Leveraging Utility Outage Data to Quantify Resilience

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Basic tools for data-driven resilience

OUTAGE DATA

EVENTS

PROCESSES

METRICS

Detailed outage data

Distribution system

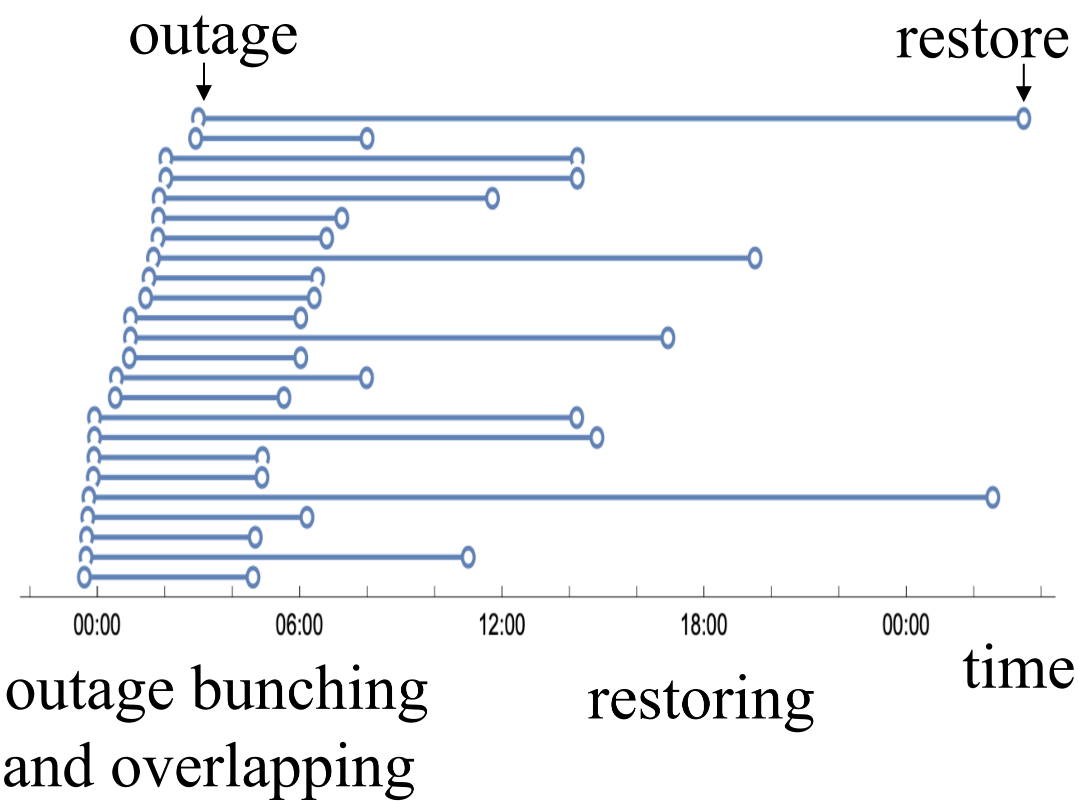
- Data include outage and restore times of lines and other components to the nearest minute, customers disconnected, cause codes
- Data logged by Outage Management System. We process ~32000 outages from 5 years of data into 6650 events

Transmission system

- TADS data include outage and restore times of lines and transformers to the nearest minute, cause codes
- North American utilities report TADS data to NERC.
  We use 6 years of forced (automatic) outages across North America. We process ~62,000 outages and select 352 events with at least 10 outages. Most events are weather-related.

Events

- Events come from a combination of external stresses such as weather (common cause) and cascading within the grid (dependent failures)
- Events are characterized by bunching (outages in close succession) and overlapping accumulation of outages in time.

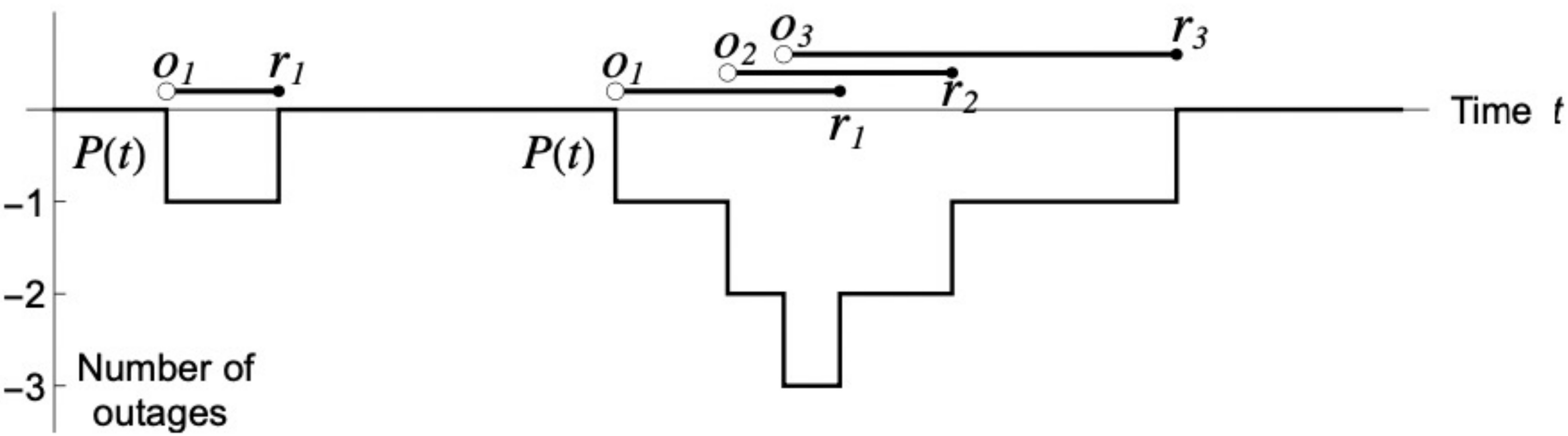


Key point is to have algorithms to automatically extract events from data

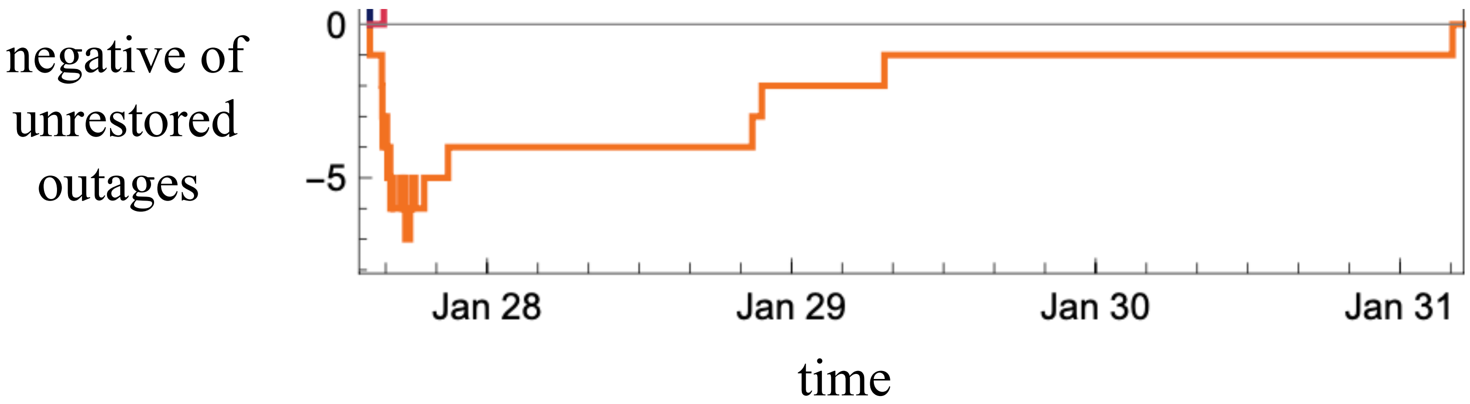
Events and Performance curves

Resilience events happen when outages bunch up and accumulate

Performance curves P(t) track number of unrestored outages:



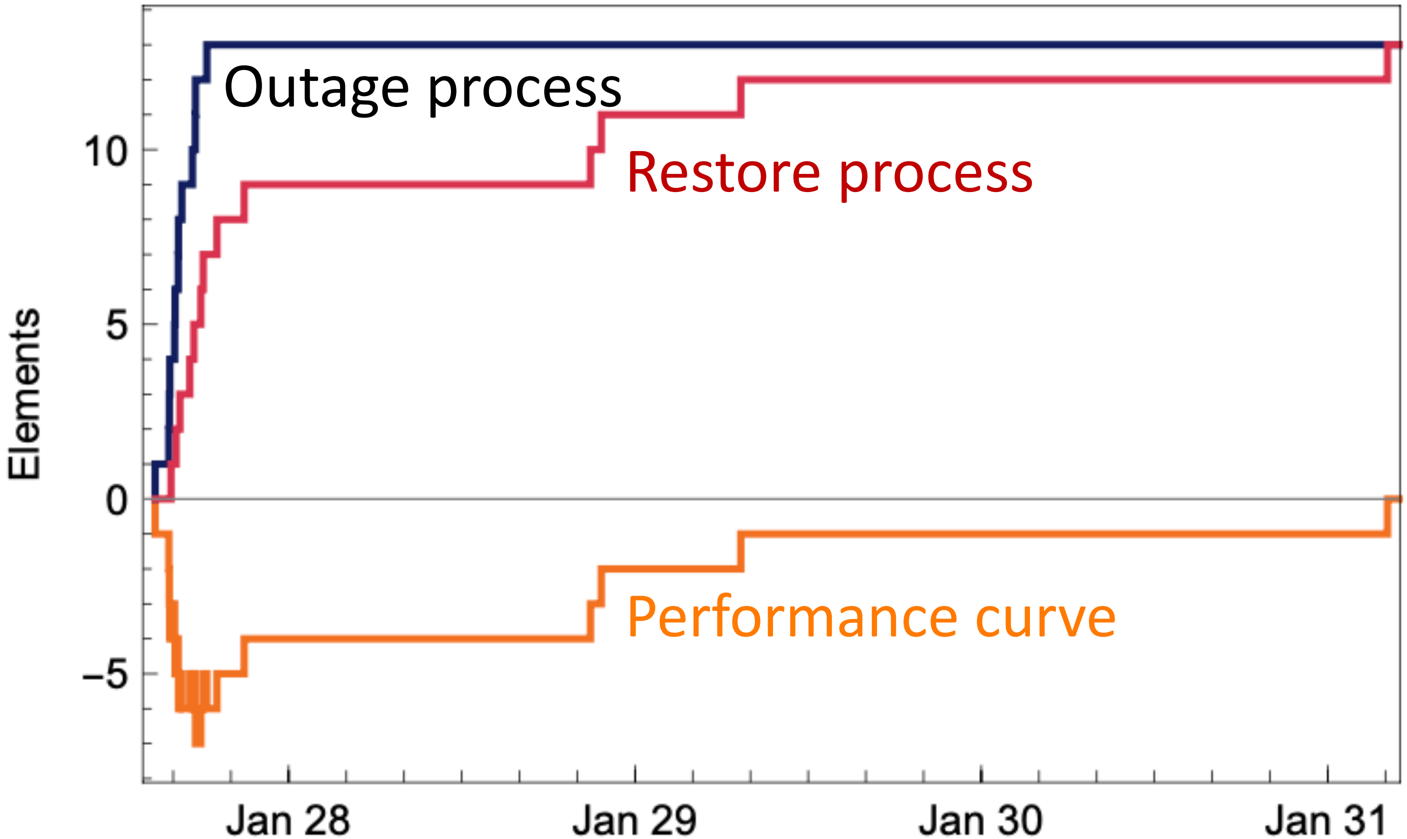
Performance curve tracks in an event the unrestored outages over time



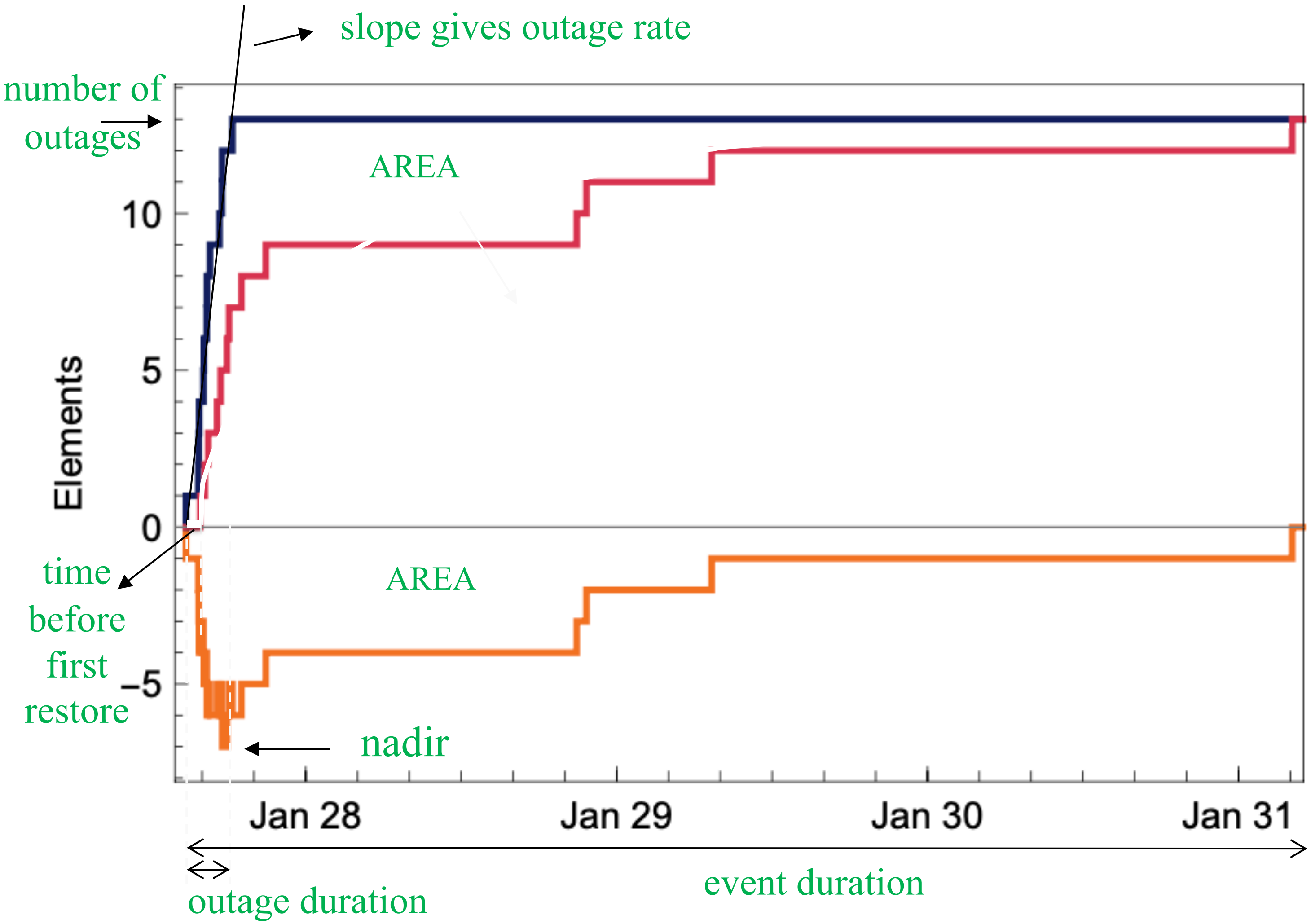
Decompose Performance curve into Outage and Restore processes

Outage process
= cumulative
outages

Restore process
= cumulative
restores



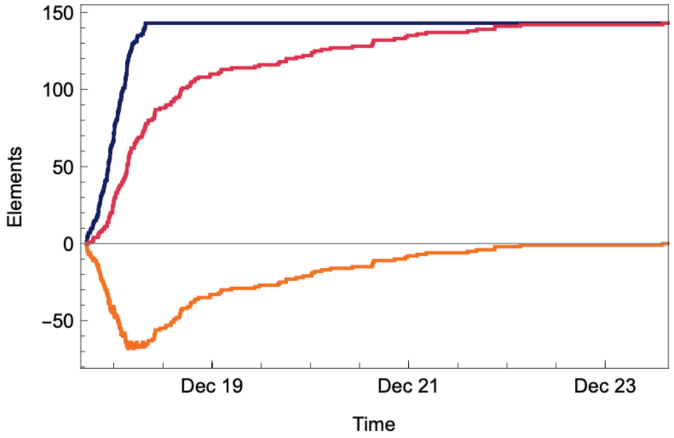
Performance curve = Restore process - Outage process

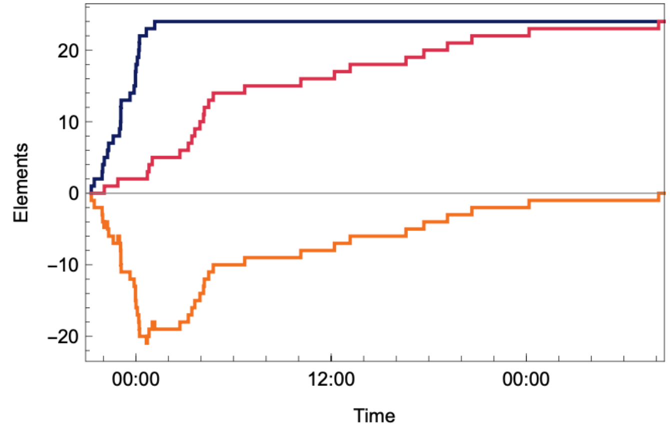


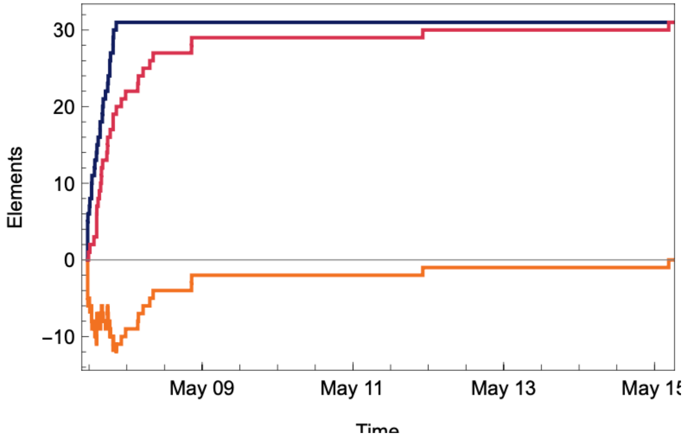
Get
resilience metrics
from
outage,
restore, and
performance
processes

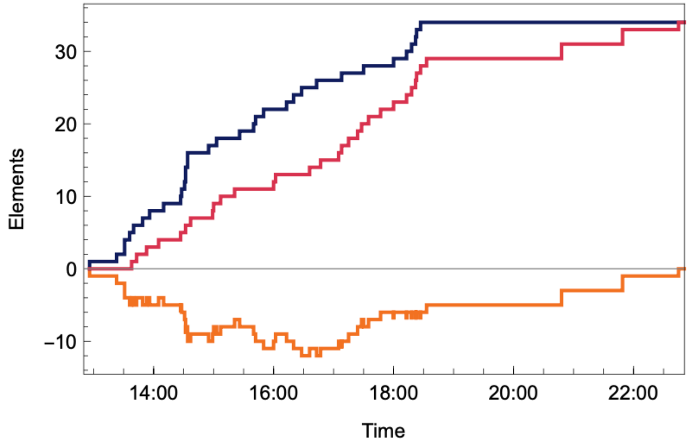
Can put any quantity from the data on vertical axis. e.g. MVA impact

Transmission system events



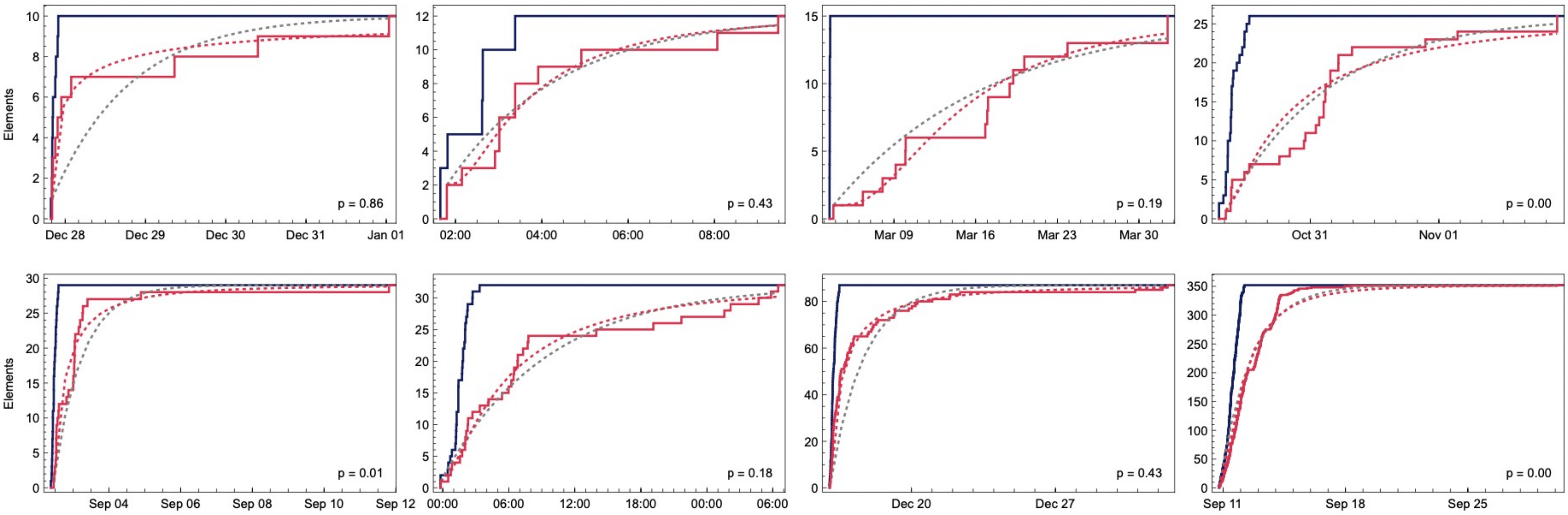






Outage rate is roughly constant but Restore rate is slowing

Transmission system events

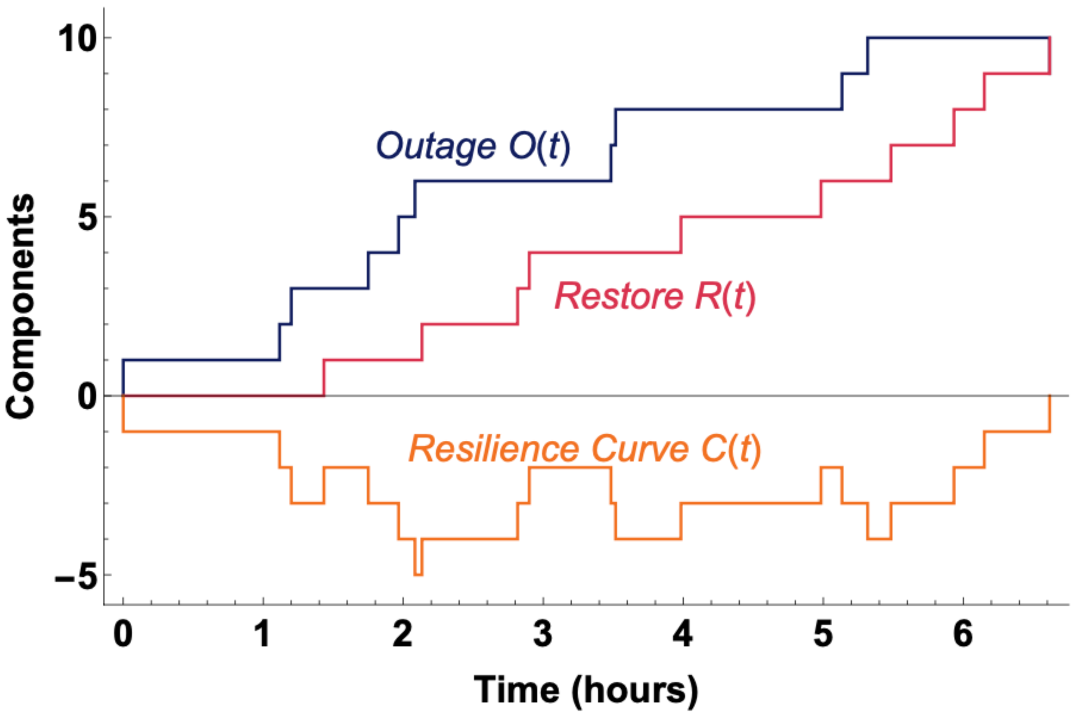


Resilience metrics for large transmission events

Process	Event Statistics	Mean	Std Dev	Minimum	Maximum	Median	95th Pctl	Fitted distribution
Outage process	Event size (# outages)	44.9	50.0	20	352	27	143	No good fit
	Miles affected	1175	1173	233	6461	850	3638	Lognormal
	MVA affected	17165	18514	4223	120064	10769	55323	Lognormal
	TADS elem affected	38.6	42.5	11	295	25	117	No good fit
	Outage process duration Hrs	6.3	5.3	0.9	35.2	4.7	15.0	No good fit
	Outage rate (elem/Hr)	7.46	3.76	3.4	26.7	6.4	14.5	Lognormal
	Outage rate (MVA/Hr)	3008	2765	997	22260	2220	6343	Lognormal
Restore process	Restore Process Duration Days	14.5	33.1	0.11	246.0	4.6	58.8	Lognormal
	Time to First Restore Minutes	46	51	0	208	31	169	Exponential
	Time to restore 95% outages Days	3.9	5.4	0.05	38.2	2.3	12.4	Lognormal
	Time to restore 95% MVA Days	4.2	6.3	0.05	39.8	2.2	17.1	Lognormal
	% Event Duration to Restore 95%outages	58%	31%	3%	100%	63%	100%	No good fit
	% Event Duration to Restore 95% MVA	58%	33%	1%	100%	61%	100%	No good fit
Performance process	EventDuration Days	14.6	33.1	0.13	246	4.6	58.8	Lognormal
	Max Elemements Out	26.72	28.19	7	181	17	69	Lognormal
	Max MVA Out	9724	10721	1870	60133	6283	32406	Lognormal
	Element-Days Lost	59	104	0.34	558	18.7	336.9	Lognormal
	MVA-Days Lost	21394	39499	73	241730	5535	105772	Lognormal

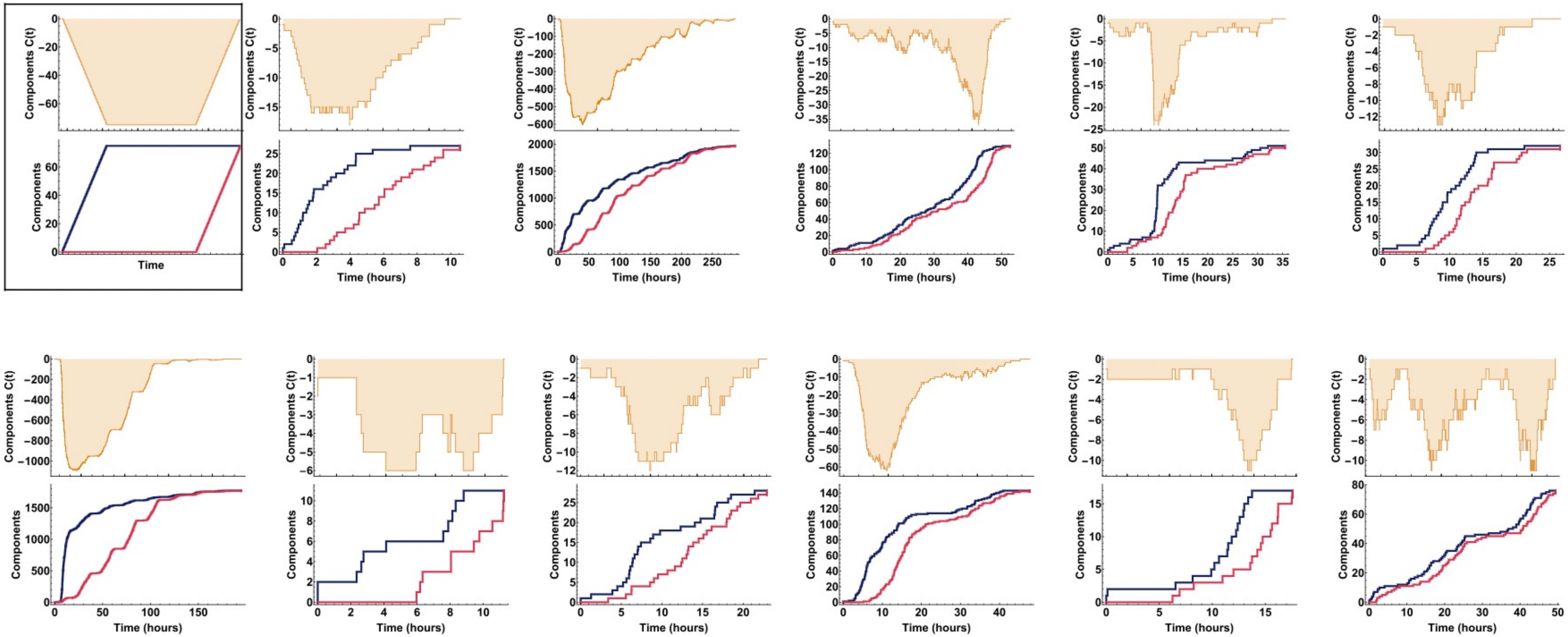
Metrics for Outage process OR Restore process OR Performance curve

Tracking components in a distribution system resilience event

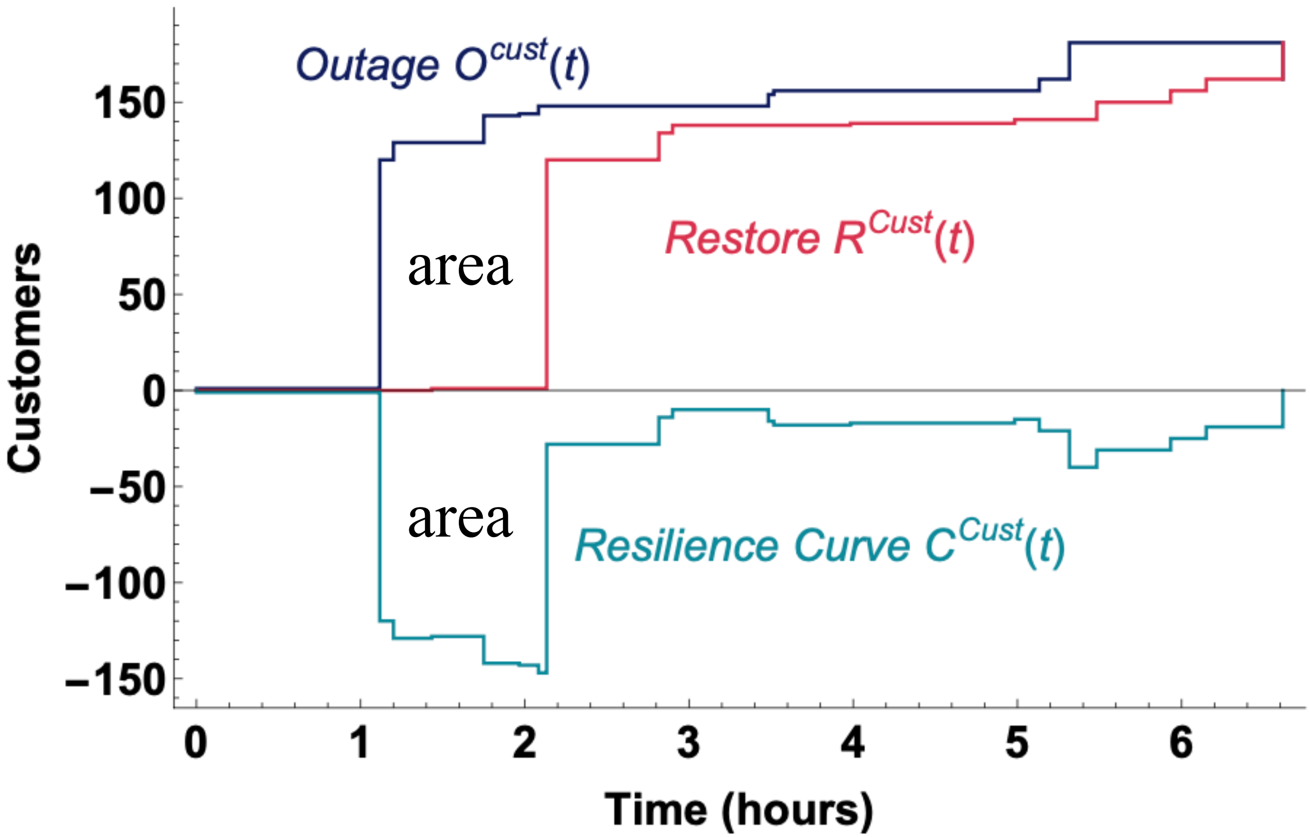


Easily get event metrics such as
number of outages,
duration,
outage rate,
restore rate,
area under curve

Distribution system events

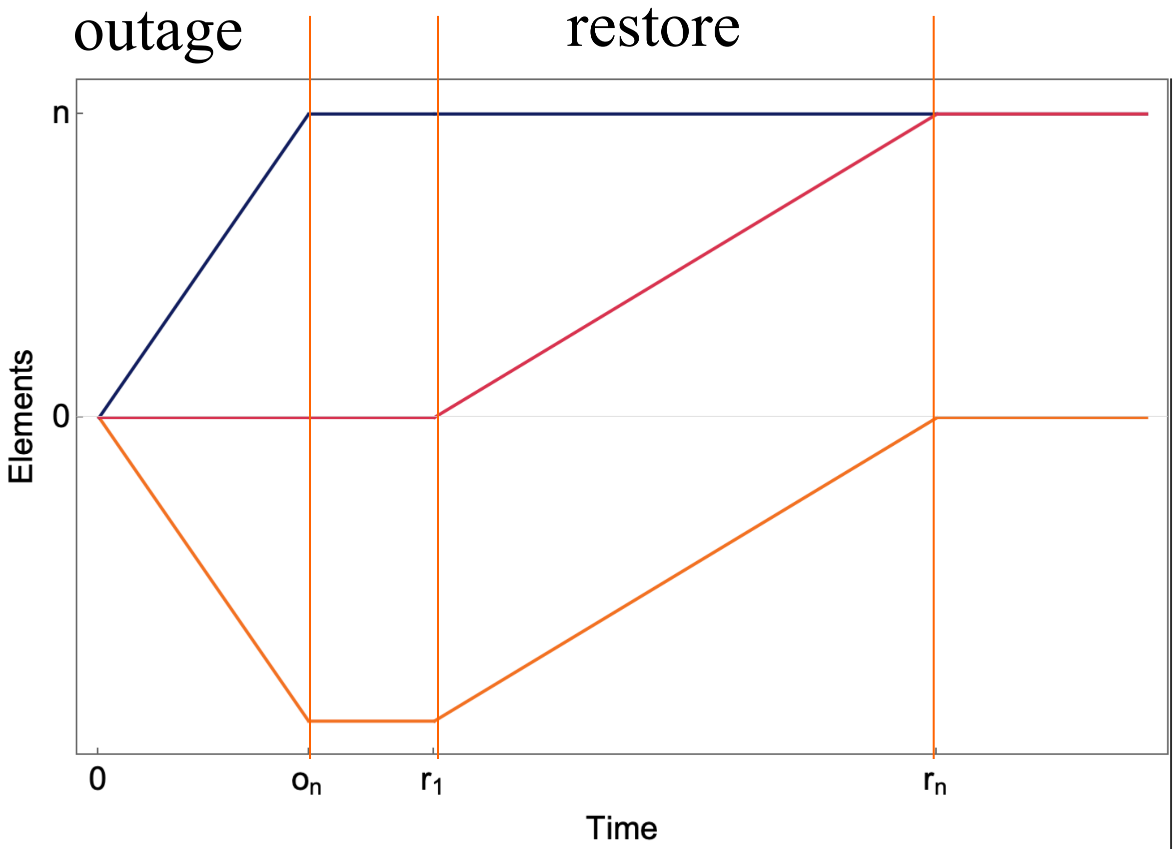


Tracking customers in a distribution system event



area = customer hours

Real events do not look like idealized performance trapezoid where outage process stops before restore process starts:



Processes not phases in time!

Emerging outcomes for data-driven resilience

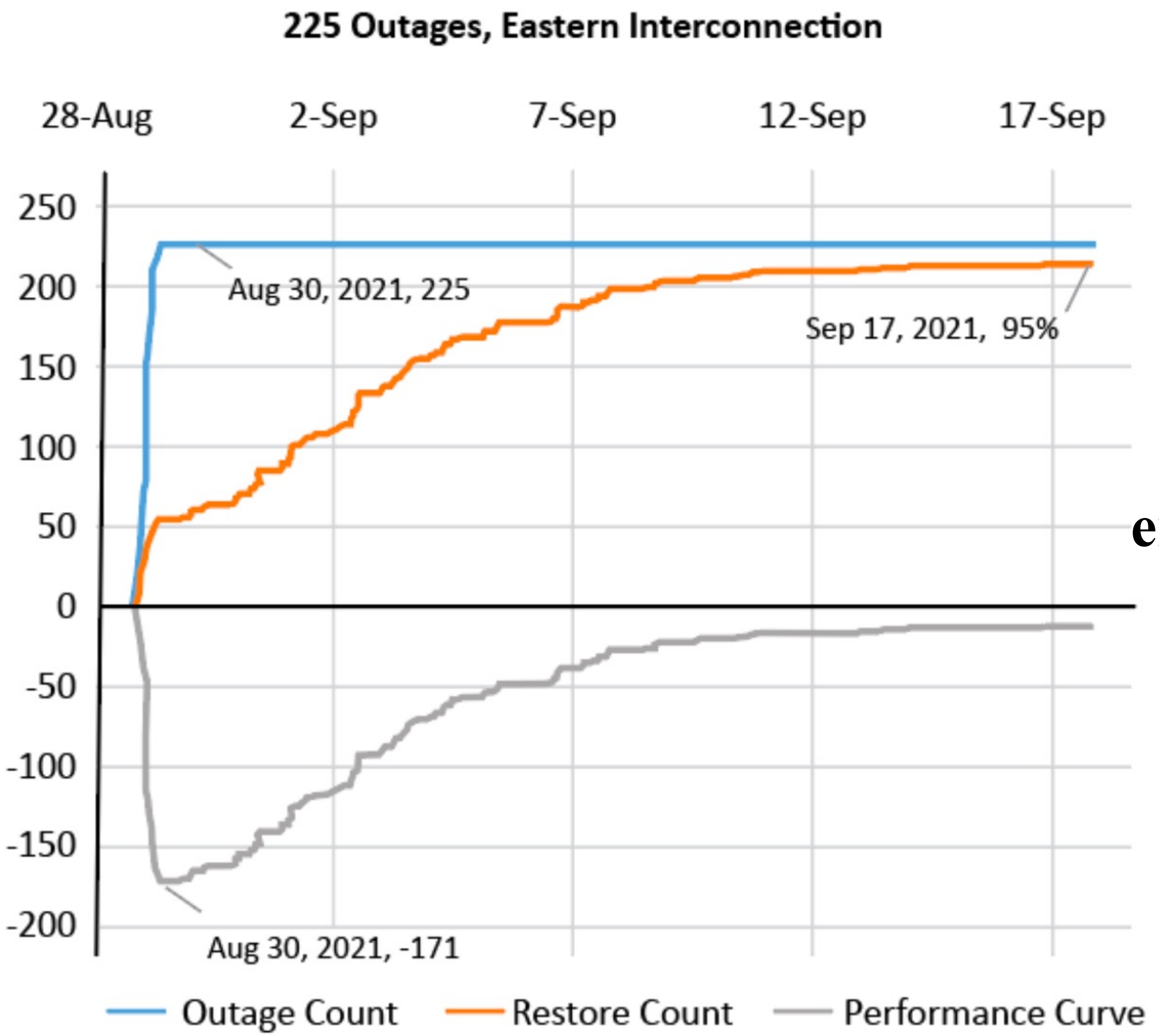
EVENT STATISTICS

START ON RISK ANALYSIS

POISSON PROCESS MODELS

QUANTIFY RESILIENCE INVESTMENTS

Hurricane Ida



Look at specific events: a start on further detailed engineering analysis

from NERC State of Reliability Report 2022

North American transmission statistics

TABLE III. AVERAGE METRICS BY WEATHER TYPE

Average Statistics	Hurricane	Fire	Thunderstorm, wind	Tornado	Winter weather
Event Size	92.7	36.5	34.6	38.4	33.6
Outage Process Duration (Hrs)	10.7	7.2	4.8	7.3	5.3
MaxElemOut	57.3	23.0	21.7	25.6	15.9
Timeto95%elemRestored (Hrs)	135.4	472.1	68.4	153.7	47.0
Element-Days Lost	148.4	116.9	45.6	52.8	19.7

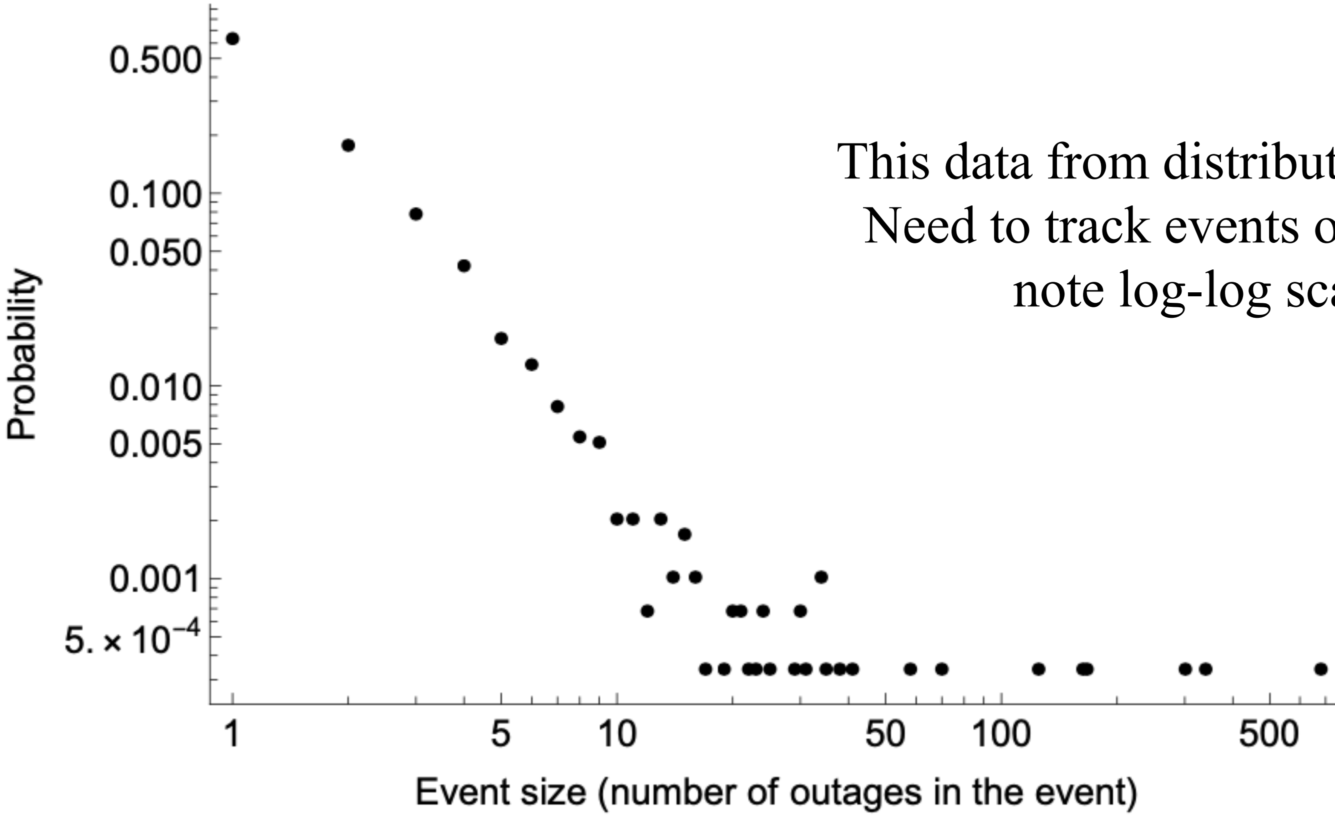
TABLE IV. RESILIENCE METRICS BY SEASON

Season	Number of Events	Average by Season					
		Event Size	Restoration Process Duration Hrs	Time to 95% elements Restored Hrs	Time to 95% MVA Restored Hrs	Element-Days Lost	MVA-Days Lost
Winter	11	31	120	85	73	28	9977
Spring	25	36	486	80	125	48	19799
Summer	17	55	335	134	103	73	21768
Fall	16	58	307	81	81	84	31337

North American transmission resilience for events >10 outages

- Most are weather related; largest are hurricanes
- Outages increase linearly
- Restores according to lognormal is most common; exponential restore is a noticeably worse fit
- Duration metrics are statistically variable:
  Straightforward duration very bad
  (also last few restores usually not relevant)
  Time to 95% restoration is better
  Geometric mean = median of restore times is best
- Automatic extraction of events and processes and metrics supports further engineering analysis of specific events.

Heavy tailed distribution of event size
… a start on Risk Analysis



This data from distribution system
Need to track events of all sizes
note log-log scale

Probability of event goes down as size increases, but slowly.
Cost of event increases as size increases
Event Risk = Probability x Cost
How do small and large events compare in risk?
Future work: get better cost information, especially for large events

Poisson Process

Poisson process rate $\lambda(t)$ means that
probability of a point occurring in a small interval $(t,t+h)$ is $\lambda(t)h$

Suppose 50 points of a Poisson process on an interval with uniform rate.
Then the points are 50 samples from a uniform distribution on the interval:

grayscale shows the probability density

Suppose 50 points of a Poisson process with lognormal rate.
Then the points are 50 samples from a lognormal distribution:

Poisson models of outage and restore for transmission systems

n = number of outages

outage rate = n x uniform distribution over the outage duration

restore rate = n x lognormal distribution after first restore

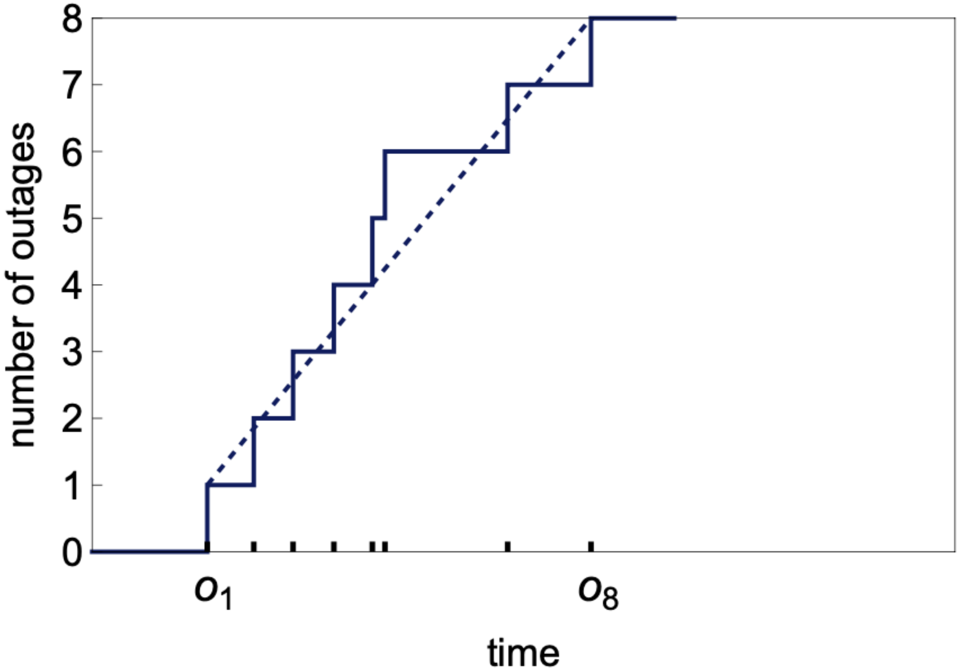
outage process(t) = integrate outage rate to time t

… increases linearly

restore process(t) = integrate restore rate to time t

… increases as n x lognormal CDF

Outage process O(t) with uniform rate λ_O

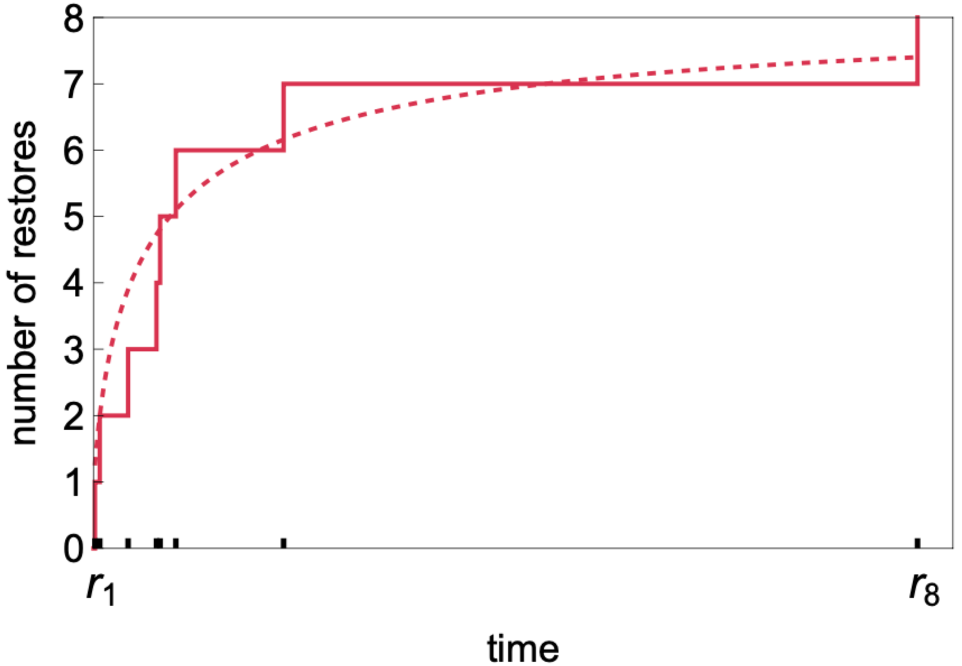


Outage process O(t)
(step function)
is cumulative number of
outages at time t

Average outage process $\overline{O}(t)$
is dotted line of slope λ_O

Averaged model: $\overline{O}(t) = \mathrm{E}[O(t)] = \lambda_O(t - o_1)$ for $o_1 \leq t \leq o_n$

Restore process R(t) with rate $\lambda_R(t)$ proportional to lognormal



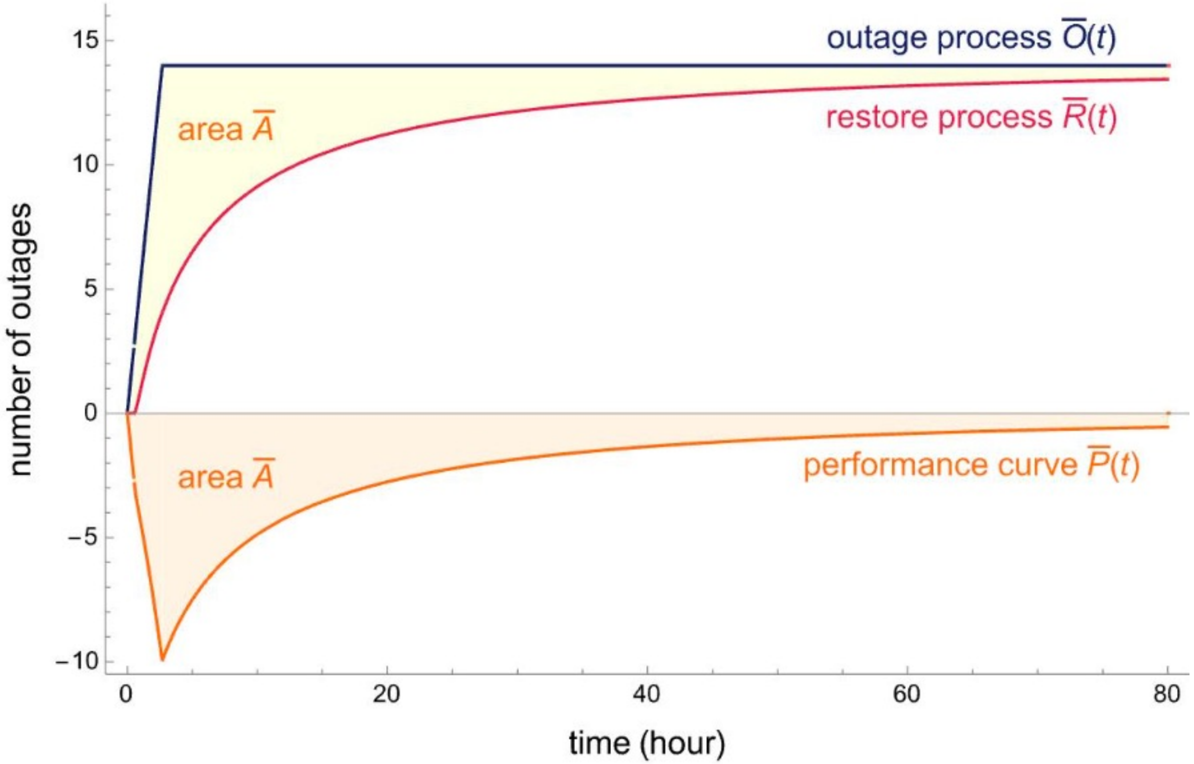
Restore process R(t) (step function) is cumulative number of restores at time t

Average restore process R(t) is dotted line with slope proportional to lognormal

$$\lambda_R(t) = n f_{\mu,\sigma}(t - r_1) = n \times \text{lognormalPDF}[\mu, \sigma]$$

Averaged model: $\overline{R}(t) = \mathrm{E}[R(t)] = \int_{r_1}^{t} \lambda_R(\tau) d\tau = n\Phi\left[\frac{\ln(t - r_1) - \mu}{\sigma}\right]$ for $t \geq r_1$

Typical North American transmission event with averaged processes



$$n = \text{total number of components out}$$

$$\overline{A} = n(\text{mean restore time} - \text{mean outage time})$$

$$\overline{A} = n(\text{mean component repair time})$$

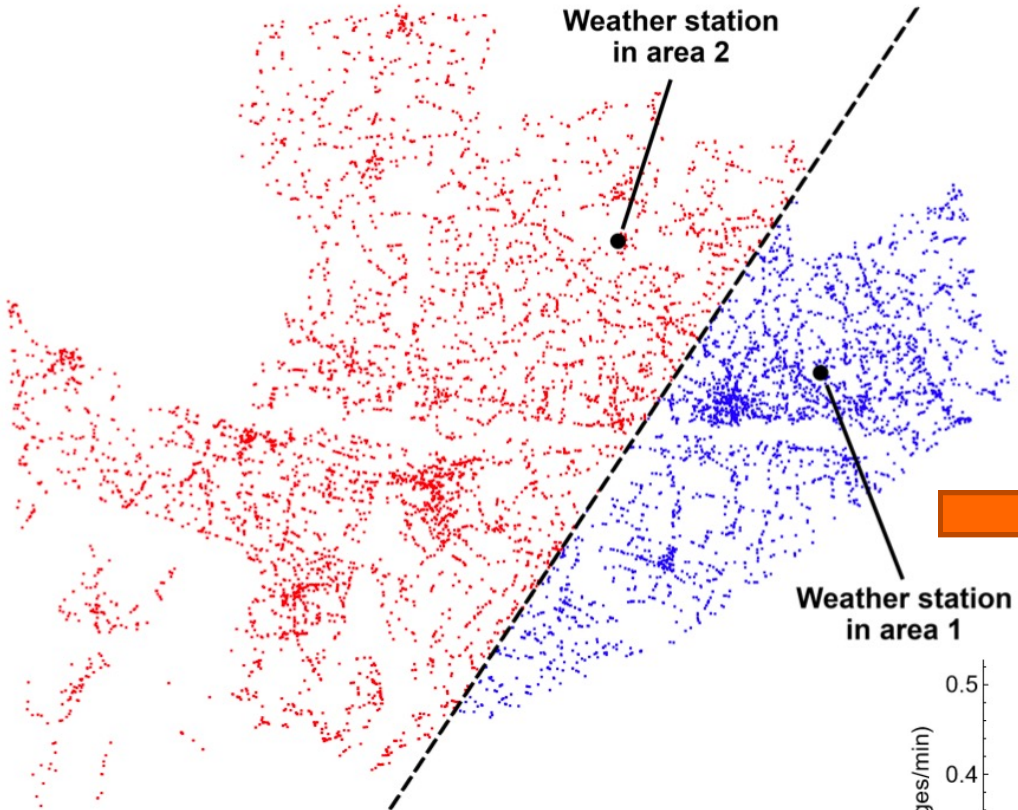
for distribution systems, n_c = total number of customers out

$$\overline{A} = n_c(\text{mean customer out time}) \text{ with assumption}$$

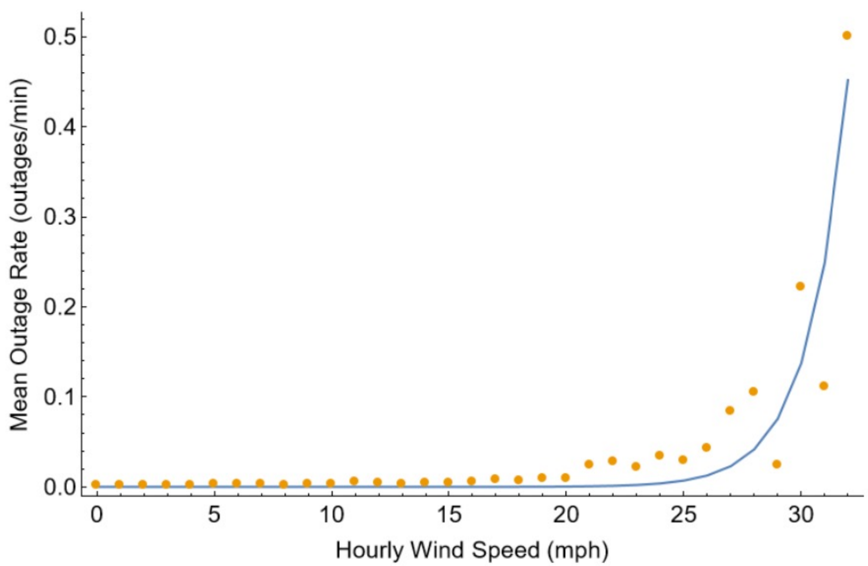
Quantify resilience investments in a distribution system

- Key idea:
  Quantify the impact the investment **would have had** if it was made in the past
- A new way to make the case for resilience investments to customers, stakeholders, regulators
- First process historical data to get resilience metrics. Then "rerun history" with overall resilience mitigation to get the change in metrics
- We will look at impacts of hardening with respect to wind and of faster restoration in a distribution system

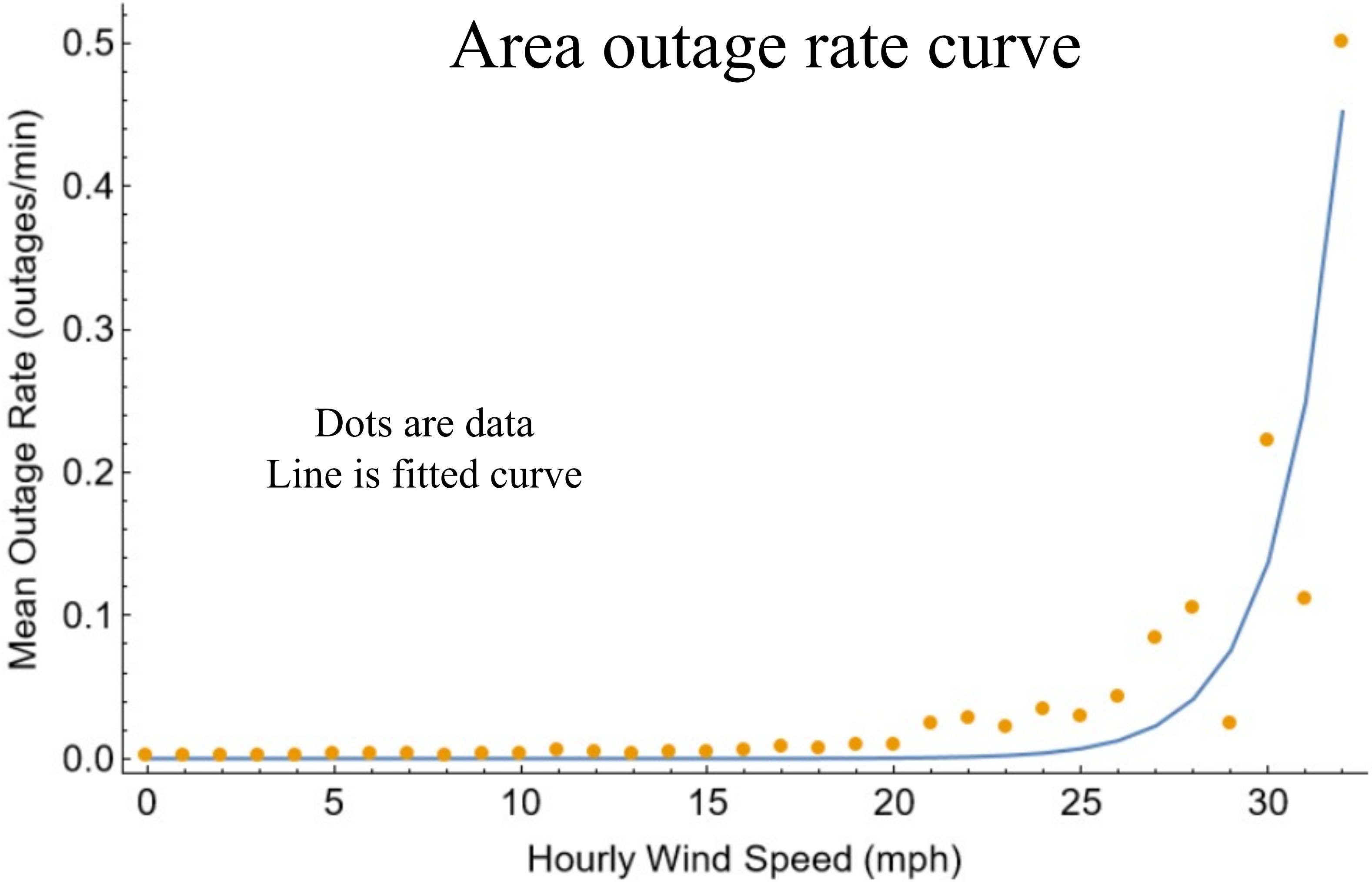
Geographic location of outages in distribution system and their nearest NOAA weather station giving hourly wind speed



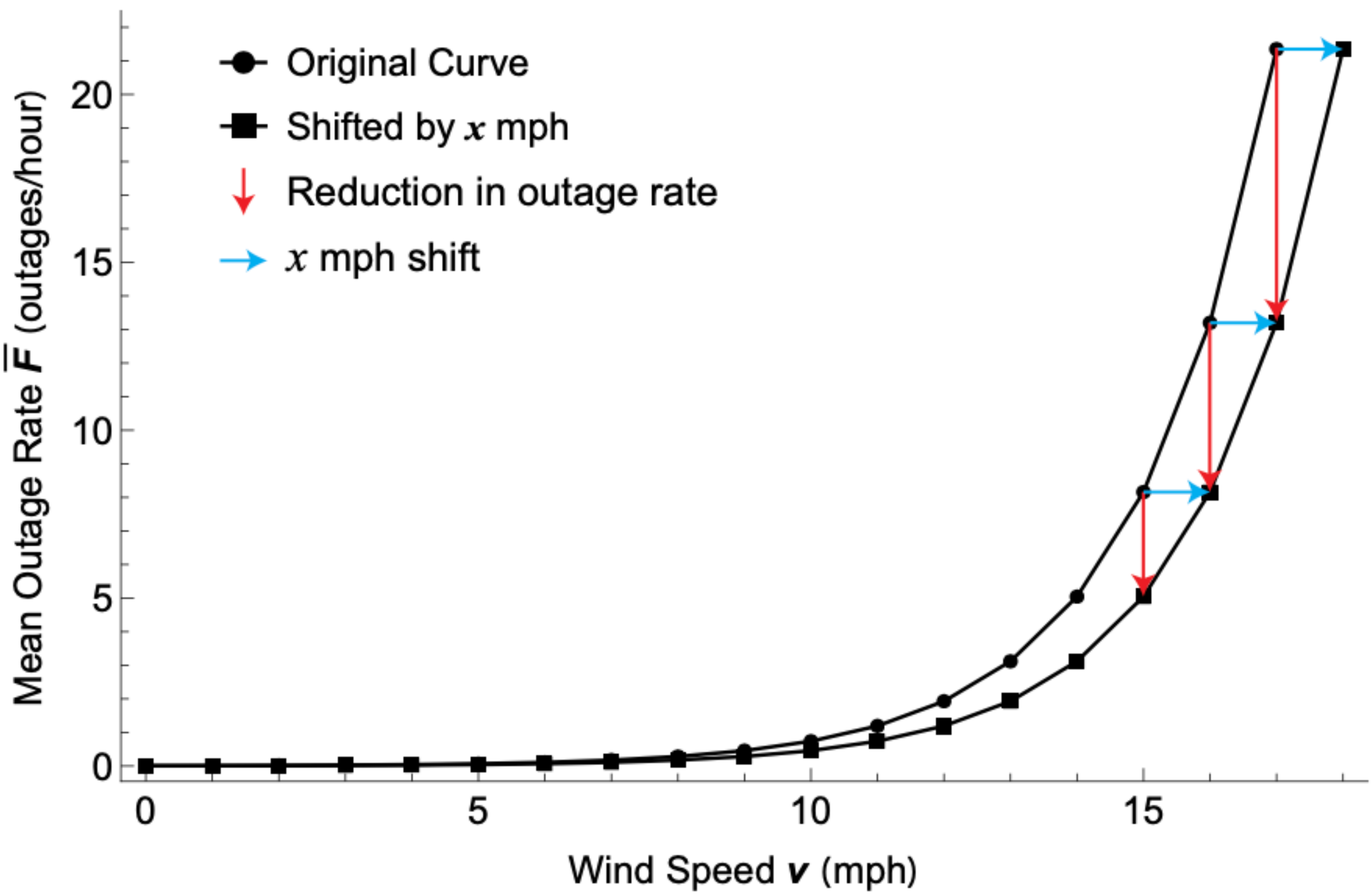
Area outage rate curve for area 1



Outage and wind data → mean outage rate as a function of wind speed



Hardening for wind shifts curve to the right and reduces outage rates



Hardening → Reduced outage rate

Implement reduced outage rate by sampling reduced number of outages

Historical outages → Base case metrics

Hardening → Reduced outages → Improved metrics

Hardening → Change in resilience metrics

Consider x mph wind hardening → Shift Area Outage Rate Curve by x mph → Sample from outages as per reduced outage rates → Evaluate improved Resilience Metrics

Wind hardening results

10% reduced outage rate = 0.22 mph hardening

	Base Case Events			Change with Hardening		
Resilience Metric	small	medium	large	small	medium	large
number of outages	1.25	4.75	62.48	-10.0%	-10.0%	-10.0%
outage hours	2.71	15.28	1142	-10.0%	-10.0%	-10.0%
event duration	2.39	7.51	37.67	-8.8%	-4.5%	-1.3%
time to first restore	2.10	2.66	2.56	-7.4%	1.6%	3.0%
restore duration	0.28	4.85	35.11	-19.0%	-10.8%	-2.9%
customers out	50.74	242.98	4084	-10.0%	-10.1%	-10.0%
customer hours	85.51	547.28	58700	-10.0%	-10.0%	-10.1%

all time quantities in hours

small events have 1 or 2 outages
medium events have 3-15 outages
large events have >15 outages

Faster Restore results

faster restore rate (times 0.95) that gives 10% reduction in outage hours for large events

Resilience Metric	Base Case Events small	medium	large	Change with Faster Restore small	medium	large
number of outages	1.25	4.75	62.48	0%	0%	0%
outage hours	2.71	15.28	1142	-0.5%	-4.6%	-10.0%
event duration	2.39	7.51	37.67	-0.6%	-3.1%	-4.0%
time to first restore	2.10	2.66	2.56	0%	0%	0%
restore duration	0.28	4.85	35.11	-4.8%	-4.8%	-4.3%
customers out	50.74	242.98	4084	0%	0%	0%
customer hours	85.51	547.28	58700	-0.3%	-4.7%	-9.0%

all time quantities in hours

small events have 1 or 2 outages
medium events have 3-15 outages
large events have >15 outages

DATA-DRIVEN ANALYSIS OF OVERALL RESILIENCE INVESTMENTS

- Can quantify probability of small, medium, large resilience events from historical outage data

- We have historical outage data ➡ metrics such as customer hours.

What if we had invested in resilience and got a 10% reduction in outages?
What would have been the reduction in customer hours?
We can find out by sampling 10% fewer outages.
This quantifies the effect that investment in resilience **would have had**

- New way to quantify benefits of resilience to stakeholders because it relates to the lived experience of customers

However, data-driven only evaluates an overall change in resilience
(e.g. x mph wind hardening, 10% faster restoration)
Need modeling to find and optimize detailed engineering
to realize the overall changes

Conclusion: Key ideas and opportunities for data-driven resilience

- Transmission utilities and many distribution utilities already collect the necessary detailed outage data. The data processing is tractable and practical.
- Data-driven resilience quantification is driven by extracting events of all sizes
- Analyze events with outage and restore processes, performance curves and their corresponding metrics. Event processes not phases!
- For transmission systems, duration metrics are variable, so use 95% restoration or median/geometric mean of restoration time
- System-level and statistical analyses complement and support detailed engineering analysis of each event.
- New Poisson process models of outage and restore processes driven by data are promising typical models for transmission systems resilience. Nice simple formulas for area under performance curves.
- Quantify and communicate effect of investments: Can "rerun history" to get the change in resilience metrics when the overall effect of investments reduces or changes the outages. Promising, much simpler than model-based alternatives.
- Resilience analysis can engage with events, processes, transients, extremes, and heavy tails at systems level… complements traditional reliability which focusses on steady state of individual components averaged over the year, models with exponential tails, and excluding extreme events.

Any further questions?: email dobson@iastate.edu

REFERENCES

DISTRIBUTION SYSTEMS

- A. Ahmad, I. Dobson, Towards using utility data to quantify how investments would have increased the wind resilience of distribution systems, preprint arXiv:2306.06526 https://arxiv.org/abs/2306.06526
- N.K. Carrington, I. Dobson, Z. Wang, Extracting resilience metrics from distribution utility data using outage and restore process statistics, IEEE Trans. Power Systems, Nov. 2021.

TRANSMISSION SYSTEMS

- S. Ekisheva, I. Dobson, R. Rieder, J. Norris, Assessing transmission resilience during extreme weather with outage and restore processes, PMAPS, 2022
- I. Dobson, S. Ekisheva, How long is a resilience event in a transmission system?: Metrics and models driven by utility data, to appear in IEEE Trans. Power Systems
- I. Dobson, Models, metrics, and their formulas for typical electric power system resilience events, to appear in IEEE Trans. Power Systems