Scalable Solutions for Grid-edge Integration for Resilience

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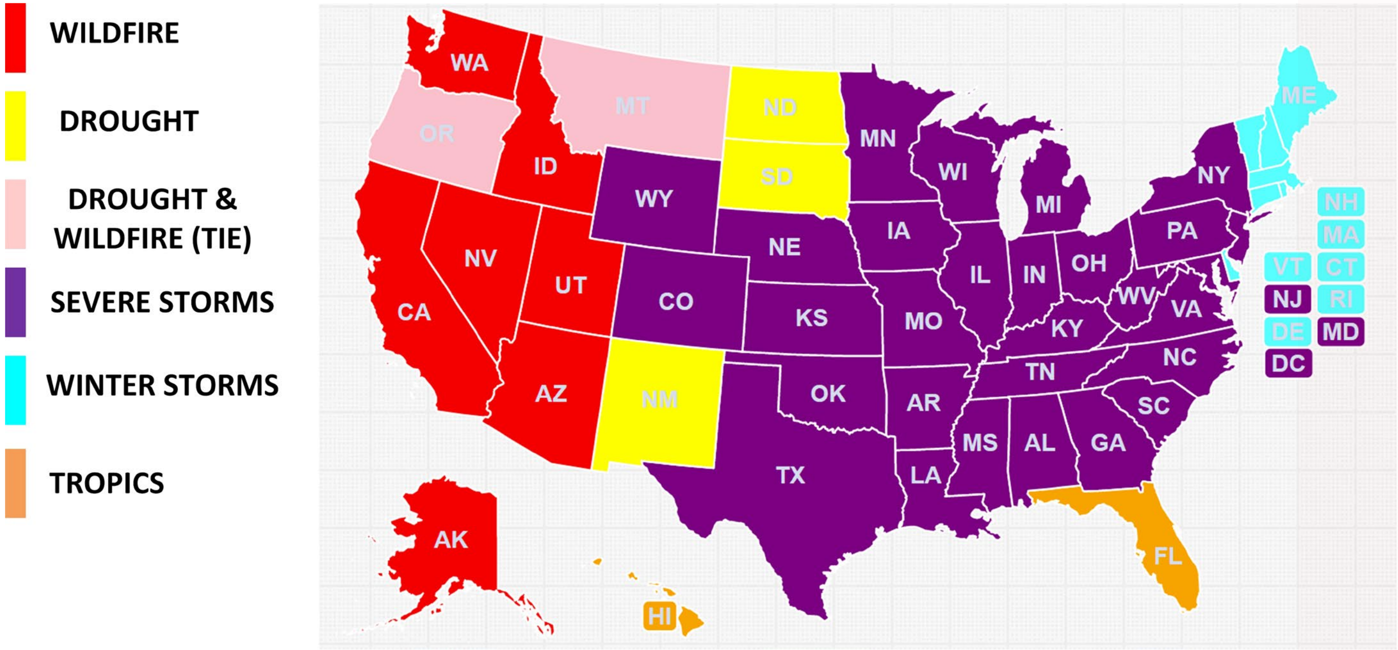
Electric Power Grid: Changing Nature and Requirements

Dramatic increase of extreme events related outages



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

- 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)

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

Electric Power Grid: Changing nature and requirements

Changing nature and requirements of the grid: decarbonized and distributed future

- Very-large penetration of distributed energy resources - 2.5 million solar PV installations (2020)
- Emergence of new load types: 1.6 million PHEVs/EVs sold (2020), in 5 years data centers to use 10% of the U.S. energy
- Power electronic devices will be ubiquitous and layered hierarchical control schemes
- Distributed coordination of all controllable assets for higher level of flexibility among DERs

How can Grid-Edge Provide Resilience?

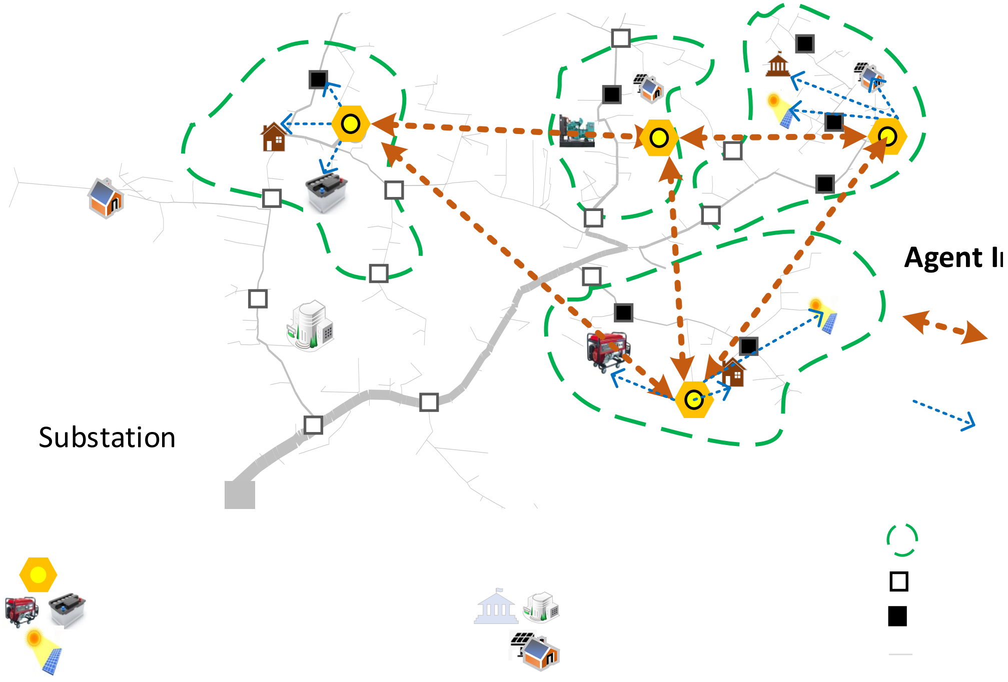
How to keep the lights on?

- Non-traditional ways of operating grid:
    - Networked microgrids
    - Demand-side flexibility to manage rare contingencies
    - DERs for bulk grid support

Distributed Resources for Grid Support:

- Distribution-level services (e.g., restoration)
- Bulk grid support (frequency and voltage regulation)
- Bulk grid support (black-start capability)

Climate-resilient Power Grids: Operational Flexibility using Distributed Energy Resources

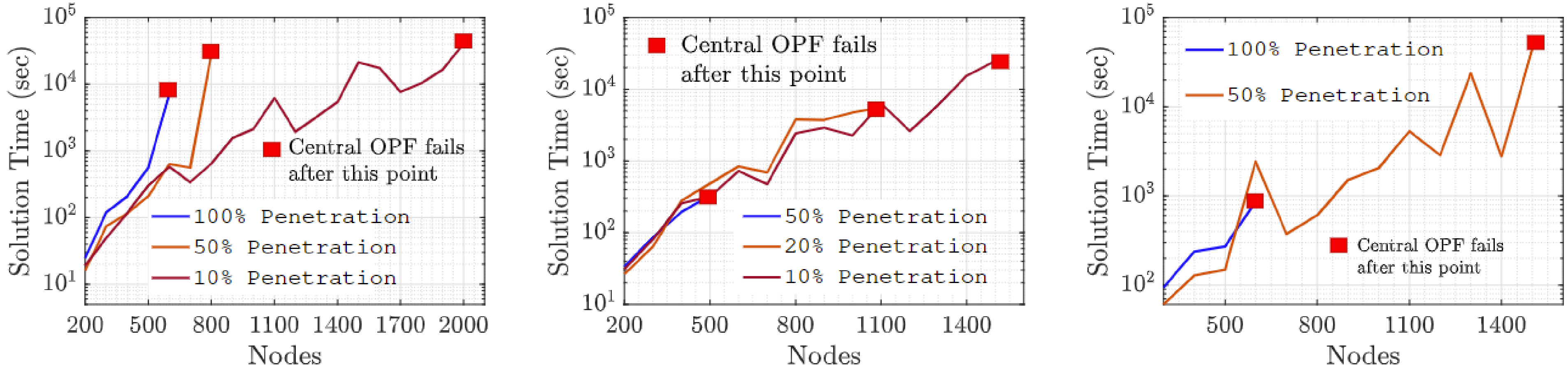


Example: Networked Microgrid for restoration and bulk grid support

Need: Add Operational Flexibility using Grid-Edge

Advanced operations to activate operational flexibility for Resilience using Grid-Edge resources:

- **Scalable and robust approaches to coordinate/operate heterogenous distributed resources for operational flexibility.**
- **Challenge: Large-scale Simulation and Optimization for non-linear (possibly high-order) systems.**



(a) Loss minimization objective (b) DER maximization objective (c) ΔV minimization objective

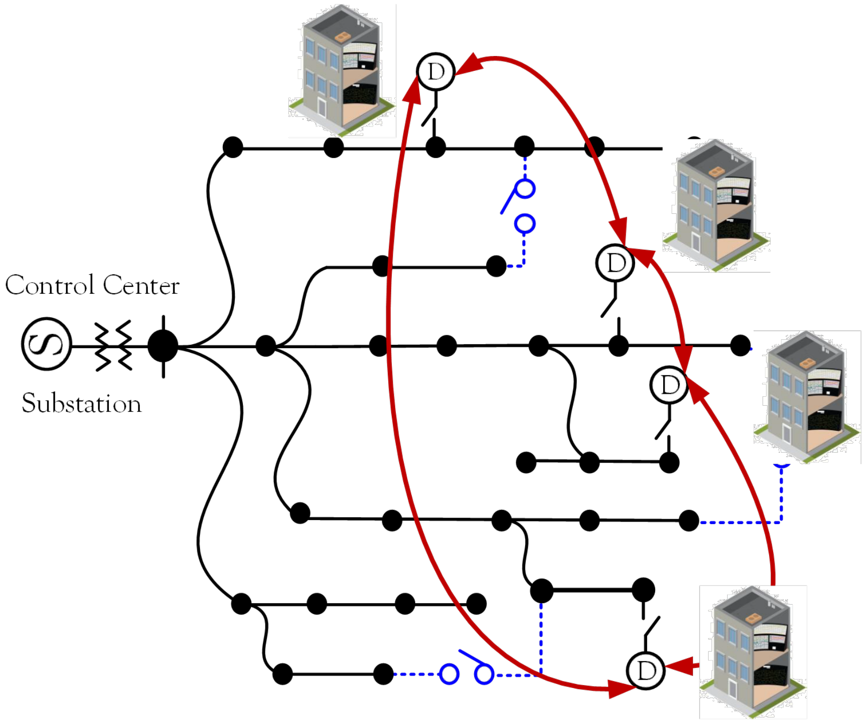
How to Coordinate Grid-edge Resources for Resilience?

Summary of our work in this domain

- Developed computationally tractable centralized algorithm[1]: iterative algorithms using approximation and relaxation
- Mathematical decomposition to achieve scalability[2]: nodal decomposition with distributed computing for scalable nonlinear programming algorithms
- Online feedback-based distributed control[3]: real-time control methods via nodal decomposition
- Local control using Extremum-seeking algorithms[4]: combine IEEE 1547 volt-var curve with extremum-seeking controller for loss minimization
- Several applications of the proposed centralized and distributed OPF to conservation voltage reduction, distribution system restoration, topology and state estimation
- Ongoing benchmarking studies on OPF Algorithms

[1]R. R. Jha and A. Dubey, "Network-Level Optimization for Unbalanced Power Distribution Systems: Approximation and Relaxation," IEEE Transactions on Power Systems, March 2021.
[2]R. Sadnan and A. Dubey, "Distributed Optimization using Reduced Network Equivalents for Radial Power Distribution Systems," IEEE Transactions on Power Systems, Jan 2021.
[3]R. Sadnan, A. Dubey, "Real-Time Distributed Control of Smart Inverters for Network-level Optimization," IEEE SmartGridComm 2020, Nov. 11-12, 2020, virtual format.
[4]H. Ren, R.R. Jha# , A. Dubey, "Extremum-Seeking Adaptive-Droop for Model-free and Localized Volt-VAR Optimization," IEEE Transactions on Smart Grid, June 2021.

Scalable Approaches for Grid-Edge Optimization



- **Distributed Optimization –**
  - State-of-the-art for requires ≥ 100 communication rounds to solve one step of optimization
- **Feedback/Online distributed control -**
  - Several steps of iteration to track the optimal solution
  - Intermediate iterates may violate the operating constraints

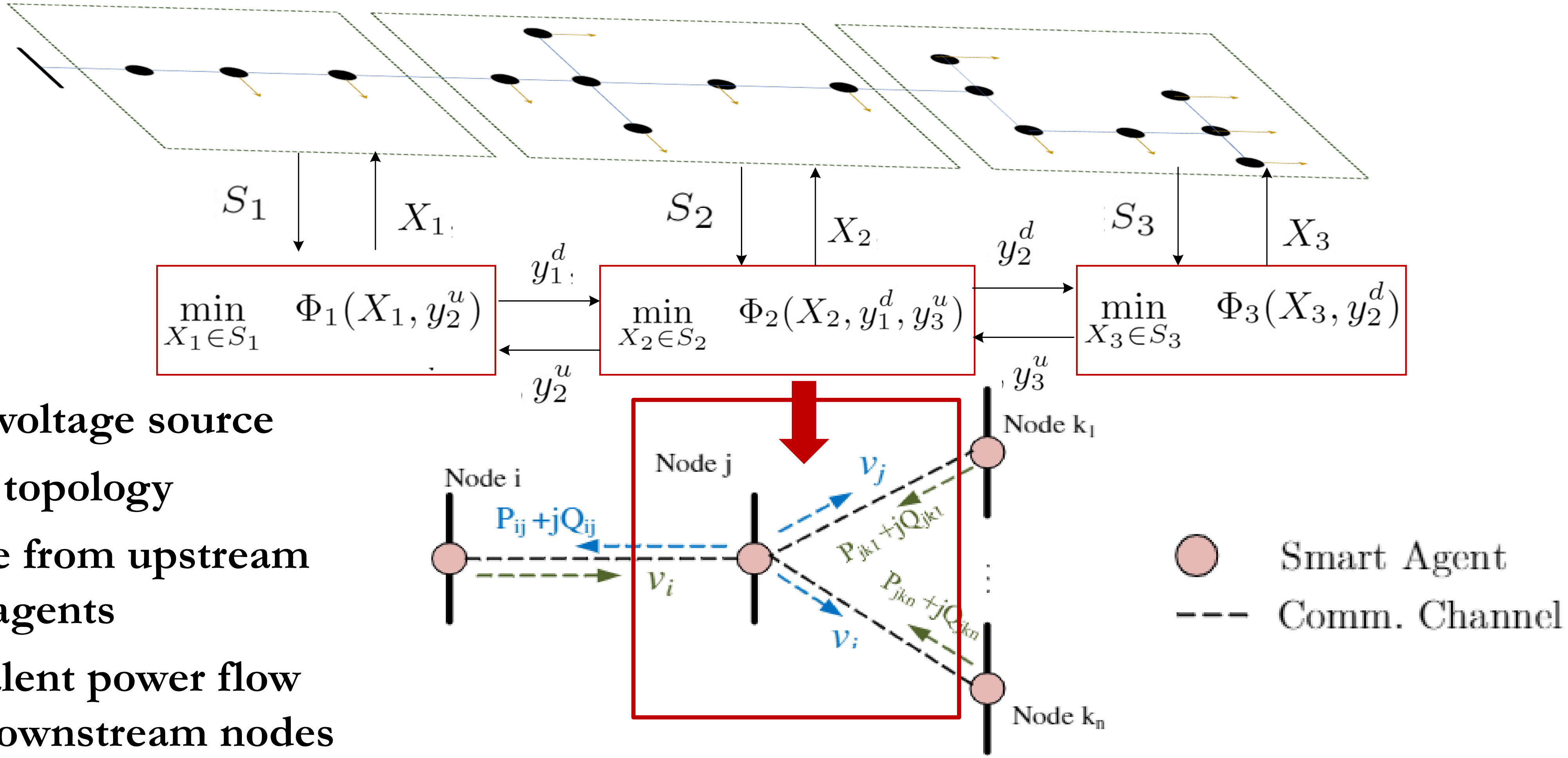
Solutions:

(1) Distributed optimization algorithms that take fewer macro-iterations to converge

(2) Feedback/Online Control algorithms that can track the optimal solutions within a few steps

Key observation – Distribution feeders are operationally radial or weakly meshed

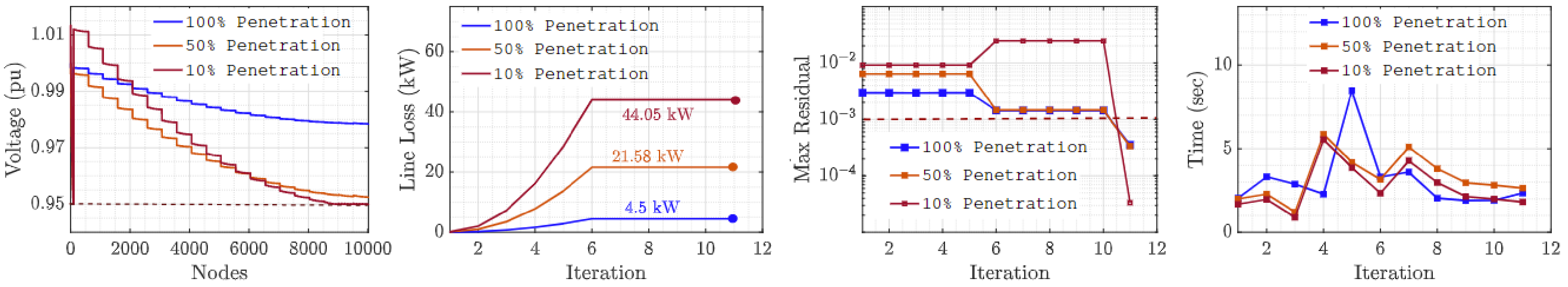
Proposed Distributed Optimization Algorithm



- Single voltage source
- Radial topology
- Voltage from upstream smart agents
- Equivalent power flow from downstream nodes

Results and Discussions

Distributed computing/distributed optimization:



(a) Nodal voltages (b) Objective value (c) Convergence (d) Simulation time

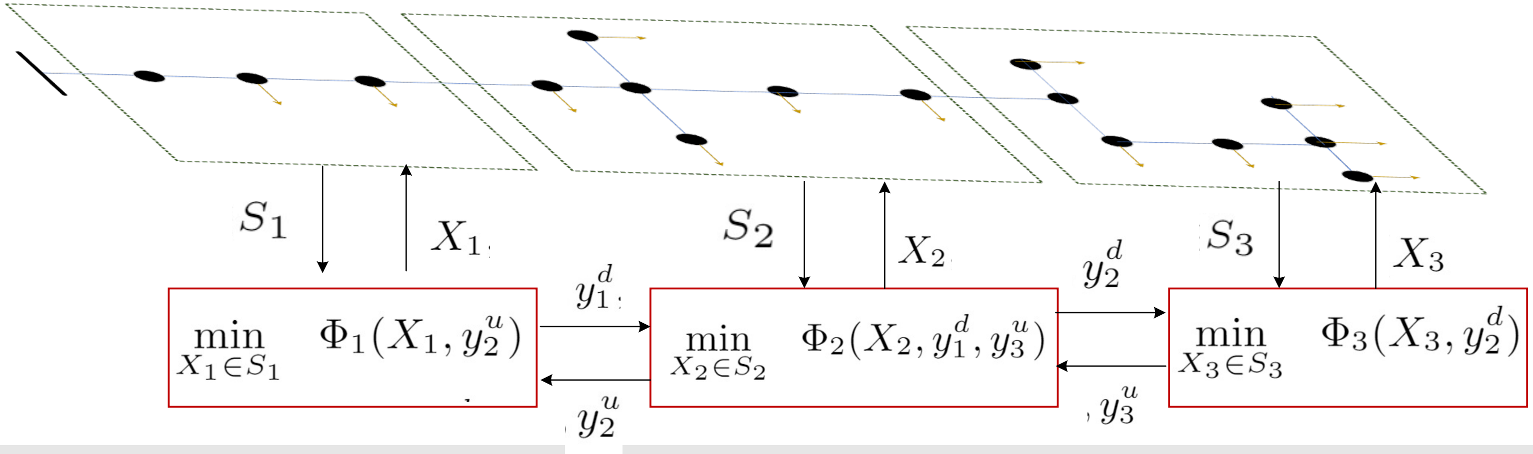
Figure 2.3: Numerical Results for Loss Minimization Objective for Synthetic 10,000 Node System. The proposed problem decomposition and distributed computing approach easily scale for large feeders for all DG penetration levels. The number of communication exchanges among decomposed sections is in the order of 10s; thus, the proposed structured decomposition significantly improves upon the existing primal or dual decomposition approaches.

- **Worked on convergence proof for single-phase system**
- **Expanded to three-phase systems**
- **Incorporated mixed-integer formulations (cap banks, regulators)**

R. Sadnan#, S. Poudel, and A. Dubey, "Layered Coordination Architecture for Resilient Restoration of Power Distribution Systems," submitted to IEEE Transactions on Industrial Informatics, May 2022.

Applications: Distributed Control of Islanded Microgrids

Robust Distributed Control for Power Sharing in Islanded Industrial Microgrids - stable voltage and frequency response



Decomposable problem structure

Use of mathematical optimization techniques to decompose problem into distributed structure and design real-time control law.

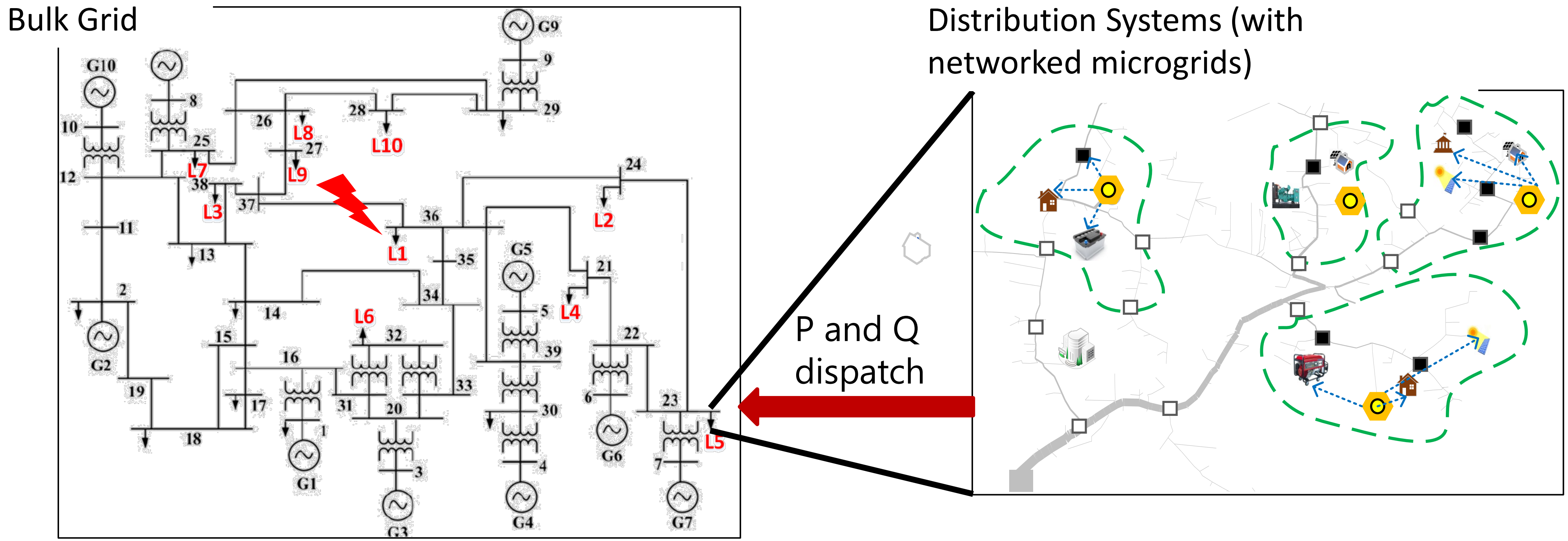
Contributions

- Distributed controllers for power sharing with an emphasis on minimizing communication and integrating local droop control methods and proper network models
- Performance and stability of the proposed distributed power sharing controllers via theoretical analysis and simulations.

- Andrew I.H. Cannon, A. Dubey, G. Zweigle. and E. Blood, "Distributed Optimal Reactive Power Control in Islanded Microgrids with Voltage-Source Inverters," IEEE PowerTech 2021.
- A.A. Maruf, A. Dubey, and S. Roy, "Small-Signal Voltage Stability Analysis for Droop Controlled Inverter-based Microgrids: An Algebraic Graph Theory Perspective," IEEE PES GM 2021
- Abdullah Al Maruf, Mohammad Ostadijafari#, Anamika Dubey, and Sandip Roy, "Small-Signal Stability Analysis for Droop-Controlled Inverter-based Microgrids with Losses and Delays," ACM e-Energy Conference'19, June 2019, Phoenix, AZ, USA

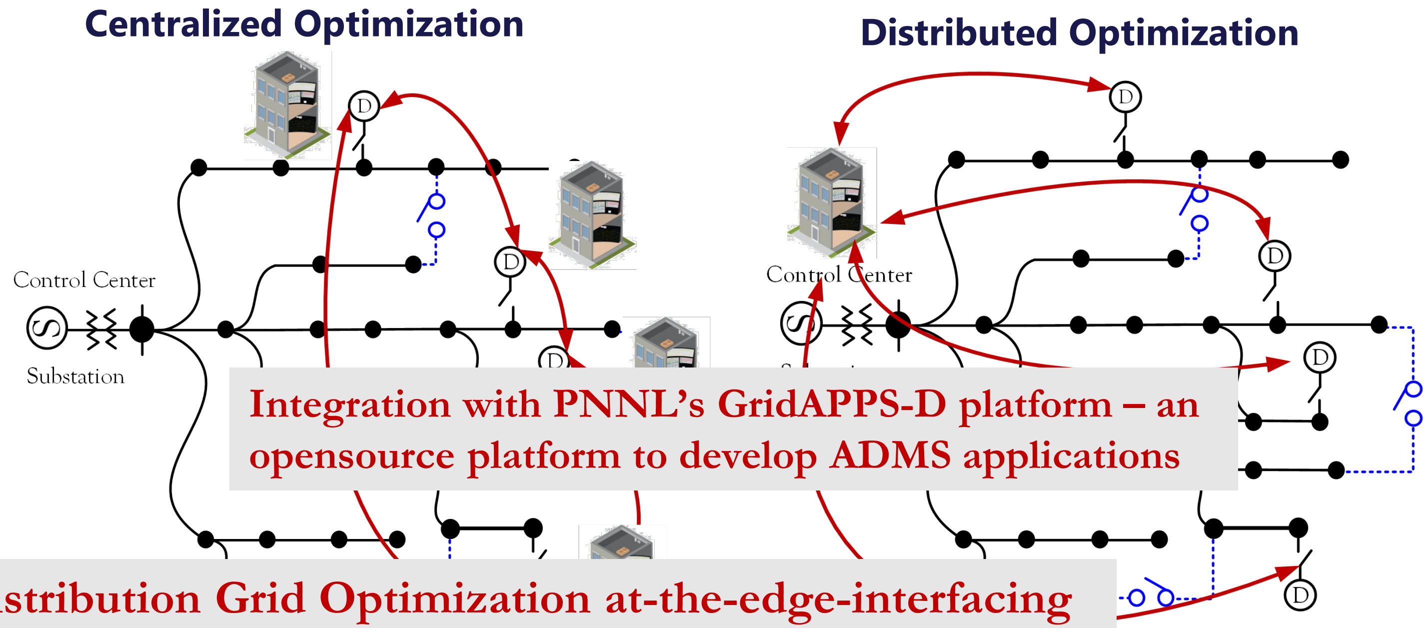
Applications: DERs for Bulk Grid Support

- Algorithms for Distributed Coordination of Networked Microgrids for bulk grid service
  - Active power dispatch for frequency support
  - Voltage control and Reactive Power Support
- Impact in Transmission Systems Dynamic Response
- Effects of Communication Systems on Control for Bulk-grid services



Control and Optimization: Active Power Distribution Systems

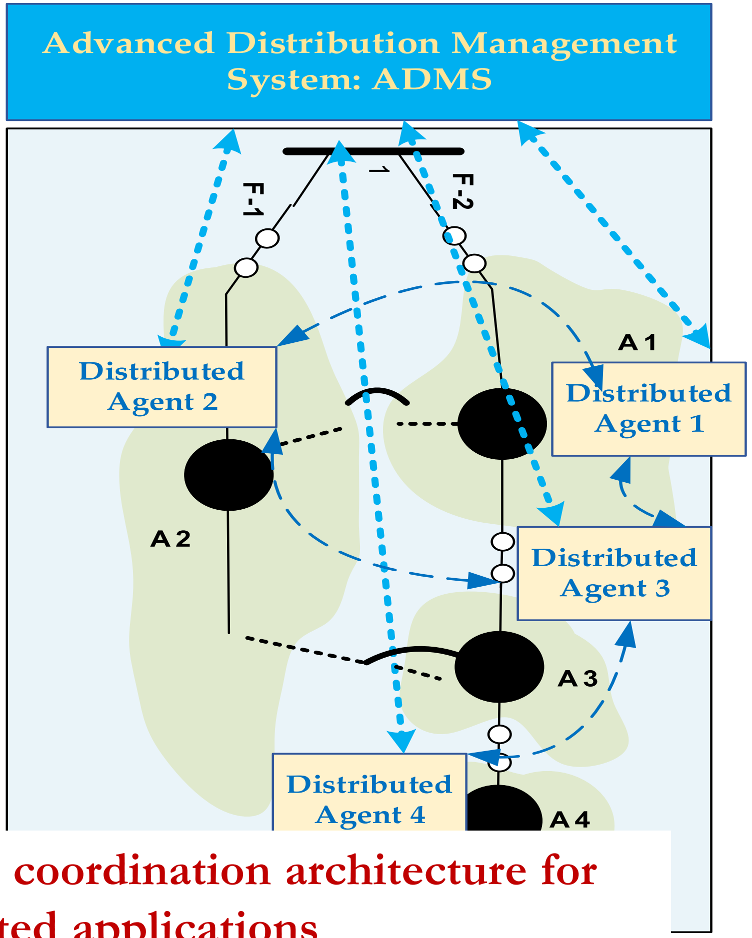
Coordinate grid-edge devices by integrating data, measurement, and control to optimize distribution operations for grid services



Integration with PNNL's GridAPPS-D platform – an opensource platform to develop ADMS applications

Distribution Grid Optimization at-the-edge-interfacing

- ✓ Algorithmic bottlenecks
- ✓ Ownership boundaries and privacy concerns
- ✓ Information unavailability and uncertainty
- ✓ Visibility and situational awareness



Layered coordination architecture for distributed applications

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.

Next Steps - Motivation for Learning-based Approach

Optimal power flow algorithms have

- Limited capability in handling fast dynamic systems – frequency support?
- Computation complexity increases linearly with network size
- The solution timescale is not sufficient for fast response required from frequency regulation applications

Learn to control - Reinforcement learning (RL) algorithms

Our Contributions:

- RL algorithms for Fast/real-time optimization/operations
- Imitation Learning: Use data to improve approximate (low-compute) optimization models for very fast decisions[1]
- An opensource environment to call packages and make it easy to implement RL for power distribution systems application[2]

[1]Gayathri Krishnamoorthy, Anamika Dubey, and Assefaw H. Gebremedhin, "Reinforcement Learning for Battery Energy Storage Dispatch augmented with Model-based Optimizer," presented, IEEE SmartGridComm 2021, Aachen, Germany, 24-28 Oct. 2021

[2]G. Krishnamoorthy, A. Dubey, and A. H. Gebremedhin, "An Open-source Environment for Reinforcement Learning in Power Distribution Systems," IEEE PES General Meeting, 2022 (accepted)

Next Steps – Complex Models for Grid-Edge Devices

Optimal power flow algorithms have

- Limited capability to manage complex nonlinear and possibly high-order models for grid-edge devices, such as grid-interactive building with programmable thermostat
- Enabling operational flexibility requires simulating and solving some optimization problem with these complex grid-edge devices

Surrogate (reduced-order dynamic) models for Grid-Edge to manage complexity.

Ongoing work:

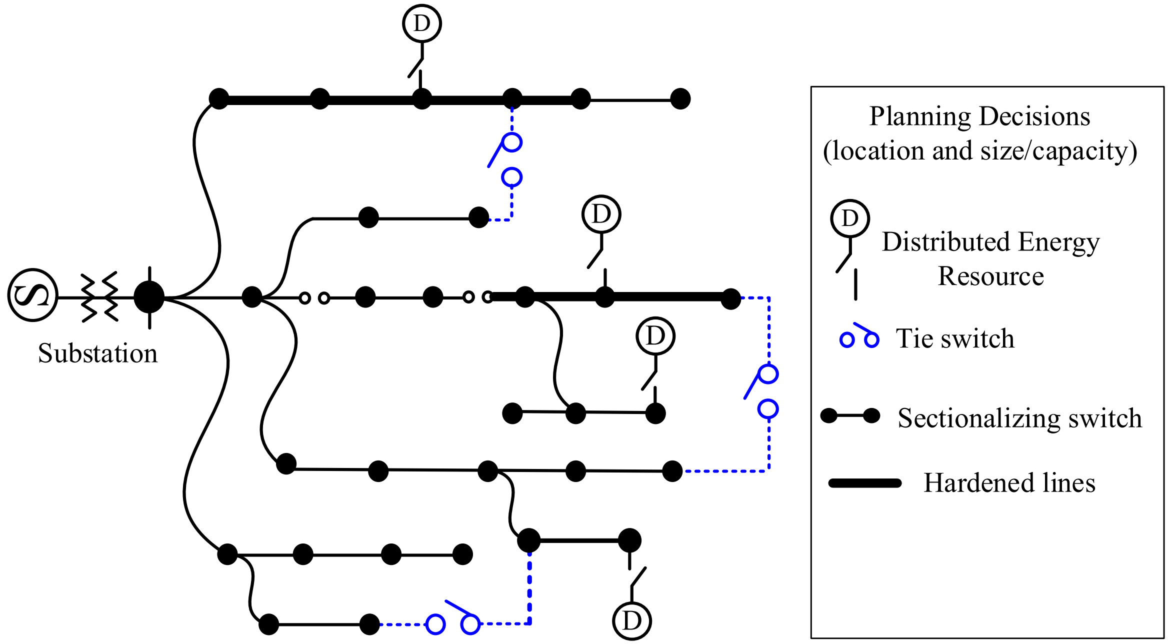
- **Large-scale simulations with multiple grid-interactive commercial building**
- **Grey-box (controllable) model using dynamic single-zone approximation**
- **Validation on Pecan Steet Data for residential buildings and against EnergyPlus simulator for commercial buildings**
- **Similar questions for power-electronics-interfaced grid-edge devices especially in an islanded condition.**

Need – Add Operational Flexibility at the Grid-Edge

Planning to Enable Operational Flexibility from Grid-Edge Resources: How to economically add operational flexibility to the grid to improve their response during extreme weather events?

- High-impact low-probability event
  - Weather-grid impact model – Multiple sources of uncertainty
  - Risk quantification – HILP and tail probabilities
  - Evaluate planning tradeoffs
- Algorithmic framework to evaluate risk-cost tradeoffs to optimally plan for operational flexibility
- **Challenge:** Large-scale Risk-averse Optimization

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



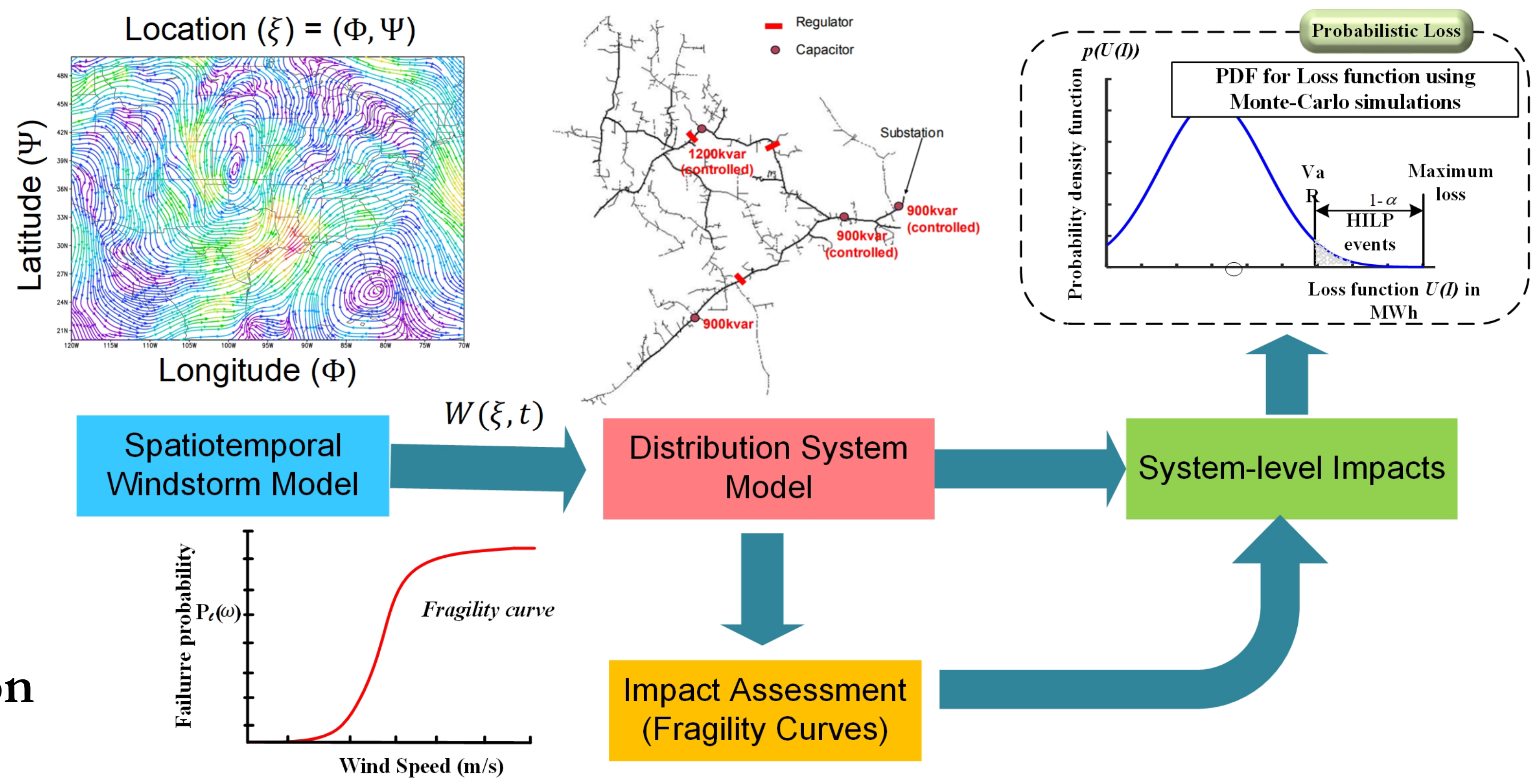
Quantifying Weather-grid Impacts

A simulation-based approach

Data generation

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

Probabilistic quantification of the impacts (risks)



A. Poudyal, V. Iyengar, D. Garcia-Camargo, and Anamika Dubey “Spatiotemporal Impact Assessment of Hurricanes on Electric Power Systems,” IEEE PES General Meeting, 2022 (accepted).

Defining Objective Function

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.

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

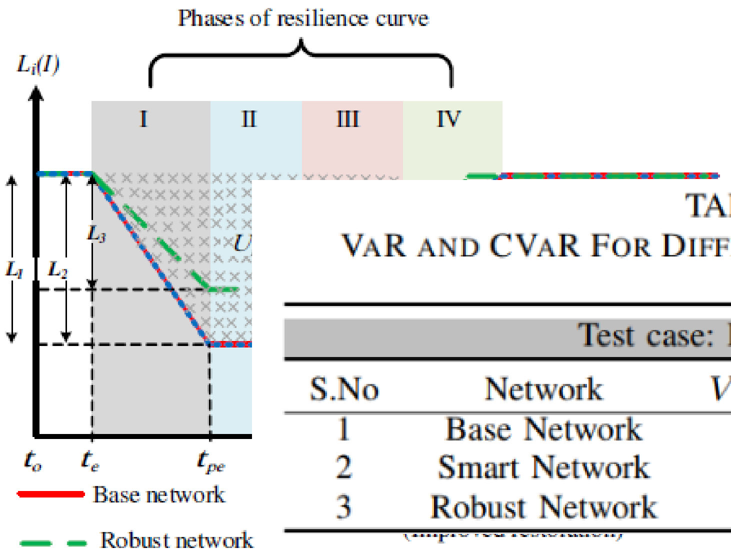


TABLE II

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

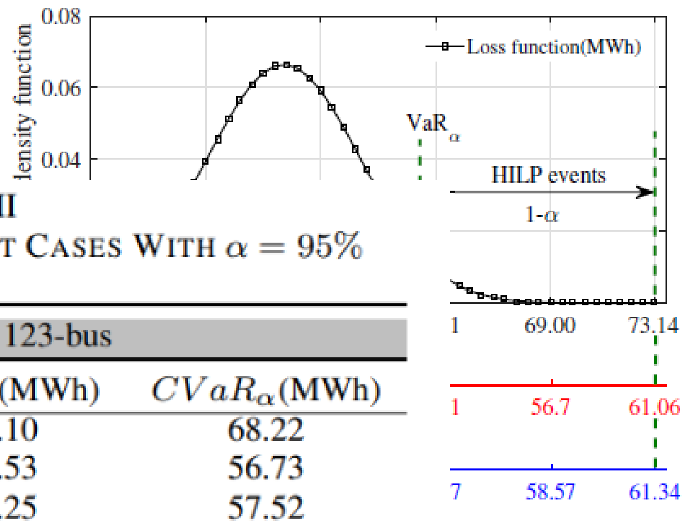


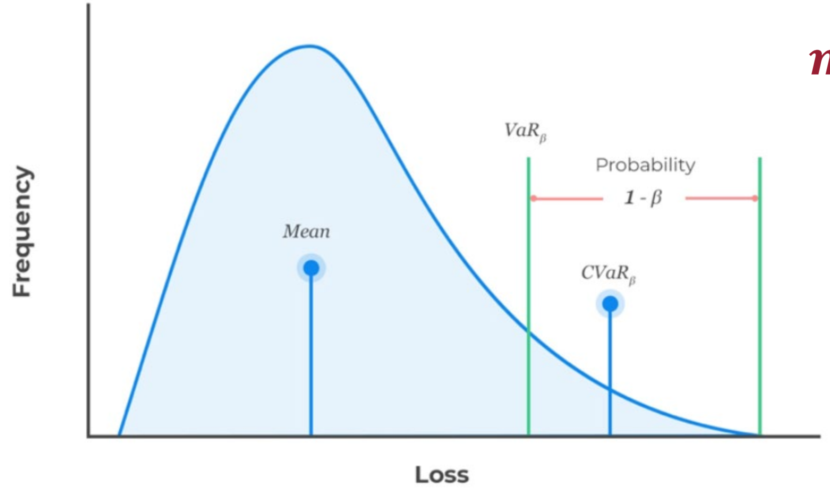
Figure 3: (a) Approximated resilience curve for an event. The different colored lines correspond to effects of proactive planning: (1) Base network - does not include any proactive planning measure; (2) Smart network - includes DERs to support intentional islands; (3) Robust network - includes hardening 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 on Aug 2019.

Risk-averse Optimization

Conditional value at risk in the objective :

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



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

tradeoff for risk-neutral vs risk-averse

where,

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

where, η = value-at-risk

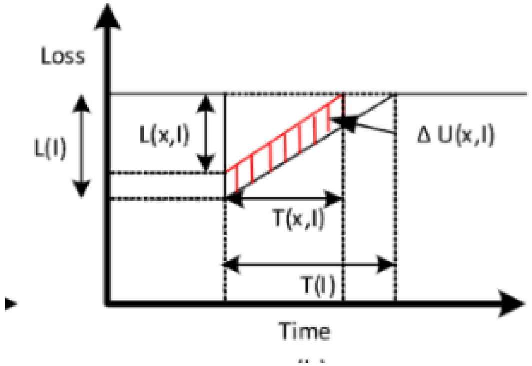
Mean-risk function with $CVaR_\alpha$ as risk measure: $\min_{x \in \mathbb{X}} \{\mathbb{E}[f(x, \omega)] + \lambda CVaR_\alpha[f(x, \omega)]\}$

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

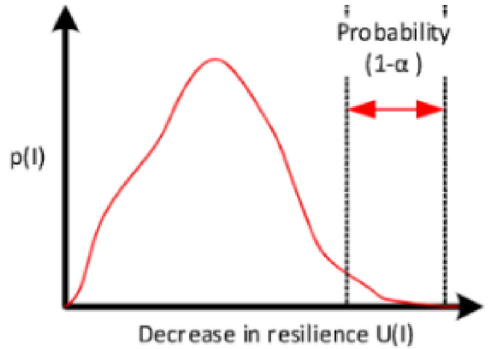
Higher the value of λ, higher is the risk aversion

Risk-averse Optimization to Improve Resilience

[1]Optimal coordination of all assets for a given realization of extreme event



[2]Numerically quantify the impacts of an event with and without planning solutions



$$\min_{x} c^T x + CVaR_{\alpha}(x)$$

$$\begin{aligned} U(I) &= f(L(I), T(I)) \\ \Delta U(x_i, I) &= f(L(x_i, I)T(x_i, I)) - f(L(I)T(I)) \end{aligned}$$

$$U(X, I) = U(I) - \sum_{i=1}^{n} \Delta U(x_i, I)$$

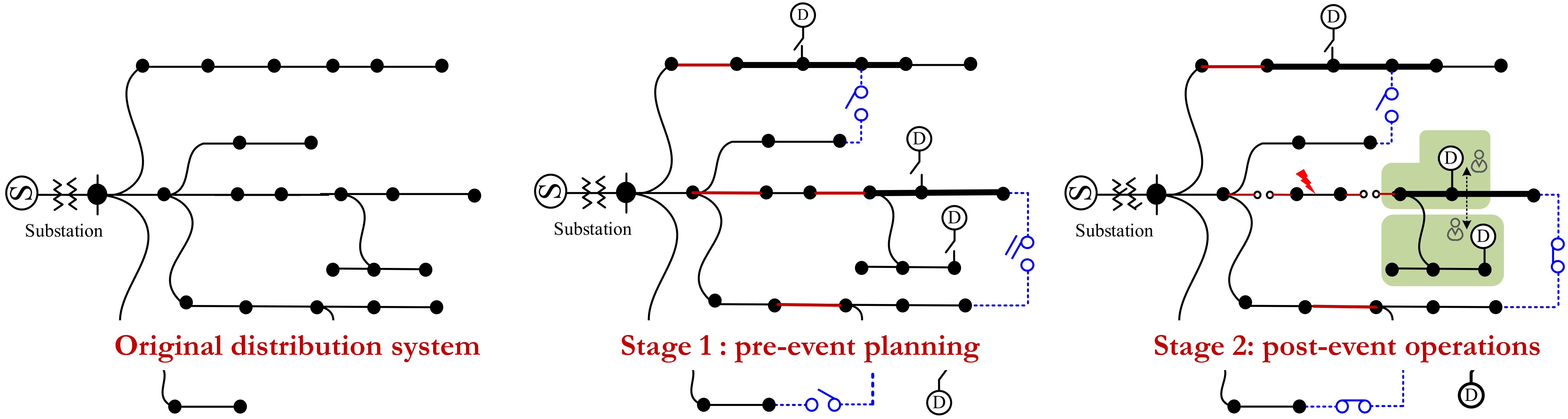
$$\begin{aligned} \psi(X, \xi) &= \int_{U(X,I)\leq\xi} p(I)dI \\ VaR_{\alpha}(X) &= min\{\xi \in R : \psi(X, \xi) \geq \alpha\} \\ CVaR_{\alpha}(X) &= \frac{1}{1-\alpha} \int_{U(X,I)\geq VaR_{\alpha}(X)} U(X, I)p(I)dI \end{aligned}$$

Example - Resilience Planning: Two-stage Stochastic Program

Optimize CVaR metric - Resilience planning for power distribution system

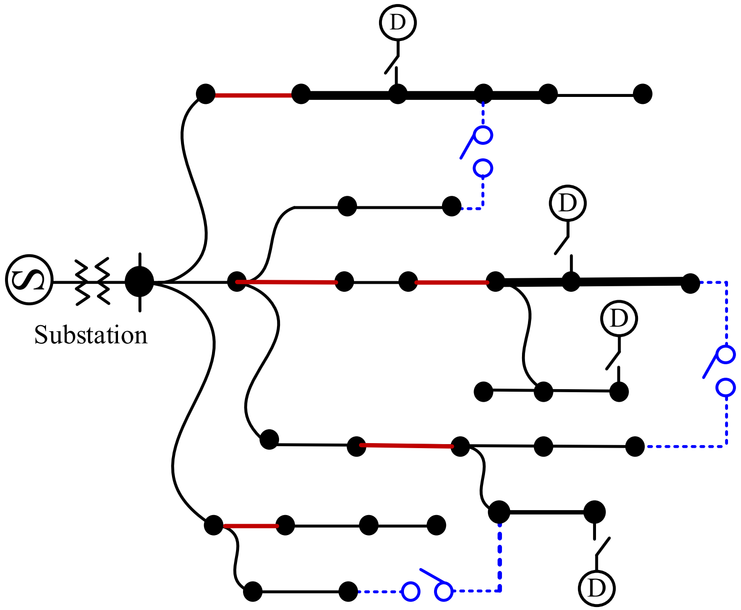
A two-stage stochastic optimization formulation

- 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)



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:

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

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

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

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

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

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

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

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

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

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

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

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

Solving the two-stage problem: Methods

All methods convert stochastic problem to a deterministic problem

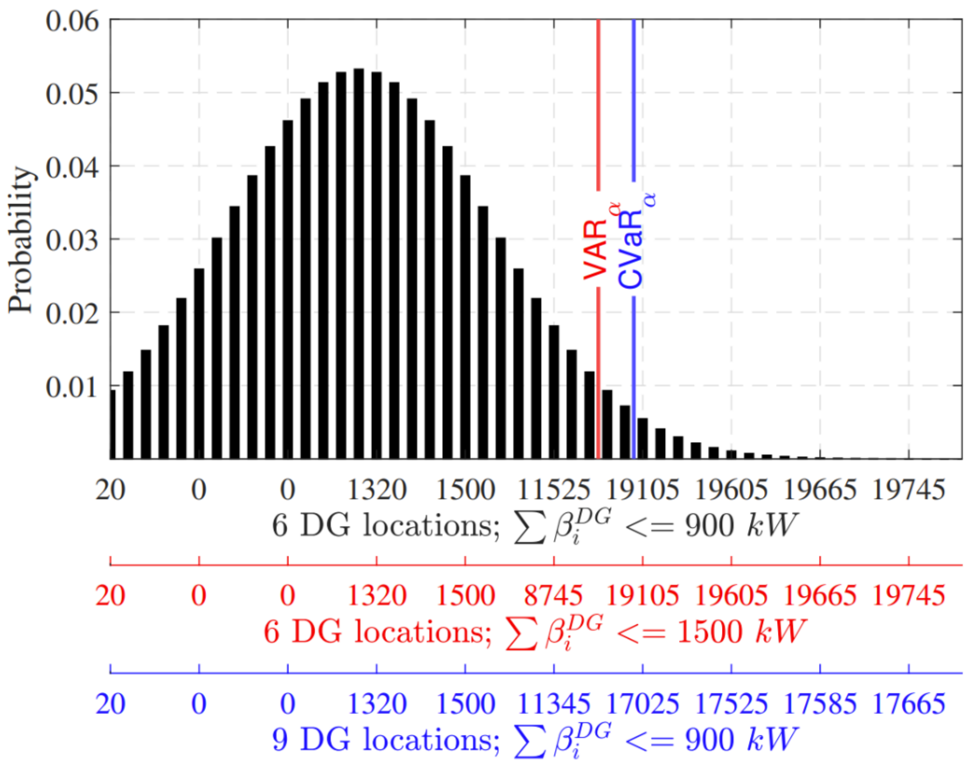
- Sampling-based approaches: Extensive form, create multiple copies of second stage problem, solve a large single-stage deterministic optimization problem, most accurate, scenario selection is crucial
- Progressive hedging: relax non anticipativity constraint, primal and dual of convex stochastic problems, fast algorithm → parallelizable
- Stochastic Dual Dynamic Programming: Great in a multi-stage setting, stage-wise decomposition of the problem

Results and Discussions

- Tested with IEEE 123 bus test system upgraded with sectionalizing and tie switches for restoration.
- Question was – what are optimal DG locations if the budget for DGs is constrained
- Goal was to compare risk-neutral and risk-averse planning decisions

	λ = 0 (risk-neutral)	λ = 1 (risk-averse)
VAR	3210	3210
CVaR	19093.89	18885.9
Expected value	3567.12	3595.51
Expected Prioritized Critical Load Pickup	15043.93	15006.62
CVaR Of Prioritized Critical Load Pickup	3406.59	3603.06

Impacts of DG budget constraints



Abodh Poudyal, Shiva Poudel, Anamika Dubey, Risk-based Active Distribution System Planning for Resilience against Extreme Weather Events, submitted to IEEE Transaction on Sustainable Energy (second round of review)

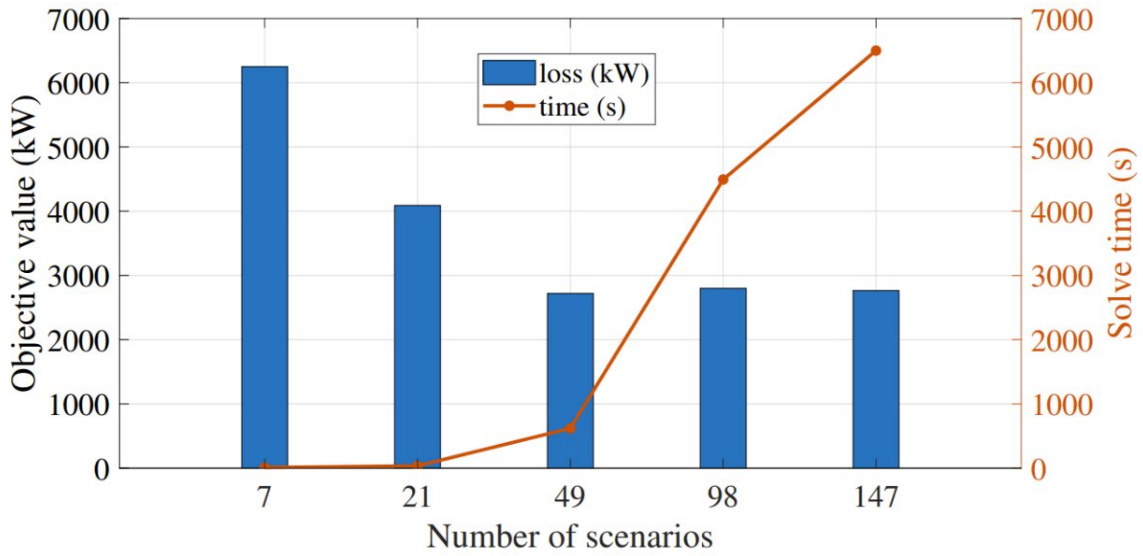
Ongoing and Future Work

- Scaling for lager feeders and higher number of scenarios:
  - Extensive form leads to a very large-scale mixed-integer linear program, progressive hedging results in large optimality gap

- Future work includes: (1) use of parallel computing techniques to scale for larger number of scenarios, (2) value-function approximation to scale the problem for large networks

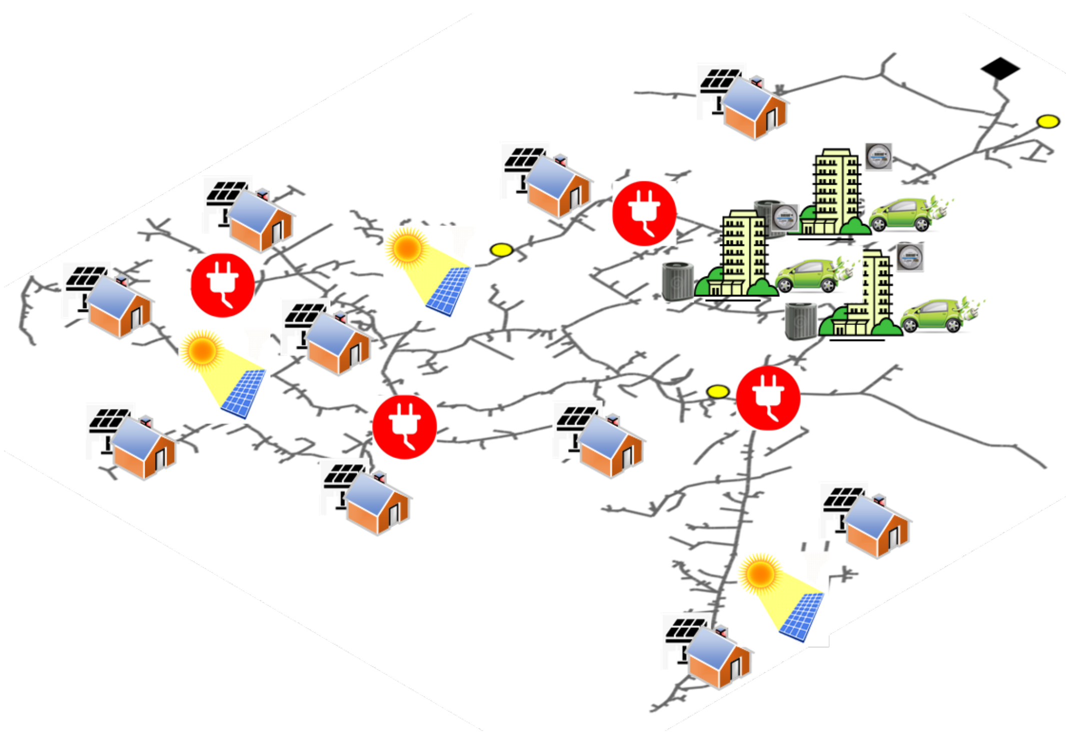
- Collaboration with utility companies on using real-world data to improve weather-grid impact models

For a small 123-bus distribution system: see accuracy vs. compute time tradeoff



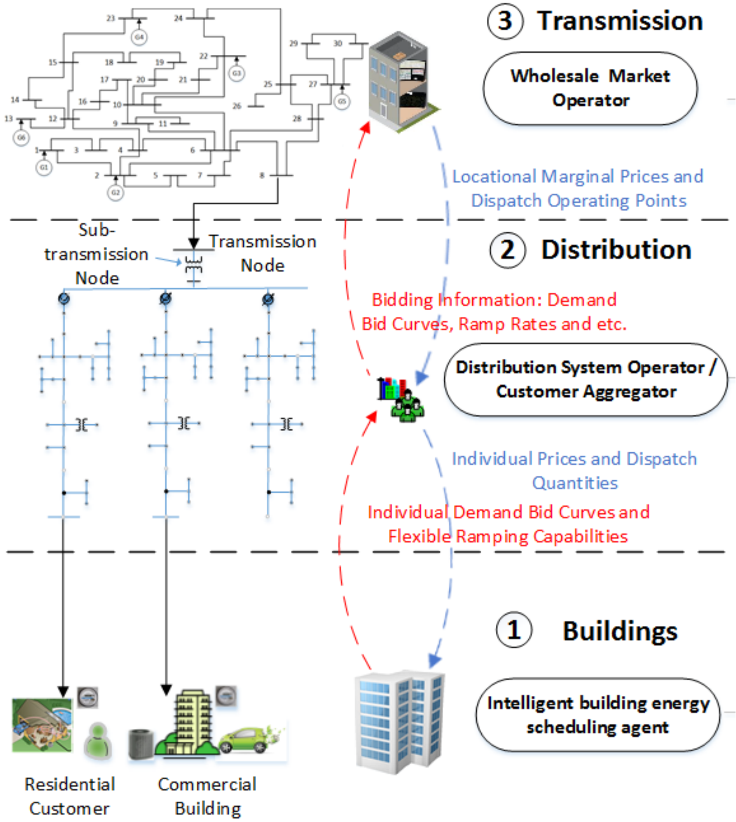
Key Takeaways

Changing nature and requirements of the grid at the edge interfacing



Scalability for interconnected T&D systems

System of systems – complexity



- Growing complexity of Grid operations: Scalable simulation and optimization is key to study and operate the complex power grid.

Acknowledgments

Current students:

- Abodh Paudyal (WSU, PhD student), Rabayet Sadnan (WSU, PhD student), Daniel Glover (WSU, PhD student), Nathan Gray (WSU, PhD student)

Past Students:

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Thank you

Questions?