NREL
Transforming ENERGY

Real-Time Resilience of Energy Systems

23 August 2022

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What is Resilience?

Resilience is a property of an energy system that reflects its ability to adapt to changing operational conditions and recover rapidly from disruptions

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Resilience is a property of an energy system that reflects its ability to adapt to changing operational conditions and recover rapidly from disruptions

As opposed to reliability, resilience mostly concerns with low-probability high-impact events

Scientific Challenges

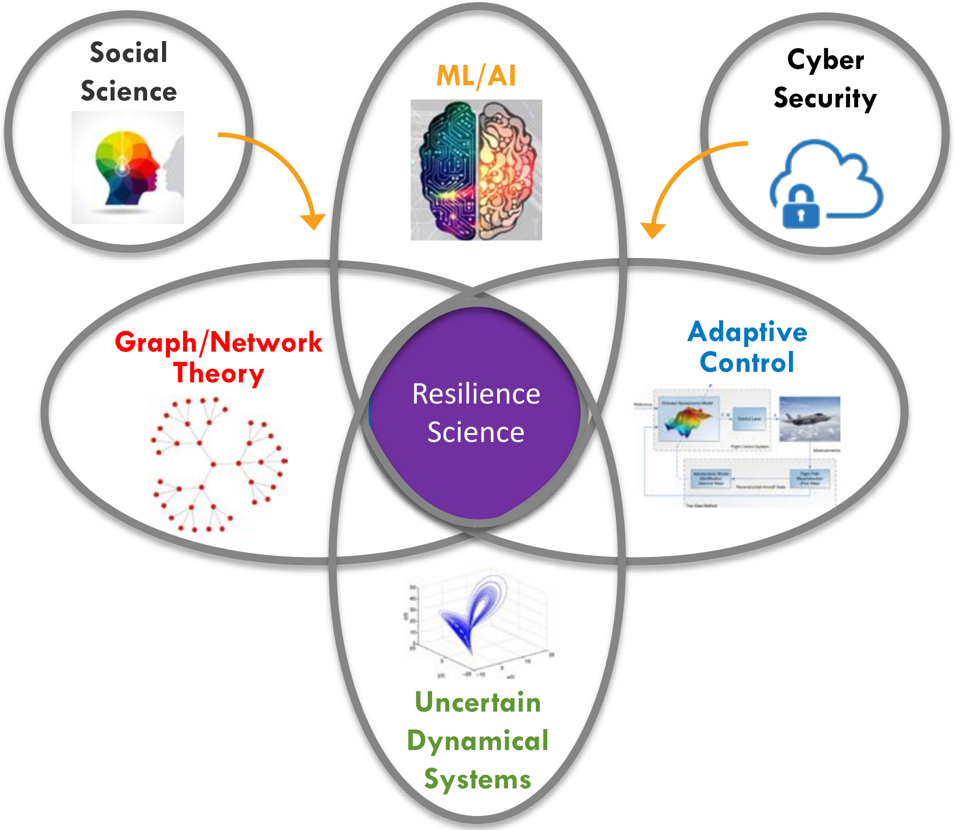
What is the formal definition of energy system resilience?

What mathematical frameworks can rigorously assess and ensure resilient operation of complex energy systems?

How to assess and ensure system resilience in conditions of uncertainties in data and models and with human-in-the-loop?

How to leverage highly distributed system structure for resilience?

Transforming **ENERGY** through Foundational Science



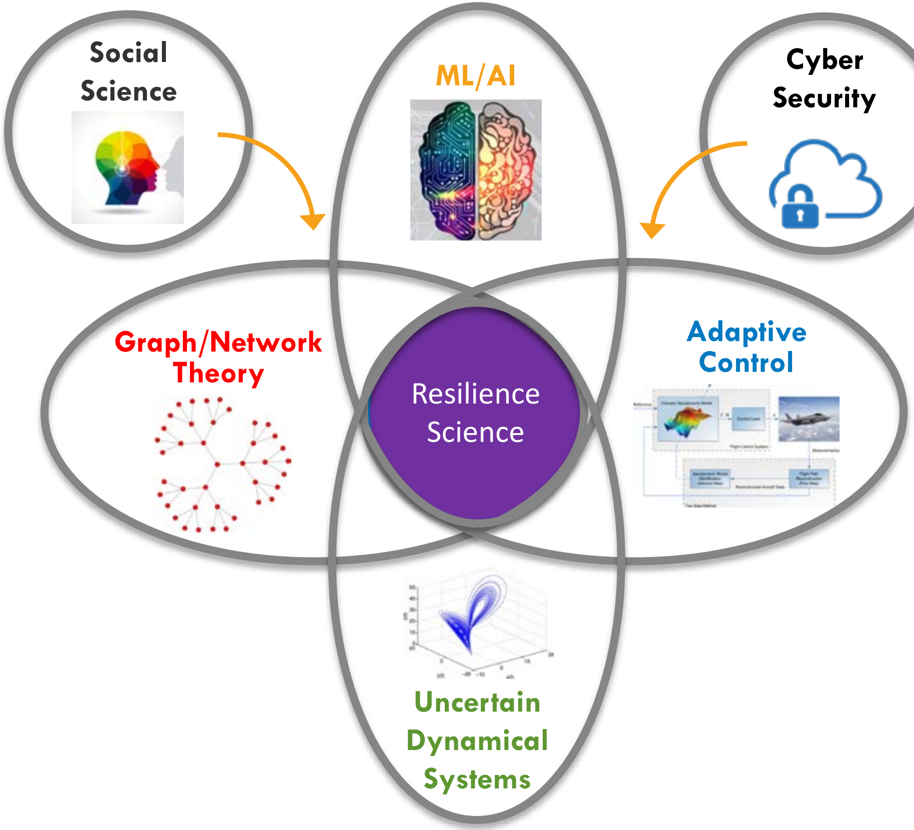
The **main scientific goal** is to develop analytical foundations for adaptive control algorithms that:

- **utilize data efficiently**
- **leverage the highly-distributed network structure**
- **tackle highly uncertain system dynamics**

in order to **steer energy systems throughout disruption events.**

- Need inputs from:
  - Social science experts
  - Cyber security experts
- Need to advance foundational science in:
  - Adaptive control theory
  - Machine learning/artificial intelligence
  - Graph/network theory
  - Solvability theory of uncertain differential equations and projected dynamical systems

Transforming ENERGY through Foundational Science



The **main scientific goal** is to develop analytical foundations for adaptive control algorithms that:

- utilize data efficiently
- leverage the highly-distributed network structure
- tackle highly-uncertainty system dynamics

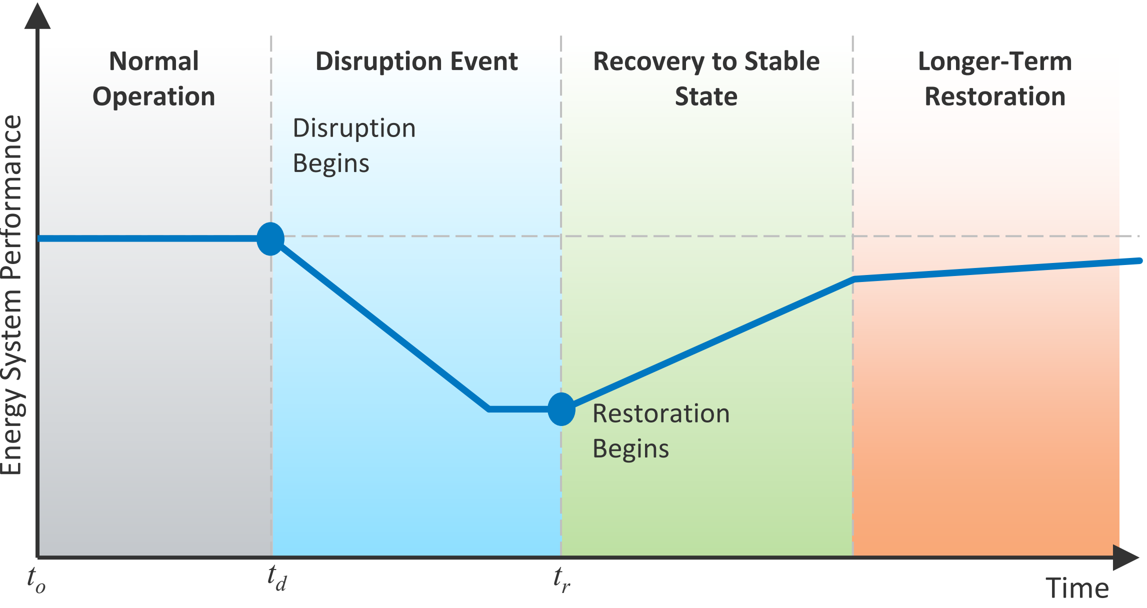
in order to represent a complex energy system and

The main outcome: Modeling and algorithmic framework for real-time resilience of energy systems

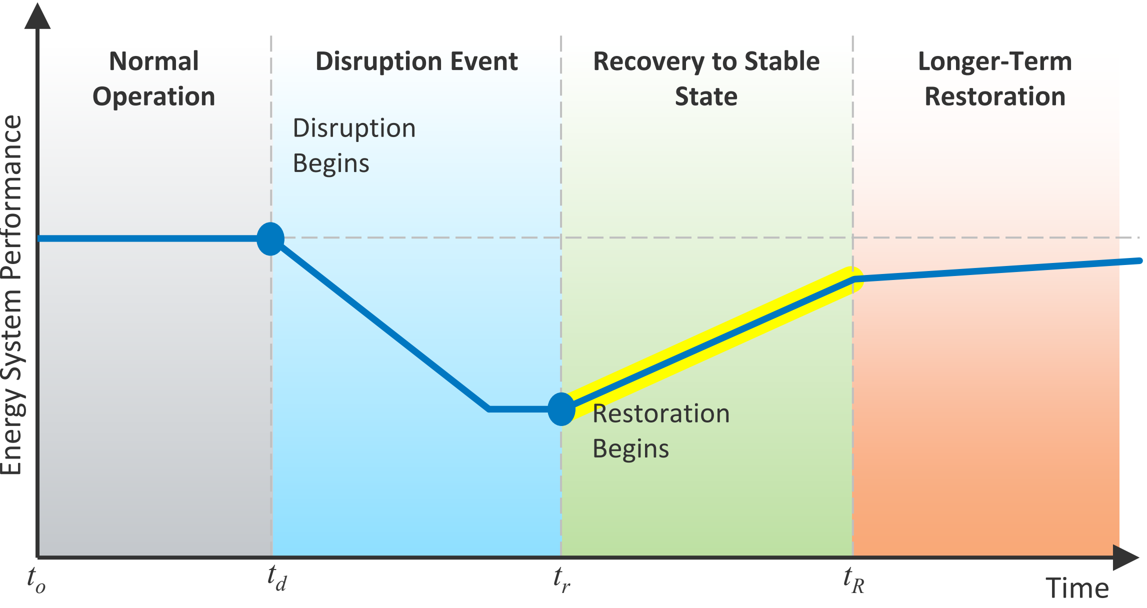
- Graph/network theory
- Solvability theory of uncertain differential equations and projected dynamical systems

Goals

Develop multi-dimensional representation of complex network resilience metrics



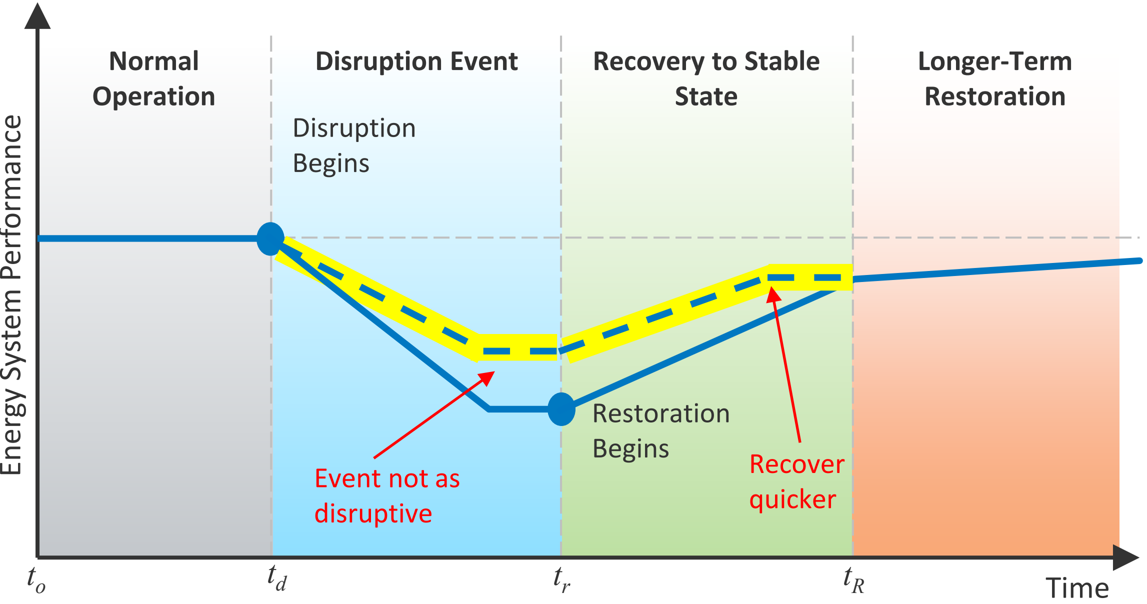
Goals



Develop multi-dimensional representation of complex network resilience metrics

Identify contingency and steer the system from an established disrupted condition to acceptable operation

Goals



Develop multi-dimensional representation of complex network resilience metrics

Identify contingency and steer the system from an established disrupted condition to acceptable operation

Steer the system from a nascent disruption to acceptable operation
= ``riding through contingencies''

Focus: Real-Time Resilience

Develop multi-dimensional representation of complex network resilience metrics

Planning for Resilience

- How to plan a more resilient energy system?
- Which investments should be made?

Real-Time Resilience

Identify contingency and steer the system from an established disrupted condition to acceptable operation

Steer the system from a nascent disruption to acceptable operation
= ``riding through contingencies”

Outcomes

- **Establishing energy systems real-time resilience science field**
- **Scalable, adaptive algorithms** to autonomously manage system response to a nascent disruption, minimizing net impact, and tying into the previous methodology to optimize the degradation/ recovery sequence.
- **Apply** to steer power systems through contingencies

Summary of FY22 Accomplishments

- Co-simulation of power grid and human network
- Application of emergency real-time control on Texas hurricane scenario
- Development of control algorithms accounting for human behavior
- Development of optimal shutoff methods for equitable wildfire mitigation
- International AES Workshop, fifth in the series of AES workshops (held on July 13-15, in person)

Co-Simulation of Grid and Human Behavior

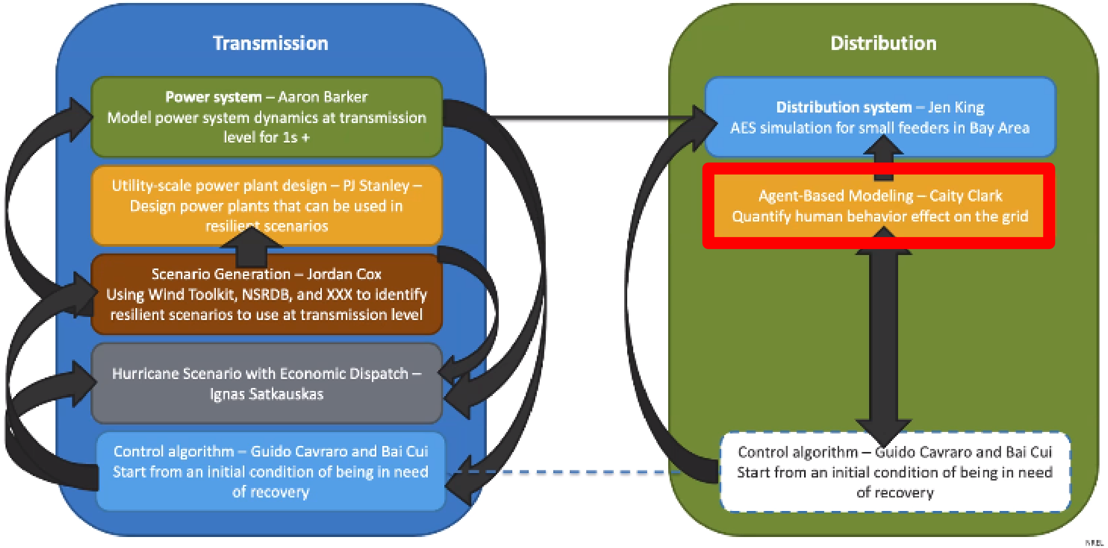
Integrated Approach

Extreme event happens and:

1. Recover quickly to normal operations (serve all loads within operational bounds)
2. Robust operation: ability to “limp” along out of voltage bounds but eventually get back to normal operation
3. Partial recovery: prioritize critical loads

How do we do this:

- Build up a simulation infrastructure
- Introduce extreme events
- Demonstrate outcomes with and without operational resilient controls



What about the humans?

Why do we care about human behavior?

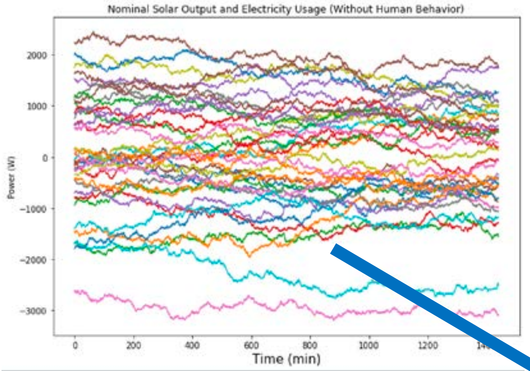
- Distribution systems have increasing amounts of generation and storage
- Changes in our controls are required to handle device-owner decisions
- In resilience scenarios, behavior is particularly non-standard

If human behavior is so illogical and unpredictable, how are we supposed to model it?

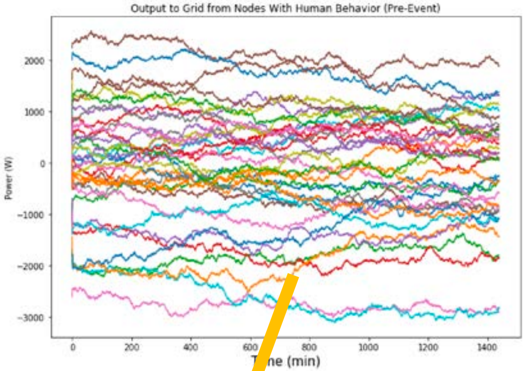
Agent-Based Modeling

ABM stochastically models each agent separately to explore *emergent* behavior

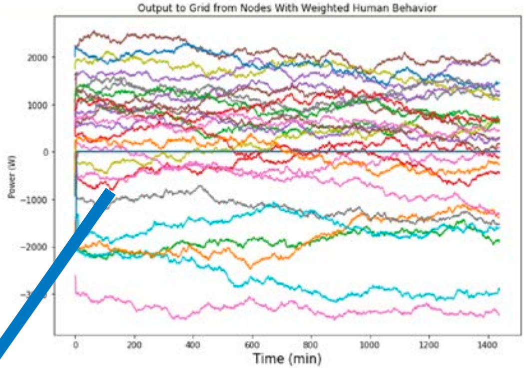
No Human Behavior

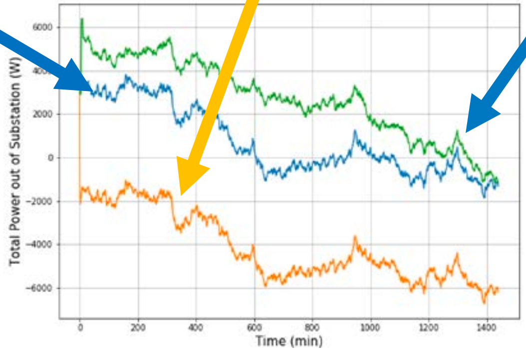


Baseline Human Behavior

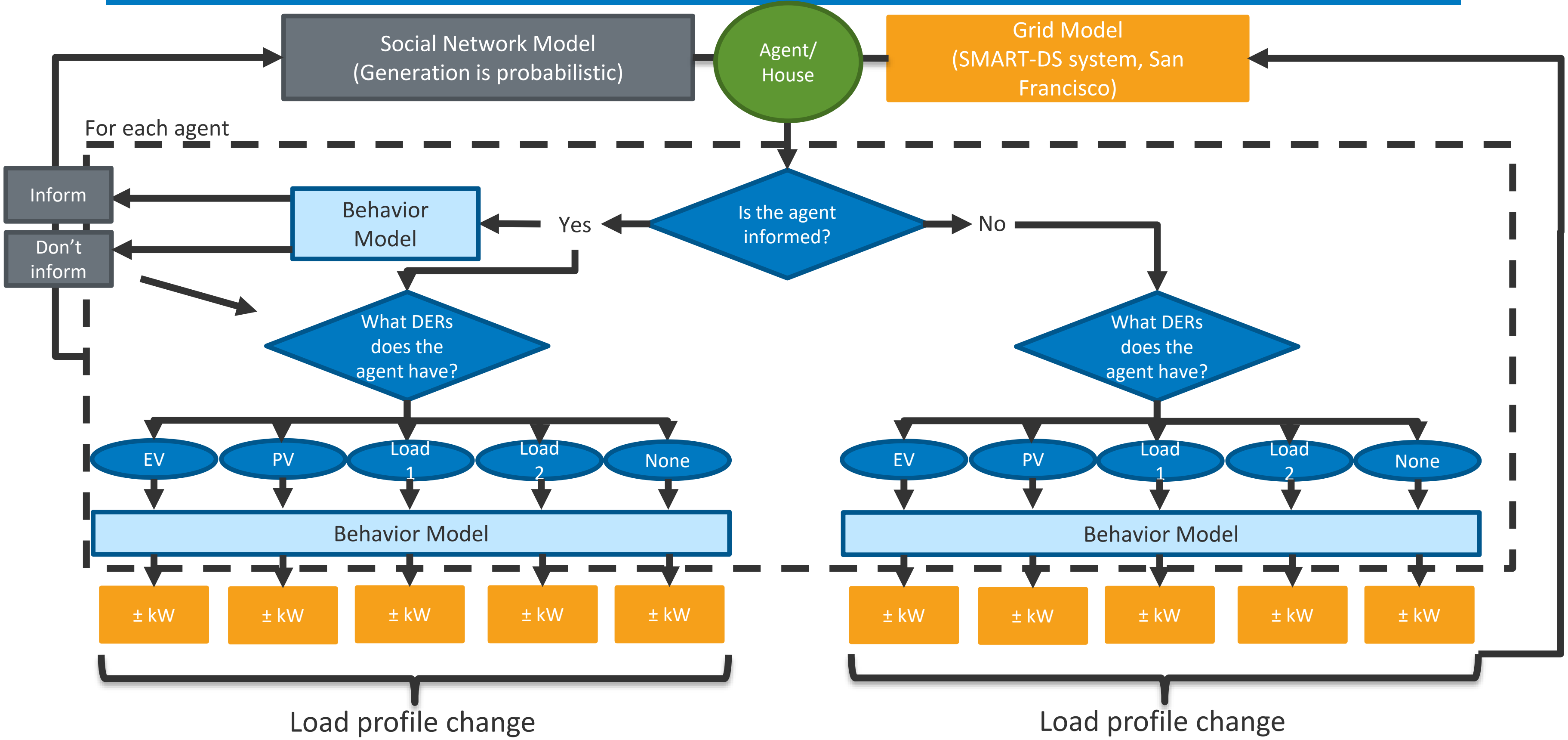


Event-Based Human Behavior



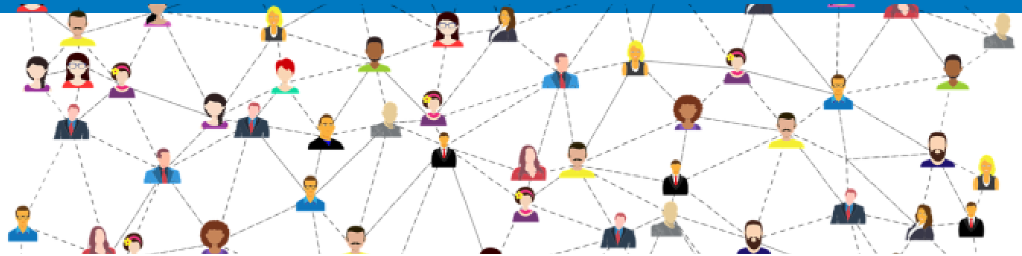


Human Behavior Modeling Flowchart



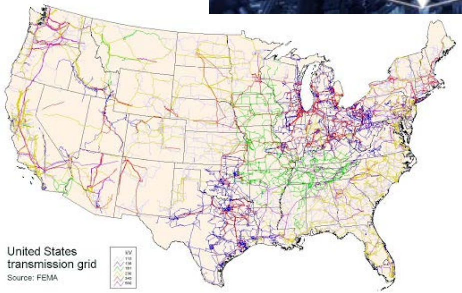
Complex Network Problem

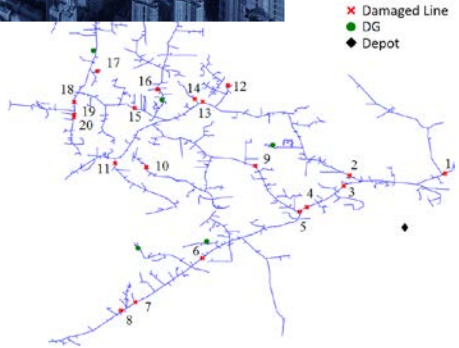
Social network
Highly dynamic



Communication Network
(can be dynamic especially when under attack)

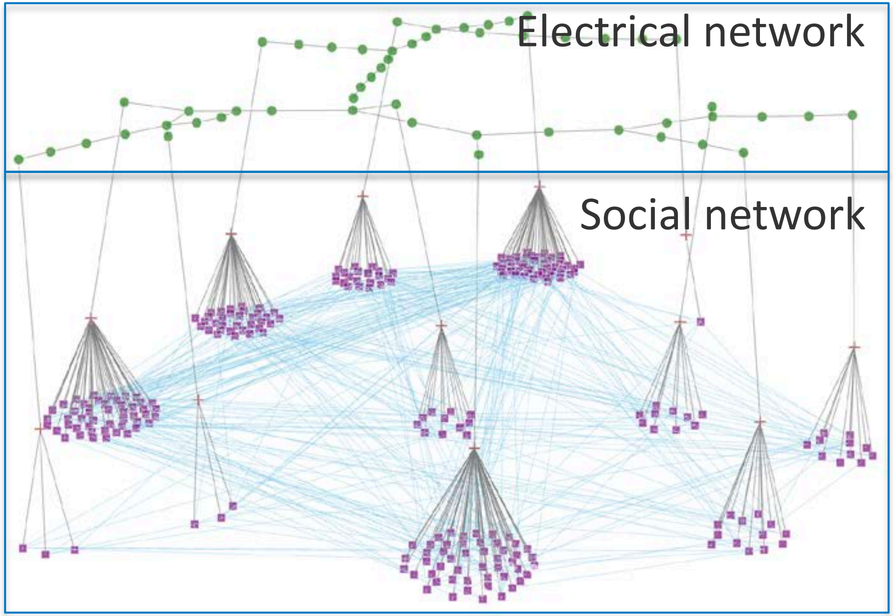
Power network
(roughly static)





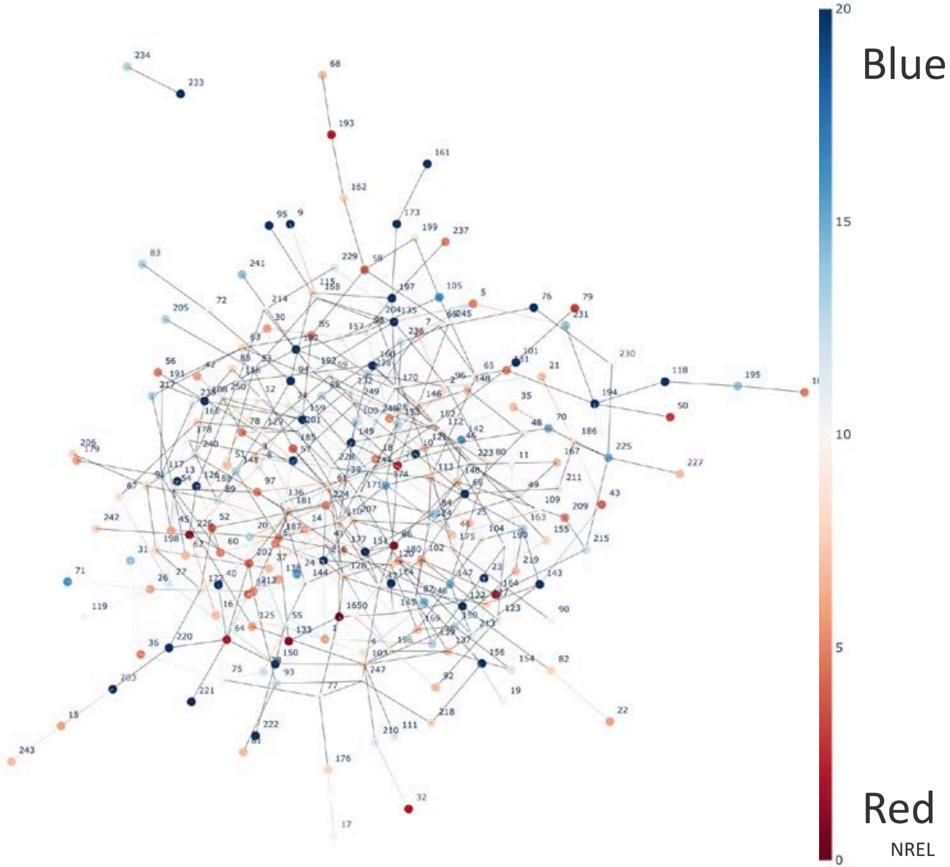
Electrical network Co-simulated with Behavior network

- Co-simulate impact of human behavior on electrical grid.
- Human behavior modeling in MESA framework (agent-based modeling framework in Python).
- Electrical grid with controllable DERs modeling in Simulation/Emulation of Advanced Energy Systems (SEAS) framework. HELICS is the co-simulation engine.
- Synthetic electrical grid from the SMART-DS project with 251 houses =>



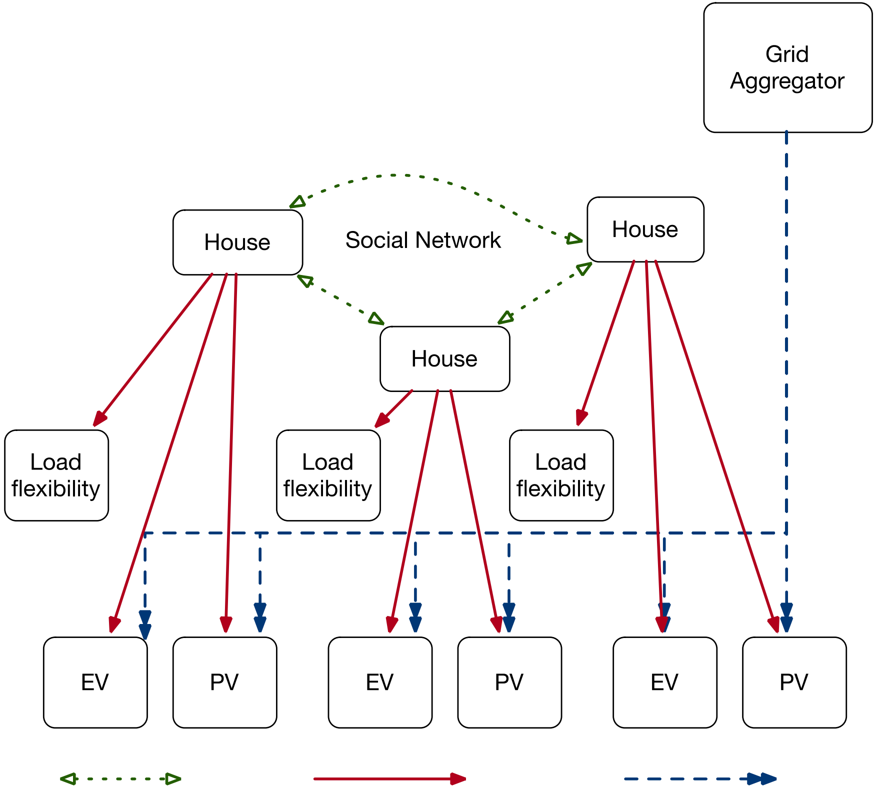
Modeling information spread over time

- MESA framework is used to model information spread.
- Communication links between houses are modeled using a network.
- Spread of information is modeled within the social network.
- Houses/nodes on social network are colored based on when they become informed of an event.



Dataflow diagram for grid-controller and behavior

- Real-time Optimal Power Flow (RTOPF) controller from the ARPA-E NODES / AES
- Virtual Power Plant (VPP) service using distributed energy resources (DERs) (PV and EVSE)
- VPP control is overridden by human behavior

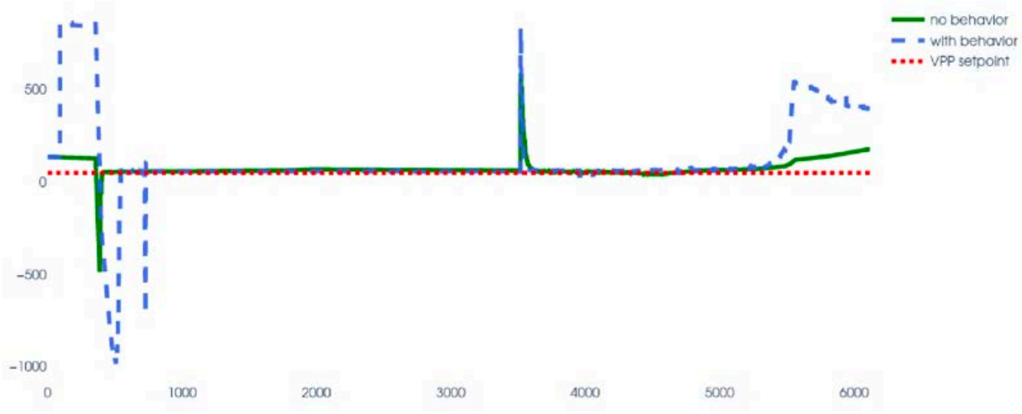


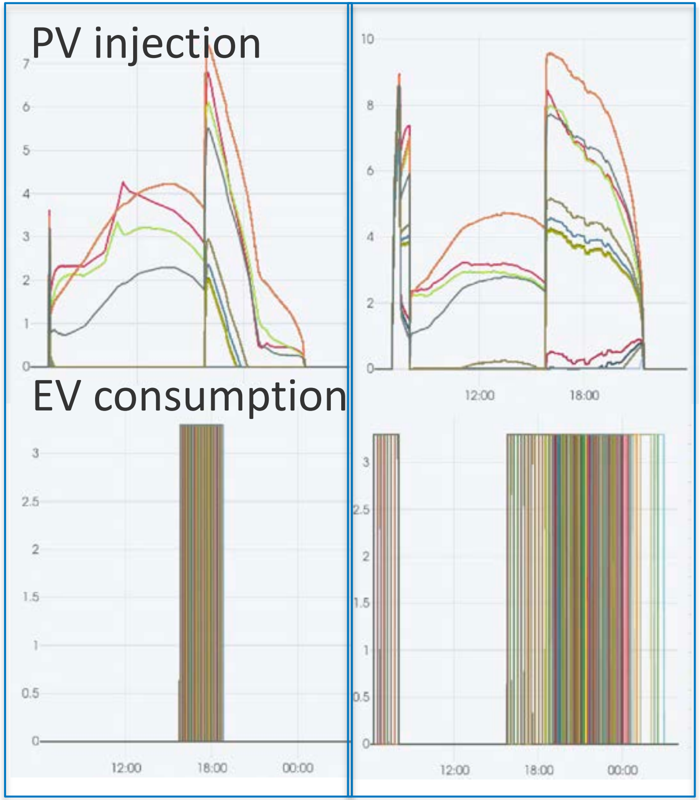
Co-simulation status

Two use-cases:

- 50% of the houses have 3.3 kw level-2 EV charger and Rooftop PV of 3kW.
- 100% of the houses have 3.3 kw level-2 EV charger and Rooftop PV of 3kW.

In preparation: Journal Article- “Incorporating Human Behavior and Distributed Control for Grid Resilience” Caitlyn Clark, Deepthi Vaidhynathan, Jennifer King, Patricia Romero-Lankao and Andrey Bernstein



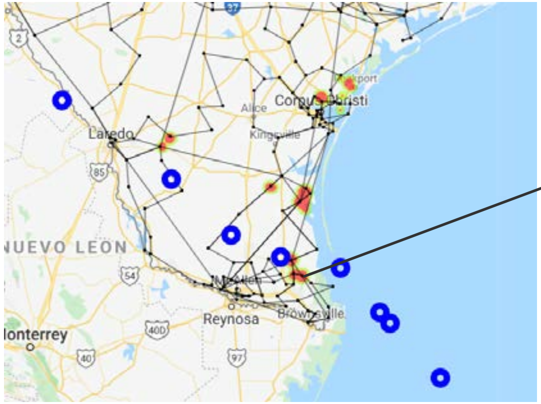


No behavior With behavior

Emergency Control during Hurricane

Fragility curves: main idea via wind plant example

Using Wind Toolkit wind speed data and fragility curves to damage structures



Wind plant

GenID	1
GenMWMax	$\boxed{200}$
GenMWMin	$\boxed{60}$
GenWindPowerFactor	1
GenFuelType	Wind
GenUID	4050_Wind_1
BusName	SEBASTIAN21
Latitude	$\boxed{26.3307}$
Longitude	$\boxed{-97.5857}$
Zone	19
Point	POINT(-97.5857 26.33072)

100 2MW turbines; toss a biased coin 100 times

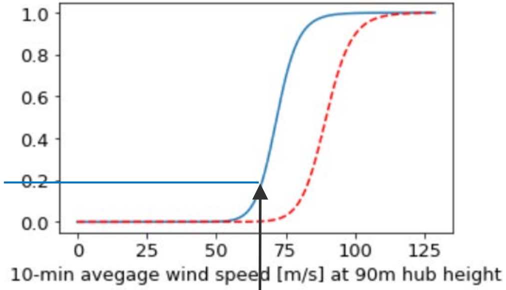
Use WTK windspeed data to define biased coin

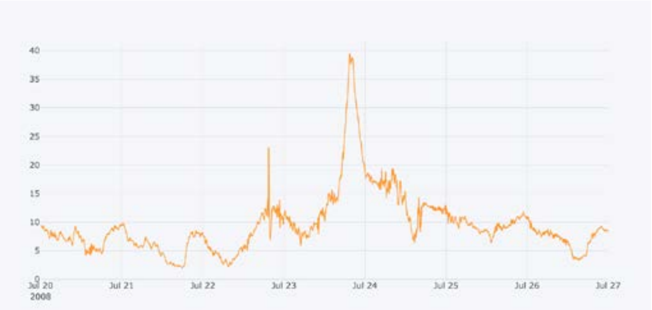
Fragility curve: Fisk CDF

Coin toss: sample from U(0,1)

operational

damaged

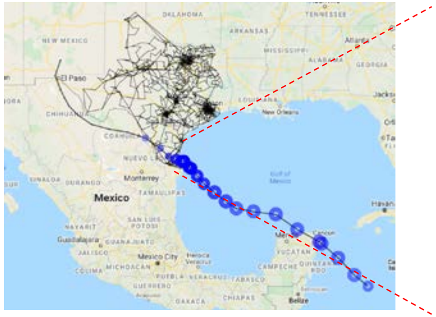




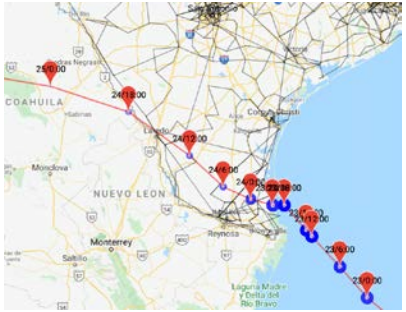
obtain 10-min wind speed maximum

$$F(u;\alpha,\beta) = \frac{\left(\frac{u}{\alpha}\right)^{\beta}}{1+\left(\frac{u}{\alpha}\right)^{\beta}}$$

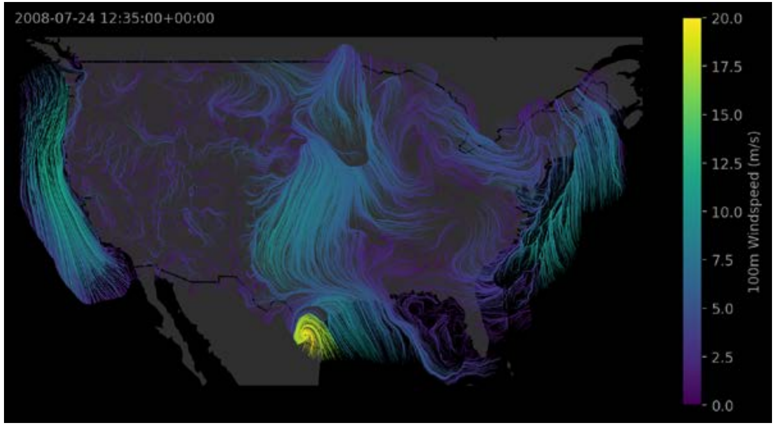
Hurricane Dolly’s caused damages



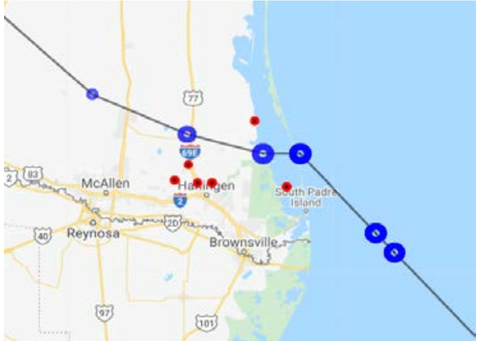
Path of the Hurricane Dolly (July 20 -27) and synthetic TAMU 2000-bus transmission grid. Size of the blue circles corresponds to hurricane’s radii and their color intensity correspond to maximum wind speed.



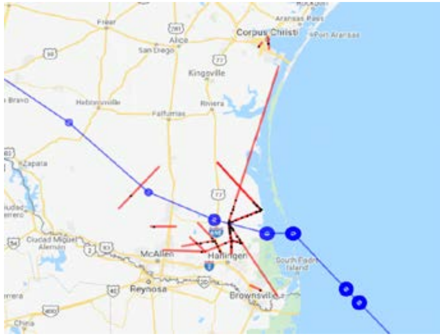
Landing and overland period: July 23, 00:00 – July 25, 00:00. Most damage occurs during 8-hour period: July 23, 18:00 – July 24, 02:00



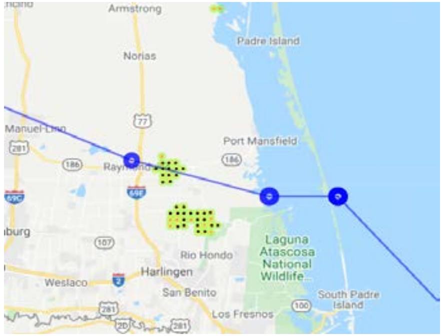
Hurricane Dolly: WIND Toolkit wind field at 100m above ground



Substations: a realization when max number of substations (red dots) were damaged



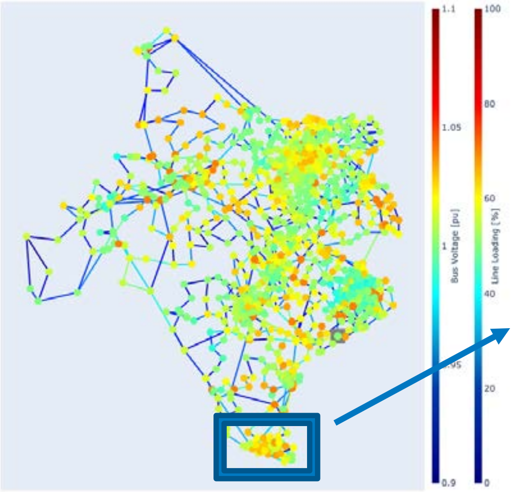
Transmission lines: a realization when max number of branches were damaged. Damaged lines (red lines) and damaged poles (black dots)



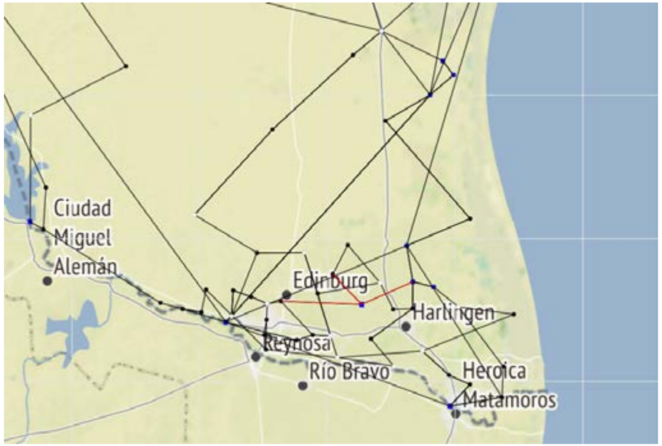
Wind turbines: 3 wind farms (heat map) composed of individual wind sites. Most wind sites had at least one damaged turbine (black dots).

Voltage control use-case scenario

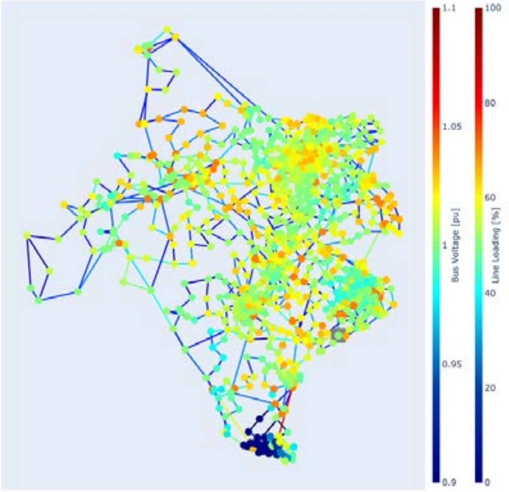
- Creating scenarios of hurricane damage leading to voltage drops
- Low-voltage scenarios are then used for application of Ripple-Type Control (developed last year)



Original PF solution on TAMU2k (pandapower, using Newton-Raphson with Iwamoto multiplier)

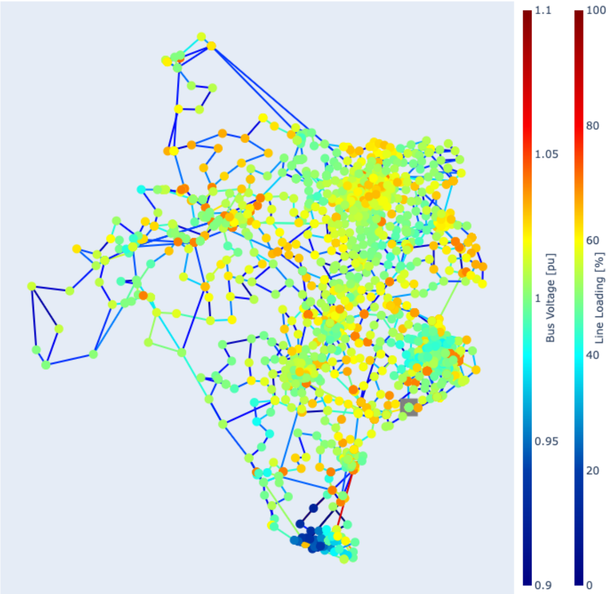


Lines 519, 542, 702 (red) connect to node 4089 with 9 coal generators to the rest of the grid.

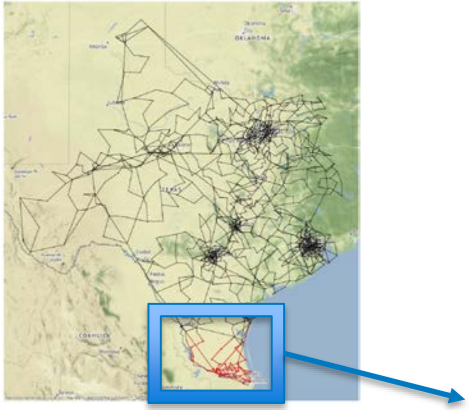


Scenario PF solution for Ripple-Type control algorithm:
breaking line 519 causes 22 bus voltages to dip below .9

Specific scenario with 13 buses under required minimum:



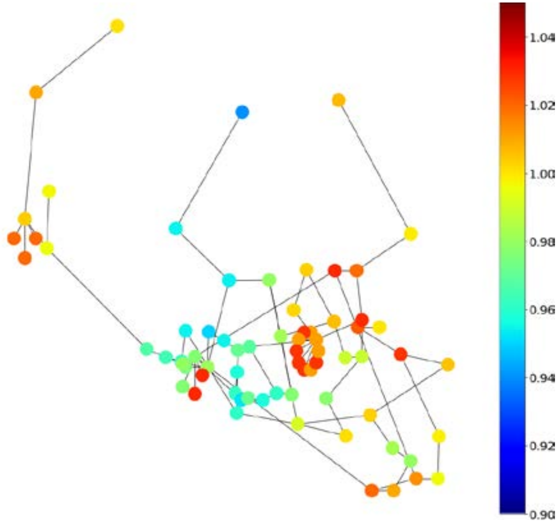
- We use this specific contingency scenario to test ripple-type algorithm
- Communication network is assumed over zone 19 subgraph.



Zone 19 (red): 71 nodes, 84 edges

	vm_pu	va_degree	p_mw	q_mvar
373	0.930329	-79.855220	127.29	36.070000
377	0.931349	-84.525091	183.66	52.040000
397	0.936160	-84.472683	65.12	18.450000
404	0.935973	-81.795876	37.64	10.660000
411	0.933353	-73.741487	0.00	0.000000
412	0.934931	-79.720335	215.18	60.970000
418	0.939556	-71.690820	13.10	3.710000
449	0.929324	-77.404764	171.21	48.510000
477	0.936217	-83.131384	118.36	33.540000
494	0.922780	-63.407864	24.38	6.910000
498	0.929982	-77.922365	123.51	-43.763399
524	0.933903	-74.195499	26.32	7.460000
527	0.930696	-81.394228	104.67	29.660000

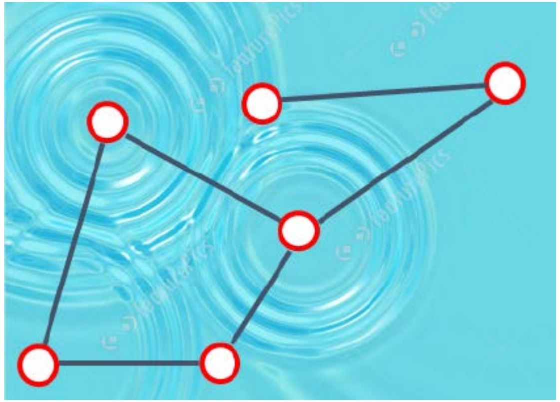
13 nodes with voltage violations below 0.94



Initial ACPF solution with under-voltage buses concentrated in the middle of the zone 19

Ripple-type control Paradigm

- First, agents try to fix local voltages autonomously
- Agents ask assistance when they depleted their control resources
- The process continues until all the voltages are within desired limits



Algorithm: agent n performs

1- Actuation

Compute increment Δ_n ($\Delta_n \neq 0$ if $v_n < v_{min}$ or if n is helping another agent)

Update the control input $u_n(t) = u_n(t-1) + \Delta_n$

2- Request of help

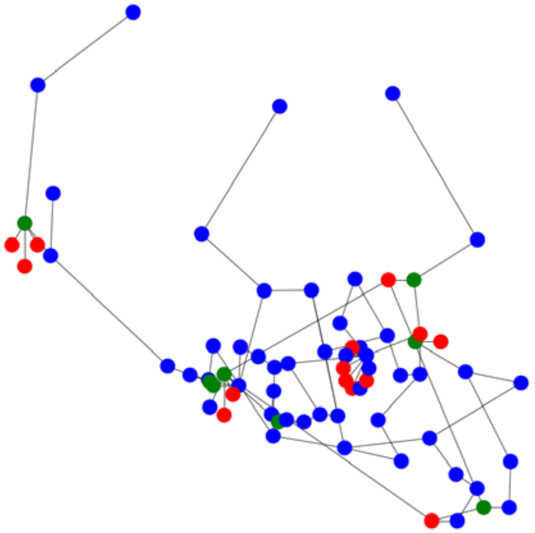
If $u_n(t) = u_{max}$ and $v_n < v_{min}$

If $u_n(t) = u_{max}$ and n is helping another agent

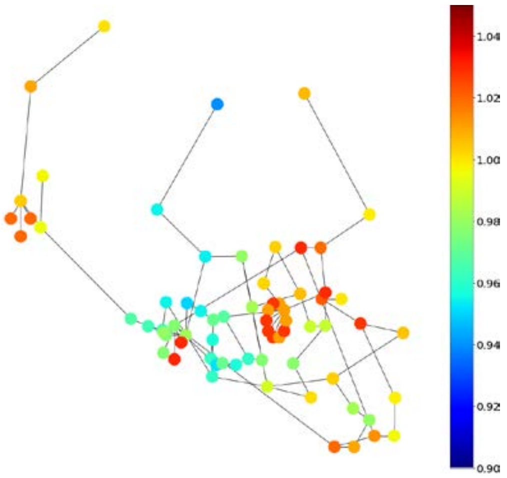
3- Reset request of help

If $v_n(t-1) < v_{min}$ and $v_n(t) \geq v_{min}$

Communication network details



- Communication network follows 84 physical connections in zone 19 of ACTIVSg2000 test grid (does not have to)
- 48 PQ buses (green): load or static generators, control Q
- 14 PV buses (red): active generators, control V
- 8 PQ-zero buses (green): neither load not generator buses, no control

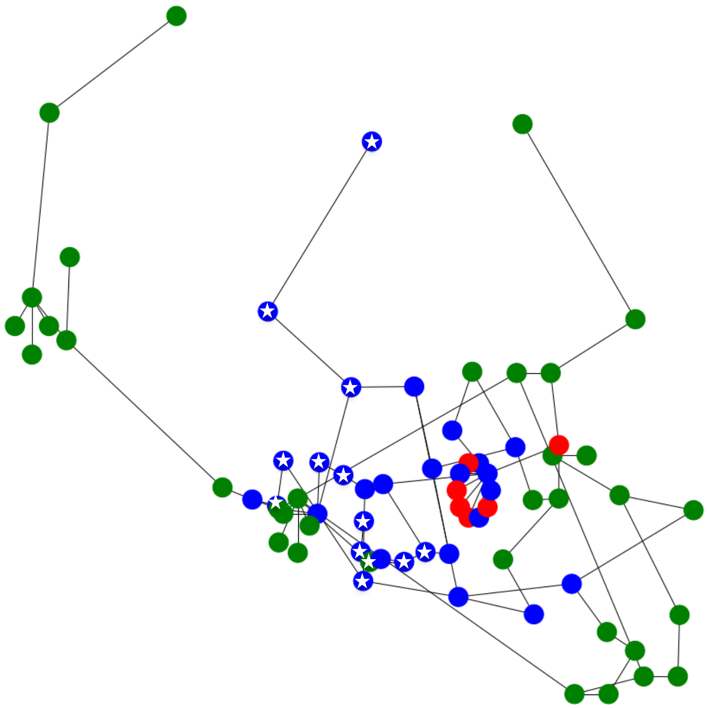


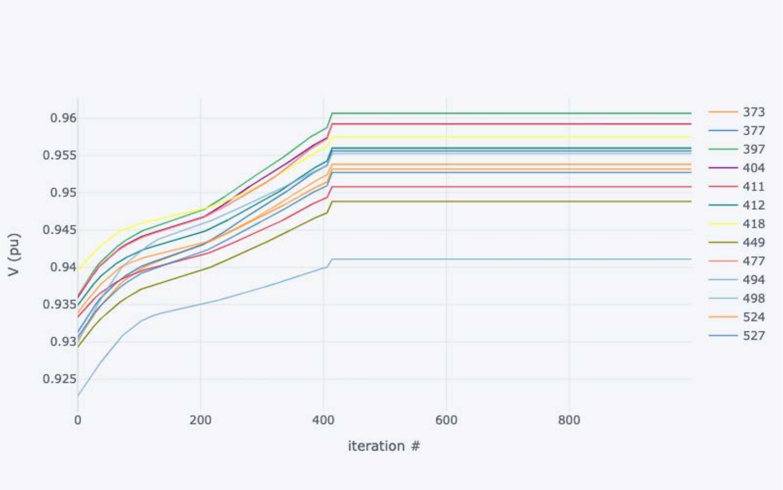
- Initial solution on the damaged network (displayed over zone 19 only) results in 13 buses being under minimum required voltage of 0.94 pu

Initial network topology

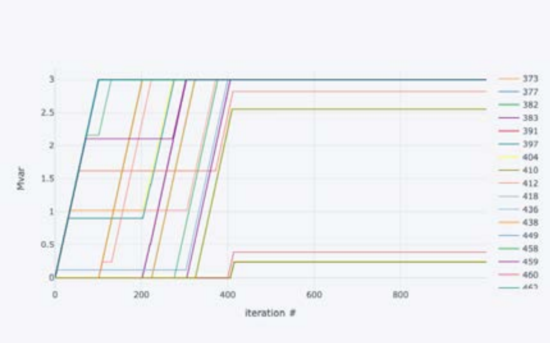
- BLUE: PQ buses
- RED: PV buses
- GREEN: neither buses

Ripple-type control results

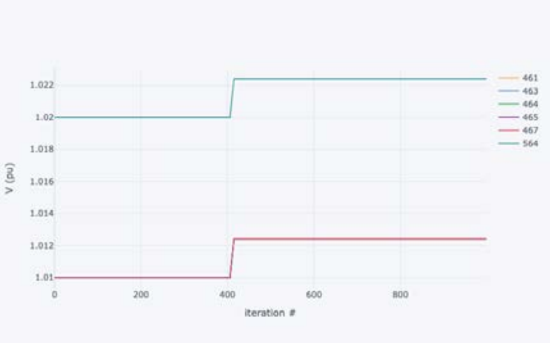




Restored voltage at the 13 buses that were initially under required minimum voltage



30 PQ buses that participate in ripple-type control

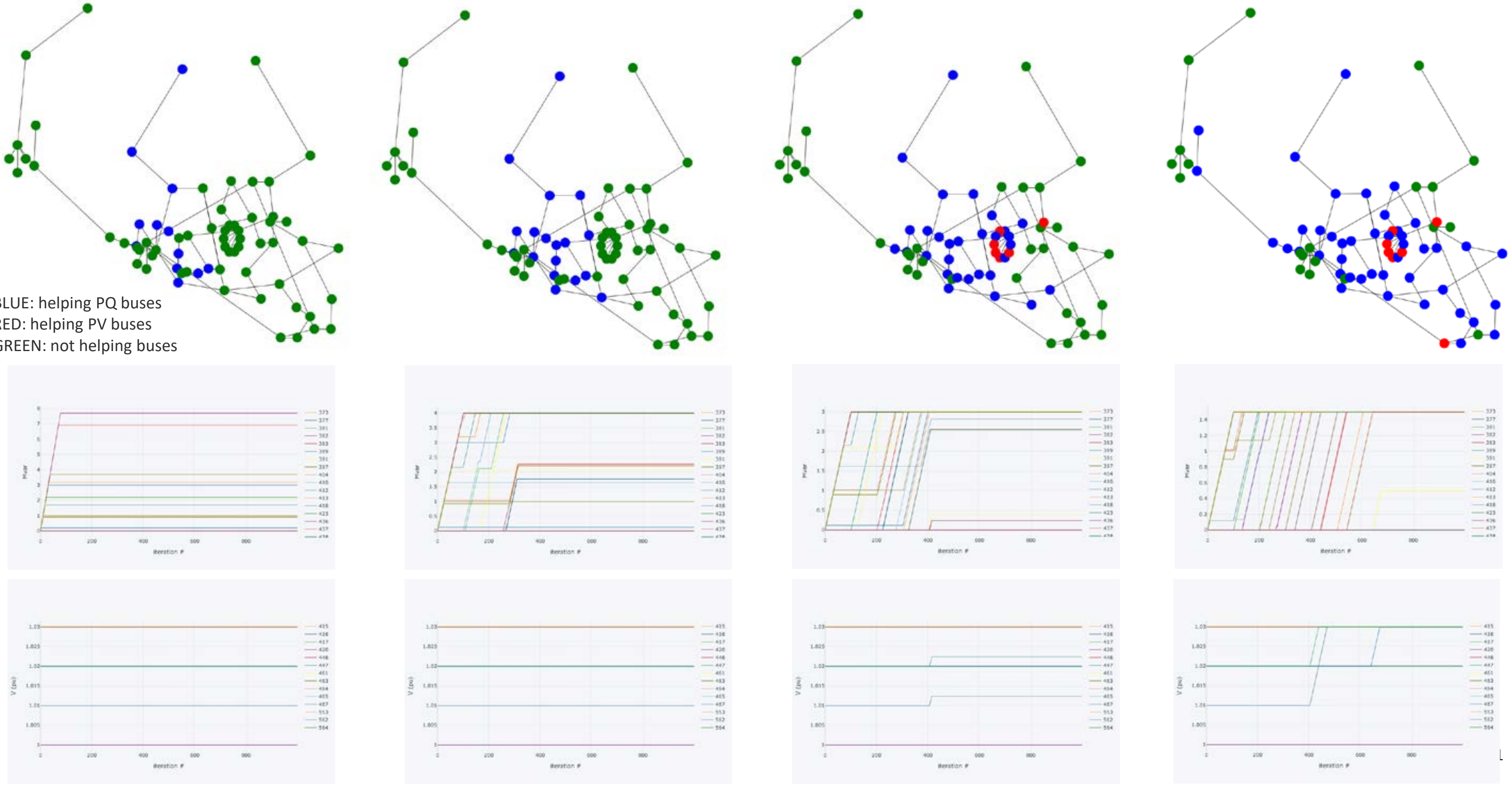


6 PV buses that participate in ripple-type control

- STARRED: initially under-voltage
- BLUE: helping PQ buses
- RED: helping PV buses
- GREEN: not helping buses

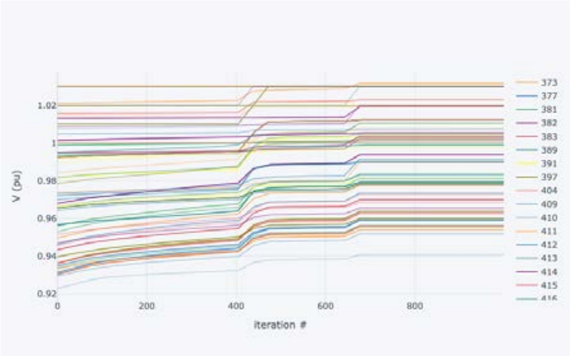
Ripple hop distance increases as available help decreases

PQ bus effort = 10 Mvar | PQ bus effort = 4 Mvar | PQ bus effort = 3 Mvar | PQ bus effort = 1.5 Mvar

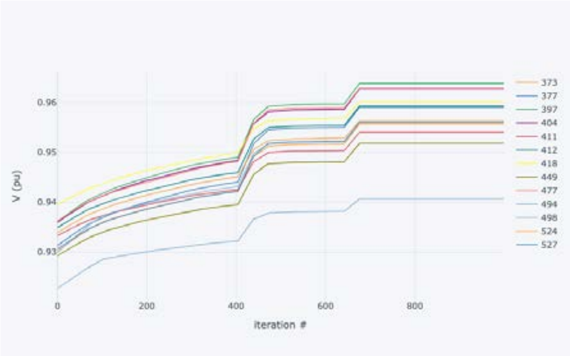


- BLUE: helping PQ buses
- RED: helping PV buses
- GREEN: not helping buses

Control fraction step: convergence speed vs. overshooting

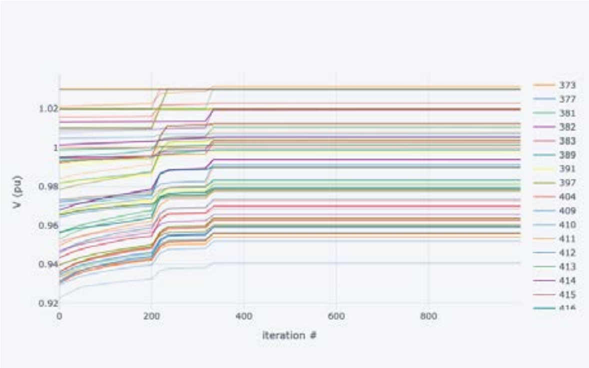


All buses in zone 19

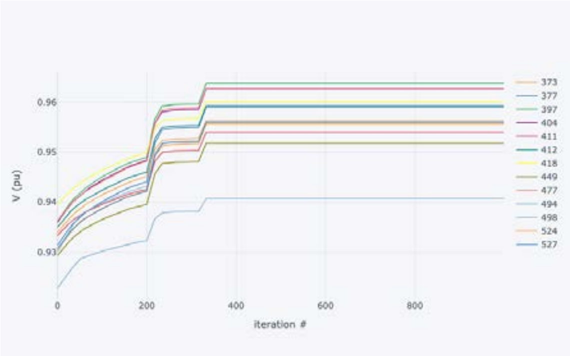


Only under-voltage buses in zone 19

Control fraction step = 1%
PQ: 0.015 Mvar
PV: 0.003 pu



All buses in zone 19



Only under-voltage buses in zone 19

Control fraction step = 2%
PQ: 0.03 Mvar
PV: 0.006 pu

Next Steps

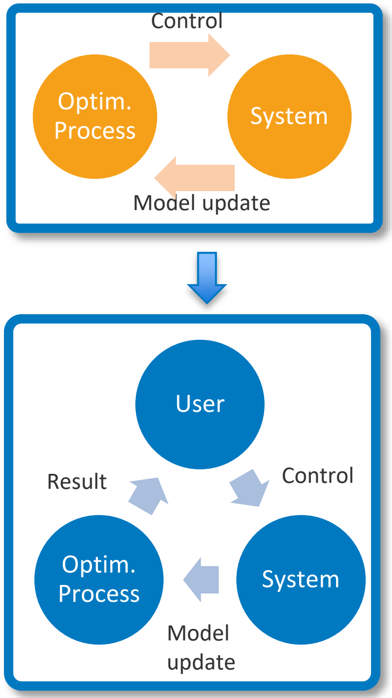
- Consider multi-step problem where the hurricane progressively trip lines as it moves
- Consider other extreme scenario application, such as cold/hot weather

Control Algorithms Accounting for Human Behavior

Human-in-the-Loop Optimization in Power Systems

Incorporating human factor in power system modeling and decision making is more important than ever.

- With increased observability and controllability in distribution systems, more **customer-level edge devices are incorporated**. Human behavior/response plays an important role in these problems.
- Extreme events lead to an **increased number of unplanned scenarios** (e.g., large-scale restoration) that require human intervention.
- Advancing energy justice requires the modeling of human dimension in various operation and planning problems to ensure equity in decision making.



We explore one specific example: Distribution system voltage control with human in the loop.

Formulation: Chance-Constrained Optimization

- **Objective:** Minimize customer interruption while ensuring constraint satisfaction.
- **Modeling:** Since customer participation is voluntary, we can only guarantee constraint satisfaction **with high probability** by chance-constrained optimization.

$$\min_{0 \leq u \leq -d_0} \quad \|u\|_1$$ → Power demand reduction from customer

$$\text{s.t.} \quad d = d_0 + [u]\xi$$ → Actual power demand (original consumption - reduction)

$$v = Rd + Xq + v_0$$ → Linearized power flow equations

$$\text{Prob}\{v_i \geq \bar{v}_i\} \leq \epsilon$$ → Bound on the probability of voltage upper bound violation

$$\text{Prob}\{v_i \leq \underline{v}_i\} \leq \epsilon$$ → Bound on the probability of voltage lower bound violation

$$\xi_i \sim \mathbb{B}(p_i) := \begin{cases} \text{Prob}[\xi_i = 1] = p_i \\ \text{Prob}[\xi_i = 0] = 1 - p_i \end{cases}$$ → Customer participation follows Bernoulli distribution

Solution Method: Convex Safe Approximation

- **Goal:** replace the complicating chance constraint with a safe approximation.

$$\mathrm{Prob}\{A\xi \geq b\} \geq 1-\epsilon,$$
$$\xi_i \sim \mathbb{B}(p_i)$$

Original chance constraint

Safe Approx.

Proposition. *Given random variable* $\xi_i \sim \mathbb{B}(p_i)$, $\eta := \sum a_i \xi_i$ *is a new random variable with mean* $\sum a_i p_i$ *and standard deviation* $\mathrm{std}(\eta) = \sqrt{\sum a_i^2 p_i(1-p_i)}$.

$$\sum_j a_{ij} p_j - \sqrt{-2\ln\left(\frac{\epsilon}{n}\right)} \cdot \sqrt{\sum_j a_{ij}^2 p_j (1-p_j)} \geq b_i, i = 1, \ldots, n$$

Deterministic convex (SOC) constraint

Safe Approximation (SOCP)

$$\begin{aligned}
\min_{0 \leq u \leq -d_0} \quad & \|u\|_1 \\
\text{s.t.} \quad & \text{(for all node } i\text{)} \\
& \sum_j R_{ij} p_j u_j + x_i \sqrt{-2\ln\left(\frac{\epsilon}{2n}\right)} \leq \\
& \qquad \bar{v}_i - \sum_j R_{ij} d_{0,j} - \sum_j X_{ij} q_j - v_{0,i} \\
& -\sum_j R_{ij} p_j u_j + x_i \sqrt{-2\ln\left(\frac{\epsilon}{2n}\right)} \leq \\
& \qquad \sum_j R_{ij} d_{0,j} + \sum_j X_{ij} q_j + v_{0,i} - \underline{v}_i \\
& \sqrt{\sum_j p_j (1-p_j)(R_{ij} u_j)^2} \leq x_i
\end{aligned}$$

Solution Method: Mixed-Integer Reformulation and Iterative Algorithm

Original formulation

$$
\begin{aligned}
\min_{\mathbb{0}\preceq u\preceq -d_0} \quad & \|u\|_1 \\
\text{s.t.} \quad & d = d_0 + [u]\xi \\
& v = Rd + Xq + v_0 \\
& \text{Prob}\{v_i \geq \bar{v}_i\} \leq \epsilon \\
& \text{Prob}\{v_i \leq \underline{v}_i\} \leq \epsilon
\end{aligned}
$$

=

MILP reformulation (scenario enumeration)

$$
\begin{aligned}
\min \quad & \|u\|_1 \\
\text{s.t.} \quad & y^i = A(\xi^i)u, && i = 1,\ldots,N \\
& y_i \geq b z_i, && i = 1,\ldots,N \\
& \sum z_i p_i \geq 1-\epsilon \\
& z \in \{0,1\}^N, \mathbb{0} \preceq u \preceq -d_0
\end{aligned}
$$

- **Problem:** large problem size (exp. in # customers). Efficient algorithm needed!
- **Solution:** iterative algorithm based on **Augmented Lagrangian Decomposition (ALD)**.
    Guarantee on convergence ☺
    No guarantee on optimality ☹

ALD Algorithm:

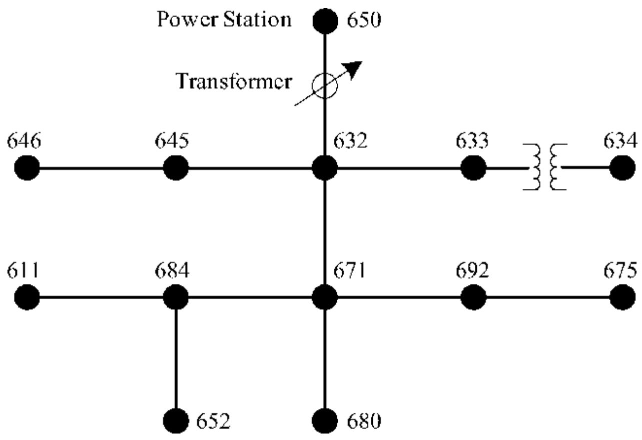
$$
\mathcal{L}(u, y, \lambda) = \|u\|_1 + \sum_{i=1}^{N} {\lambda^i}^{\top}[y^i - A(\xi^i)u] + \frac{\rho}{2}\left\|y^i - A(\xi^i)u\right\|^2
$$

$$
u^{(k+1)} = \arg\min_{\mathbb{0}\preceq u\preceq -d_0} \mathcal{L}(u, y^{(k)}, \lambda^{(k)})
$$

$$
y^{(k+1)} = \arg\min_{\substack{\sum_{i=1}^{N} p_i z_i \geq 1-\epsilon \\ y^i \geq z_i b,\ z\in\{0,1\}^N}} \mathcal{L}(u^{(k+1)}, y, \lambda^{(k)})
$$

$$
\lambda^{(k+1)} = \lambda^{(k)} + \kappa\rho\left(y^{(k+1)} - A(\xi)u^{(k+1)}\right)
$$

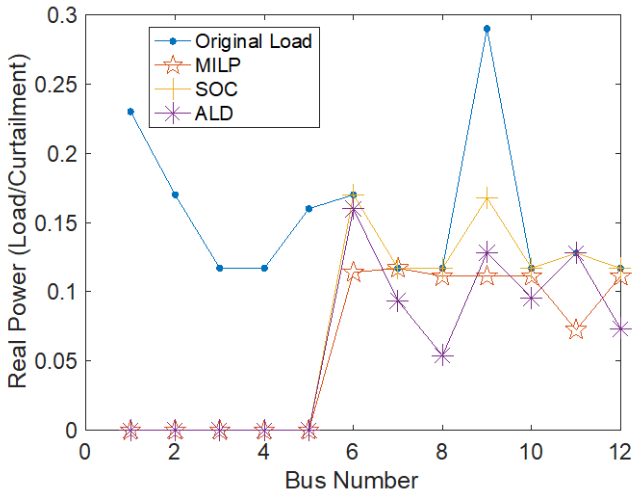
Numerical Simulation



IEEE 13-bus test system with 1 substation bus and 12 customers (with 90% participation probability).

Comparison of simulation results by different approaches

	Time (sec.)	Objective value	Optimality
MILP	5205	0.7487	Y
SOCP	0.09	0.9338	N
ALD	0.43	0.9335	N



Optimal load curtailment strategies by different approaches. Original power consumption of each customer shown by blue dots.

Conclusion & Future Research

Conclusion:

- A chance constrained optimization formulation is proposed to model stochasticity from human behaviors in distribution system voltage control problem.
- An exact formulation based on scenario enumeration is proposed, which works well for small size system.
- Two approximate solution approaches based on safe convex approximation and Augmented Lagrangian decomposition are presented, strike good balances between optimality and time complexity.

Future research:

- Improve the performance of the ALD algorithm through specialized techniques such as warm start and network partition.
- Modeling and control of human behavior as a function of incentives.

Equitable Wildfires Mitigation

Power Systems-Induced Wildfires

Many wildfire events were ignited by electrical components failures.

Pacific Gas & Electric equipment is blamed for 2019 Kincade fire in Sonoma County

PG&E inspections of equipment that s[...] deadly Camp fire were flawed, state regulators say

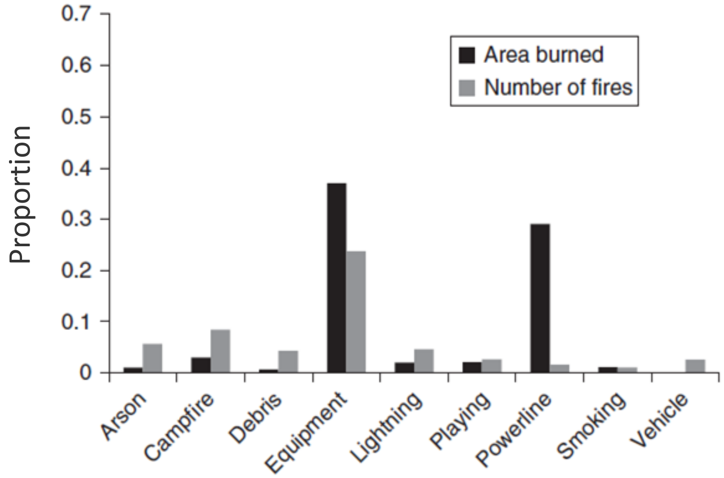
Kilmore East fire, deadliest of the Black Saturday Fires 2009, was started by a power line and killed 159

- Camp Fire was the deadliest wildfire in the history of California
- **A nearly 100-year-old electrical transmission line** owned and operated by Pacific Gas and Electric was identified as the cause of the Camp Fire
- $8.4 billion in insured losses were reported to the California Department of Insurance as of January 2019

Credit: Priyanka Boghani (PBS)

Q: How to plan transmission networks operations to minimize wildfires risks?

Wildfire Ignition Sources



Syphard, et al. (2015). Location, timing and extent of wildfire vary by cause of ignition. International Journal of Wildland Fire.

- Wildfires ignited by power lines tend to be larger
- Wildfires ignited by power lines in San Diego County account for 5% of all ignitions, but 25% of the total acres burned
- Wind can lead to both higher fault probability and fire spread

Wildfires Risk Modelling

Wildfires Risk	=	**Probability** of Ignition	×	**Impact** of Wildfire
Power Outage Risk	=	**Probability** of Outage	×	**Impact** of Outage

- Infrastructure updates and vegetation management represent long-term solutions and are NOT our focus
- This work focuses on operational decisions, e.g., line switching and load shedding, to manage wildfire risks

$$\textbf{Cost} = \alpha\, \boldsymbol{R}_{\text{Fire}} - (\mathbf{1} - \alpha)\, \boldsymbol{D}_{\text{total}}$$

Multi-Period Optimal Power Shutoff Scheduling

$$R_{\text{fire}} = \sum_{t\in\mathcal{T}} \left(\sum_{i\in\mathcal{B}} R^D_{i,t} \frac{P^D_{i,t}}{\overline{P}^D_i} + \sum_{i\in\mathcal{L}} R^L_{\ell,t} \frac{|f_{\ell,t}|}{\overline{f}_\ell} + \sum_{i\in\mathcal{G}} R^G_{i,t} z^G_{i,t} + \sum_{i\in\mathcal{G}} R^B_{i,t} z_{i,t} \right)$$

$$D_{\text{total}} = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{B}} x_{i,t} P^D_{i,t}$$

$$\begin{aligned}
\min \quad & \alpha R_{\text{fire}} - (1-\alpha) D_{\text{total}} \\
\text{s.t} \quad & \text{(operational constraints)} \\
& \text{(power flow constraints)} \\
& \text{(switching constrains)} \\
& \text{(connectivity constraints)} \\
& \text{(ramping limits)} \\
& \text{(energy storage constraints)}
\end{aligned}$$

$$z_i^G \underline{P}_i^G \le P_i^G \le z_i^G \overline{P}_i^G, \quad \forall i \in \mathcal{G}$$

$$\underline{\theta}_i \le \theta_i \le \overline{\theta}_i$$

$$\underline{\theta}_s = \overline{\theta}_s = 0$$

$$-\overline{f}_\ell z_\ell^L \le f_\ell \le \overline{f}_\ell z_\ell^L, \quad \forall \ell \in \mathcal{E}$$

$$\mathbf{f} - M(1-\mathbf{z}^L) \le \mathbf{B}\mathbf{A}^\top \boldsymbol{\theta} \le \mathbf{f} + M(1-\mathbf{z}^L)$$

$$P_i = -P_i^D - P_i^E + \sum_{j\in\mathcal{G}(i)} P_j^G, \quad \forall i \in \mathcal{B}$$

$$\sum_{i\in\mathcal{G}} (1 - z_i^G) \le \overline{G}$$

$$\sum_{\ell\in\mathcal{E}} (1 - z_\ell^L) \le \overline{L}$$

$$z_i \ge z_i^D, \quad \forall i \in \mathcal{B}$$

$$z_i \ge z_j^G, \quad \forall i \in \mathcal{B}, j \in \mathcal{G}(i),$$

$$z_i \ge z_\ell^L, \quad \forall i \in \mathcal{B}, \ell = (i,j) \text{ or } (j,i) \text{ and } \ell \in \mathcal{E}$$

$$-r_i^G \le P_{i,t}^G - P_{i,t-1}^G \le r_i^G, \quad \forall i \in \mathcal{G}, t \in \mathcal{T}$$

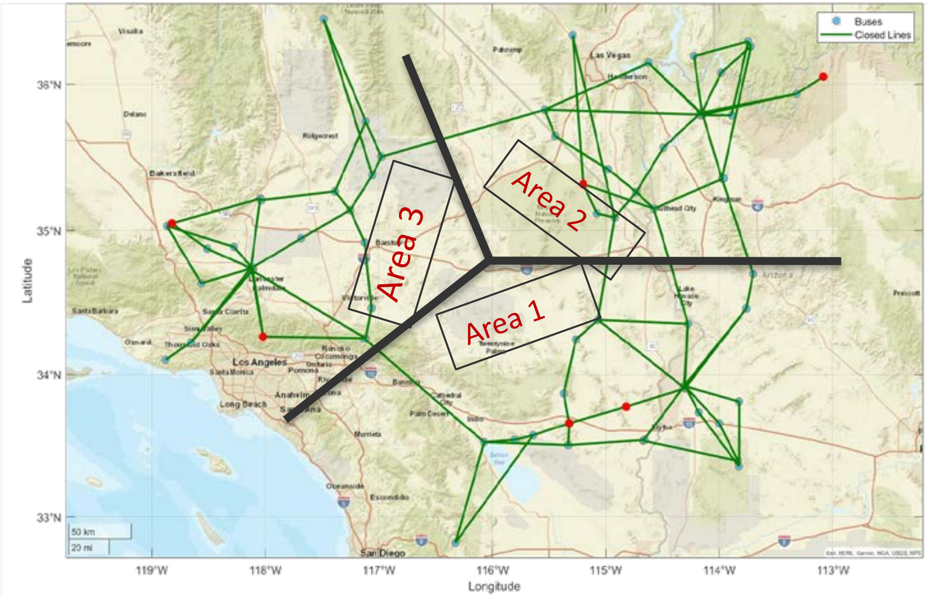
$$-r_i^D \le P_{i,t}^D - P_{i,t-1}^D \le r_i^D, \quad \forall i \in \mathcal{B}, t \in \mathcal{T}$$

$$S_{i,T} \ge S_{i,0}, \quad \forall i \in \mathcal{Q}$$

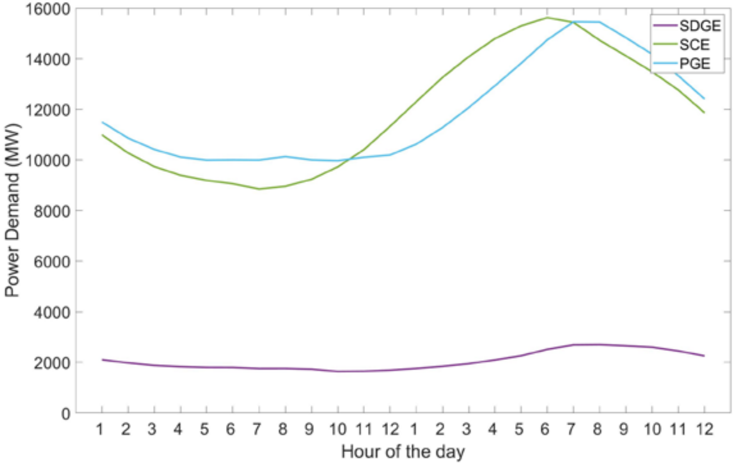
$$\underline{P}_i^E \le P_i^E \le \overline{P}_i^E, \quad \forall i \in \mathcal{Q}, t \in \mathcal{T}$$

$$S_{i,t} = S_{i,t-1} + P_{i,t-1}^E \Delta t \quad \forall i \in \mathcal{Q}, t \in \mathcal{T}$$

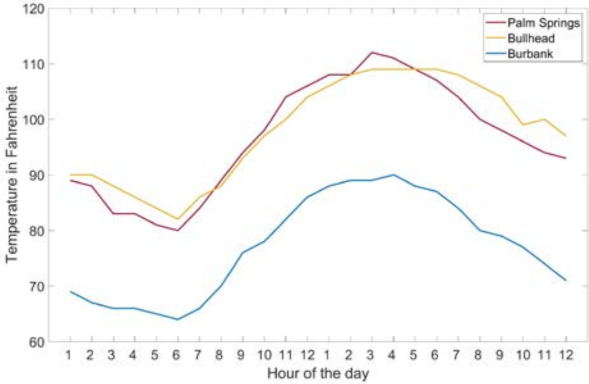
Test Case: IEEE RTS-GMLC



RTS GMLC test system consists of 73 buses, 120 transmission lines, and 96 active generators. Red dots depict energy storage units.



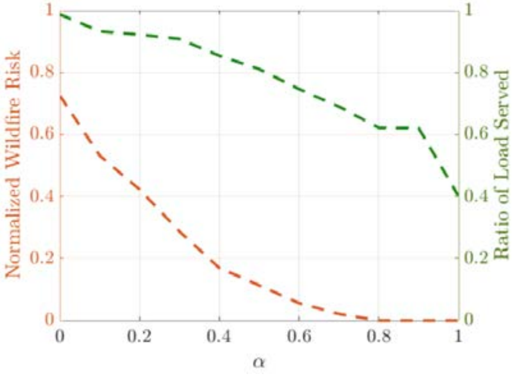
Power demand throughout July 4, 2020



Temperature throughout July 4, 2020

Numerical Example

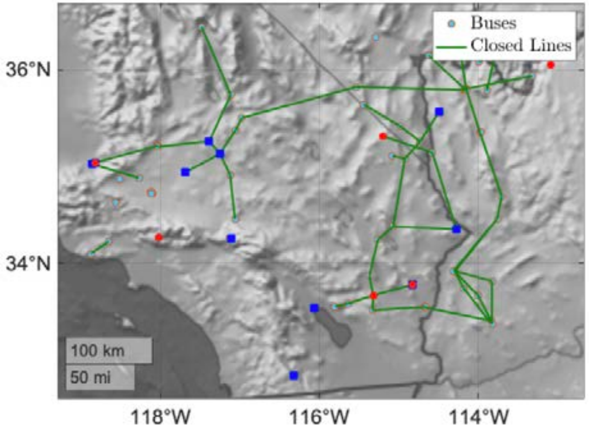
- Optimized the operations over one day with different settings of α.
- Added six energy storage unites (2 units in each area).



Demand vs Risk of Wildfire for a range of α values

TABLE I: Ratings of Energy Storage Units

Bus No.	Capacity	Max Charge Rate	Max Discharge Rate
114	350	50	−50
116	450	50	−50
207	400	50	−50
221	300	45	−45
301	400	40	−40
313	550	60	−60



Map of the operational system when α = 0.3 at 12:00 PM.
Blue squares represent shutoff generators.

A. Astudillo, B. Cui and A. Zamzam, "Managing Power Systems-Induced Wildfire Risks Using Optimal Scheduled Shutoffs," PESGM, 2022.

Social Equity Considerations

Image: time.com/5732376/california-power-wildfire

Socially vulnerable communities are disproportionately impacted by power shutoffs[1] *and* wildfires.

Challenges:

- Ability to purchase emergency items (incl. back-up generators)
- Ability to evacuate
- Health concerns (e.g. electrically powered medical equipment, heat-related illnesses)
- Food spoilage
- Communication barriers

[1] Ham, Youngjib and Lee, Seulbi "Behavior Analysis of Socially Vulnerable Households Responding to Planned Power Shutoffs." University of Colorado-Boulder, Natural Hazards Center. 2022.

Representing Social Equity in Our Modeling

- ***Social vulnerability*** – extent to which a community can absorb and recover from the impacts of a natural or human-caused hazard
- Influenced by intersecting factors such as income, medical conditions, linguistic isolation, and more
- In this model, the vulnerability parameters weigh the importance of serving particular loads and de-energizing particular components

$$\min \quad \alpha R^{\text{ignition}}_{\text{total}} - \beta D_{\text{total}}$$

s.t.

social vulnerability to power outages

$$D_{\text{total}} = \sum_{i \in \mathcal{B}} v_i^D x_i P_i^D$$

social vulnerability to wildfires

$$R^{\text{ignition}}_{\text{total}} = \sum_{i \in \text{comp}} v_i^R z_i R_i$$

Topology and switching constraints

Power balance constraints

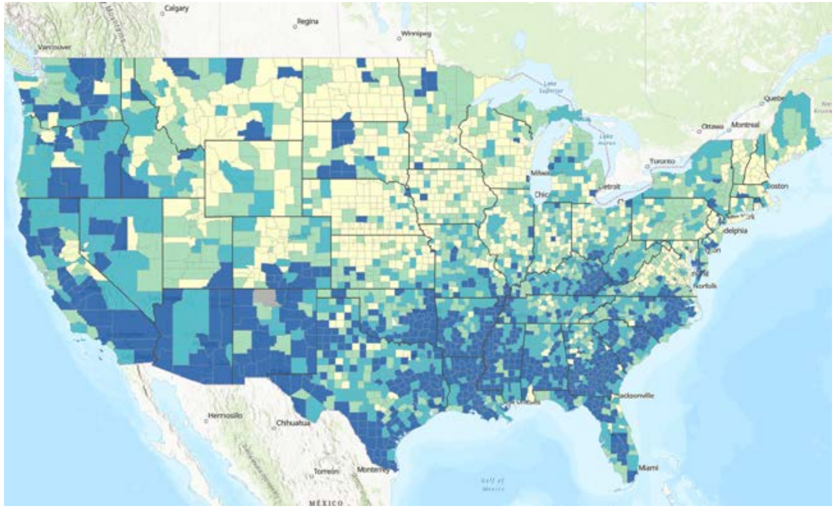
Branch, bus, load, generation, constraints (incl. binary on/off variables)

Inverter, storage, and transformer constraints

Vulnerability to Power Outages

Numerous social equity map tools are leveraged to determine community vulnerability level:

- CDC Social Vulnerability Index
- US Census Community Resilience Estimates
- US Council on Envt. Quality Climate and Economic Justice Screening Tool
- US DOE Disadvantaged Community Reporter
- HHS emPOWER – Medically vulnerable communities



CDC Social Vulnerability Index map

Conclusion & Future Research

- We modeled how to mitigate wildfire risk from an existing power network while serving a significant amount of the power demand.

- Significant reduction in wildfire risks was achieved with relatively small power shutoffs.

- We presented an energy justice-aware modeling approach to manage climate change-induced extreme weather events in the operation of future grids.

Future research:

- Model the optimal shut-off problem for joint transmission-distribution operation.

- Security constrained optimal shut-off formulation considering N-1 contingencies.

Publications

18 published: 7 journal, 11 conferences:

- J. Miller, H. Villegas-Pico, I. Dobson, A. Bernstein, and B. Cui, “Feedback control approaches for restoration of power grids from blackouts.” Electric Power Systems Research, 2022.
- B. Cui, A. Zamzam, and A. Bernstein, “Enabling grid-aware market participation of aggregate flexible resources.” In Proceeding of the 11th Bulk power systems dynamics and control symposium (IREP 2022), Banff, Canada, 2022.
- I. Satkauskas, J. Maack, M. Reynolds, D. Sigler, K. Panda, W. Jones, "Simulating Impacts of Extreme Events on Grids with High Penetrations of Wind Power Resources," 2022 IEEE PES Transmission & Distribution Conference & Exposition, April 2022 New Orleans, LA, 2022.
- Trager Joswig-Jones, Kyri Baker, and Ahmed Zamzam, “OPF-Learn: An Open-Source Framework for Creating Representative AC Optimal Power Flow Datasets,” in Proc. 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 2022
- A. Astudillo, B. Cui, and A. Zamzam, “Managing power systems-induced wildfire risks using optimal scheduled shutoffs.” In Proceedings of the 2022 IEEE Power & Energy Society General Meeting, Denver, CO, 2022.
- S. Wang, B. Cui, and L. Du, “An efficient power flexibility aggregation framework via coordinate transformation and Chebyshev centering optimization.” In Proceedings of the 2022 IEEE Power & Energy Society General Meeting, Denver, CO, 2022.
- A. P. J. Stanley and J. King, “Optimizing the Physical Design and Layout of a Resilient Wind, Solar, and Storage Hybrid Power Plant,” Applied Energy, 2022.
- Y. Liu, A. Zamzam, and A. Bernstein, “Multi-Area Distribution System State Estimation via Distributed Tensor Completion,” IEEE Trans. Smart Grid, 2022.
- B. Cui, A. S. Zamzam, and A. Bernstein, “Network-Cognizant Time-Coupled Aggregate Flexibility of Distribution Systems Under Uncertainties,” IEEE Control System Letters, 2021
- M.K. Singh, G. Cavraro, A. Bernstein, V. Kekatos, “Ripple-Type Control for Enhancing Resilience of Networked Physical Systems,” American Control Conference, 2021.
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- Y. Nie, A. S. Zamzam, and A. Brandt, "Resampling and data augmentation for short-term PV output prediction based on an imbalanced sky images dataset using convolutional neural networks." Solar Energy 224 (2021): 341-354.
- Y. Zhou, A. S. Zamzam, A. Bernstein, and H. Zhu, "Substation-Level Grid Topology Optimization Using Bus Splitting," American Control Conference, 2021.
- M. Q. Tran, A. S. Zamzam, P. H. Nguyen, and G. Pemen, "Multi-Area Distribution System State Estimation Using Decentralized Physics-Aware Neural Networks." Energies 14.11 (2021): 3025.
- M. Q. Tran, A. S. Zamzam, and P. H. Nguyen, “Enhancement of Distribution System State Estimation Using Pruned Physics-Aware Neural Networks,” IEEE PowerTech Conference, 2021.
- B. Cui, A.S. Zamzam, G. Cavraro, A. Bernstein, “Novel Region of Attraction Characterization for Control and Stabilization of Voltage Dynamics,” IEEE Transactions on Control of Network Systems, 2021.
- Y. Liu, A. S. Zamzam and A. Bernstein, "Multi-Area Model-Free State Estimation via Distributed Tensor Decomposition," 54th Asilomar Conference on Signals, Systems, and Computers, 2020.

4 in preparation:

- C. Clark, D. Vaidhyanathan, J. King, P. Romero-Lankao and A. Bernstein, “Incorporating Human Behavior and Distributed Control for Grid Resilience”
- B. Cui, G. Cavraro, and A. Bernstein, “Human-in-the-loop optimization for distribution system voltage control.”
- I.Satkauskas, G. Carvaro, A. Bernstein “Discrete Ripple-Type Voltage Control For Extreme-Event Contingencies”
- A. S. Zamzam, B. Cui, G. Cavraro, and A. Bernstein, “Efficient Conic and Linear Formulations for Distribution Systems Reconfiguration and Micro-Grid Formation.”
- F. Hasan, A. Zamzam, A. Bernstein, and A. Kargarian, “Unsupervised Learning Approach for Distribution System State Estimation.”

Patent applications:

- Guido CAVRARO, Andrey BERNSTEIN, Manish Kumar SINGH: “Ripple-Type Control of Networked Physical Systems”, Nonprovisional Patent Application

Other Outcomes

Presentations/Workshops:

- Organized the 5th Autonomous Energy Systems international workshop at NREL, July 13-15 2022
- Presented work at American Control Conference, PES GM, Conference on Decision and Control.

Thank you

NREL/PR-5D00-84155

This work was authored by the National Renewable Energy Laboratory (NREL), operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. This work was supported by the Laboratory Directed Research and Development (LDRD) Program at NREL. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.