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Abstract—**Regional managers require adaptive strategies to enhance resilience against severe weather events and disasters. Critical infrastructure sectors are interconnected such that disruptions in one sector to cascade through others, exposing system-wide vulnerabilities. This paper presents a scenario-based framework that integrates network theory and scenario analysis to assess resilience within regional infrastructure networks of a metropolitan region. The framework quantifies disruptions in system orders by evaluating how critical infrastructure sector priorities change across scenarios. Scenarios are various timeframes following or preceding a disruptive event, from a few hours to a few months. Inserting features of a large flood in Nashville, TN, USA, as a case study, the analysis examines how disruptions alter the order of sectors and interdependencies, identifying which sectors are most vulnerable to cascading failures, as well as those with greater stability. Results indicate that sectors such as healthcare, communications, and energy remain consistently critical to resilience of the cyber-physical system, while transportation and water services show higher sensitivity to disruption. By assessing the disruptiveness of each scenario, this framework provides a greater understanding of system dynamics and supports strategic resilience planning by prioritizing sectors critical to regional stability.**

Keywords—risk analysis, complex systems, network models, scenario modeling, interdependencies

I. Introduction

Regional resilience supports communities in developing scalable, actionable solutions to mitigate these impacts [1]. Recent extreme weather events, such as hurricanes Helene and Milton, have caused damages estimated at $50 billion or more per storm. Such events underscore the urgency for communities to adopt resilience frameworks that can guide infrastructure investments and reduce vulnerabilities within critical systems [2]. Resilience in complex systems depends on understanding interdependencies among infrastructure sectors. These interdependencies create a network where the functionality of one sector impacts others [3]. Disruptions in the energy sector cascade into transportation, healthcare, and public safety, amplifying the effects of the initial event. Systems engineering provides a structured method to represent these interdependencies as graphs, enabling analysis of infrastructure sector risk and resilience. In this network representation, each sector is a node, and interdependencies are edges, forming a map of influence and vulnerability across the system. A critical component of resilience management involves using scenario analysis to assess disruptions to interdependent systems and evaluate their effects on sector functionality [4]-[5]. Disruptions such as natural disasters or economic stressors shift sector operational capacities and alter the rank order of system components [6]. Defining risk as the disruption of system order provides a way to gauge disruption severity by observing shifts in priority orders, identifying sectors that become more vulnerable or critical under disruption [7]. This allows decision-makers to prioritize resilience initiatives that mitigate potential cascading failures within the network.

This paper presents a technique for analyzing regional resilience using a scenario-based approach to assess disruptiveness in critical infrastructure systems. The methodology includes defining baseline sector interdependencies, applying network metrics such as eigenvector centrality to establish sector rankings, and using scenario analysis to observe shifts in system order. The contribution of this paper is the development of a scenario-based framework that quantitatively assesses regional resilience by analyzing shifts in critical infrastructure sector priorities and interdependencies under disruptive scenarios, providing insights into system vulnerabilities and guiding resilience planning to strengthen regional stability. This paper provides insights into vulnerabilities of infrastructure sectors and guides infrastructure investment priorities. Although many studies address cascading failures in interconnected infrastructure systems, few evaluate how the system orders of critical sectors change across scenarios as a measure for system resilience [7], [14]. The proposed framework fills this gap by directly linking scenario-based shifts in system orders to a disruptiveness measure, enabling a quantitative assessment of resilience. This approach highlights which sectors become critical under disruption, offering actionable guidance for response and recovery planning.

II. Literature Review

Regional resilience frameworks emphasize the role of regional governance in addressing extreme conditions and events, highlighting the importance of localized strategies to address unique environmental and infrastructural vulnerabilities [8]. Adaptation efforts often require the integration of diverse policy domains and stakeholder networks, as interconnected systems face increased complexity and fragmentation [9]. Regional resilience frameworks are continuously evolving to incorporate resilience metrics and balance trade-offs in sustainable adaptation, ensuring infrastructure systems can recover effectively while addressing long-term impacts and concerns [10]. Scenario analysis is a key approach within resilience literature for addressing complex disruptions by modeling potential impacts on critical infrastructure [11]. This enables planners to explore a range of future disruptions, assessing how various stressors affect system performance and identifying conditions that might compromise resilience [12]. By evaluating multiple scenarios, resilience frameworks gain insight into the potential range and severity of impacts, informing strategic actions that can enhance adaptive capacity across interconnected systems [13]. Critical infrastructure systems are inherently interdependent, where interactions between sectors can lead to cascading failures and emergent behaviors across the network [14]. These interdependencies create complex vulnerabilities, as failures in essential services like energy or transportation can propagate rapidly, producing emergent behaviors that increase the severity of an initial disruption across interconnected systems [15]. Infrastructure resilience can be modeled through network-based approaches that map interconnected system components and evaluate how disruptions propagate across these links [16]. This network representation allows researchers to simulate how cascading effects, or emergent behaviors, arise from interdependencies, providing insight into vulnerabilities and potential failure points within the infrastructure [17]- [18]. In resilience planning, the systems-of-systems (SoS) approach provides a structured framework for assessing interdependent infrastructure networks and managing performance degradation over time. Recent studies introduce event-triggered reconfiguration within SoS models, using time-varying hypergraphs to represent complex, bidirectional relationships among infrastructure components [19]. This approach aligns resilience planning with the adaptive needs of interconnected systems, ensuring robust responses to varying degrees of external disturbance. Scenario analysis in resilience modeling evaluates how disruptions impact infrastructure interdependencies, analyzing disruptions to improve mitigation to cascading failures [20].

Scenario analysis is a foundational approach in resilience assessment, enabling planners to identify and prioritize strategies under various disruptive conditions [7]. In regional resilience planning, scenario analysis provides a framework for coordinating priorities among agencies with differing perspectives, addressing natural and human-caused hazards through a structured, systems-based approach [21]. Scenario analysis is an integrative approach that combines diverse data sources and analytical methods to evaluate regional resilience, providing a dynamic framework to anticipate system responses under varying conditions [22]. The methods presented in this paper combine graph-based network modeling, scenario analysis, and disruptiveness assessment to address a gap in resilience research by quantitatively capturing interdependencies and shifts in system orders, providing insights into system vulnerabilities and resilience.

III. Methods

The resilience assessment methodology begins by defining a network graph based on critical infrastructure sectors of a region as identified by the Cybersecurity and Infrastructure Security Agency (CISA), as well as interdependent relationships between sectors [23]. The method follows four steps: (1) defining a network graph of critical infrastructure sectors and their interdependencies, (2) calculating eigenvector centrality to rank sector importance to establish baseline rankings, (3) applying a temporal disruption scenario to adjust edge weights and recalculate centrality scores, and (4) assessing changes in system order over time to gauge disruptiveness. This approach enhances understanding of regional resilience by identifying critical sectors, evaluating their vulnerability to cascading failures, and highlighting which components are essential for maintaining stability under stress.

A. *Network Representation of Critical Infrastructure Sectors*

A network graph $G \coloneqq (V, E)$, represents the region where V is the set of nodes corresponding to critical infrastructure sectors and E is the set of edges representing interdependencies between sectors. Each edge a_{vt}, between sectors v and t has a value of 1 if there is an interdependency and 0 otherwise. $A = (a_{vt})$ is the adjacency matrix.

$$a_{vt} = \begin{cases} 1, & \text{if nodes } v \text{ and } t \text{ are connected} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

B. *Rank Order of Critical Infrastructure Sectors*

Sectors are ranked by their structural importance to network using eigenvector centrality. Eigenvector centrality quantifies sector influence by assigning higher values to sectors that are connected to other highly connected sectors. Eigenvector centrality x_v for node v is defined as:

$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} a_{vt} x_t \quad (2)$$

Where λ is the largest eigenvalue of the adjacency matrix A, a_{vt} is the connection between sectors v and t, and $M(v)$ is the set of sectors that connect to v. The eigenvector centrality scores for V are used to rank the baseline system orders of infrastructure sectors of the region.

C. *Disrupting the Critical Infrastrucutre Network*

To assess the impact of a disruptive event on a region, the network is subjected to a set of scenarios SSS that reduce the operational functionality of the sectors. This reduction is expressed as a percentage of maximum functionality for each sector. Let c_v represent the capacity of sector v as a percentage of maximum functionality between 0 and 100%. The scenarios $s \in S$ represent specific time points after a disruptive event, such as 24 hours, 48 hours, 72 hours, one week, and one month, capturing the loss and gradual regain of functionality after events like hurricanes or floods. Each scenario s affects the network by modifying the weights of interdependencies and adjusting the adjacency matrix. The adjusted weight a_{vt}^s for an edge connecting sectors v and t under scenario s is defined as:

$$a_{vt}^s = a_{vt} \times \left(\frac{c^s{}_v + c^s{}_t}{2 \times 100}\right) \quad (3)$$

Where a_{vt} is the original edge weight connecting sectors v and t, $c^s{}_v$ *and* $c^s{}_t$ are the capacities of sectors v and t for scenario s, and $\left(\frac{c^s{}_v+c^s{}_t}{2 \times 100}\right)$is the average capacity sectors v and t scaling the edge weight to reflect the impact of disruption. This formulation allows each scenario s to dynamically alter the interdependency structure of the network, providing insight into the resilience of sectoral connections over different time intervals following a disruptive event.

D. *Disruption of System Order*

Following the disruptive event and the subsequent adjustment of edge weights, eigenvector centrality for each node is recalculated using the adjusted adjacency matrix for each scenario $s \in S$, denoted as $A^s = (a_{vt}^s)$. The revised centrality scores for each scenario s reflect changes in the system order, and shows how system priorities change due to the impact of disruption. Sectors that experience significant changes to rank in system order indicate disproportionate effects, revealing vulnerabilities within the network.

To evaluate the disruptiveness of each scenario compared to the baseline (non-disrupted) order of sectors, Spearman's rank correlation coefficient is applied. This measures the degree to which the rank order of sectors, as measured by eigenvector centrality, shifts across the various scenarios. Spearman's rank correlation is preferred over alternatives such as the sum of squares error or Kendall's tau because it assesses ordinal relationships between ranked variables, rather than focusing on the exact distances between values or pairwise rank comparisons. This makes Spearman's correlation well-suited for examining the relative rank changes in sector importance and provides a robust measure of how structural importance shifts across the scenarios. Spearman's Rank Correlation Coefficient ρ between the ranking of a node between two scenarios is defined as:

$$\rho = 1 - \frac{6\sum_{v \in V} d_v^2}{n(n^2-1)} \quad (4)$$

Where d_v is the change in ranking of node v between two scenarios, and n is the total number of sectors in the network. This captures how the relative importance of a sector changes within the network under disruptive scenarios. The coefficient ρ quantifies the correlation between rankings, with values closer to +1 indicating minimal disruption to the baseline ranking, values close to 0 representing no correlation between rankings, and values close to -1 indicating a negative correlation. This allows for an easier comparison of disruptiveness across the different scenarios relative to the baseline.

IV. Results and Case Study

A. *Case Study Background*

In May 2010, Nashville and the surrounding Middle Tennessee region experienced catastrophic flooding caused by an unprecedented two-day rainfall event. Between May 1-2, the area received more than 13 inches of rain, which set records across multiple watersheds. In Nashville, the Cumberland River crested at 51.86 feet, which was 12 feet above flood stage, causing substantial flooding of urban areas. The flood resulted in 18 fatalities, displaced 10,000 residents, and damaged or destroyed approximately 11,000 properties. The economic toll exceeded $2 billion, impacting public infrastructure, local businesses, and Nashville's tourism sector, which saw the closure of major sites like the Opry Mills Mall and the Country Music Hall of Fame [24]. The flooding event also revealed the vulnerabilities in the critical infrastructure network of Nashville. Floodwaters disrupted essential services by disabling one of Nashville's two water treatment plants, flooding two wastewater treatment plants, and damaging power substations. The flooding event caused more than 9,000 residents to lose power and compromised transportation systems. The U.S. Army Corps of Engineers (USACE) faced operational challenges, including disrupted communications and limitations in real-time data from stream gauges. These disruptions highlighted gaps in interagency coordination and resource allocation, leading to subsequent changes in response protocols, hydraulic modeling, and water management plans to enhance resilience against future flood events [24]- [25].

B. *Case Results and Discussion*

The results assess the resilience of critical infrastructure of the during extreme flooding scenarios, focusing on shifts in sector functionality and interdependencies for the Nashville region after the 2010 flooding event. Using network analysis and scenario-based modeling, this study identifies the infrastructure sectors most vulnerable to cascading failures under disrupted conditions, and addresses this disruptiveness over time. Table 1 describes the 13 critical infrastructure sectors as outlined by CISA. These sectors are linked into the network graph structure shown in Fig. 1, which visualizes the interdependencies among the critical infrastructure sectors. Each sector is represented as a node, while edges between nodes indicate direct interdependencies based on functional and operational linkages. The size of each node corresponds to its eigenvector centrality score, reflecting the influence and connectivity of the sector within the network. Higher centrality scores, represented by larger nodes, signify sectors with stronger interconnections to other highly connected nodes, identifying them as critical points in the infrastructure network.

TABLE I. CRITICAL INFRASTRUCTURE SECTORS OF A METROPOLITAN REGION

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

Fig 2. Shows the degree of interdependency across critical infrastructure sectors, as measured by eigenvector centrality scores. The sectors are in descending order, with healthcare exhibiting the highest centrality, followed by communications and energy. Sectors with higher eigenvector centrality scores play a more influential role in the network, as they are more interconnected with other critical sectors. Eigenvector centrality captures the notion that the importance of a sector grows if it is connected to other influential sectors, making it appropriate for identifying nodes with high impact in an interdependent network. Its recursive nature aligns with analyzing how disruptions propagate, the value of a sector depends not only on its degree of connectivity but also on the importance of its neighbors. Other measures such a degree centrality or betweenness centrality are correlated with eigenvector centrality, but would provide slightly different results [26]. Future work will examine the sensitivity of results to chosen centrality measures. Eigenvector centrality offers a well-established method for highlighting mutually reinforcing hubs within a network. This highlights their importance in maintaining overall network resilience, as disruptions in these sectors are likely to have cascading effects across the system. Lower-scoring sectors, such as information technology and financial services, are less central within this network, suggesting that their disruptions may have less immediate impact on other sectors. This ranking is used to establish the baseline system order for the temporal scenario analysis.

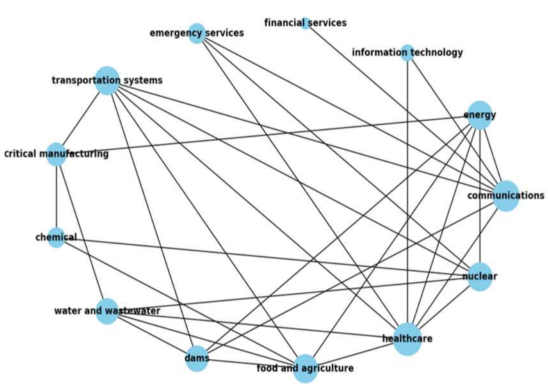

Fig. 1. Network representation of interdependencies among 13 critical infrastructure sectors for the cyber-physical systems of a metropolitan region

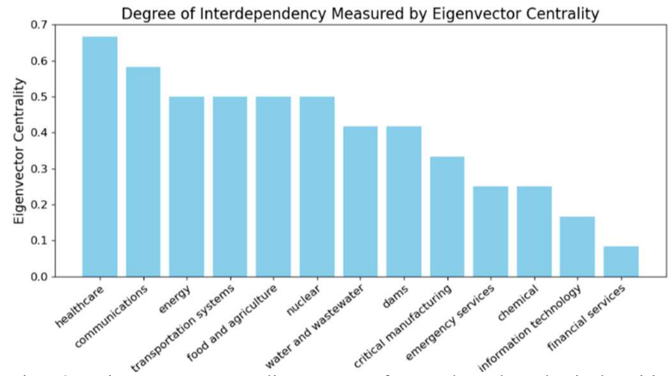

Fig. 2. Eigenvector centrality scores for each cyber-physical critical infrastructure sector, indicating the degree of interdependency within the network of the metropolitan region

Table 2 describes the recovery of critical infrastructure sectors following a disruptive event, with functionality levels measured at five intervals: 24 hours, 48 hours, 72 hours, 1 week, and 1 month. Each scenario (s.1 to s.5) represents the functionality percentage of each sector at a specific time post-disruption, with 100% indicating full operational capacity. The values are derived from reports describing the events and loss of functionality and discussion with subject matter experts on the 2010 Nashville flooding event. Initial impact varies significantly across sectors, with transportation systems and water and wastewater experiencing the most severe disruptions, as shown by their low functionality in early scenarios. Emergency services, healthcare, and nuclear maintain higher functionality levels. A month after the disruptive event, all sectors but transportation systems have returned to full function. These values are used to calculate the adjusted interdependency scores for the scenarios as in (3).

TABLE II. FUNCTIONAL PERFORMANCE OVER TIME FOR EACH CYBER-PHYSICAL CRITICAL INFRASTRUCTURE SECTOR, EXPRESSED AS A PERCENT OF FULL FUNCTIONALITY FOLLOWING A DISRUPTIVE EVENT IN THE METROPOLITAN REGION

	Scenario - Time Since Disruptive Event				
Node	s.1 24-hours	s.2 48-hour	s.3 72-hour	s.4 1-week	s.5 1-month
Communications	70	80	90	95	100
Energy	50	70	85	95	100
Information Technology	60	75	90	95	100
Financial Services	90	90	95	95	100
Emergency Services	100	100	100	100	100
Transportation Systems	20	40	60	80	95
Critical Manufacturing	100	100	100	100	100
Chemical	100	100	100	100	100
Water and Wastewater	30	50	70	90	100
Dams	90	90	100	100	100
Food and Agriculture	100	100	100	100	100
Healthcare	80	80	90	95	100
Nuclear	100	100	100	100	100

Fig 3. shows the baseline, minimum, and maximum rankings of each critical infrastructure sector across the scenarios. The baseline ranking is represented by the black diamond, and the red and blue bars show the range that the sector's ranking shifts across the disruptive scenarios. The blue

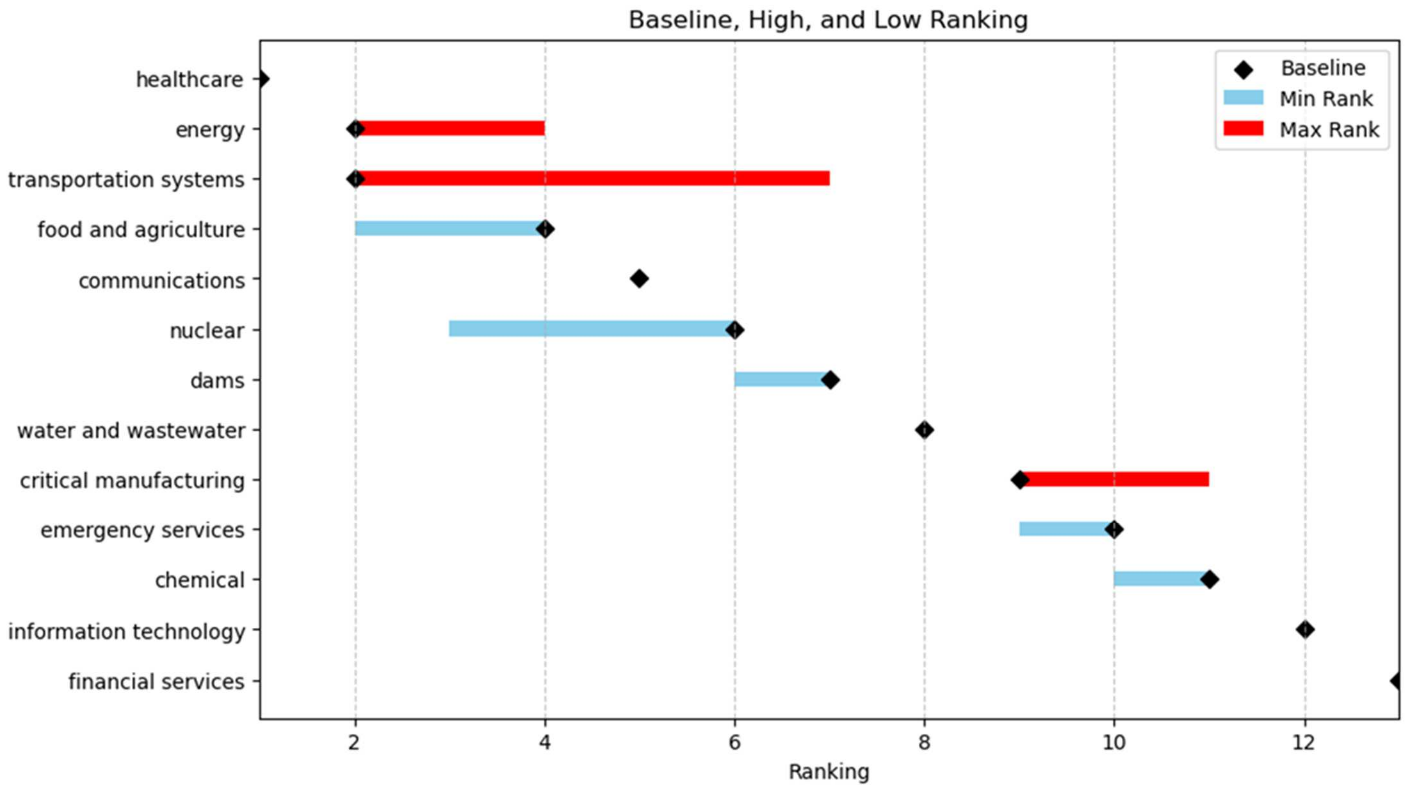

Fig. 3. Baseline, minimum, and maximum rankings of cyber-physical critical infrastructure sectors across scenarios for the metropolitan region. The black diamonds represent the baseline ranking of the sector. Blue and red bars indicate the range of rank change under disruption. The blue bar shows the highest rank of a sector, and the red bar shows the lowest.

segment represents the highest rank a sector achieves, and the red segment represents the lowest. This allows for the assessment of stability of system orders of sectors under disruption. Sectors with minimal movement in minimum and maximum ranking, such as healthcare, indicate stable ranking and reflects consistent criticality in the network across scenarios. Sectors with large shifts in ranking like transportation systems or nuclear are more sensitive to disruption across scenarios, and represents a potential vulnerability. In this case, healthcare is always the top-ranked sector, with information technology and financial services always the lowest ranked. Transportation systems has the largest potential change in rank.

Fig 4. describes the disruptiveness of each scenario relative to the baseline ranking. Using Spearman's rank correlation coefficient. As all coefficients are between 0 and 1, the value is given as $1 - \rho$ so that higher scores equate to greater disruptiveness. Higher disruptiveness scores correspond to scenarios with greater deviations from the baseline ranking, indicating greater shifts in sectoral priorities and interdependencies. The s.1 - 24-hour and s.2 - 48-hour scenarios have the highest disruptiveness scores, indicating greater changes in ranking during the early stages of disruption. The scores for s.5 – 1-month is close to 0, indicating that the infrastructure system has stabilized over time, nearly back to the baseline. This shows how the periods immediately after a disruptive event experience the most significant shift in critical infrastructure sector priorities. The disruptiveness in the days and weeks following the disruption can be used to assess how the region is recovering as whole.

V. Conclusions and Future Work

This paper presents a scenario-based resilience assessment framework for analyzing interdependent critical infrastructure systems. It analyzes how a disruptive event changes infrastructure sector priority orders. This approach identifies sectors most vulnerable to cascading failures and highlights how recovery dynamics affect the stability of sector interdependencies over time after a disruptive event. This is demonstrated on the Nashville region following the 2010 flooding event. The results demonstrate that sectors like healthcare, communications, and energy remain consistently critical to system functionality, while the transportation systems and water and wastewater sectors are sensitive to disruption. The results emphasize the importance of developing resilient infrastructure systems due to the high levels of interdependency across disparate sectors.

Future work will expand on these methods by refining the models of sector interdependencies. For instance, adjusting edge weights to account for bidirectional dependencies or introducing directional interdependencies could offer a more nuanced view of how disruptions cascade through critical infrastructure networks. Expanding the model to include specific infrastructure elements, such as roads, railways, or dams could provide a more detailed view of the assets of a region.

These extensions would allow decision-makers to tailor the network to the specifications of a region and better prepare communities for future challenges. A preliminary sensitivity analysis suggests that the sector rankings remain stable even under moderate perturbations to the original network links. Future research will address how network composition, including severing only a subset of interdependencies between sectors, impacts results.

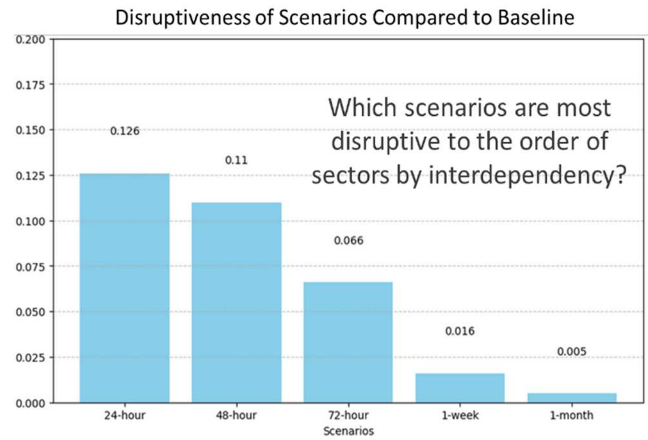

Fig. 4. Disruptiveness of scenarios relative to the baseline ranking of cyber-physical critical infrastructure sectors in the metropolitan region

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