Infrastructure Network Resilience Analysis with Disruptions of System Order

Davis C. Loose, *M.IEEE*
Department of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
dcl6d@virginia.edu

Megan C. Marcellin, *M.IEEE*
Department of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
mcm5ft@virginia.edu

Igor Linkov
U.S. Army Corps of Engineers
U.S. Army Engineer Research and Development Center
Concord, MA, USA
Igor.Linkov@usace.army.mil

Gigi Pavur, *M.IEEE*
Department of Civil and Environmental Engineering
University of Virginia
Charlottesville, VA, USA
gp3vd@virginia.edu

Maksim Kitsak
Electrical Engineering, Mathematics and Computer Science
Delft University of Technology
Delft, The Netherlands
maksim.kitsak@gmail.com

Michael A. Deegan
U.S. Army Corps of Engineers
Insititute for Water Resources
Washington, DC, USA
michael.a.deegan@usace.army.mil

James H. Lambert, *F.IEEE*
Department of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
lambert@virginia.edu

Abstract— **Disruption of complex infrastructures systems involves cascading failures and interdependencies. This paper presents a network-based approach to assessing infrastructure resilience using scenario-based disruptions that remove entire sectors from the network. This approach evaluates system-wide vulnerabilities by modeling structural failures through the removal of nodes from the infrastructure graph. The framework uses a directed graph to represent interdependencies and uses eigenvector centrality to rank sector influence. Disruptive scenarios, including power outages, communication failures, and hybrid threats are applied to evaluate changes in system order. Spearman's rank correlation quantifies the disruptiveness of each scenario, identifying which sectors experience the most significant shifts in importance. Results show that disruptions to the communications sector cause the greatest reordering of system orders, while disruptions to water & wastewater have a lower impact. The analysis demonstrates how different hazards affect regional resilience and provides insights for decision-makers to schedule the risk countermeasures.**

Keywords— *risk management, emergency management, interdependencies, systems engineering, decision analysis*

I. Introduction

Disruptive events and disasters have cascading effects on critical infrastructure systems, threatening the stability of essential services [1]. Extreme events, such as hurricanes, fires, and freezes, have caused widespread damage, highlighting the need for adaptive strategies that improve regional resilience [2]. Building regional resilience requires scalable, actionable frameworks that support decision-making to reduce vulnerabilities across interconnected infrastructure sectors [3].

Resilience in infrastructure systems refers to the ability of critical sectors to withstand, adapt to, and recover from disruptive events while maintaining essential functions [4]. Infrastructure networks are highly interconnected such that disruptions in one sector such as energy or transportation can create disruptions in others such as manufacturing. It is critical to understand how these infrastructures are connected and how disruptions propagate to assess system resilience [5]-[6]. Disruptive scenarios are analytical tools used to assess the vulnerability and resilience of infrastructure systems under conditions of stress or failure. These scenarios can represent a wide range of hazards, including natural disasters, technological failures, and human-induced events, each with the potential to cause cascading effects across interconnected sectors [7].

This paper presents a scenario-based framework for assessing the resilience of critical infrastructure systems by analyzing shifts in sectoral orders and interdependencies under disruptive conditions. The framework is demonstrated on a regional case study, where a network model of critical infrastructure sectors is used to evaluate the impacts of various hazard scenarios. The methodology involves defining baseline sector interdependencies, applying network analysis techniques to establish sector rankings, and using disruptive scenarios to observe how system order changes in response to node removals. The degree of disruptiveness is quantified through Spearman's rank correlation, allowing for the identification of sectors that experience the greatest shifts in importance under disruption. This work advances prior methodologies in key ways. First, it uses disruptive scenarios and hybrid threats by removing nodes entirely, enabling the assessment of structural disruptions that reflect real-world failures. Second, it employs a directed graph to capture asymmetrical interdependencies, highlighting how sectors depend on others without reciprocal influence. Third, the analysis compares not only baseline conditions but also differences between disruptive scenarios, offering deeper insights into how various hazards uniquely affect system order [8].

II. BACKGROUND

Resilience in infrastructure systems is a key focus in systems engineering due to the cascading effects that disruptions have across interconnected infrastructure networks. Infrastructure systems are complex and interdependent, where the failure of one sector can rapidly propagate through others, amplifying impacts. Network-based approaches offer a robust framework to model these interdependencies, allowing for the assessment of both direct and indirect effects of disruptions on critical infrastructure sectors [9]. By representing infrastructure components as nodes and their interconnections as edges, these models enable the identification of vulnerabilities and potential cascading failure points [10]. Disruptive scenarios provide a way to evaluate how different hazards affect critical infrastructure systems. These scenarios include extreme events, technological failures, and other hazards, each influencing system performance differently. Scenario analysis enables the exploration of potential impacts by simulating uncertain conditions and observing how disruptions affect system stability [11]. This approach is valuable in resilience management, as it helps identify which sectors are most susceptible under various conditions and provides strategies to mitigate cascading risks [12]. This concept of resilience extends beyond the immediate recovery of infrastructure systems to encompass the ability to maintain or quickly restore functionality under stress. Resilience is assessed through changes in system order, where disruptions can shift system orders and interdependencies of system components. By quantifying these shifts, decision makers can evaluate the severity of disruptions and the robustness of the structure of the system [13]-[14].

III. METHODS

This study extends prior methodologies to assess the resilience of critical infrastructure systems under various disruptive scenarios. The resilience assessment begins by defining a network graph based on critical infrastructure sectors within a metropolitan region, as identified by the Cybersecurity and Infrastructure Security Agency (CISA) [15]. This network graph represents sectors as nodes and their interdependencies as edges, illustrating how the functionality of one sector influences others. Sector interdependencies are graphed as a directed network. Each of the sectors is then ranked based on centrality measures. This study utilizes eigenvector centrality, but other measures are discussed in subsequent sections. Then, scenario-based disruptions are applied by removing one or more nodes to simulate sector failures. Finally, the changes to the order of sector ranks is analyze to evaluate the impact of disruptions. This approach enables a comprehensive understanding of regional resilience by identifying critical sectors, evaluating their vulnerability to cascading failures, and highlighting which components are essential for maintaining system-wide stability under various hazard conditions.

A. Network Graph of Critical Infrastructure Sectors

The network graph represents critical infrastructure sectors within a metropolitan region, with nodes corresponding to sectors identified by CISA, and edges representing interdependencies between them. The graph is directed because some nodes depend on another node, while those other nodes do not depend on the first, reflecting the asymmetrical nature of sectoral dependencies. An adjacency matrix encodes these relationships, with an entry of 1 indicating an interdependency and 0 otherwise.

B. Measures of Centrality

The sectors are ranked by the eigenvector centrality of each node. For a node i the eigenvector centrality x_i is defined as:

$$x_i = \frac{1}{\lambda}\sum_j A_{ij}x_j \qquad (2)$$

Where A is the adjacency matrix, λ is the largest eigenvalue of A and x_j represents the centrality of node j. A higher score for a sector represents greater importance relative to the other sectors in the system.

C. Disruptive Scenarios

This study uses five disruptive scenarios to assess the resilience of critical infrastructure sectors. The scenarios are hazards or hybrid threats that compromise system stability. Each scenario involves the full removal of specific nodes from the network, simulating halted operations of the affected sectors and the immediate severance of all their interdependencies.

The *Power Outage* scenario models the failure of the energy sector, whose removal represents the widespread loss of power infrastructure. The *Communications Outage* scenario involves the elimination of the communications sector, reflecting scenarios where critical communication channels are entirely disabled, thereby impacting coordination across other sectors. The *Water Crisis* scenario removes the *Water & Wastewater* sector, showing the consequences of water infrastructure failure on both public health and industrial operations. The first three scenarios utilize the removal of a single node.

The *Sociotechnical Disruption* scenario represents the simultaneous collapse of transportation systems and critical manufacturing sectors. This dual removal models complex disruptions that blend social factors with technical failures, emphasizing the related vulnerabilities between logistics and production capacities. The *Deep Freeze* scenario considers the concurrent failure of transportation systems and dams, showing the compound effects of extreme weather conditions that can incapacitate both mobility and water management infrastructure. Node removals are conducted without consideration for recovery or restoration within the scenario, focusing solely on the immediate structural impacts. All edges connected to the removed nodes are also removed to reflect the complete loss of functionality and dependency relationships. This approach provides a consistent framework for evaluating resilience by isolating the effects of sector failures, allowing for analysis of how different scenarios disrupt the broader infrastructure network.

D. Disruptiveness and Resilience Assessment

After each scenario is applied to the network, eigenvector centrality is recalculated to assess changes to sector importance. Eigenvector centrality for each node is recalculated using the adjusted adjacency matrix for each scenario $s \in S$, denoted as $A^s = \left(a_{ij}^s\right)$. The sectors are then reranked based on the new eigenvector centrality score for scenario s, describing how system order is disrupted. The disruptiveness of each scenario is evaluated by comparing the new rankings to the baseline. Spearman's Rank Correlation Coefficient is used to quantify the degree of change in system order. The coefficient is calculated as [17]:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \tag{4}$$

where d_i represents the difference in ranks for sector i between the baseline and the disrupted scenario, and n is the total number of sectors. A ρ value close to +1 indicates minimal disruption, while values approaching -1 signify a complete reorder of sectors.

E. Assessment of Centrality Measures

In the process of evaluating critical infrastructure resilience, several centrality measures were considered to determine the most effective metric for capturing sectoral influence within the network. These include eigenvector, degree, betweenness, and closeness centrality. Each measure provides strengths and weaknesses for understanding system resilience. However, centrality measures are often correlated. Degree centrality quantifies the immediate influence of a node based on the number of direct connections it has within the network. It identifies sectors with extensive direct interdependencies. While degree centrality effectively highlights sectors with numerous connections, it lacks the capacity to account for the significance of the connected nodes, thereby limiting its ability to capture system-wide influence beyond immediate relationships. Betweenness centrality assesses the extent to which a node functions as a "bridge" within the network, measuring how often a node appears on the shortest paths between other nodes. This metric identifies potential bottlenecks or critical control points in the network.

Closeness centrality evaluates shortest paths in the network. It is calculated based on the average length of the shortest paths from the node to all other nodes. Closeness centrality provides insight into the efficiency of communication or resource flow within the network. Closeness centrality tends to underemphasize the roles of peripheral yet highly influential nodes that are critical in specific contexts but not centrally located within the network structure. Eigenvector centrality measures the influence of a node based on the importance of its connections within the network. Eigenvector centrality assigns greater value to nodes that are connected to other highly influential nodes. Eigenvector centrality may overemphasize nodes within densely connected clusters, and reduce the relative importance of isolated but critical nodes.

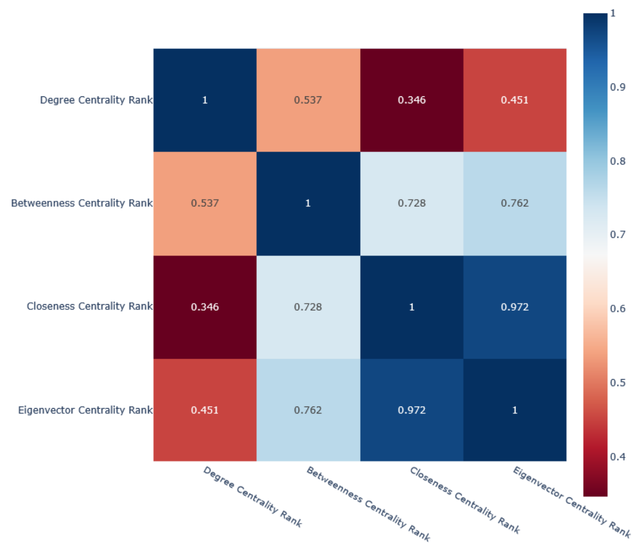

Fig 1. Spearman's rank correlation coefficient comparing the four centrality measures, identifying which are most and least similar

When selecting which centrality measure best suit the resilience analysis in this case, it is noted that there is some significant correlation across measures. The Spearman's rank correlation coefficients in Figure 1 highlight both overlaps and distinctions among the centrality measures. Degree centrality shows moderate correlation with betweenness (0.537) and eigenvector centrality (0.451), reflecting how sectors with extensive direct connections often serve as key intermediaries or are linked to influential nodes. However, its weaker correlation with closeness centrality (0.346) underscores its limited scope in capturing influence beyond immediate connections. Eigenvector and closeness centralities show a strong correlation (0.972). Both emphasize sectors integrated within influential clusters, though closeness centrality leans more on accessibility across the network. Betweenness centrality bridges these perspectives with moderate correlations to both (0.728 with closeness, 0.762 with eigenvector), reflecting its role in capturing critical pathways without fully aligning with measures of direct or recursive influence. Eigenvector centrality was chosen for the remainder of the analysis because it captures both direct and indirect connections, giving a clearer picture of sector influence. It also correlates well with other centrality measures. Its focus on how sectors are tied to other important sectors makes it effective for understanding network resilience. Future work will consider other centrality measures to capture different aspects of network vulnerability.

IV. Results and Case Study

A. Background of Case Study Area

This study focuses on a city and surrounding region located in the southeastern United States. The region is landlocked but situated along a major river, which plays a critical role in its economic and infrastructural dynamics. With a population exceeding two million residents, the area encompasses a region characterized by dense population centers, critical infrastructure hubs, and extensive transportation networks [16]. The region is subjected to a range of natural hazards, including significant flood risks due to river proximity, periodic extreme freezes that can disrupt essential services, and other threats that challenge infrastructure resilience. This hazard landscape provides a robust context for evaluating the resilience of interconnected infrastructure systems under various disruptive scenarios.

B. Infrastructure Interdependencies and Resilience

The analysis considers 13 critical infrastructure sectors and interdependencies (nodes and edges of the graph, respectively) as defined by the Cybersecurity and Infrastructure Security Agency (CISA), outlined in Table 1. These sectors form the nodes of the network, while the interdependencies between them are represented as directed edges. Figure 2 visualizes the network structure, where sectors with numerous dependencies, such as *Energy* and *Healthcare*, have a high number of connections, indicating their relative importance to the system. Each node in the network represents a distinct infrastructure sector, and edges indicate functional dependencies between sectors. The network is directed, which reflects the asymmetric dependencies among sectors. For example, *Energy* is a key supplier to multiple sectors but does not directly depend on them in return. Highly connected nodes, such as *Communications* and *Water & Wastewater*, are crucial for system stability, as their removal could have cascading effects across sectors.

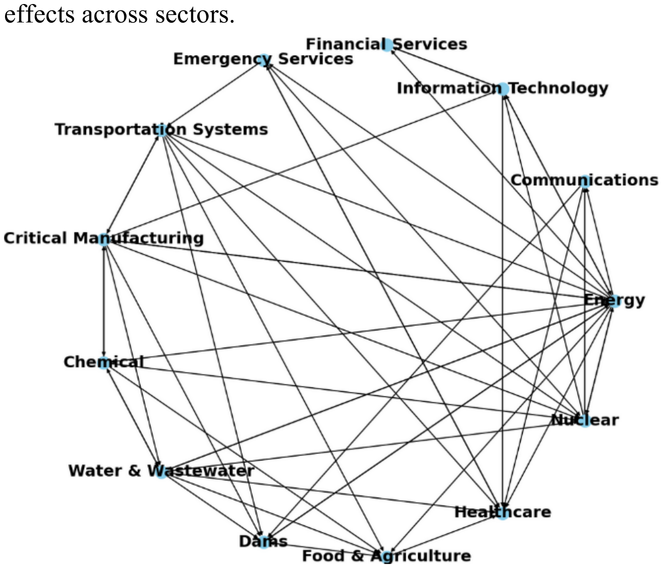

Fig 2. Network graph of critical infrastructure sector interdependencies. Arrows indicate that the origin node depends on the target node.

TABLE I. CRITICAL INFRASTRUCTURE SECTORS AND CORRESPONDING LABELS

Sector ID	Sector Name
x.1	Communications
x.2	Emergency Services
x.3	Energy
x.4	Financial Services
x.5	Information Technology
x.6	Nuclear
x.7	Water and Wastewater
x.8	Dams
x.9	Food and Agriculture
x.10	Healthcare
x.11	Transpiration Systems
x.12	Critical Manufacturing
x.13	Chemical

Figure 3 illustrates the eigenvector centrality scores in the baseline scenario for each critical infrastructure sector, ranked in descending order. *Healthcare* has the highest centrality score followed by *Energy*, *Dams*, and *Nuclear*. These sectors are highly influential due to their connections with other highly interconnected sectors, indicating their central role in maintaining overall system resilience. Sectors with lower centrality scores, such as *Financial Services*, *Communications*, and *Water & Wastewater*, while still integral to the network, exhibit less influence in terms of their direct and indirect connections. This provides the baseline ranking of critical infrastructure sectors.

TABLE II. DISRUPTIVE SCENARIOS THAT INFLUENCING CRITICAL INFRASTRUCTURE SYSTEMS

Scenario Name	Sector(s) Removed
s.1 - Power Outage	Energy
s.2 - Communications Outage	Communications
s.3 - Water Crisis	Water & Wastewater
s.4 - Sociotechnical Disruption	Transportation Systems; Critical Manufacturing
s.5 - Deep Freeze	Transportation Systems; Dams

Table 2 outlines the disruptive scenarios used in this analysis, each representing a distinct hazard or hybrid threat with corresponding node removals to simulate system disruptions. The *Power Outage* scenario removes the *Energy* node, reflecting the critical role of energy infrastructure in sustaining interdependent sectors. The *Communications Outage* scenario eliminates the *Communications* node, simulating the cascading effects of a widespread loss of connectivity. In the *Water Crisis* scenario, the *Water & Wastewater* node is removed, representing vulnerabilities related to resource scarcity or contamination. Hybrid threats are modeled through the *Sociotechnical Disruption* and *Deep Freeze* scenarios involve the simultaneous removal of multiple nodes; *Transportation Systems* with *Critical Manufacturing* and *Transportation Systems* with *Dams*, respectively.

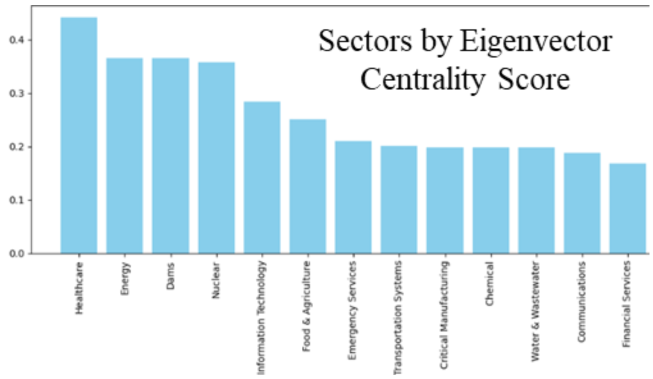

Fig 3. Sector interdependency in descending order as measured by eigenvector centrality

Figure 4 describes the baseline, minimum, and maximum rankings of each critical infrastructure sector across the baseline and disrupted scenarios. The black diamonds represent the baseline rankings, while the blue and red bars show the maximum and minimum ranks attained for each sector, with the blue segment indicated the highest rank under disruptive scenarios, and the red segment represents the lowest. In scenarios in which a particular node is removed (for example, *Communications*), the eigenvector centrality score would be reduced to zero and fall to rank 13. For these scenarios, the second lowest rank is used.

Sectors like *Healthcare* and *Energy* are relatively stable, with *Healthcare* never losing its top rank. These sectors remain highly ranked across scenarios. sectors such as *Transportation Systems*, *Critical Manufacturing*, and *Financial Services* exhibit variability in rankings, indicating their sensitivity to different types of disruptions. This indicates that certain scenarios can alter the importance of these nodes. *Nuclear* is of particular interest – while it is the fourth highest rated sector in the baseline, it can rise to second in some scenarios, and never falls in rank. Contrast this with *Food & Agriculture*, which only falls in rank. Sectors with lower baseline rankings, such as *Financial Services*, *Communications*, and *Water & Wastewater*, exhibit the greatest variability across scenarios. This suggests that while these sectors may not be central under normal conditions, their importance can shift depending on the nature of the disruption. This variability indicates a latent vulnerability within the network, where sectors that are typically peripheral can become critical under specific disruptions. This highlights the need for resilience strategies that account for dynamic changes in sector importance.

Figure 5 presents the disruptiveness of each scenario relative to the baseline ranking, calculated using Spearman's rank correlation coefficient. To better illustrate the degree of disruption, the values are expressed as *1 - ρ*, where higher scores indicate greater shifts in sectoral rankings and, consequently, more significant disruptions to system order. The *Communications Outage* scenario exhibits the highest disruptiveness score (0.14), suggesting that the removal of this sector causes the most pronounced reordering of critical infrastructure orders within the network. The *Water Crisis* scenario shows the lowest disruptiveness score (0.051), indicating relatively minor changes in the overall network structure. This suggests that while water services are essential, their removal does not drastically alter the hierarchy of sectoral influence. The *Power Outage*, *Sociotechnical Disruption*, and *Deep Freeze* scenarios fall in between, with moderate disruptiveness scores (0.091, 0.091, and 0.11, respectively), highlighting varying levels of impact depending on which nodes are affected and the extent of cascading effects.

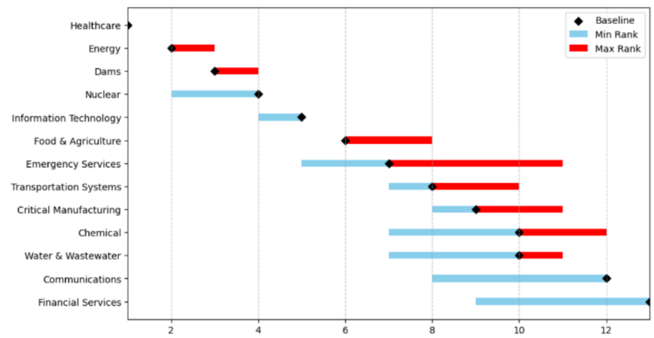

Fig 4. Baseline, minimum, and maximum rankings of critical infrastructure sectors across the disruptive scenarios, reflecting changes to system order

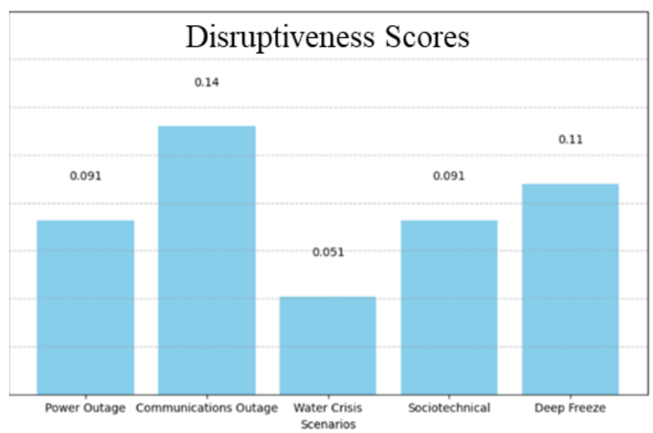

Fig 5. Disruptiveness scores of scenarios relative to baseline expressed as 1 – *ρ* such that higher values are more disruptive

Figure 6 shows the Spearman rank correlation coefficients for all scenarios relative to one another. Higher correlation values indicate more stability in the system order, while lower values reflect significant shifts in sectoral importance. The *Communications Outage* scenario shows the lowest correlation with both the baseline (0.86) and other scenarios, particularly with the *Power Outage* scenario (0.699). This suggests that disruptions to communication infrastructure result in a more unique and pronounced reordering of critical sector orders, reinforcing its status as the most disruptive scenario. In contrast, the *Water Crisis* scenario maintains high correlation values with both the baseline (0.949) and other disruptions, such as the *Sociotechnical* scenario (0.988), indicating minimal shifts in sectoral rankings and greater system stability.

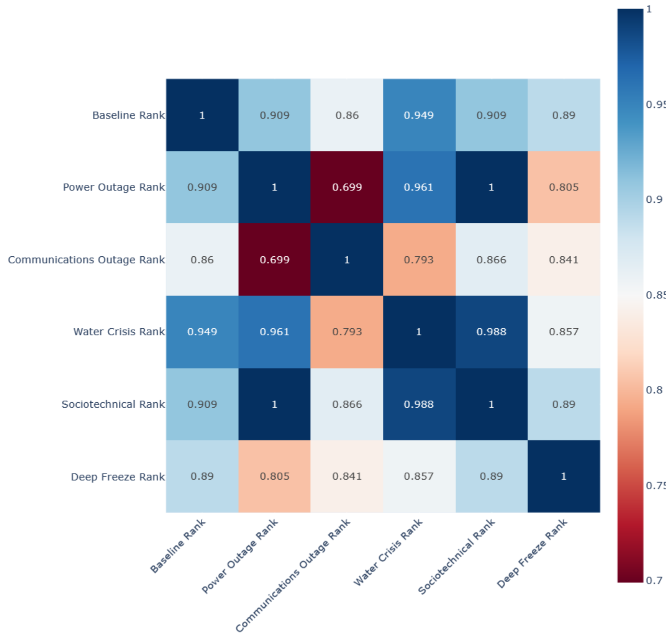

Fig 6. Spearman's rank correlation coefficient used to quantify the disruption of system order for the infrastructure systems

V. Conclusions and Future Work

An interesting and unexpected finding from this analysis is the relatively low disruptiveness score of the *Water Crisis* scenario. Given the critical role of water infrastructure in supporting daily life and industrial operations, this result suggests that the removal of the *Water & Wastewater* sector does not significantly alter the overall system order. This outcome highlights the need for further analysis to better understand the underlying network dynamics and interdependencies dependencies that may not be fully captured through the current modeling approach.

This study assessed the resilience of critical infrastructure networks under various disruptive scenarios using a network-based approach focused on eigenvector centrality. The resulting changes in rankings were evaluated using Spearman's rank correlation coefficient, providing insights into how different hazards affect system order and sectoral influence. The analysis revealed that *Healthcare* and *Energy* consistently maintained high importance across scenarios, while sectors like *Transportation Systems* and *Financial Services* showed greater variability, indicating sensitivity to specific disruptions. The *Communications Outage* scenario caused the most significant disruptions to system order. *Water Crisis* had more localized effects with minimal shifts in overall system order. Future work will expand on this framework by incorporating additional centrality measures to capture multiple dimensions of network influence, exploring dynamic recovery processes post-disruption, and considering the sequential nature of multi-hazard events to better reflect real-world complexities. This will improve understanding of critical infrastructure resilience and inform more robust strategies for risk mitigation.

VI. Acknowledgment

This effort was supported in part by the U.S. Army Corps of Engineers (USACE), the National Science Foundation Center for Hardware and Embedded System Security and Trust (NSF CHEST), and the Commonwealth Center for Advanced Logistics Systems (CCALS).

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