Non-Stationary Stochastic Modeling and Learning for Large-Scale Failure and Recovery of Power Distribution Networks

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Disruption of Power Distribution

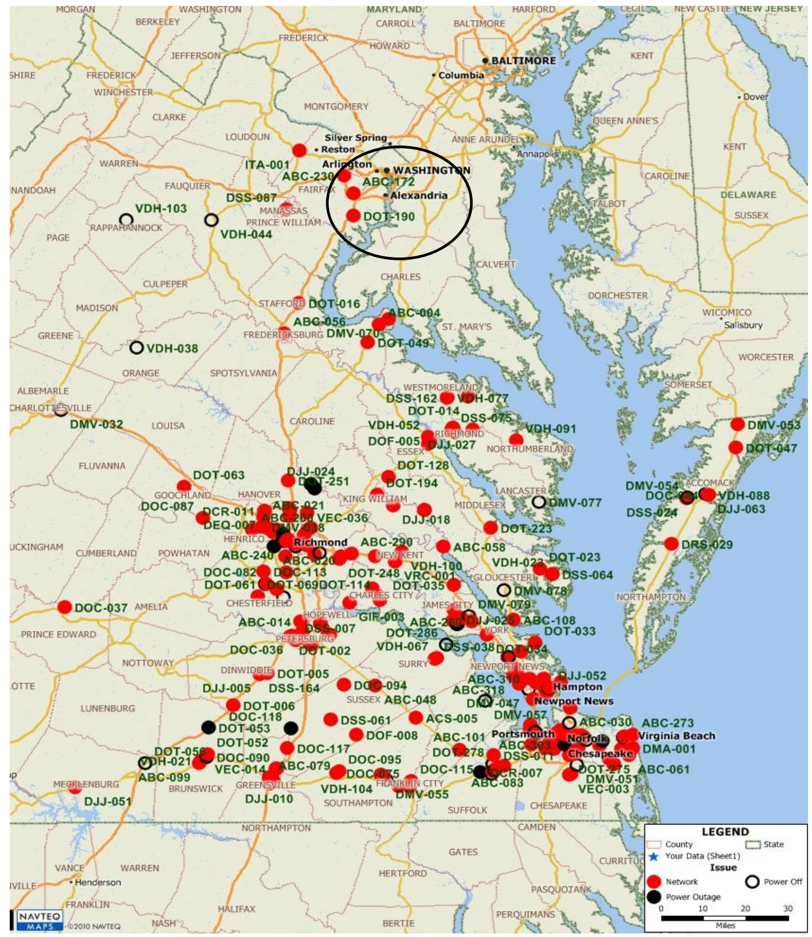
- Hurricane Irene 2011:

  South to East Coast

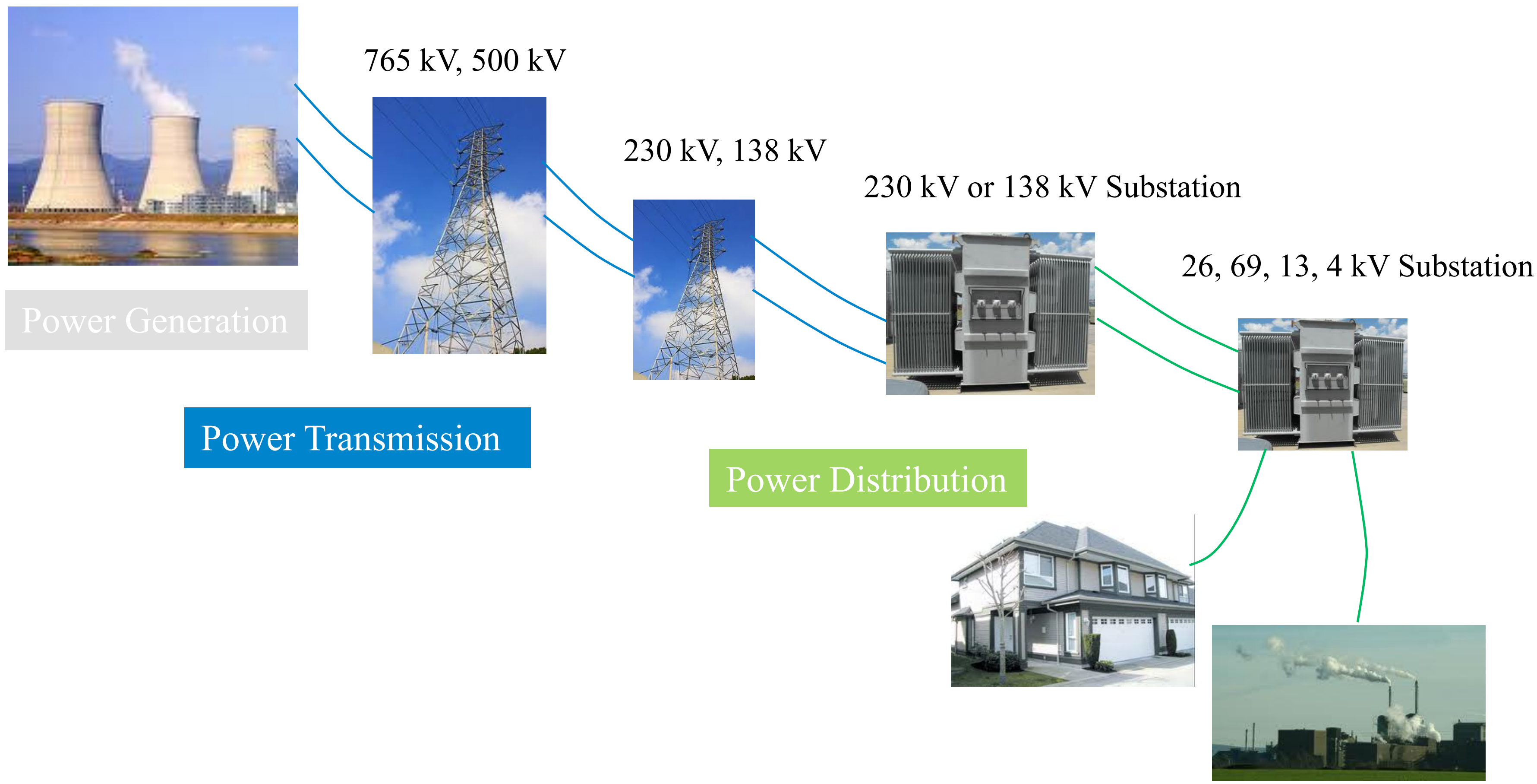
  4 million customers affected

- >10 major hurricanes, snow/ice storms in America, 2005-2011

Outages at DC/Virginia (Google)



Vulnerable Last Mile: Power Distribution Networks



Last Mile: Substations to end-users

Prior Work

- Focus:
  - Transmission networks, cascading blackout:
    - Bienstock (11), Dobson (04), Hines et.al. (09), Illic et. al. (05)…
  - Distribution networks: Zhu (05)
- Approaches:
  - Stationary failure/recovery probability, resilience
  - Liew (94), Smith (11), Zhu (05)
- Needs: Distribution network
  - Challenges: Randomness, dynamics, external disturbance.

Basic Question

How resilient are power distribution networks to large-scale external disturbances?

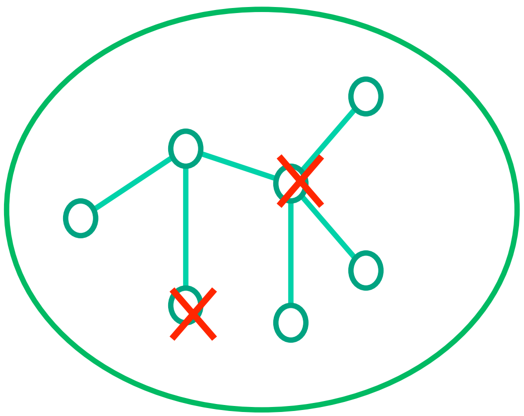
- Modeling: Non-stationary large-scale outages?

- Learning: Real data to concept (resilience)?

Challenge: How to learn from “one” disturbance ?

Our Approach: Modeling + Learning

Modeling:



Failure process

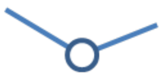
Recovery process

Resilience metric

Learning:

Real data → Empirical process → Resilience

Formulation: Spatial Temporal Process



$X_i(t) = 0$

$X_i(t) = 1$

i: space, t: time

0: Normal, 1: Failure

Assume Markov state transition in time: At t+dt

Failure: $X_i(t+dt)=1, X_i(t)=0$

Recovery: $X_i(t+dt)=0, X_i(t)=1$

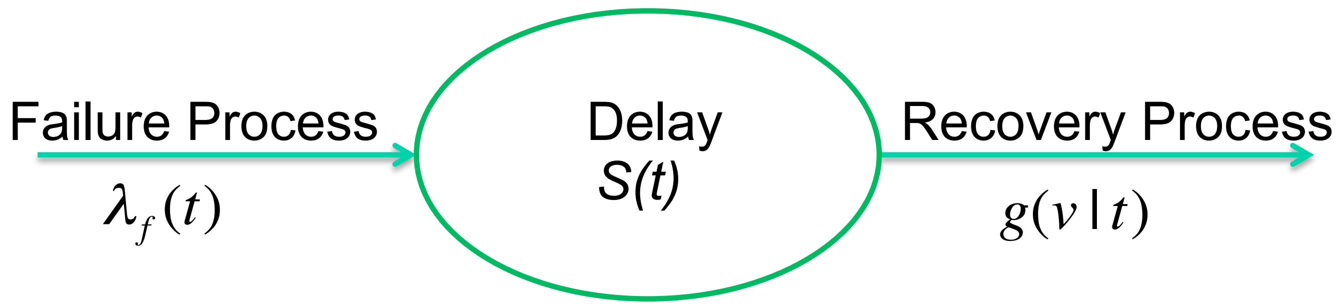
In failure: $P(X_i(t+dt)=1, X_i(t)=0)$

$- P(X_i(t+dt)=0, X_i(t)=1)$

n equations for a network of *n* nodes

Temporal Process: Model

- Aggregation over nodes:



$\lambda_f(t)$: Failure rate, determined by external disturbance, network

g(v|t): Recovery time distribution, determined by resource, environment, network

$GI(t)/G(t)/\infty$ queue: ∞ --- Recovery can start post failure

t: Non-stationary

Resilience Metric

- Probability of (delayed) recovery: *P(S < t)*

$$P(S<t)=C\int_{0}^{t} g(t-u\,|\,u)\lambda_f(u)\,du$$

"Weighted sum": Distribution of recovery time, of failure time

Learning

Given data set *D={failure time, recovery-time}*, learn

- failure rate $\lambda_f(t)$,
- Probability density function of recovery time *g(v|t)*,
- Resilience *P(S<t)*.

From Real to Virtual Data

Real

- A strong hurricane
- Affected large areas
- Affected millions of customers

Virtual (Anonymized)

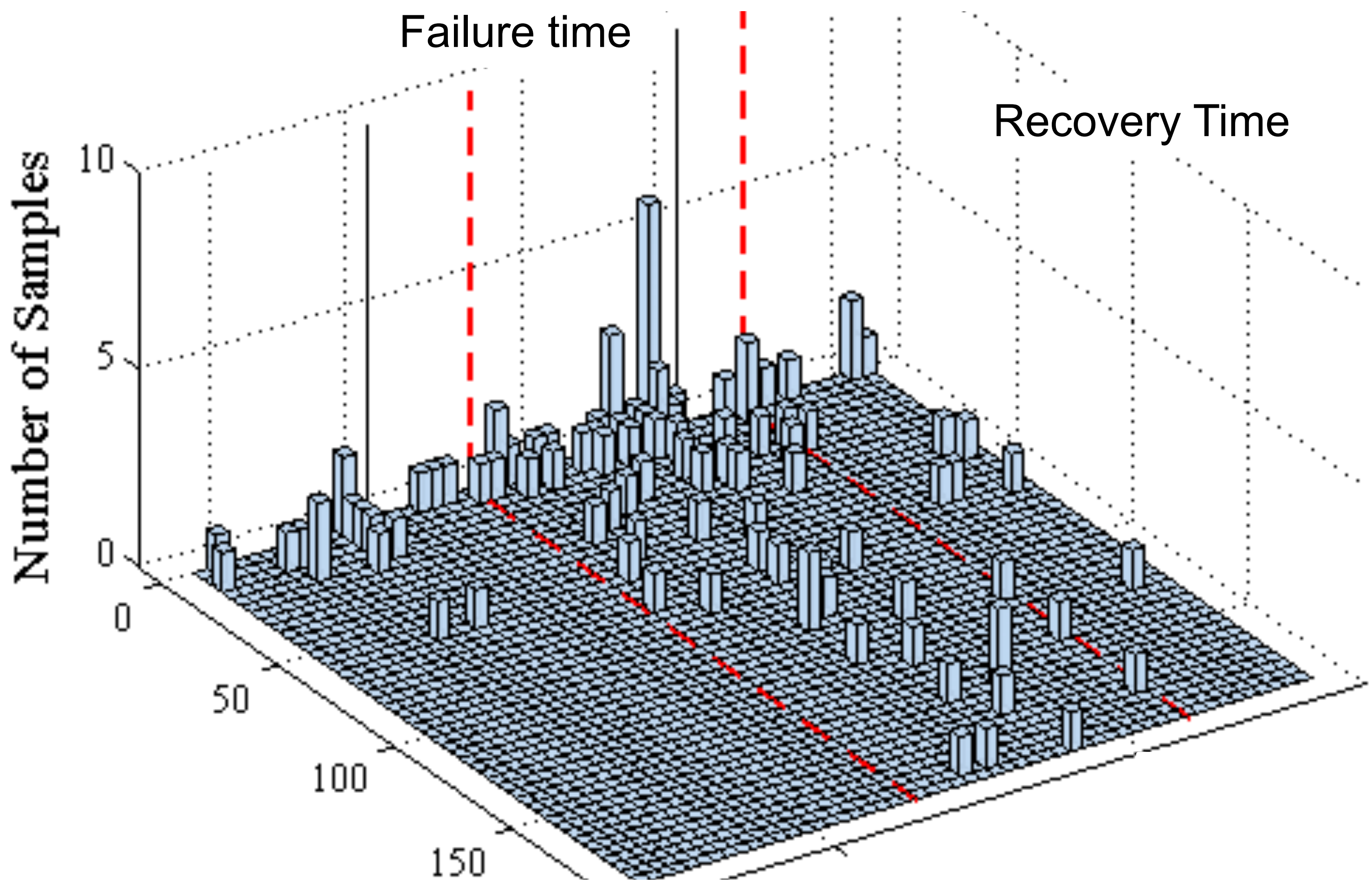
- Location/Time of the hurricane
- "Power outage":

  Loss of communication connectivity
- 106 samples (outages)
- Sample = {failure time, duration}

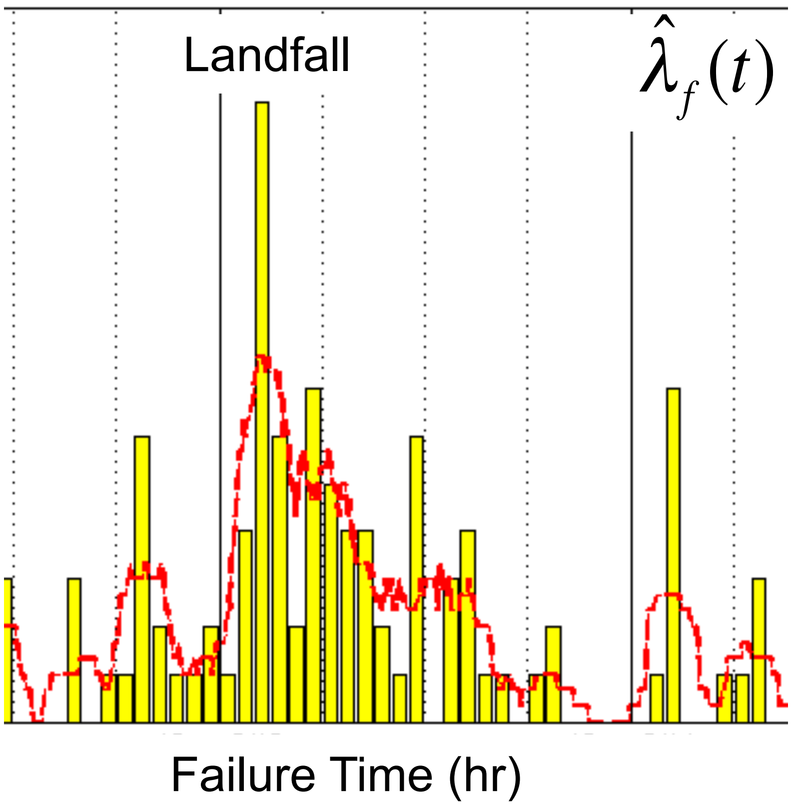
Authentic: Pertinent properties of the data after aggregation

(Erjongmanee and Ji, IEEE Trans. Network and System Management, 2011)

Histogram: Non-Stationary Failure/Recovery



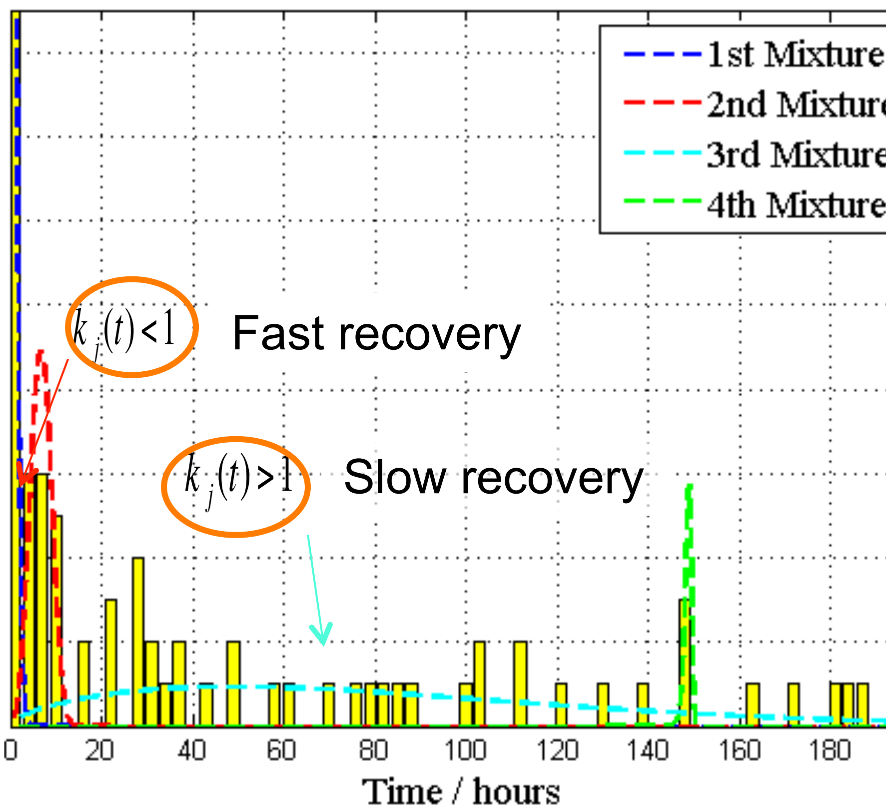
Learned Failure Process



- Non-stationary failure rate
- Independent new failures
- Non-Homogeneous Poisson

$$P(N_f(t)=k)=e^{-\int_0^t \lambda_f(u)du}\frac{\{\int_0^t \lambda_f(u)du\}^k}{k!}, k=0,1,\ldots$$

Learned Recovery Time Distribution



- Mixture model (Weibull):

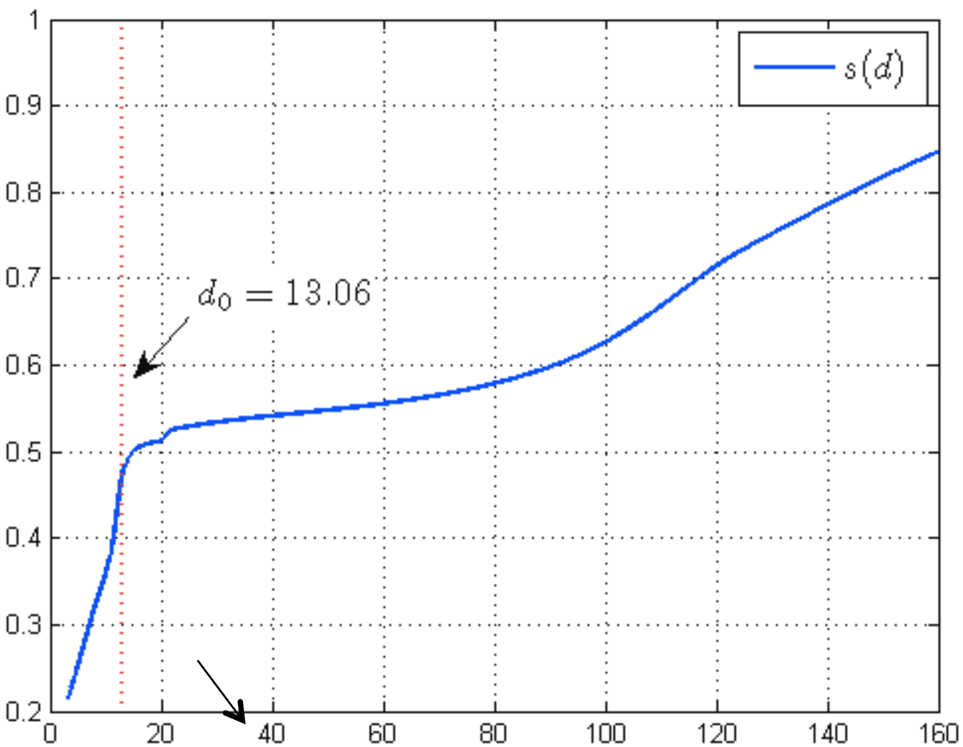
$$g(v \mid t) = \sum_{j=1}^{L(t)} \rho_j(t) g_j(v \mid t)$$

$$g_j(v \mid t; k_j(t), \gamma_j(t))$$

- Non-stationary: Coefficients vary with time

Resilience Metric

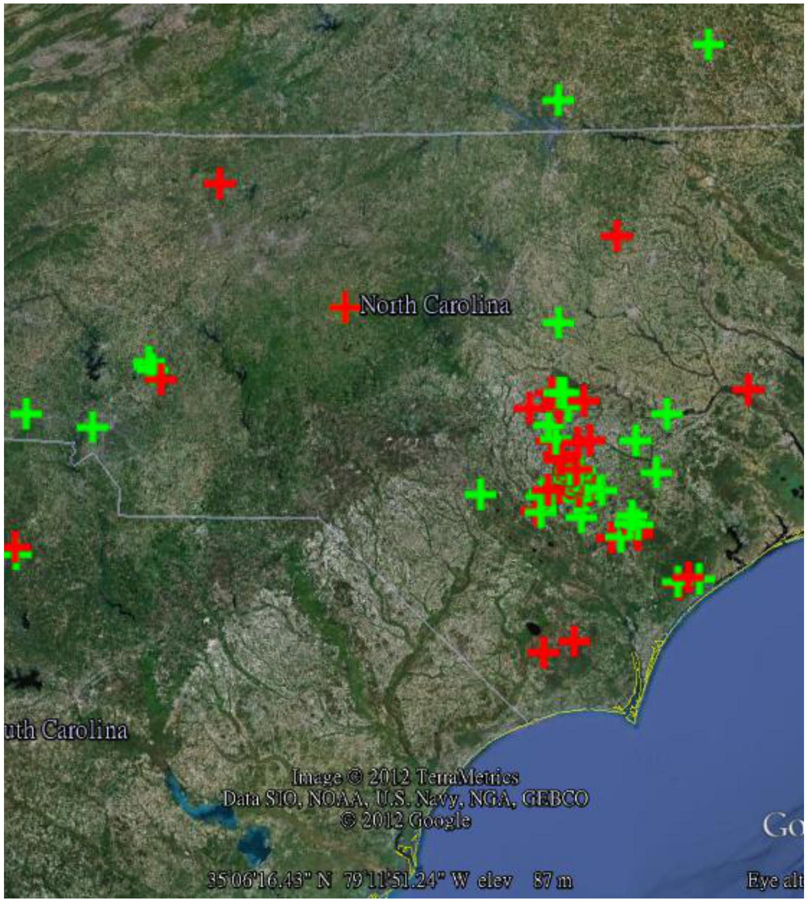
$$P(S < t)$$



Fast recovery (<13hrs): 47%

Slow recovery: 53%

"Locations of Outages"



Google Map

Summary

- Model: Non-stationary random processes
- Resilience metric: Probability of fast recovery
- Learning: from one external disturbance to network resilience.

- Practicality: Usable to utility providers for their serviced networks

Why Use “Virtual” Outage Data?

- Real data: Inspiration and insights. A lot is collected.
- Outages: Not faults of utility providers’
- Security/privacy: Enable, not hinder, learning from data

Reference

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