Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260326
Published: June 9, 2026

Power Grid Robustness and Infrastructure Resilience Under Extreme Storm Threats Using Network Science

Shane Menezes
School of Systems Science and Industrial Engineering
Binghamton University (BU)
Binghamton, NY, USA
smenezes@binghamton.edu

Sadamori Kojaku
Assistant Professor
School of Systems Science and Industrial Engineering
Binghamton University (BU)
Binghamton, NY, USA
skojaku@binghamton.edu

Abstract

Power grid infrastructure is increasingly vulnerable to aging assets, growing electricity demand, climate-related extreme weather events, and interconnected infrastructure dependencies. This study applies network science methods to evaluate the robustness and resilience of the power grid infrastructure serving the five boroughs of the New York City metropolitan region under extreme storm threats, including Hurricane Sandy. Network analytical models were developed to assess connectivity, centrality, and robustness behavior of critical transmission substations and distribution infrastructure under simulated node failure conditions. The analysis compares steady-state network performance against storm-induced infrastructure disruptions based on nodes impacted during Hurricane Sandy in October 2012. Robustness and connectivity measures were evaluated under multiple attack strategies, including degree, closeness, betweenness, and random node removal simulations. The study further evaluates resilience-oriented infrastructure enhancements through the introduction of distributed energy resources, including renewable energy nodes, energy storage systems, and combined heat and power (CHP) assets. Results demonstrate that the power grid exhibits strong dependence on critical transmission and substation infrastructure, where limited node failures can significantly reduce network connectivity and increase cascading vulnerability. The inclusion of distributed and independent energy assets improved robustness measures and reduced network degradation under simulated storm disruptions. The study also highlights interdependencies between the electric grid and supporting infrastructure systems, including gas pipelines, transportation tunnels, hospitals, and commercial districts.

Keywords
Power Grid, Network Science, Robustness, Resilience, Extreme Storms.

1. Introduction
Extreme weather events pose significant risks to electric power grid infrastructure, particularly in densely populated urban regions with aging transmission and distribution systems. Climate change, rising electricity demand, and increasing infrastructure interdependencies have intensified concerns regarding power grid vulnerability, restoration performance, and cascading failures during severe storm events (Popovich and Plumer 2023). Hurricane Irene in 2011 and Hurricane Sandy in 2012 both caused major disruptions across the northeastern United States, resulting in

widespread flooding, infrastructure damage, and large-scale customer outages. However, Hurricane Sandy produced substantially greater infrastructure impacts, longer restoration durations, and more severe flooding conditions across the New York City metropolitan region (Department of Energy 2013). Table 1 compares the impacts of Hurricane Irene and Hurricane Sandy on regional energy infrastructure systems.

Table1: Comparison of impacts from Hurricane Irene and Hurricane Sandy

	Irene	Sandy
Landfall Date	August 27, 2011	October 29, 2012
Strength at First U.S. Landfall	Category 1 Hurricane	Post-Tropical Cyclone
Landfall Location (sustained winds)	8/27 – Cape Lookout, NC (90 mph) 8/28 – Little Egg Inlet, NJ (80 mph) 8/28 – Coney Island, NY (75 mph)	10/29 – Atlantic City, NJ (80 mph)
Distance of Tropical Storm-Force Winds from Center	300 miles	500 miles
Peak Flooding	New York City* – 9.5 feet Philadelphia – 9.9 feet	New York City* – 14.1 feet Philadelphia – 10.6 feet
Property Damage	$10 billion	Est. $20+ billion
Deaths	45	131

*The Battery
Sources: NOAA, EQUECAT, Property Claim Services, press

Hurricane Sandy caused extensive damage to electric, gas, steam, and transportation infrastructure throughout New York City and surrounding regions. More than 800,000 customers in New York experienced power outages, with restoration efforts extending from several days to multiple weeks depending on infrastructure accessibility and damage severity (A Stronger, More Resilient New York n.d.). Table 2 summarizes the causes of electric system outages and customer impacts resulting from Hurricane Sandy in the New York City metropolitan area, while Table 3 presents restoration milestones for electric, gas, and steam infrastructure systems. Traditional power system reliability assessments primarily focus on operational redundancy and restoration metrics; however, network science methods provide additional insight into structural vulnerability, node importance, connectivity degradation, and cascading infrastructure behavior during extreme disruptions. Prior studies have demonstrated the use of robustness analysis and network-based approaches for evaluating complex infrastructure systems and renewable-integrated power grids (Hu et al. 2021; Macmillan et al. 2022). Understanding how critical substations, transmission infrastructure, and interconnected systems respond to storm-induced failures is important for improving long-term infrastructure planning and grid hardening strategies.

Table 2: Causes of electric system outages and customer impacts
due to Hurricane Sandy in the New York City metropolitan area

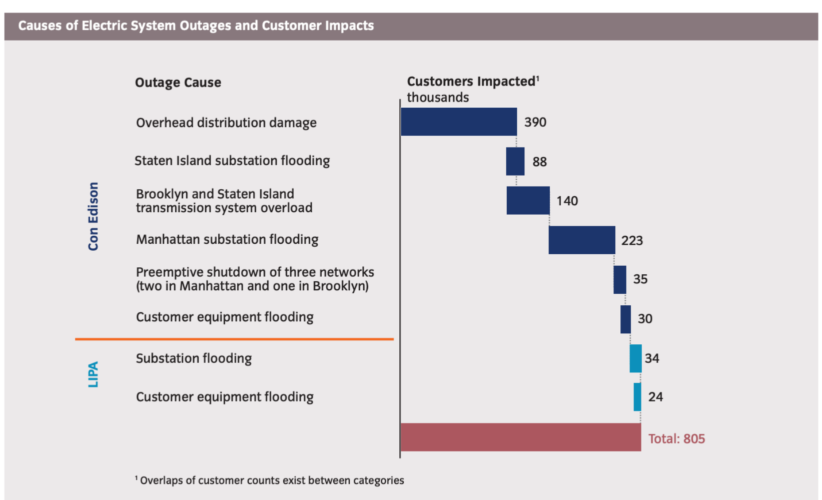
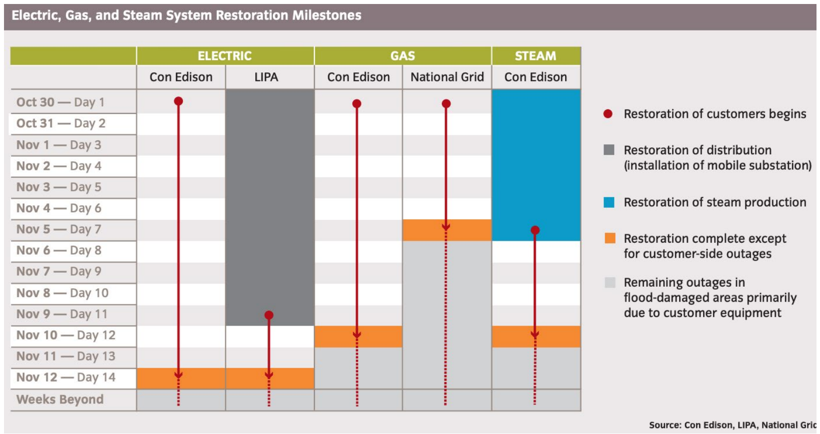


Table 3: Electric, gas, and steam system restoration milestones following Hurricane Sandy



This study applies network science methods to evaluate robustness and connectivity behavior of the New York City metropolitan power grid under simulated storm-related node failures based on Hurricane Sandy impacts. The study further examines how distributed energy resources, renewable generation, energy storage, and combined heat and power (CHP) assets influence overall grid robustness and resilience. In addition, the interdependence between the electric grid and supporting infrastructure systems, including gas pipelines, transportation tunnels, hospitals, and commercial districts, is evaluated. Figure 1 presents the Con Edison electric power delivery system overview used to support the network representation in this study (Con Edison 2013).

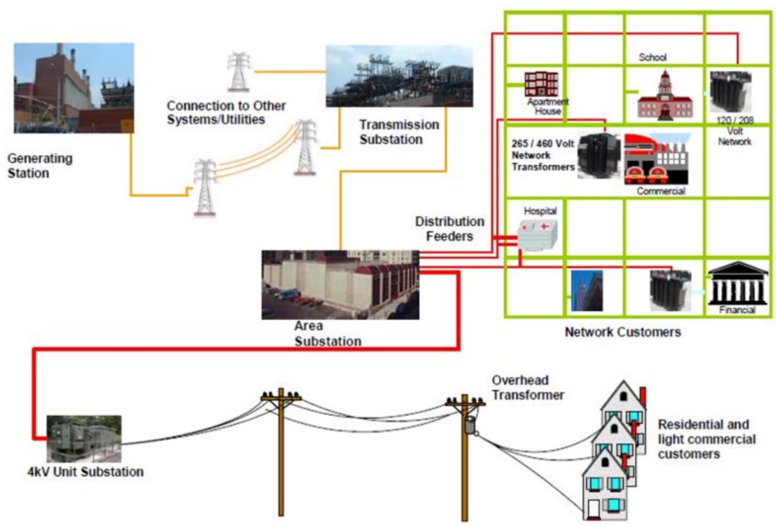


Figure 1: Con Edison electric power delivery system overview

1.1 Objectives

The objectives of this study are to model the New York City metropolitan power grid using network science methods and evaluate robustness and connectivity behavior under simulated storm-induced node failures based on Hurricane Sandy impacts. The study further analyzes the influence of critical transmission and substation nodes using centrality and connectivity measures while assessing the impact of distributed energy resources, energy storage, and combined heat and power (CHP) infrastructure on overall grid robustness and resilience. In addition, the study examines infrastructure interdependencies between the electric grid and supporting systems such as gas pipelines, transportation networks, hospitals, and commercial districts.

2. Literature Review

Hurricane Sandy caused extensive damage to electric power infrastructure across the New York City metropolitan region due to storm surge, flooding, and substation failures. In the Rockaways, flooding disabled multiple Long Island Power Authority (LIPA) substations, resulting in widespread power outages throughout the peninsula. In Manhattan, storm surge overtopped protective barriers at Con Edison's East 13th Street complex, flooding transmission substations and damaging critical electrical control equipment. Flooding also impacted substations in Staten Island and Lower Manhattan, contributing to large-scale outages affecting approximately 370,000 electric customers across New York City (A Stronger, More Resilient New York n.d.).

The United States electric grid consists of three major interconnections serving the eastern, western, and Texas regions with limited interregional power sharing capability. Existing transmission infrastructure was primarily designed around conventional fossil-fuel-based generation systems and presents challenges for large-scale renewable energy integration and long-distance power transfer requirements associated with clean energy transitions (Popovich and Plumer 2023). Expanding transmission infrastructure and improving grid flexibility are increasingly important for supporting renewable energy deployment, infrastructure reliability, and climate adaptation planning.

Recent studies have examined power system resilience and robustness under extreme weather conditions and renewable energy integration scenarios. Macmillan et al. (2022) explored acute weather resilience and renewable energy planning objectives within modern energy systems, noting that resilient systems must maintain acceptable service levels and operational continuity during disturbances. Hu et al. (2021) evaluated robustness behavior of renewable-integrated power grids using network science methods under earthquake and heavy snow scenarios. Their study applied electrical degree centrality, electrical betweenness centrality, and clustering coefficient metrics to identify vulnerable power grid nodes and assess network degradation behavior under infrastructure disruptions.

Network science methods provide a useful framework for evaluating structural vulnerability, node importance, and connectivity degradation within complex infrastructure systems. However, comparatively fewer studies have examined robustness and resilience behavior of urban electric grid infrastructure under hurricane-induced disruptions while incorporating interdependent infrastructure systems and distributed energy resource enhancements within the network representation.

3. Methods

The methodology used to study the effects of storm threats to the power grid and measure interdependence and community structures, the below Figure 2, shows the process flow to study and measure robustness and connectivity on the power grid. A similar robustness and connectivity study was conducted to interpret findings when new nodes are added to the power grid model such as Wind, solar generation farms, tunnels that depict the flow of traffic that rely on the power grid, gas pipelines network that runs in parallel and addition of energy storage and CHP (Combined heat and Power) that work independently of the transmission and area substations.

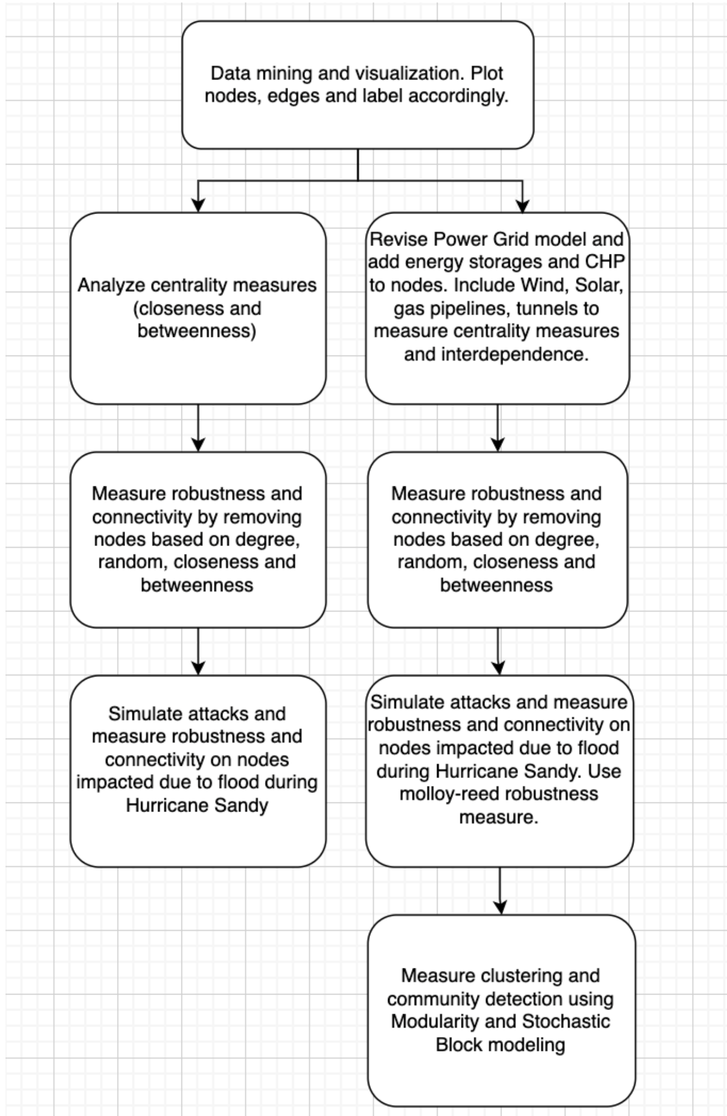


Figure 2: Methodology framework for robustness and connectivity analysis of the power grid

Molloy-reed criterion:

$$\kappa \equiv \frac{\langle k^2 \rangle}{\langle k \rangle} > 2$$

Using this criterion and an involved mathematical proof, one can derive a critical threshold for the fraction of nodes needed to be removed for the breakdown of the giant component of a complex network.

$$f_c = 1 - \frac{1}{\frac{\langle k^2 \rangle}{\langle k \rangle} - 1}$$

In addition, clustering and community detection was used for determining when an attack was to occur, which key clusters would contain the nodes and would there be a cascading failure in that cluster. The modularity and stochastic block modeling techniques were used.

Modularity is a measure of the structure of networks or graphs which measures the strength of division of a network into modules (also called groups, clusters or communities). Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules (*Modularity (Networks)* 2024).

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

The stochastic block model is a generative model for random graphs. This model tends to produce graphs containing *communities*, subsets of nodes characterized by being connected with one another with edge densities (*Stochastic Block Model* 2024), (Lee and Wilkinson 2019).

$$\pi\left(\mathbf{Y}|\mathbf{Z},\mathbf{C}\right) = \prod_{p<q}^{n} \pi(\mathbf{Y}_{pq}|\mathbf{Z},\mathbf{C})$$

4. Data Collection

The data mining required collecting nodes such as in city generation plants, transmission, area substation and Customer zones of the five boroughs, from ConEdison and Wiki sources. Data mining also included setting up edges that linked nodes to boroughs. Closeness and betweenness centrality measures were taken to measure which nodes were closely linked and were more influential other among other nodes. Robustness and connectivity measures were collected by performing simulated attacks or node removal of 10 nodes based on randomness, high degree, high closeness and high betweenness. Similar measures for robustness and connectivity were collected by simulating hurricane Sandy by removal of nodes that were impacted, and graph visualization plots was run. The next phase required looking at improving the grid by adding additional nodes for tunnels, energy storage, CHP, gas pipeline and wind and solar farms. This would allow for robustness and connectivity measures to be captured and insights on network interdependence. The gas pipeline was added as one of the impacts seen during hurricane sandy was a disruption to the gas pipeline supply channel along the northeastern corridor. To measure robustness for scale free networks, Molloy-reed robustness criterion was used to determine if a giant component existed or a fragmented network. The Molloy–Reed criterion is derived from the basic principle that for a giant component to exist, on average each node in the network must have at least two links. This is analogous to each person holding two others' hands to form a chain (*Robustness of Complex Networks* n.d.). The node and edge tables were populated with key grid component data and labeled for further analysis. Information and location data for critical Con Edison power grid infrastructure were obtained from Con Edison system documentation and Public Service Commission substation records (Con Edison 2013; Public Service Commission n.d.).

5. Results and Discussion

5.1 Numerical Results

In Table 4, centrality scores for closeness and betweenness, we can see top scores for Midtown Manhattan due to presence of substations and transmission stations. This could suggest more businesses and residential customers are close in vicinity with high demand for power. This also shows how close and influential this business district and how influential it is to nearby nodes or boroughs.

Table 4: Centrality scores and network plot of the NYC metropolitan power grid substations

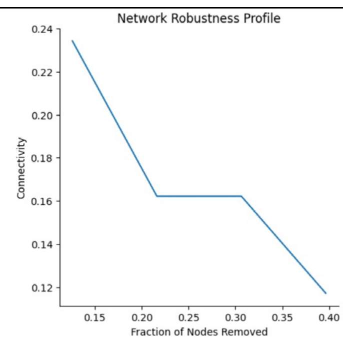
```
def top_k_closeness_centrality(g, top_k):
    closeness_list = tuple(zip(g.vs["Name"], g.closeness()))
    c_list = sorted(closeness_list, key=lambda x: x[1], reverse=True)
    d_list=c_list[:top_k]
    return(d_list)
top_k_closeness_centrality(g, 5)
```

```
[('ManhattanCust_Midtown', 0.28608923884514437),
 ('ManhattanCust_EastSide', 0.2678132678132678),
 ('ManhattanCust_Uptown', 0.2665036674816626),
 ('OBP Cogen', 0.2607655502392344),
 ('Hilton NY Co Gen Plant', 0.25829383886255924)]
```

```
def top_k_betweenness_centrality(g, top_k):
    betweenness_list = tuple(zip(g.vs["Name"], g.betweenness()))
    c_list = sorted(betweenness_list, key=lambda x: x[1], reverse=True)
    d_list=c_list[:top_k]
    return(d_list)
top_k_betweenness_centrality(g, 5)
```

```
[('ManhattanCust_Midtown', 1682.6452380952383),
 ('ManhattanCust_Uptown', 1506.9380952380955),
 ('ManhattanCust_EastSide', 1157.6999999999998),
 ('Queens Cust_NW', 907.7499999999999),
 ('BronxCust_West', 851.0285714285715)]
```

Table 5: Robustness and connectivity measure against attacks based on closeness, betweenness, degree and random



method	frac_nodes_removed	connectivity
Betweenness-based attacks	0.36036	0.216216
Closeness-based attacks	0.27027	0.225225
Degree-based attacks	0.18018	0.225225
Random	0.09009	0.225225

In Table 5, robustness and connectivity measures were captured to measure attacks on the power grid in the event of a storm or other threats. Top 10 nodes were removed, and measures were assessed based on closeness, betweenness, degree based and random attacks. The connectivity scores have greatly reduced for a fraction of nodes removed from the network.

Table 6: Robustness and connectivity measure against attacks based on closeness, betweenness, degree and random

method	frac_nodes_removed	connectivity
Flood_Sandy	0.072072	0.288288

Table 6 shows the robustness and connectivity measures that were captured to measure attacks on the power grid by removal of the same nodes that were impacted by Hurricane Sandy that caused 800,000 customers to be without power. The data below shows it took only 7% of nodes to be removed to drop the connectivity to 0.28

Table 7: Robustness and connectivity measure against attacks simulated on revised Power Grid model. Molloy-reed score was 3.93.

method	frac_nodes_removed	connectivity
Betweenness-based attacks	0.292857	0.635714
Closeness-based attacks	0.221429	0.714286
Degree-based attacks	0.150000	0.735714
Random	0.078571	0.921429

```
import networkx
A = gc.get_edgelist()
G = networkx.Graph(A) # In case you graph is undirected
#print(G)
avg_deg=sum(G.degree(node) for node in G.nodes())/len(G.nodes())
# average squared degree
avg_squared_deg=sum(G.degree(node)**2 for node in G.nodes()) / len(G.nodes())
k=avg_squared_deg/avg_deg
if k > 2:
    print("The network has a giant component, suggesting robustness. The molloy-reed criterion:",  k)
else:
    print("The network does not have a giant component. The molloy-reed criterion:", k)
```

```
The network has a giant component, suggesting robustness. The molloy-reed criterion: 3.9322916666666665
```

Table 7 shows that the revised power grid model achieved a robustness and connectivity measure of 0.75 after the inclusion of nodes operating independently of transmission and area substations, including energy storage and combined heat and power (CHP) systems. The results suggest that the addition of distributed infrastructure improved grid robustness under simulated random, degree-based, closeness-based, and betweenness-based attacks. The revised model also produced a Molloy-Reed score of 3.93, indicating the presence of a stable giant connected component within the network.

Table 8: Robustness and connectivity measure against attacks simulated on revised Power Grid model for nodes impacted during Hurricane Sandy.

```
def robustness_flood_sandy(g):
    exclude_nodes=[]
    exclude_nodes=[15,6,7,72,73,74,75,83,112,126,127,138]
    delete_nodes= [v for v in g.vs if v["node_id"] in exclude_nodes]
#    delete_nodes= [v for v in g.vs if v.index in exclude_nodes]
    g.delete_vertices(delete_nodes)
    components = g.connected_components()
    connectivity = np.max(components.sizes()) / g_original.vcount()
    frac_nodes_removed=1-g.vcount() / n_nodes
    return frac_nodes_removed,connectivity
pass
```

```
robustness_flood_sandy(gc)
```

```
(0.08571428571428574, 0.35714285714285715)
```

```
import networkx
A = gc.get_edgelist()
G = networkx.Graph(A) # In case you graph is undirected
avg_deg=sum(G.degree(node) for node in G.nodes())/len(G.nodes())
# average squared degree
avg_squared_deg=sum(G.degree(node)**2 for node in G.nodes()) / len(G.nodes())
k=avg_squared_deg/avg_deg
if k > 2:
    print("The network has a giant component, suggesting robustness. The molloy-reed criterion:",  k)
else:
    print("The network does not have a giant component. The molloy-reed criterion:", k)
```

```
The network has a giant component, suggesting robustness. The molloy-reed criterion: 3.5796178343949046
```

```
critical_fc=1-(1/((avg_squared_deg/avg_deg)-1))
print("The treshhold for grpah to lose connected compondnents:",critical_fc)
```

```
The treshhold for grpah to lose connected compondnents: 0.6123456790123457
```

Table 8 presents the revised grid model under simulated node failures corresponding to infrastructure impacted during Hurricane Sandy. The revised network exhibited reduced connectivity degradation and less overall impact on grid infrastructure compared to the original model configuration. The Molloy-Reed score of 3.57 indicates that the network maintained a robust giant connected component, while the critical threshold value (f_c)of 0.61 suggests improved resistance to network fragmentation under simulated storm-related disruptions.

5.2 Graphical Results

In Figure 3, The network circular graph shows the below structure with the in-city generation transmission substations in red, area substations in blue, the NYC five boroughs as customer hubs in green.

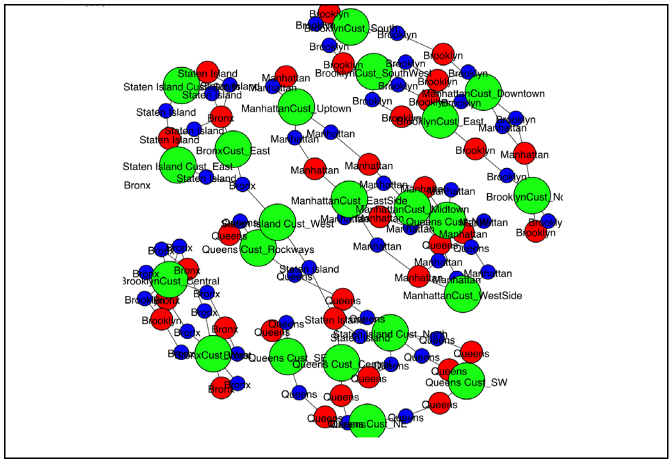


Figure 3: The network plot shows the nodes and edges for transmission and area substations that power the customer hubs.

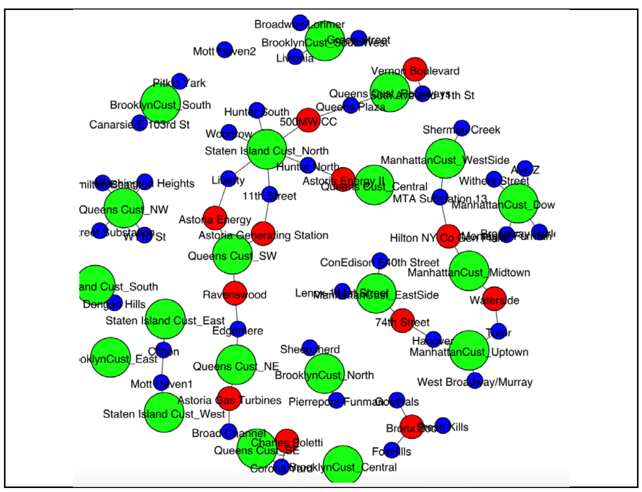


Figure 4: The network plot shows the simulated node removal.

In Figure 4, shows that the removal of top 10 nodes requires the power grid to be highly dependent of the transmission and substations to be in full operations. The transmission and substation node shutdowns would have a cascading effect on downstream distribution networks.

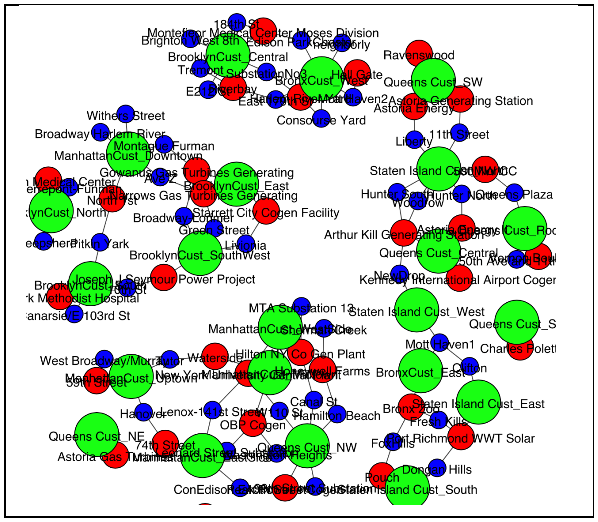


Figure 5: The network plot simulates the Hurricane Sandy nodes removed.

In Figure 5, the removal of the same nodes impacted by Hurricane Sandy that caused 800,000 customers to be without power, show the connectivity scores have greatly reduced for a fraction of nodes removed from the network.

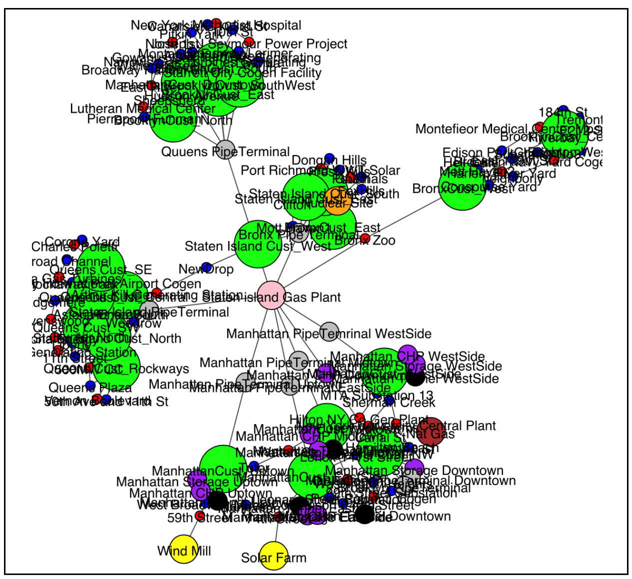


Figure 6: The network plot for Power Grid is revised with reinforcement nodes for network robustness analysis.

In Figure 6, the model was revised to include nodes that act independently of the transmission and area substations. These nodes include energy storage and CHP (Combined Heat and Power). These external sources are crucial for business and hospitals that operate 24x7. During Hurricane Sandy, people needed to be relocated, schools were closed, and businesses were shut down due to lack of power. Additional nodes for Gas pipeline that supplied gas to the northeast corridor, tunnels to depict the flow of traffic were added.

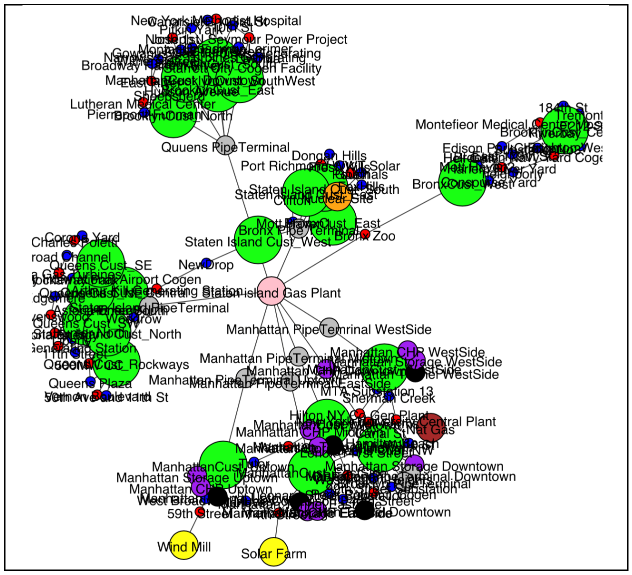


Figure 7: The Robustness and connectivity measure against attacks simulated on revised Power Grid model for nodes impacted during Hurricane Sandy.

In Figure 7, using the revised grid model. we see that the nodes that were impacted during Hurricane Sandy, had less of an impact on the overall grid. The Molloy-reed score was 3.57 which is suggesting the grid is robust. We do see the interdependence of the gas pipeline and tunnels still rely on overall Grid reliability as gas refineries and new gas supply rely on power. This was seen during Hurricane sandy which caused major supply disruption in the northeast. A ration of gas was ordered by customer's license plates to receive gas.

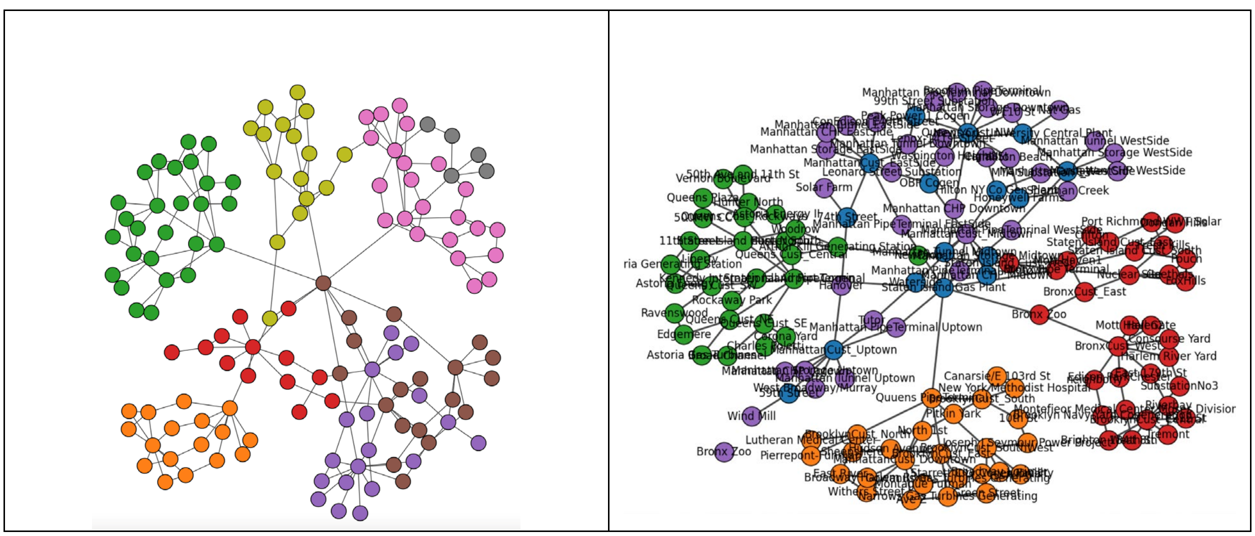


Figure 8: Community detection and clustering using modularity and stochastic block modeling

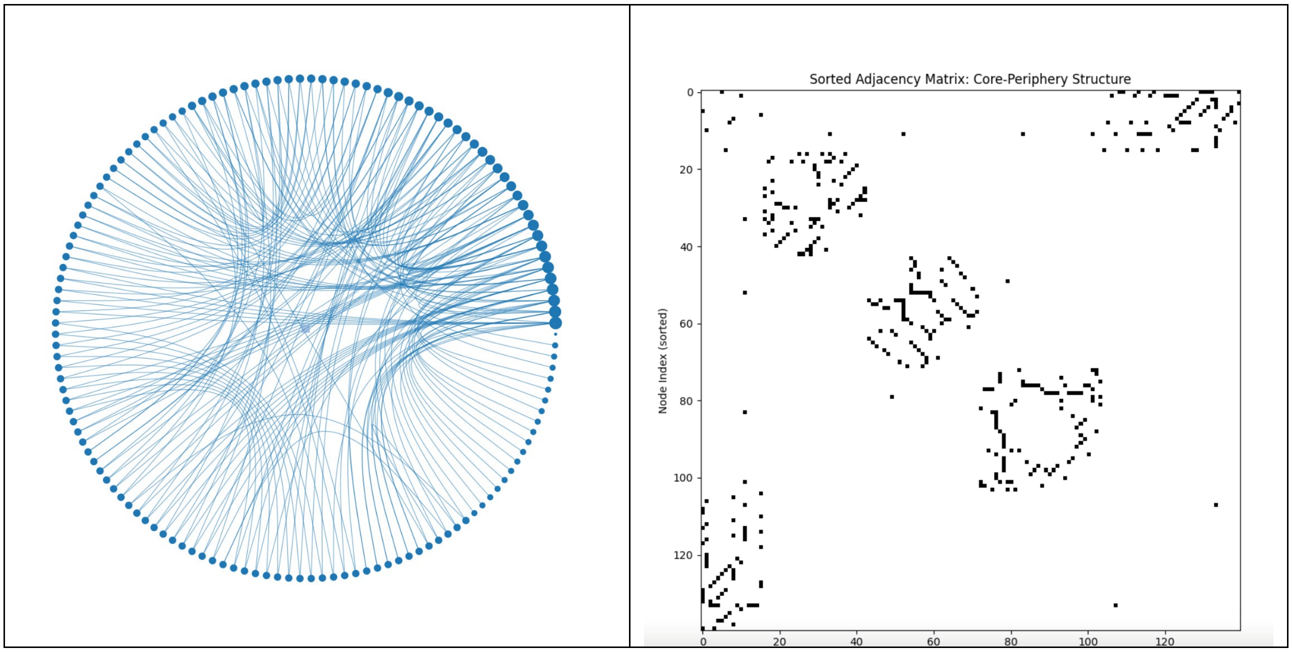


Figure 9: Degree-based community detection and core-periphery structure of the New York City power grid network

Figures 8 and 9 illustrate the community detection and clustering behavior of the New York City metropolitan power grid network. The modularity, stochastic block modeling, degree-based clustering, and core-periphery analyses identify groups of interconnected transmission and substation nodes associated with the five borough regions while highlighting highly connected core infrastructure nodes that support broader network connectivity and power distribution.

5.3 Proposed Improvements

Future analysis could be conducted to show the cascading effect as seen during hurricane Sandy as during the power outage, some transmission stations were overloaded to handle the demand which caused stress on the Grid and the substations were shut down causing power outages. Expanding the model to incorporate real-time power flow constraints, renewable intermittency, and probabilistic failure propagation could improve representation of cascading outages and infrastructure recovery under extreme weather conditions.

5.4 Validation

The network science framework was validated by comparing simulated infrastructure disruption behavior against documented impacts observed during Hurricane Sandy within the New York City metropolitan power grid (Department of Energy 2013; Con Edison 2013). Node-removal simulations corresponding to Hurricane Sandy-impacted infrastructure produced reductions in network connectivity and robustness consistent with observed cascading outage behavior. The revised grid model incorporating distributed infrastructure assets, including energy storage and combined heat and power (CHP) systems, demonstrated improved robustness and reduced fragmentation under simulated storm-related disruptions. Community detection and clustering analyses further identified geographically connected transmission and substation groups associated with the five borough regions, supporting the applicability of network science methods for evaluating power grid robustness and resilience.

6. Conclusion

This study applied network science methods to evaluate robustness, connectivity, and infrastructure interdependence of the New York City metropolitan power grid under extreme storm threats based on Hurricane Sandy impacts. The results demonstrated that critical transmission substations and area substations play a significant role in maintaining overall network connectivity and operational stability. Simulated node-removal attacks showed that failure of highly connected infrastructure nodes can produce substantial connectivity degradation and increase vulnerability to cascading disruptions across the power grid network. The study further demonstrated that the addition of distributed infrastructure assets, including renewable energy systems, energy storage, and combined heat and power (CHP) resources, improved overall network robustness and reduced fragmentation under simulated attack scenarios. Molloy-Reed robustness analysis confirmed the presence of stable giant connected network structures within the revised grid models. Community detection and clustering analysis also highlighted the importance of highly connected core infrastructure nodes serving the New York City metropolitan region. The results additionally emphasized the interdependence between the electric grid and supporting infrastructure systems, including gas pipelines, transportation tunnels, hospitals, and commercial districts. Infrastructure disruptions affecting these interconnected systems may increase restoration complexity and extend outage durations during major storm events. Overall, the study demonstrates the value of network science methods for identifying vulnerable infrastructure components, evaluating grid hardening strategies, and supporting resilience-oriented planning for future urban power systems under increasing climate and demand-related stresses.

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Biographies

Shane Menezes is a PhD candidate in Systems Science at Binghamton University (SUNY). His research focuses on the reliability, resilience, and optimization of the New York State energy grid. His work combines modeling, simulation, sensitivity analysis, operations research, and network science. His research interests extend to net-zero carbon emission policy targets and future uncertainties, including the impacts of extreme weather events.

Dr Sadamori Kojaku is an assistant Professor in Systems Science at Binghamton University (SUNY). He is an instrument maker, crafting a computational telescope/microscope to probe complex data. The foundation of his tools is rooted in extensive research on complex systems, network science and representation learning. He uses these tools for, but not limited to, research on the science of science and computational social sciences. He was a postdoctoral fellow at Indiana University, working with Professor Yong-Yeol Ahn on representation learning for the science of science. He served as a research associate at the University of Bristol, working on network science under the supervision of Professor Naoki Masuda. He obtained his PhD in computer science from Hokkaido University in 2015 (advisor: Professor Mineichi Kudo).