Large-scale Data Analytics for Resilience of Power Grids in Multiple US Service Regions

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Power Failures in US from Severe Weather

- > 10 major hurricanes, snow/ice storms in U.S. 2005-2012
- Each caused more than 500,000 customers without power for days
- Example: Failures during Superstorm Sandy 2012 at the northeast, e.g., New York, Massachusetts, …

Our Objective

- Resilience*: "Reduce failures, expedite recovery"

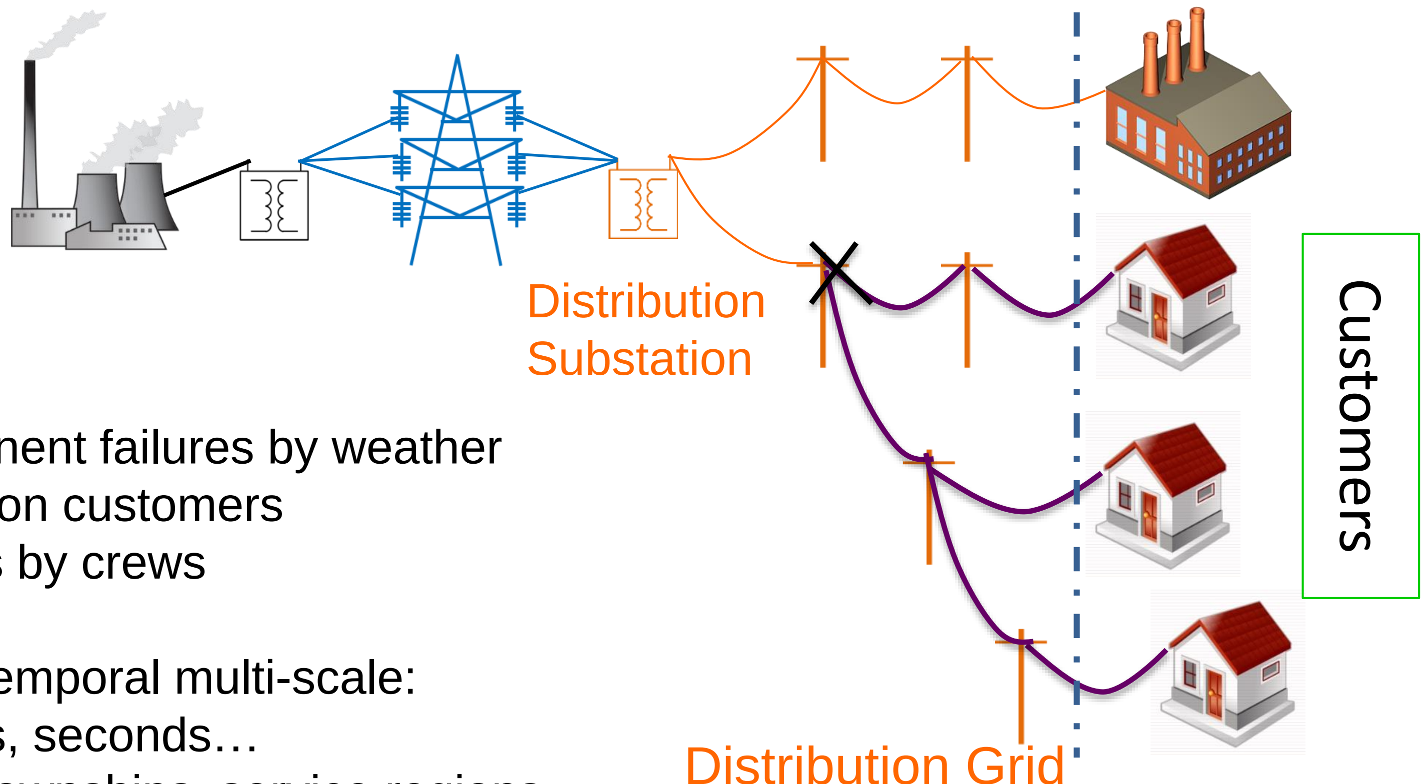
- To identify vulnerability through data analytics?
  - Infrastructural vulnerability: Failures
  - Service vulnerability: Recovery

*White House report13, Bloomberg report13

A bit of background

Severe Weather Disruptions to Power Grid

- 90% damages from power distribution [White House 13]



Component failures by weather
Impact on customers
Repairs by crews

Spatiotemporal multi-scale:
Minutes, seconds…
Node, townships, service regions,

Challenges

- Lack of models for spatiotemporally dependent failures, recoveries, and impacts on customers
  - Most prior works are on static models, e.g., Liu et al. 15, Nateghi and Guikema 11
  - Dynamic models are considered for failures only, e.g., Rudin et al. 12; aggregated recovery by Bertsimas and Mourtzinou 95.
- Real data need to be detailed and at a large scale
  - A few prior works use real data from one service regions, e.g., Liu et al. 15, Nateghi and Guikema 11, Rudin et al. 12
  - Aggregated failure data are used at a large scale across US by Larsen et al. 15

Model guided data analytics

Non-stationary Spatiotemporal Random Processes

- Randomness:
  - Failures/recoveries by weather
- Non-stationarity:
  - Probability distributions vary spatially and temporally
- Physics: Radial topology and related protection

Model: Link a large number of dependent variables on failures, recoveries and impacts

Coupled Disruption-Recovery-Cost Processes*

- Disruption Process: { $I[A_i^d(t)]$ }
  - $A_i^d(t)$: Failed component or activated protective device i
- Recovery Process { $I[D_i(v)>t-v]$ }
  - $D_i(v)$: Duration for disruption occurred at v prolonged to t
- Cost Process { $C_i(v,t)\ I[D_i(v)>t-v]$ }
  - $C_i(v,t)$: cost from delayed recovery
  - Example cost: Customer interruption time

*C. Ji, Y. Wei, …R. Wilcox, “Large scale data analytics for resilience of power grid across multiple US service regions,” *Nature Energy*, May 2016

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First-Order Model Parameters

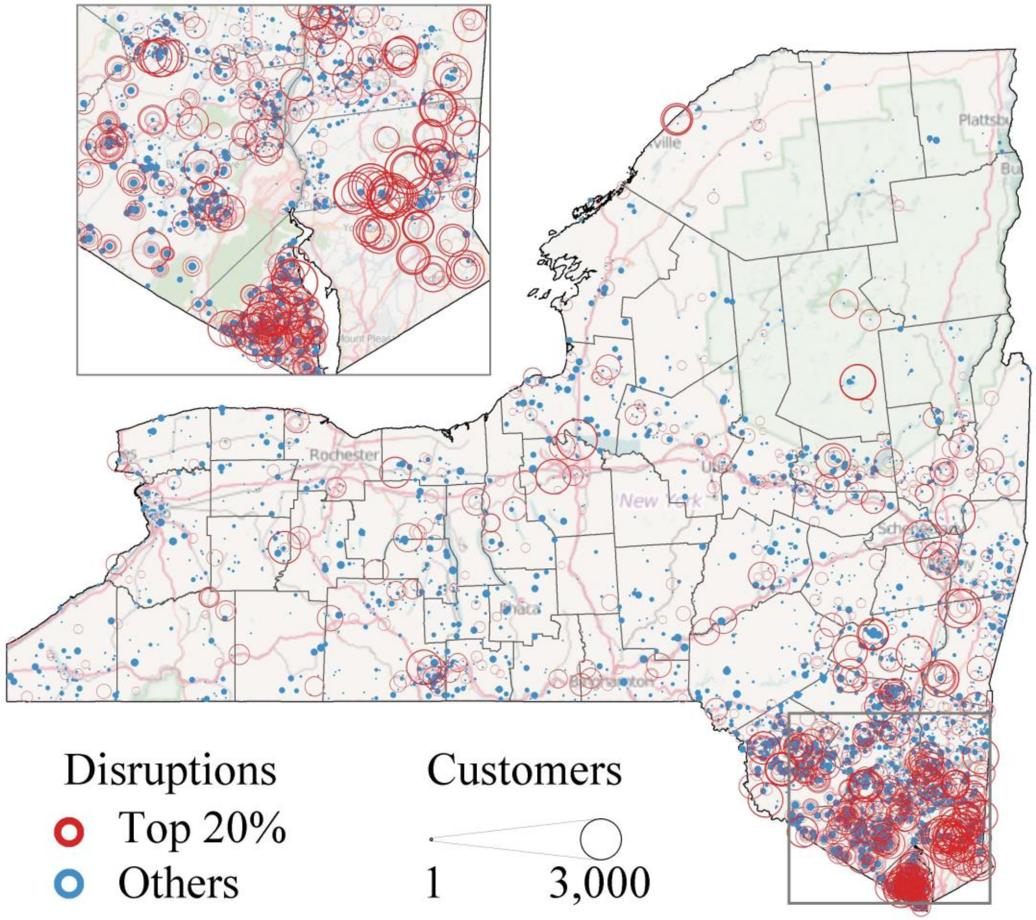
- Disruption rate: Increment of expected cost/time
- Conditional probability distribution of delayed recovery given failures
- Expected cost as the customer outage time

Data and Analysis

Detailed Data from Multiple Service Regions

- Hurricane Sandy 2012
  - Upstate NY: ~50,000 square miles, 4 service territories
- From electric grid
  - ~6600 failures in 2 days
  - Affected ~650,000 customers to 10 days
- Also data from daily operations in 2012
- Details: Failure/min, duration, locations, costs (downtime) … on activated protective devices

80-20 Scaling: 20% failures for 84% affected customers



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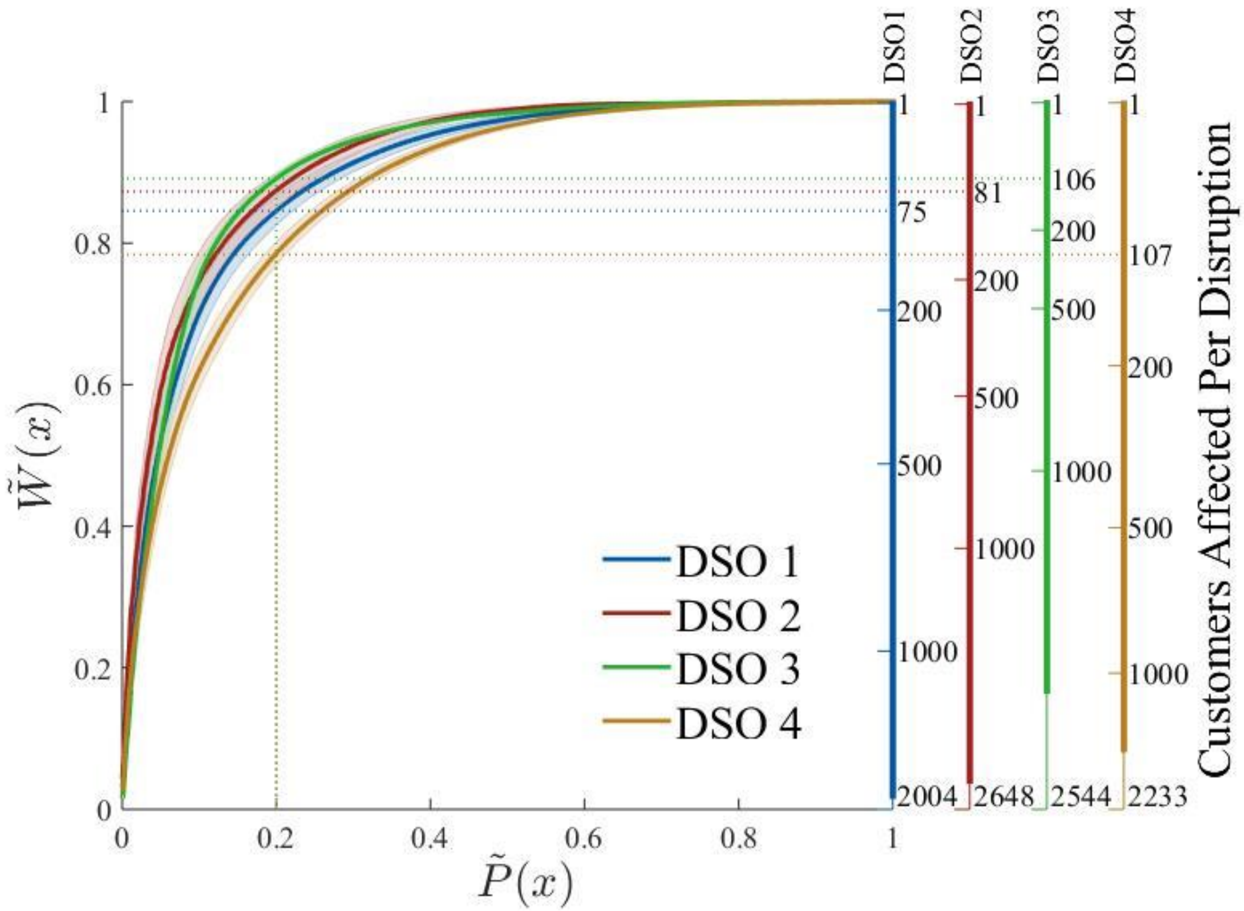
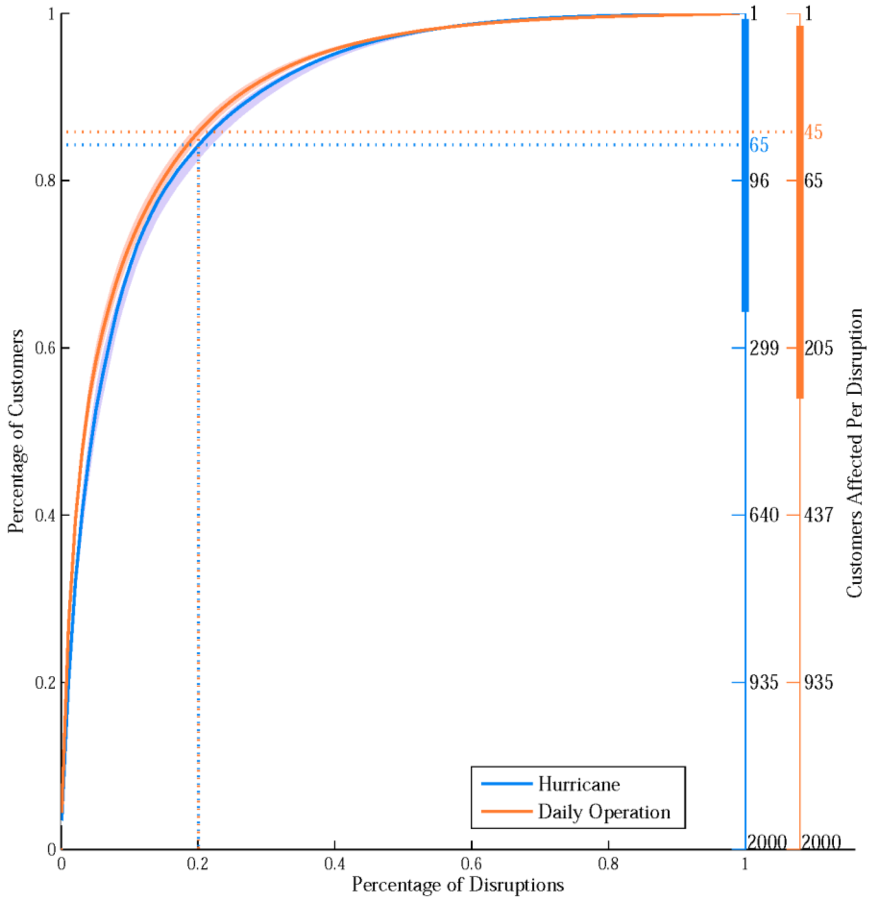
Generalized Scaling Property



The scaling property holds for all four DSOs during Sandy

DSO: Distribution System Operator

Similar Scaling Property for Daily Operations

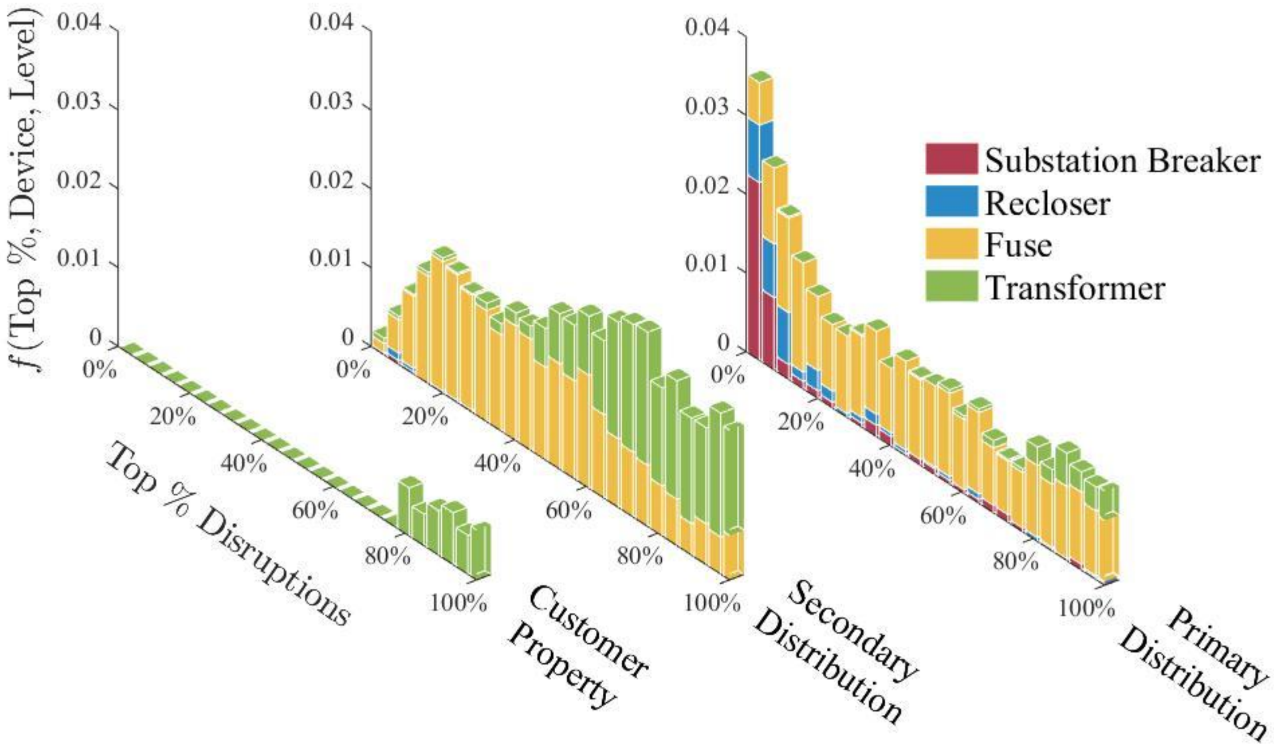


DSO 1

Hurricane Exacerbated Vulnerability

Probability	Daily Operation	Hurricane
A disruption/minute	0.0074	0.2301 (~30 times)
A top-20% disruption/minute	0.0004	0.0716 (~170 times)

A Cause of Vulnerability?

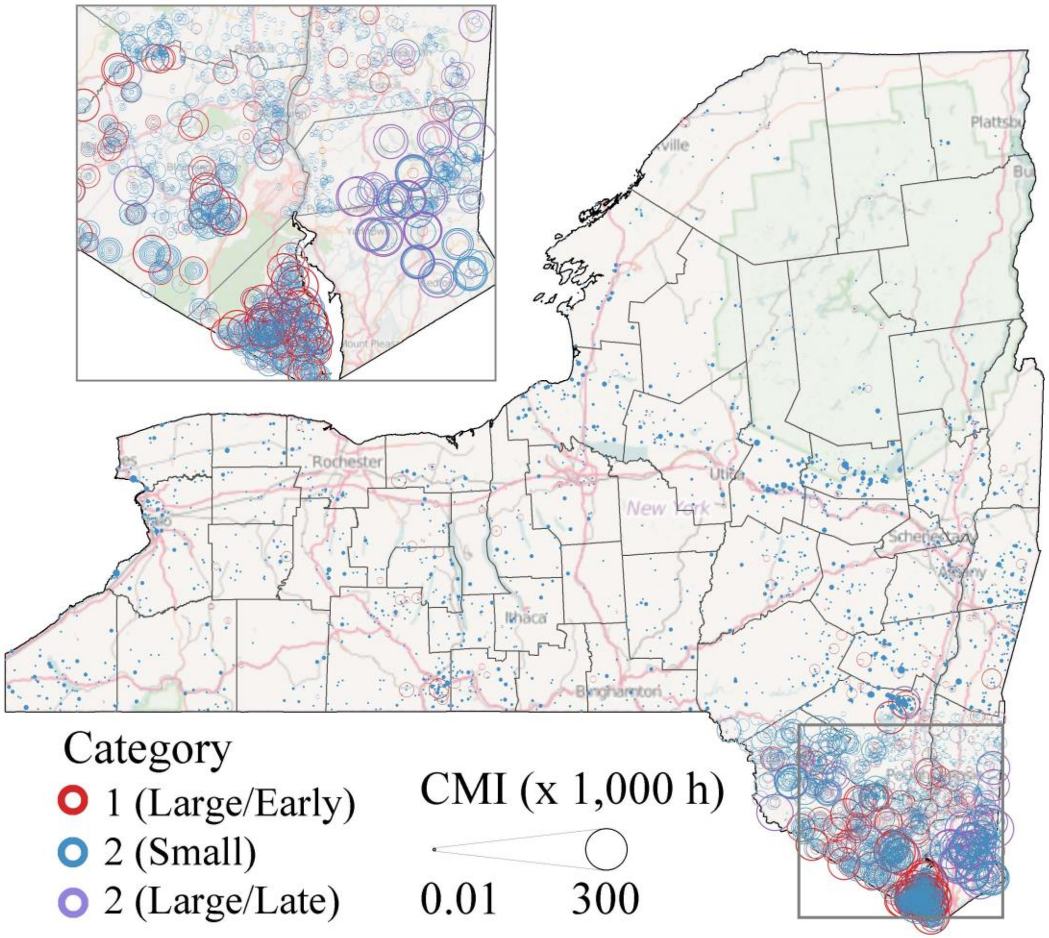


Structure distribution system: Primary, secondary, customer property
Locations of top failures: >83% at the primary distribution

Infrastructure Vulnerability

- Local failures can affect tens~hundreds customers
- Exist in daily operations but exacerbated by Super storm Sandy
- A cause: How customers are supported by overhead power distribution

Customer Downtime: Different from Failures



CMI: Customer Interruption Time

Service Vulnerability?

- Small failures matter:

A larger number (89%) of small failures (bottom 34% of customers or commonplace devices) amounts to 56% of customer downtime

- Prioritizing recovery of large failures under available resources does not solve the problem

Summary

- Infrastructural vulnerability
  - A local failure can have non-local impact to customers
  - Exists in daily operations
  - Exacerbated by Super Storm Sandy
  - A cause is the structure of power distribution

- Service vulnerability: Aggregation of a large number of small failures amounts to major portion of customer downtime

- Model-guided data analytics shows promise for identifying non-resilience of power distribution and services

How to Scale?

- Data?
- Collaboration?

Reference (see 5 for an extended list)

1 Bertsimas, D. & Mourtzinou, G. Transient laws of non-stationary queueing systems and their applications. *Queueing Syst. Theory Appl.* 25, 115—155, 1997.

2 Bloomberg MR. A Stronger, more resilient New York. *(City of New York) PlaNYC Reprot,* 2013.

3 Dobson, I., Carreras, B.A., Lynch, V.E. & Newman, D.E. "Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization." *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 17, 026103, 2007.

4 Executive Office of the President, "Economic benefits of increasing electric grid resilience to weather outages." President's Council of Economic Advisers and the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability, Washington, DC. *Technical Report*, 2013.

5 C. Ji, Y. Wei, …R. Wilcox, "Large scale data analytics for resilience of power grid across multiple US service regions," *Nature Energy*, May 2016

6 Liu, H., Davidson, R.A., David, R.V. & Stedinger, J.R. Negative binomial regression of electric power outages in hurricanes. *Journal of Infrastructure Systems*, 11, 258—267, 2005.

7 Larsen, P.H., LaCommare, K.H., Eto, J.H., & Sweeney, J.L. Assessing changes in the reliability of the U.S. electric power system. *Report LBNL*-188741, 2015.

8 R. Nateghi, S. D. Guikema, & S. M. Quiring, "Comparison and Validation of Statistical Methods for Predicting Power Outage Durations in the Event of Hurricanes," *Risk Analysis*, vol. 31, no. 12, pp. 1897– 1906, December 2011.

9 C. Rudin, D. Waltz, R. Anderson, A. Boulanger, A. Salleb-Aouissi, M. Chow, H. Dutta, P. Gross, B. Huang, & S. Ierome, "Machine Learning for the New York City Power Grid," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 2, 328–345, Feb. 2012.

10 Wei, Y, C. Ji, F. Galvan, S. Couvillon, G. Orellana, & J. Momoh. "Learning Geotemporal Nonstationary Failure and Recovery of Power Distribution." *Neural Networks and Learning Systems, IEEE Transactions on* 25, no. 1, 2014: 229-240.

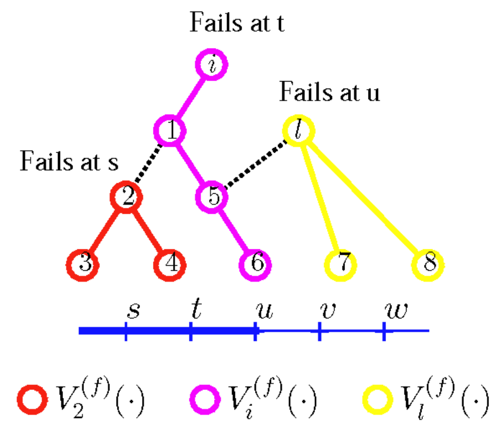
11 Executive Office of the President. Economic benefits of increasing electric grid resilience to weather outages. *Technical Repor*t, 2013.

Incorporating Physical Properties

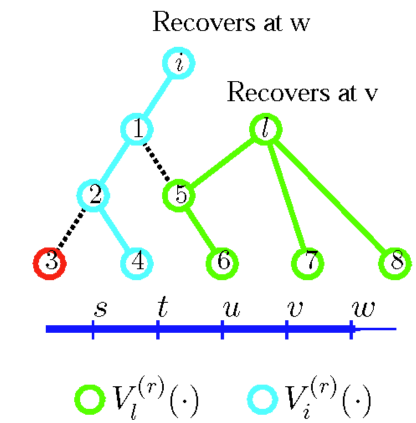
- Dynamic Disruption Process
  - Disruption at node i: $A_i^d(t)$, $d=\{f, o\}$;

    Damaged/activated component/protective devices

    Outages induced by failures
  - Failure neighborhood: $V_i^{(f)}(t)$
  - Disruption Process $N_i^d(t)=\mathrm{I}[A_i^d(t)]$



- Dynamic Recovery Process
  - Recovery event: $B_i^{(r)}(t)$,
  - Recovery neighborhood: $V_i^{(r)}(t)$
  - Recovery Process: $N_i^r(t)=\mathrm{I}[B_i^r(t)]$



Dynamic Neighborhood (Wei et.al.13)

Recoveries

- Expected cost at time *t* given location z:

$$E\{C(t,z)\} = \int_0^t E_{S(v)}\left\{ \lambda_i^f\left(v \mid S(v)\right) E\{G_i(v,t) \mid S(v)\}\right\} dv$$

  - $\lambda_i^f\left(v \mid S(v)\right) dv$: failures occurred at time v
  - $E\{G_i(v,t) \mid S(v)\}$: Cost by the failures
  - Aggregation over trajectories of failures
  - *S*(*v*): set of operational nodes at time *v*

$$E\{G_i(v,t) \mid S(v)\} = E\left\{ C_i(v,t)P[D_i(v) > t - v] + \sum_{j \in V_i(v)} C_j(v,t)P[D_j(v) > t - v] \right\}$$

Similar Scaling Property for Daily Operations