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Quantifying Interdependent Infrastructure Network Resilience

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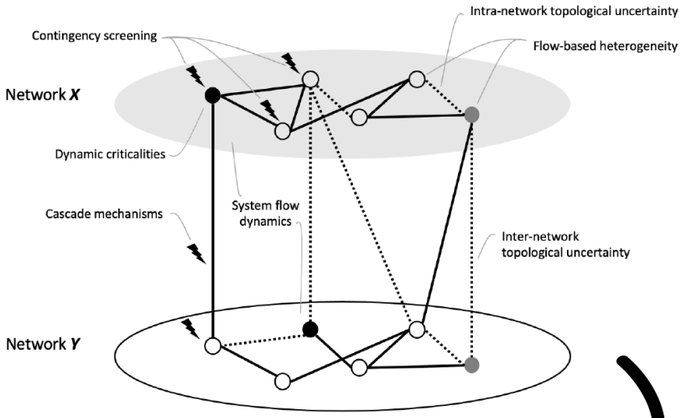
FY22 Progress Outline

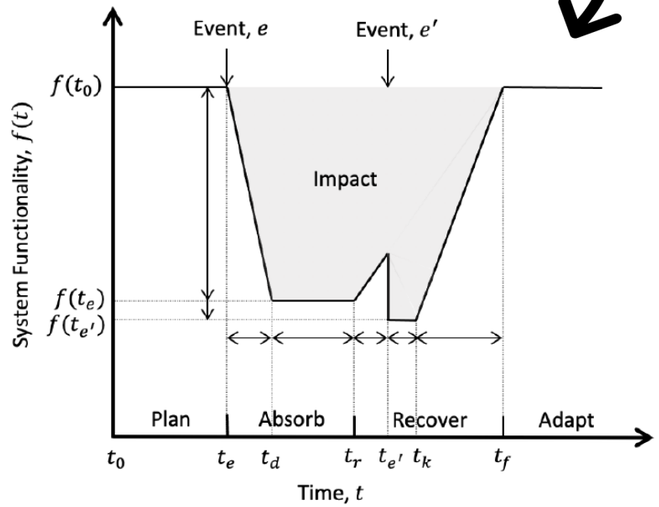
- Analytical Resilience Framing
- Urban Rail Transit Network Resilience
- Sampling Strategies for Hybrid Attack Graphs
- Disruption-Robust Community Detection
- Resilient Communication-Based Control

Analytical Resilience Framing

- Cyber-physical data-driven systems (CPDDS), such critical infrastructures, are best represented as network-of-networks
- Network-of-networks highlight challenges associated with complexity, uncertainty, heterogeneity, dynamics, safety, and reliability
- System decomposition followed by modeling, learning, and simulation can generate complex scenarios in high consequence settings
- Assuring interconnected networked CPDDS requires resilience framing with system functionality over time based on the phases of *plan*, *absorb*, *recover*, and *adapt* defined by the U.S. National Academy of Sciences



Network-of-Networks Construct for CPDDS



CPDDS Resilience Framing Illustration

NRL–PNNL–NU Team

S. Chikkagoudar, S. Chatterjee, R. Bharadwaj, A. Ganguly, S. Kompella, and D. Thorsen. (2022) “Assurance by design for cyber physical data-driven systems.” In *Internet of Things for Defense and National Security*–forthcoming, Wiley/IEEE, 1-46.

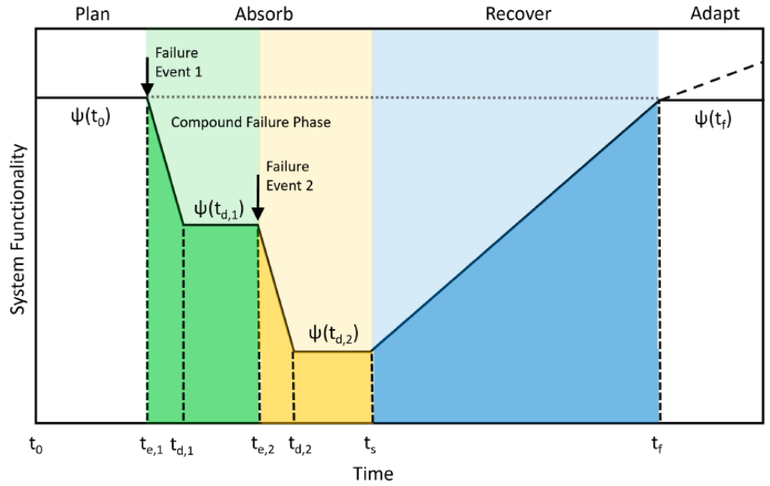
Urban Rail Transit Network Resilience

- **Resilience** quantified as ratio of area under the resilience curve and area under normal functionality

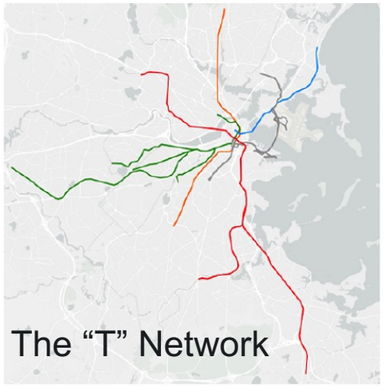
$$R(G|E, C_\rho) = \frac{\sum_{t \in \{t_{e,1}, \ldots, t_f\}} \psi(t)}{\psi(t_0)(t_f - t_{e,1})}$$

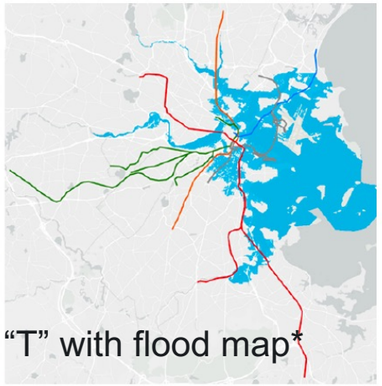
where, $0 \leq R \leq 1$.

R is resilience measure; G is a graph; E is disruption event set; C_ρ is recovery strategy; t is time; and $\psi(t)$ is system functionality at t.



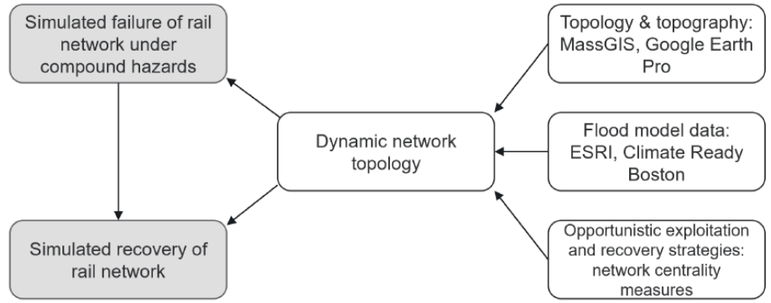
System Resilience Phases





Proof-of-Concept
Case Study Region: MA Bay Transportation Authority Rapid Transit & Light Rail System (The “T”) in Boston

* 1-in-100 year flood with baseline 36” mean sea level rise



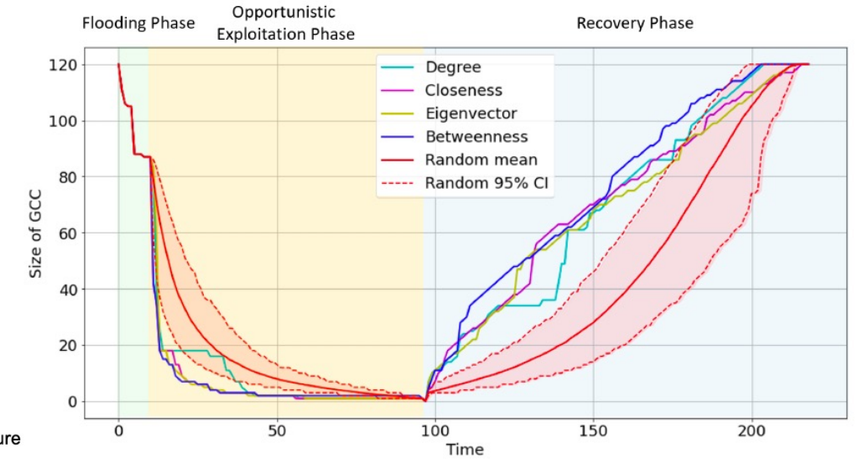
Methodological Workflow

PNNL–NU Team

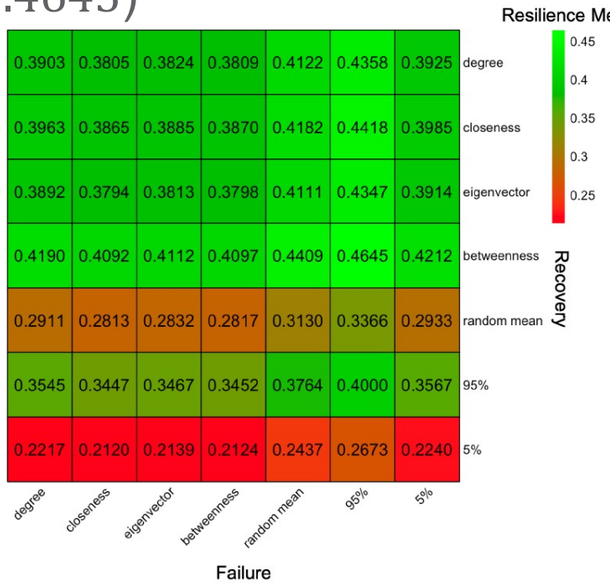
Watson, J., S. Chatterjee, and A. Ganguly. (2022) “Resilience of urban rail transit networks under compound natural and opportunistic failures.” In Proceedings of *IEEE Homeland Security Technologies (HST) International Symposium*, Virtual Symposium.

Network Simulation Results

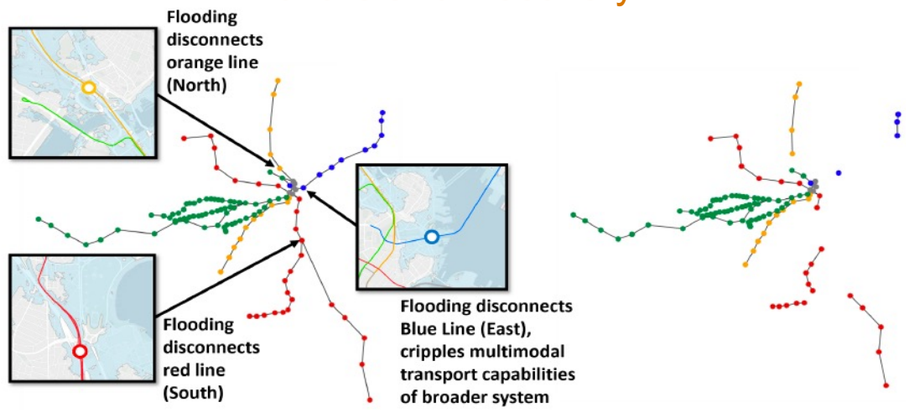
- Developed compound failure and recovery algorithms
- Simulated resilience curves were generated for compound failure (flood followed by opportunistic network centrality-based measures) and recovery
- **Best strategy**: Failure based on flood followed by 95% upper bound of random, and Recovery based on betweenness centrality ($R = 0.4645$)
- **Worst strategy**: Failure based on flood followed by closeness centrality, and Recovery based on 5% lower bound of random ($R = 0.2120$)
- Results can inform what-if scenario analyses and generate insights for stakeholder decisions



Simulated Resilience Curves with Compound (Flood followed by Opportunistic) Failure and Recovery



Resilience Measures for Compound Failure and Recovery Strategies

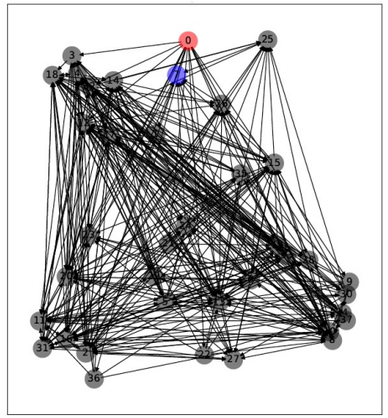


Network Fragmentation due to Flood-Based Functionality Loss

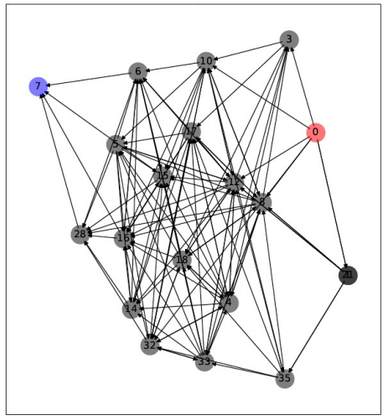
Sampling Strategies for Hybrid Attack Graphs

- Hybrid Attack Graphs (HAGs) can represent attack sequences in a cyber-physical system with discrete and continuous elements
- Analysis and testing of large-scale HAGs is costly
- Efficient graph sampling can generate reduced size ensembles while preserving key properties for rapid analysis and testing

Original

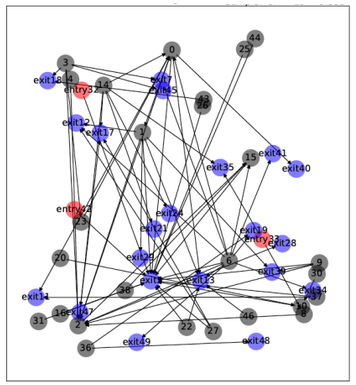


Sample



Real-world cyber-physical energy system hybrid attack graph: 47% node and 68% edge reduction while preserving coverage

Original



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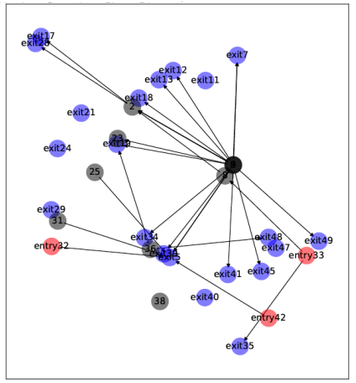


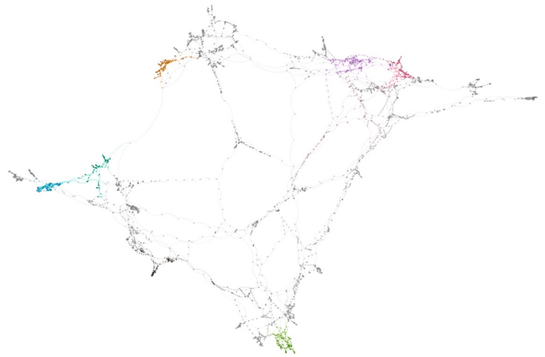
Scale-free vulnerability-oriented attack graph: 32% node and 58% edge reduction with same number of target vulnerability types

PNNL Team

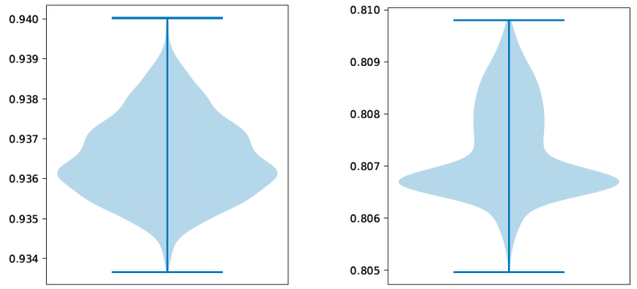
Subasi, O., S. Purohit, A. Bhattacharya, and S. Chatterjee. (2022) “Impact-driven sampling strategies for hybrid attack graphs.” In Proceedings of *IEEE HST International Symposium*, Virtual Symposium.

Disruption-Robust Community Detection

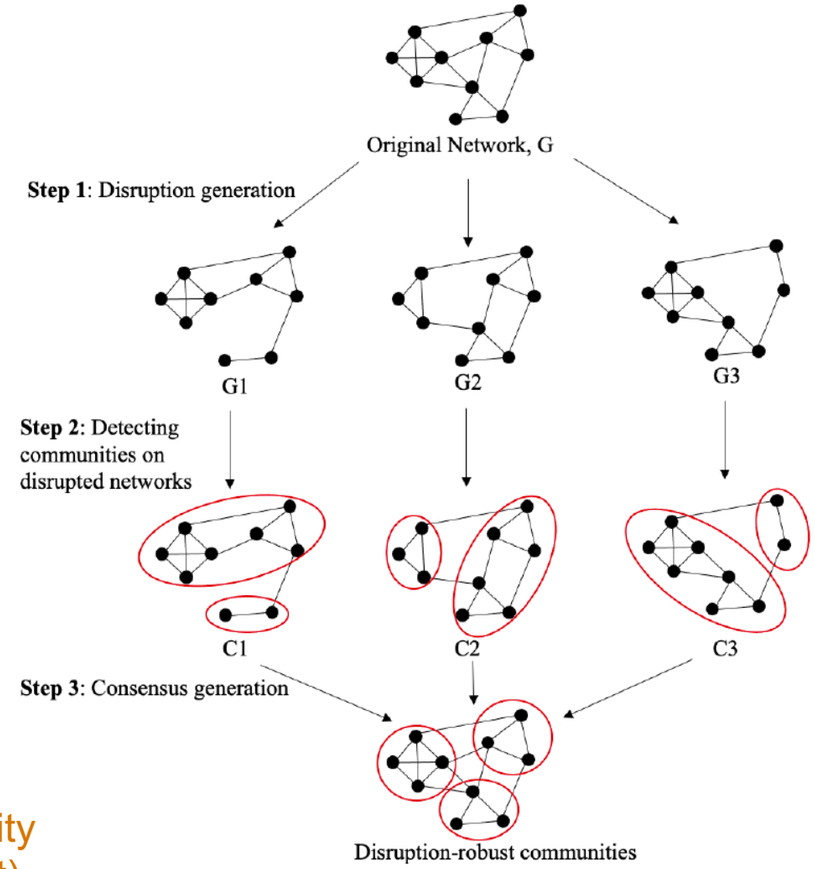
- Infrastructure networks exhibit community structures that are key for understanding failure and recovery mechanisms
- Disruption-robust communities can sustain disruptions
- Detected communities based on modularity using Louvain's method; identified consensus communities via consensus clustering; applied to U.S. power grid network data
- Clustering modularity scores lower for consensus communities



U.S. Power Grid Network



Distributions of Clustering Modularity Scores of Disrupted Networks (left) and Consensus Communities (right)



Steps for Detecting Disruption-Robust Communities

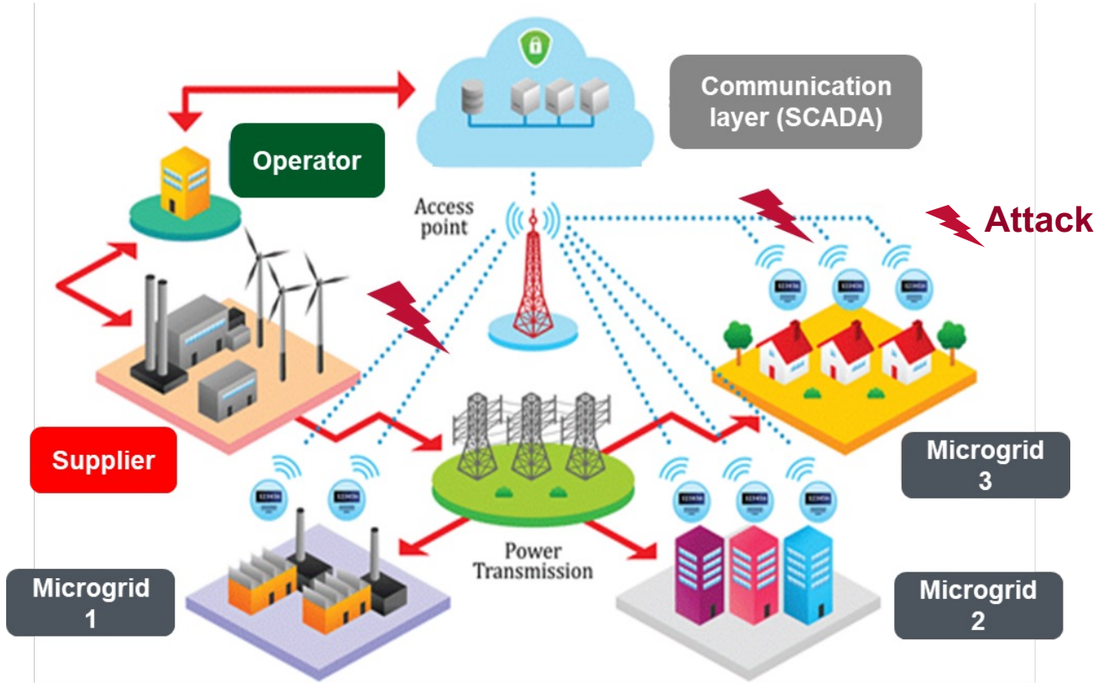
PNNL–Indiana University Team

Hussain, M.T., A. Khan, A. Azad, S. Chatterjee, R. Brigantic, and M. Halappanavar. (2022) "Disruption-robust community detection using consensus clustering in complex networks." In Proceedings of *IEEE HST International Symposium*, Virtual Symposium.

Resilient Communication-Based Control

Real-time detection and localization of stealthy data-injection attacks on communication layer of interconnected power networks subject to domain-aware dynamics, constraints, and operations

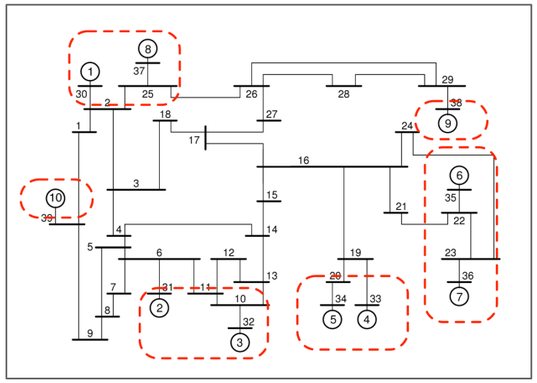
- Stealthy data-injection attacks may bypass false-data estimation algorithms (in cyber layer) when adversary has access to grid-operational data
- Spatial correlations imposed by physical, domain-aware relationships is critical in detecting and localizing attacks
  - E.g., power-flow equations and line-flow constraints limit amount of energy-flow between neighboring microgrids – can be used to detect irregularities in sensor data in communication layer
- **Approach:** Use graph neural networks to characterize temporal and spatial correlations in power-systems data
  - Measurements: real and complex power data from each node (phasor measurements) sent via communication layer
  - Graph neural-embeddings in conjunction with graph filters used to characterize the spatio-temporal correlations
  - Graph neural network solves a multi-label classification problem to estimate probability of attack at each physical node of network



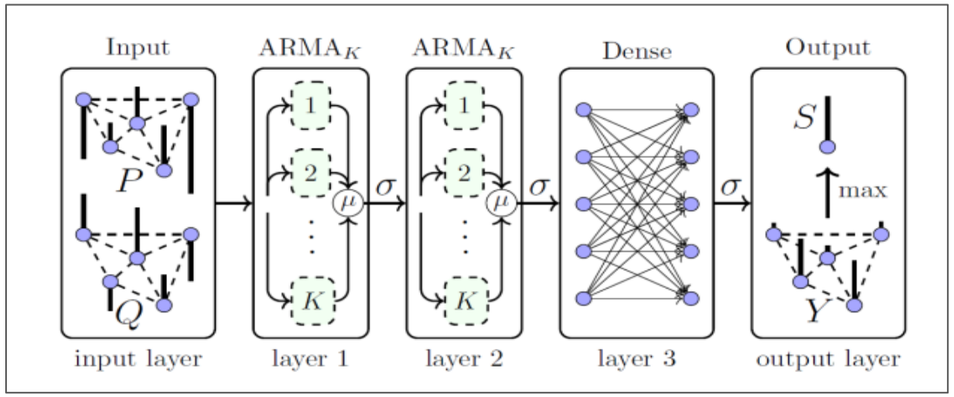
Phasor measurements from each node of a power network is transmitted using a communication layer to central SCADA to generate operational set-points. These measurements can be falsified by a stealthy adversary to affect operations in a network.

Methodology and Ongoing Work

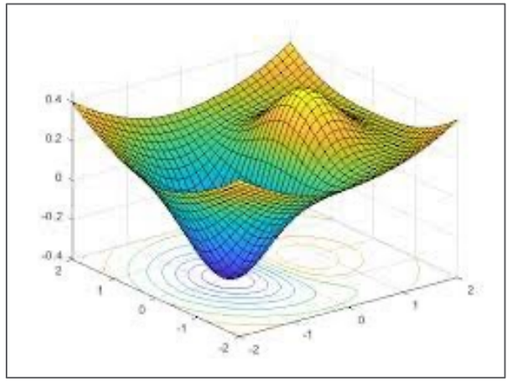
Power Network Data



Graph Neural Network (GNN) Architecture for Detection and Localization



Resilient Network Defense Optimization



- **Current test network**
  - IEEE 39-bus: simulation via GridLAB-D
- **Proposed GNN architecture**
  - Input layer: active and complex bus-power injections
  - Graph-filter layers: extract spatial features
  - Dense-layer: probability of attack at each node
  - Output: probability of attack at graph level

- **Next Steps**
  - GNN model training for different adversarial datasets in IEEE 39-bus system (ongoing)
  - Extend to larger IEEE systems to test generalizability of approach
  - Integration with a defense optimization framework for resilient operations

PNNL–NU Team

Bhattacharya, A., S. Chatterjee, M. Halappanavar, and A. Ganguly. (2023) Work-in-progress for *IEEE Transactions on Control System Technology Journal: Special Issue on Resilient Control of Cyber-Physical Power and Energy Systems*

FY23 Next Steps

- Defense optimization for resilient network operations
- Incorporate network topology and dynamics for quantifying resilience
- Topological data analysis for network resilience

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