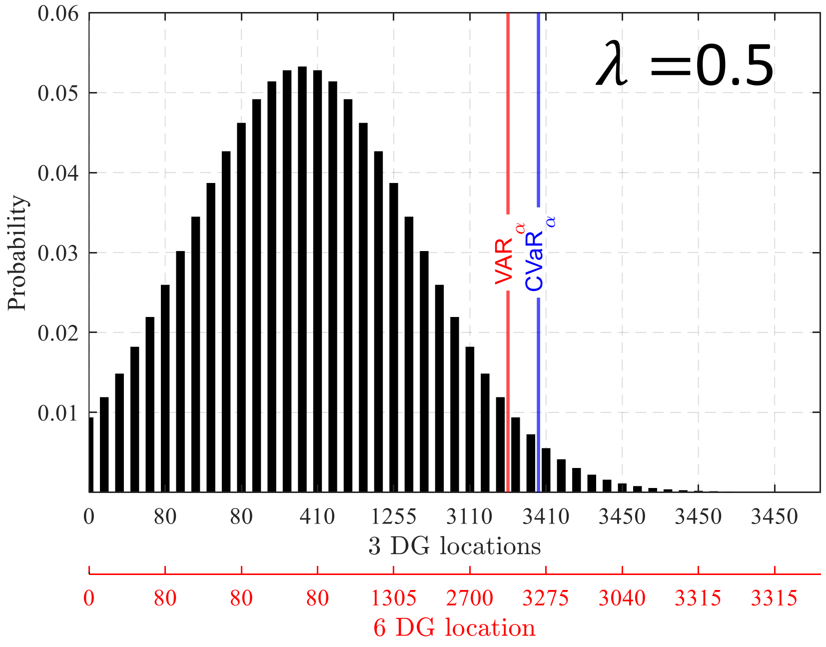
	$\lambda = 0$ (risk-neutral)			$\lambda = 0.5$ (mean-risk)			$\lambda = 1$ (risk-averse)		
VAR	3210			3210			3210		
CVaR	3356.455			3352.535			3352.5352		
Expected value	720.2485			719.27913			731.7657		
DG output	Z[39]	Z[95]	Z[122]	Z[39]	Z[95]	Z[122]	Z[39]	Z[95]	Z[122]
	40	740	120	40	720	140	60	405	435

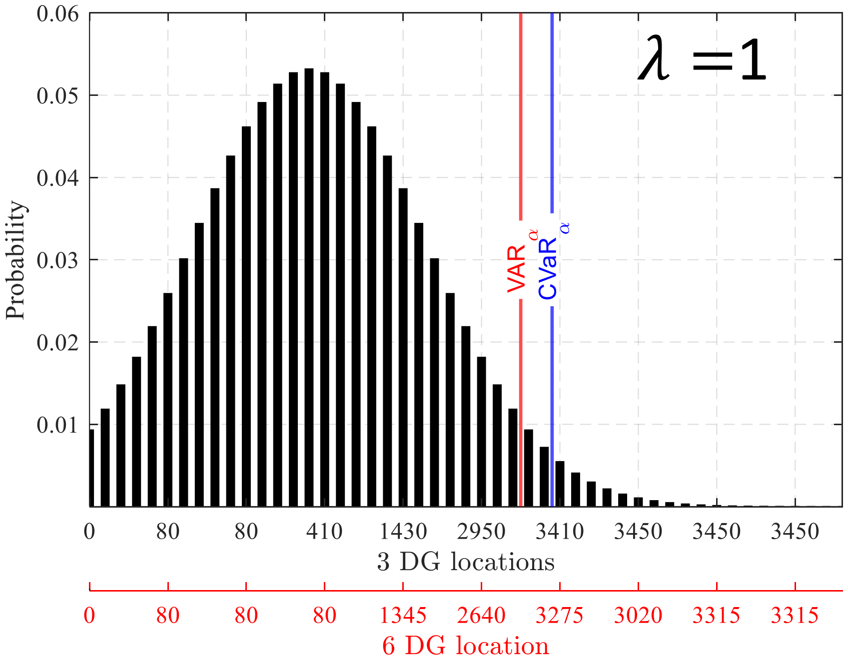
Preliminary Results: Planning Decision Tradeoffs

Sum of DG size = 900 kW

	λ = 0 (risk-neutral)			λ = 0.5 (mean-risk)			λ = 1 (risk-averse)		
#DGs	Expected Loss	VAR_{α}	$CVAR_{\alpha}$	Expected Loss	VAR_{α}	$CVAR_{\alpha}$	Expected Loss	VAR_{α}	$CVAR_{\alpha}$
3	719.89	3210	3356.45	717.13	3210	3352.51	726.916	3210	3352.51
6	654.82	3055	3192.04	653.88	3055	3180.21	659.277	3055	3180.21

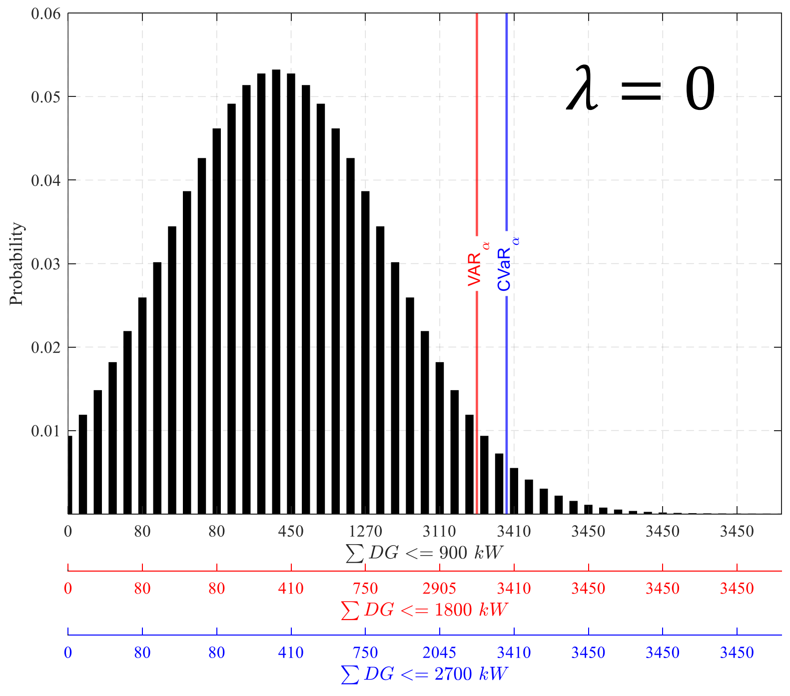


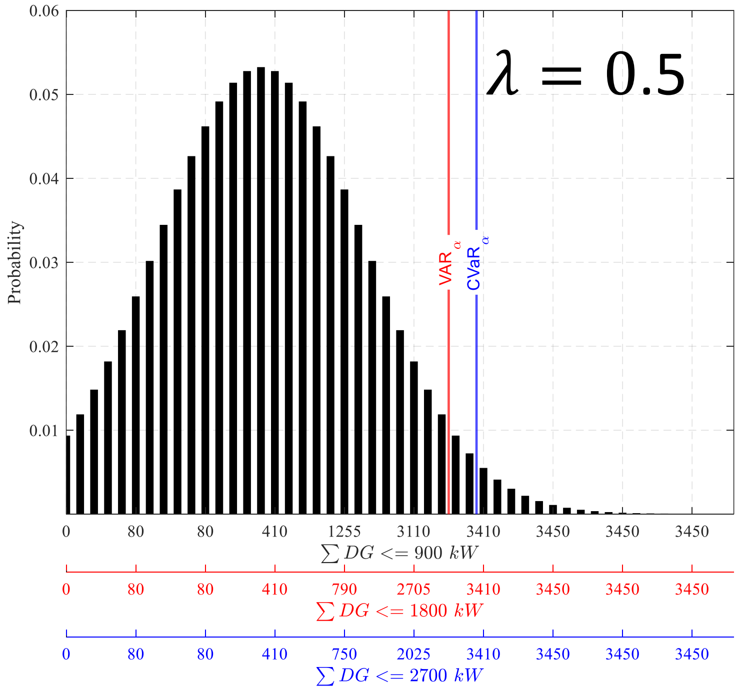


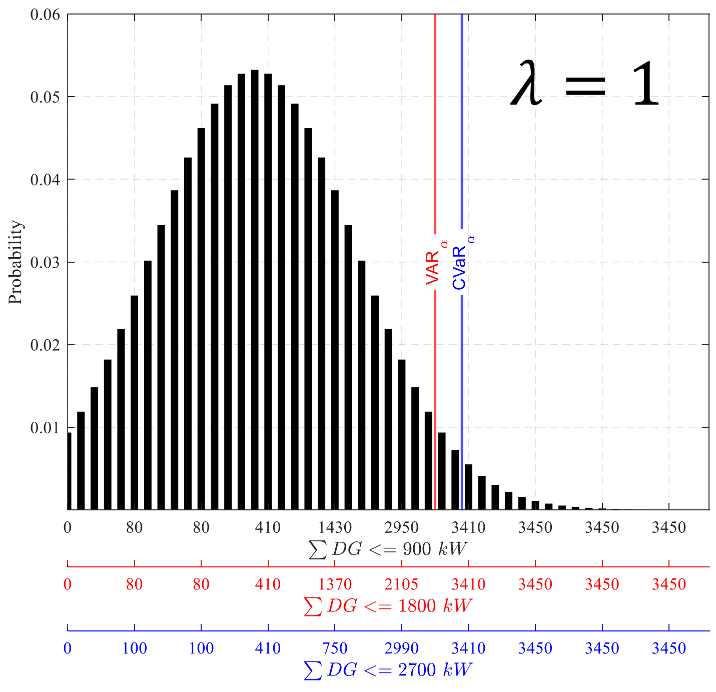


Preliminary Results: Planning Decision Tradeoffs

s	λ = 0 (risk-neutral)			λ = 0.5 (mean-risk)			λ = 1 (risk-averse)		
∑DG	Expected Loss	VAR_α	$CVAR_\alpha$	Expected Loss	VAR_α	$CVAR_\alpha$	Expected Loss	VAR_α	$CVAR_\alpha$
900	719.88	3210	3356.45	717.12	3210	3352.51	726.91	3210	3352.51
1800	657.23	3210	3352.51	647	3210	3352.51	684.83	3210	3352.51
2700	617.56	3210	3352.51	617.19	3210	3352.51	662.22	3210	3352.51







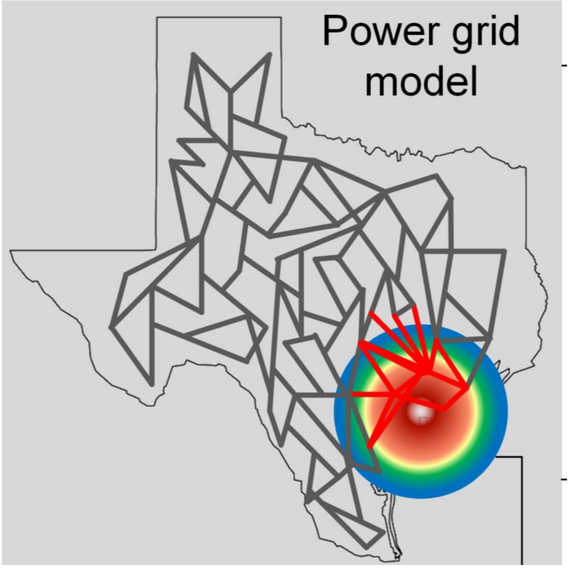
Ongoing and Future Work

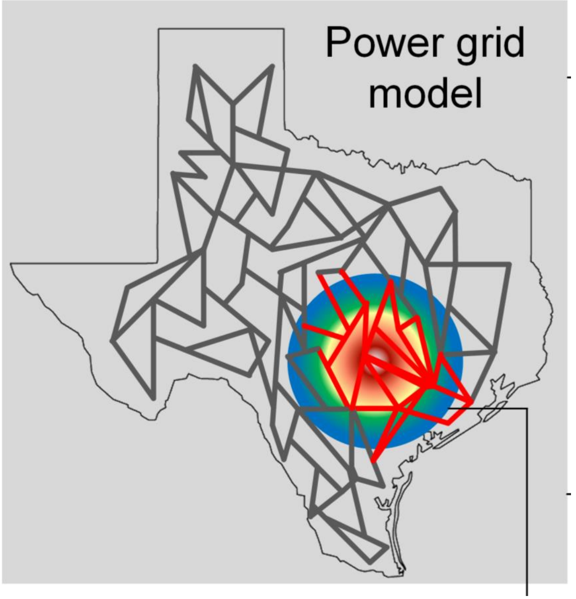
Ongoing and Future Work

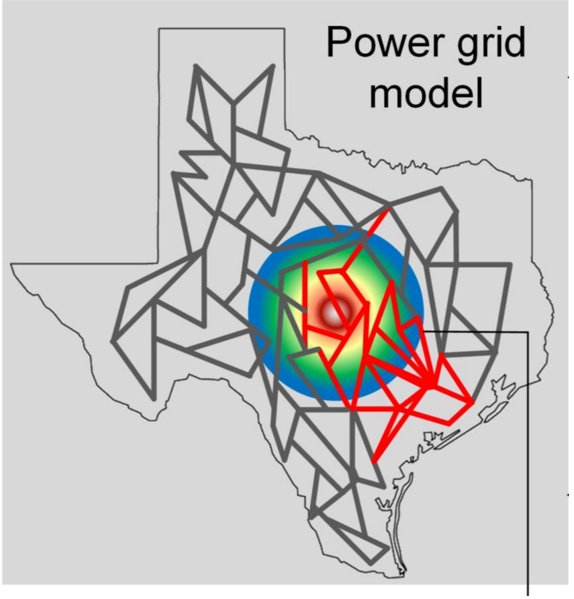
- Risk-neutral vs. Risk-averse Planning Tradeoffs:
  - Evaluation of tradeoffs for several combination of planning activities include line hardening, switch placement and DG sizing and placement.
  - The presented formulation is generic and problem complexity does not significantly increase with the increase in the number of planning decisions for a given distribution feeder.
- Scaling for lager feeders:
  - Extensive form leads to a very large-scale mixed-integer linear program, Progressive hedging results in large optimality gap as the problem is non-convex
  - We investigated the application of solving the extensive form and use of progressive hedging techniques for a small 123-bus distribution system
  - Currently working on value-function approximation with simulation-based framework to scale the problem for large networks
- Collaboration with local utility Avista on data-driven analysis

Ongoing and Future Work

Risk-modeling framework for HILP events:
simulate extreme event spatio-temporal trajectories and quantify their time-varying risks







Operational planning:

- Multi-stage operational decision-making to minimize the time-varying risks of an upcoming event
- "Curse of dimensionality" – function approximation techniques using simulation-based framework

Acknowledgments

Students:

- **Shiva Poudel (WSU, now with PNNL), Abodh Paudyal (WSU, PhD student), Andrew Ian Cannon (WSU, MS Student), Rabayet Sadnan (WSU, PhD student), Shuva Paul (Postdoc, now with Georgia Tech)**

Supporting agencies:

- **Primary: National Science Foundation (NSF),**
- **Cross-cutting themes: Pacific Northwest National Lab (PNNL), Department of Energy (DOE), Schweitzer Engineering Laboratories (SEL), Alfred P. Sloan Foundation**

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Thank you

Questions?