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Incorporating Uncertainty into the Resilience Analysis of Interdependent Critical Infrastructure: A System-Level Robustness Analysis

Paolo Trucco, Giulio Tomasini, Boris Petrenj

School of Management, Politecnico di Milano, Italy. E-mail: paolo.trucco@polimi.it, giulio.tomasini@mail.polimi.it, boris.petrenj@polimi.it

Critical Infrastructure (CI) are increasingly exposed to multi-hazard events that produce spatially correlated and multi-node failures, challenging traditional approaches to resilience assessment. This paper presents a system-level robustness analysis of interdependent critical infrastructures under uncertainty, using the Stochastic Dynamic Functional Model of Critical Infrastructure Interdependencies (S-DMCI-e). The framework integrates stochastic simulation, dynamic functional modelling, and network-based robustness metrics to evaluate the temporal evolution of system performance under complex disruption scenarios. The analysis is built upon Robustness Network Analysis (RNA), which assesses both structural and functional resilience under multi-node failures. The approach is applied to a multi-layer transportation network in the Milan Metropolitan Area, with a focus on the 2014 Seveso River flooding as a representative widespread (compound) hazard impacting numerous nodes simultaneously. Results reveal non-linear system responses, including tipping points and anomalous increases in global efficiency caused by network contraction following node failures. These "efficiency spikes" are shown to be counterintuitive indicators of local performance improvement and may instead serve as early-warning signals of systemic stress. The results show that resilience cannot be inferred from static or deterministic metrics alone and must be understood as a dynamic and probabilistic property of interdependent systems. The proposed approach supports stress testing, early-warning interpretation and robustness-oriented planning for urban infrastructures exposed to multi-hazard risks.

Keywords: Critical Infrastructure Resilience, Robustness Network Analysis, Stochastic simulation, Multi-Hazard

1. Introduction

Modern societies depend on tightly interconnected Critical Infrastructure (CI) whose performance and resilience cannot be assessed in isolation. Transportation, energy, communication, and emergency response systems are increasingly coupled through physical, functional and organizational interdependencies. While this integration improves efficiency under normal operating conditions, it also creates pathways through which local disruptions may propagate and escalate into large-scale systemic failures (Meshkati and Tabibzadeh, 2016). Recent events, such as the large-scale blackout affecting Spain and Portugal in 2025, illustrate how failures in one subsystem can rapidly escalate into regional crises, exposing the fragility of tightly coupled CI systems (ANSA, 2025). Such cascading effects challenge risk management approaches, as they often emerge from complex interactions.

Multi-hazard events, that produce spatially correlated and multi-node failures, are becoming a growing concern in metropolitan regions (Elvas et al., 2021). Floods, heatwaves, earthquakes and large-scale technical accidents frequently affect clusters of infrastructure assets simultaneously. Understanding how disruptions propagate across CI nodes and sectors has become a major challenge due to increasing interdependencies (Prezelj and Žiberna, 2013). In urban environments, where infrastructure density and CI coupling are high, even moderate hazards can trigger disproportionate system-level consequences. Assessing resilience under such conditions therefore requires modelling approaches capable of representing correlated failures, temporal dynamics and uncertainty, in both disruption and recovery processes (Pescaroli and Alexander, 2016).

Despite significant advances in network reliability and infrastructure resilience modelling, many assessments remain deterministic or quasi-deterministic in nature. Although valuable, they often fail to capture the stochastic nature of disruptions. Without explicitly representing variability, such as uncertain failure timing, magnitude and interdependency strength, deterministic assessments lead to potentially misleading results.

Addressing these limitations requires a shift from static and deterministic assessments toward stochastic, dynamic and system-oriented modelling approaches. Such approaches must account not only for whether a system fails, but also for how failure unfolds over time, how redundancy erodes under stress and how recovery processes interact with ongoing disruptions. From a risk engineering perspective, this shift enables the identification of emergent behaviors, such as abrupt fragmentation, loss of functional efficiency or anomalous performance signals, that cannot be inferred from deterministic analysis alone.

This gap motivated the development of the Stochastic Dynamic Functional Model of Critical Infrastructure Interdependencies (S-DMCI-e), which extends the DMCI-e framework (Galbusera, Trucco and Giannopoulos, 2020) by integrating stochastic simulation, dynamic visualization and enhanced robustness assessment. This paper contributes a stochastic system-level resilience assessment of interdependent CI through the application of Robustness Network Analysis (RNA) within the S-DMCI-e framework. The approach integrates dynamic functional simulation with network-based robustness metrics to evaluate how system performance evolves under multi-node, spatially correlated failures.

The methodology is applied to a multi-layer transportation network in the Milan Metropolitan Area, using the 2014 Seveso River flooding as a representative multi-hazard scenario. The analysis reveals non-linear degradation patterns, tipping points and counterintuitive performance signals that may serve as early-warning indicators of systemic stress. By explicitly incorporating uncertainty, the proposed approach supports more realistic stress testing and robustness evaluation of CI systems.

This paper contributes to advancing CI resilience research by (i) integrating stochastic dynamic functional simulation with network-based robustness metrics, (ii) explicitly analyzing variability and confidence intervals of robustness indicators under spatially correlated failures, and (iii) demonstrating that counterintuitive behaviors such as efficiency spikes can act as early-warning signals of systemic stress rather than performance improvements.

2. Background and Related Work

The assessment of risk in CI has progressively shifted from component-level reliability analysis toward a systemic perspective that accounts for interdependencies and cascading effects. Interdependent infrastructures form complex socio-technical systems in which failures may propagate across sectors through physical, cyber, geographical and logical couplings (Rinaldi et al., 2001). These interdependencies represent a main source of systemic risk, as they enable the escalation of local disruptions or disturbances into large-scale disruptions. Understanding how such propagation mechanisms affect overall system performance is central to reliability and resilience analysis (Borghetti et al., 2021).

Network-based models have become a widely adopted framework for analyzing robustness and resilience in interdependent infrastructures. By representing systems as graphs, these models enable the evaluation of structural and functional properties such as connectivity, efficiency, redundancy and fragmentation under failure conditions. Common robustness metrics include the size of the largest connected component, global and local efficiency, average path length, clustering coefficients and aggregated robustness indices. While these indicators provide valuable insights into how networks respond to disruptions, they are often interpreted as static measures, implicitly assuming deterministic system behavior under disruption.

Many robustness assessments treat failure and recovery as deterministic processes. Analyses are frequently based on predefined attack strategies or hazard, producing single trajectories of system degradation. Such approaches may underestimate variability, fail to capture non-linear responses and overlook transient phenomena that emerge under uncertainty. In particular, when failures are spatially correlated or temporally clustered (as is typical in multi-hazard events) deterministic robustness metrics may provide an incomplete or misleading picture of system behavior. From a reliability perspective, this raises concerns about the validity of robustness indicators used for stress testing and decision support.

Multi-hazard events pose a particular challenge for robustness assessment because they frequently generate spatially correlated and multi-node failures. Floods, earthquakes and extreme weather events often affect infrastructure components in clusters, due to geographical exposure and shared vulnerabilities. In such scenarios, system performance may degrade abruptly once critical thresholds are exceeded. Capturing these effects requires modelling approaches that explicitly represent correlated disruptions and their temporal evolution, rather than relying on isolated component failures or random damage assumptions.

Recent research has increasingly emphasized the need for stochastic and dynamic approaches to robustness assessment in interdependent infrastructures (König and Rass, 2018; Rehak et al., 2022). By integrating probabilistic representations of failure and recovery with time-dependent system modelling, such approaches enable the exploration of variability, tipping behavior and emergent phenomena that are central to systemic risk. However, few frameworks combine stochastic functional simulation with network-based robustness metrics in a unified environment suitable for multi-hazard analysis. This gap motivates the approach adopted in this paper, which employs Robustness Network Analysis (RNA) within a stochastic dynamic functional modelling framework to assess system-level resilience under correlated failures.

3. Methodology: Stochastic Dynamic Robustness Analysis

The robustness analysis presented in this paper is conducted using the Stochastic Dynamic Functional Model of Critical Infrastructure Interdependencies (S-DMCI-e). The framework represents interdependent infrastructures as dynamically interacting functional systems, in which disruptions and recovery processes evolve over time and propagate through functional and logical interdependencies. S-DMCI-e explicitly captures the temporal dimension of system degradation and recovery while incorporating uncertainty in key processes through stochastic simulation. This combination enables a system-level assessment of robustness under realistic multi-hazard conditions.

Within the S-DMCI-e framework, infrastructure systems are modelled as networks of nodes connected by directed interdependencies through which disruptions propagate. Each node is a vulnerable component that delivers services and can be impacted by threats or dependencies from other nodes. The state of each node is described by a time-dependent inoperability variable, representing the fraction of functionality lost at a given time. Inoperability evolves according to dynamic functional relationships that account for both direct disruptions (i.e. impact of hazard) and indirect impacts transmitted through interdependencies (due to disruptions of other CI nodes). At the system level, node inoperability translates into degradation of service provision, enabling the analysis of how local failures affect overall system performance over time.

The methodology explicitly represents uncertainty in disruption and recovery processes. Failure onset times, disruption magnitudes, buffering and latency periods and recovery durations are modelled using probability distribution functions to reflect variability high in real hazard events and operational conditions. In addition, the effects of interdependencies may vary across simulations, capturing uncertainty in how disruptions propagate across CI. To propagate these uncertainties through the system model, a Monte Carlo simulation procedure is employed, generating ensembles of system trajectories rather than single deterministic outcomes. This stochastic formulation is essential for assessing robustness under multi-hazard conditions, where variability and correlation strongly influence system response.

3.1. *Robustness Network Analysis (RNA)*

Robustness Network Analysis (RNA) is used to evaluate system-level resilience by combining dynamic functional simulation with network-based robustness metrics. RNA goes beyond node-level analysis and focuses on how the structure and functionality of the entire network evolve under disruption. At each simulation timestep, the functional network derived from S-DMCI-e is analyzed using a set of structural and functional indicators that characterize connectivity, efficiency and redundancy. By tracking these indicators over time, influenced by stochastic parameters, RNA enables the identification of degradation patterns, critical thresholds and emergent behaviors that are not observable through static or deterministic analyses.

RNA uses a set of topological and functional indicators that capture different dimensions of system resilience.

- *Largest Connected Component (LCC).* Indicates the size of the largest subgraph where all nodes remain reachable (no node is isolated). A shrinking LCC reflects fragmentation due to node failures.
- *Global Efficiency.* Measures how efficiently information or service can propagate across the entire network. Lower values indicate a decline in system-wide performance.
- *Local Efficiency.* Reflects the ability of nodes' neighbors to maintain connectivity when the node itself is removed.
- *Average Path Length (APL).* Represents the average number of steps along the shortest paths for all possible pairs of nodes in the network. Increases in APL signal growing inefficiencies.
- *Clustering Coefficient.* Captures local redundancy and interconnectivity.
- *Robustness Index (RI).* Summarizes the quantitative measure of how well a network maintains its structural integrity or functionality under progressive failures or attacks.

The selected set of robustness metrics is not exhaustive but complementary: the LCC captures network fragmentation, global and local efficiency reflect system-wide and neighborhood-level (local) functional performance, APL represents accessibility degradation, and the Robustness Index provides a synthetic measure of overall resilience. Together, these indicators offer a sufficient and balanced representation of structural integrity, functional efficiency and systemic degradation under dynamic and stochastic disruption scenarios. These metrics are computed at each timestep, allowing the dynamic evolution of network performance to be analyzed. Importantly, the metrics are interpreted in relation with the stochastic simulation results, emphasizing trends, variability and anomalies rather than absolute values.

The robustness analysis focuses on system-level behavior under multi-node and spatially correlated disruptions, rather than on the criticality of individual components. While the modelling framework also supports stochastic node-level analyses (Vital Node Analysis – VNA; Petrenj and Trucco, 2014), these are not the focus of the present study. Human decision-making processes and adaptive operational responses are represented implicitly through recovery dynamics. This scope allows the methodology to concentrate on emergent system properties relevant to stress testing and reliability assessment.

4. Case Study and Scenario Definition

The Milan Metropolitan Area is used as a case study to evaluate system-level robustness under multi-hazard conditions. As a major European urban region, Milan is characterized by dense transportation infrastructures, high intermodal connectivity and strong functional dependencies among mobility assets and networks. At the same time, the area is recurrently exposed to hydrometeorological hazards, which have repeatedly caused widespread disruptions across multiple CI systems. This makes it a suitable application case for analyzing how correlated failures affect the robustness and resilience of interdependent infrastructure systems.

The analyzed system consists of a multi-layer transportation network comprising road infrastructure (major highways, beltways, interchanges and local roads), railway lines and stations, urban metro lines and three airports (Linate, Malpensa, and Orio al Serio) serving the metropolitan area. Nodes represent key operational assets such as road or rail sections, metro and train stations and airports. Interdependencies are mapped and used to model how disruptions in one subsystem to affect others through accessibility constraints and demand redistribution mechanisms. This representation supports the analysis of cascading effects and system-wide degradation under stress.

Among the hazards affecting the Milan area, flooding associated with the Seveso River represents a recurring and disruptive threat. Historical records indicate that the river has overflowed numerous times over recent decades, causing repeated interruptions to transportation services, particularly in densely urbanized zones. The 2014 flooding event is selected as a reference scenario for this study, as it produced extended service disruptions across multiple transportation assets and exemplifies a compound hazard affecting spatially clustered infrastructure components rather than isolated nodes.

To represent the spatially correlated nature of flooding impacts, the Seveso event is modelled as a multi-node failure scenario affecting geographically clustered groups of transportation assets (Figure 1). Nodes located within flood-prone areas are grouped into spatial clusters, each associated with a probabilistic failure mechanism. Within each cluster, node failures are modelled using Bernoulli-distributed random variables, reflecting uncertainty in local exposure, protection measures and operational conditions. This approach captures the essential characteristics of flood-induced disruptions (simultaneity, correlation and variability) while maintaining a level of abstraction appropriate for system-level robustness analysis.

Fig. 1. Spatial distribution of transportation assets exposed to the Seveso River flooding scenario. Spatial clusters of flood-prone nodes represent multi-node disruptions under hydrometeorological stress.

Two scenarios are analyzed. A reference scenario without external hazards is simulated to establish baseline system behavior and to isolate the effects of internal dynamics and stochastic variability. The Seveso flooding scenario is then simulated using the correlated multi-node failure model described above. For each scenario, 100 Monte Carlo simulations are run to capture variability in disruption and recovery processes. This approach enables the estimation of confidence intervals for robustness metrics, revealing variability that would remain hidden under deterministic modelling.

5. Robustness Analysis Results

The reference scenario (no external hazards) provides a baseline for assessing system robustness under nominal operating conditions (Figure 2). Across all Monte Carlo simulations, the transportation network shows stable behavior over time, with limited variability in structural and functional robustness metrics. Indicators such as global efficiency, largest connected component size and average path length remain within narrow confidence intervals, reflecting the inherent stability of the system in the absence of external stressors. This baseline confirms that deviations in the hazard scenario can be attributed to the imposed disruptions rather than to internal model dynamics.

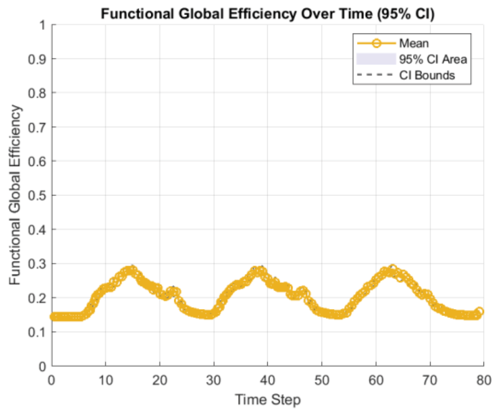

Fig. 2. Temporal evolution of global efficiency under the reference (no-hazard) scenario. Shaded areas represent 95% confidence intervals across Monte Carlo simulations, indicating stable system behavior in the absence of external stressors.

Under the Seveso flooding scenario, the system shows significantly different behavior. The concurrent failure of clustered nodes leads to rapid degradation of both structural and functional robustness metrics. Reductions in the size of the largest connected component (LLC) and increases in average path length (APL) indicate network fragmentation, while decreases in global and local efficiency reflect impaired system-wide accessibility. These effects emerge early in the simulation timeline and persist over time, highlighting the limited capacity of the system to absorb simultaneous disruptions affecting multiple interdependent components.

In contrast to the reference scenario, robustness metrics under the flooding scenario show substantial variability across stochastic simulations. Confidence intervals widen significantly, indicating sensitivity to variations in failure onset, disruption magnitude and recovery dynamics. This variability demonstrates that system robustness cannot be characterized by a single trajectory or point estimate, even when the hazard scenario is fixed. From a risk engineering perspective, these results highlight the importance of ensemble-based analysis for capturing the range of possible system responses under multi-hazard conditions.

The robustness analysis reveals the presence of non-linear system responses under correlated failures. In several simulations, relatively small additional disruptions within already affected clusters produce disproportionate declines in connectivity and efficiency metrics, indicating the existence of tipping points beyond which system performance degrades abruptly. Such behavior is not observable in deterministic or single-scenario analyses and highlights the role of interdependencies in amplifying the effects of multi-node failures. Identifying these thresholds is critical for understanding systemic vulnerability and for designing effective stress-testing strategies.

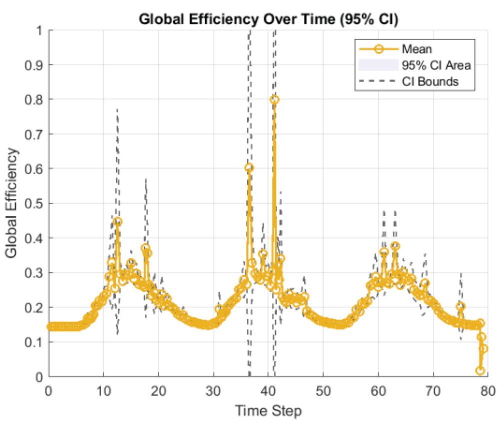

Fig. 3. Temporal evolution of global efficiency under the Seveso flooding scenario. Transient increases in efficiency coincide with hazard-induced node failures and network contraction, indicating structural stress rather than performance improvement.

In the flooding scenario, *efficiency spikes* (sudden and short increases in global efficiency) occur during ongoing disruption (Figure 3). At first glance, such increases could be misinterpreted as improvements in system performance. However, that these spikes result from structural contraction of the network following node failures: as nodes become inoperable (removed from the functional network), the remaining network may temporarily exhibit shorter average path lengths. Rather than indicating enhanced local performance, these efficiency spikes signal structural change since network becomes smaller and sometimes more compacts, but losses redundancy. These spikes may serve as early-warning indicators of systemic stress and structural changes due to node failures. Their absence in the reference scenario and consistent presence in the flood scenario confirm their association with hazard-induced disruptions.

Taken together, the robustness metrics illustrate that system performance under multi-hazard conditions cannot be inferred from any single indicator. Structural measures capture fragmentation and loss of connectivity, while functional measures reveal degradation in service efficiency and accessibility. Importantly, the temporal evolution of these metrics (and their variability across simulations) provides richer insight than static values. The results demonstrate that robustness assessment must account for dynamic interactions among failures, recovery processes and interdependencies to capture emergent behaviors relevant to systemic risk.

RNA demonstrates that multi-node, spatially correlated disruptions produce significant effects compared to simple (single node) disruptions. When several nodes fail simultaneously, the network cannot absorb the disturbance as redundancy collapses faster, especially in areas with limited intermodal alternatives. Temporal dynamics are volatile (wide confidence intervals across most metrics) and tipping points appear, where small additional failures lead to abrupt drops in network connectivity or efficiency.

These insights also highlight that modelling multi-hazard scenarios must account not only for the magnitude of disruptions but also for the variability and timing of cascading effects.

From a decision-making standpoint, RNA outputs inform:

- Spatial prioritization, identifying regions where small disruptions can fragment the network.
- Investment strategies, directed at reinforcing links or nodes that preserve large connected components.

- Early-warning analytics, where anomalous spikes in efficiency or sudden LCC reductions indicate rapid system degradation.
- Cross-sector coordination, as transportation impacts often mirror or amplify failures in other CIs, such as electricity or emergency response.

6. Discussion

The robustness analysis shows that resilience of interdependent CI systems is not fixed or deterministic. Instead, it is a dynamic and probabilistic property shaped by the interaction of failures, interdependencies and recovery processes. Under multi-hazard conditions that produce spatially correlated and multi-node failures, system performance does not follow a single and predictable degradation path. It evolves along multiple possible trajectories. This variability challenges traditional robustness assessments based on fixed scenarios or deterministic metrics and highlights the need to explicitly consider uncertainty and time-dependent behavior when assessing systemic risk.

The most important insight concerns how robustness indicators change over time and across stochastic simulations. Structural metrics such as the LLC and APL capture network fragmentation and loss of accessibility, while functional metrics such as global and local efficiency reflect degradation in service performance. The widening confidence intervals across these indicators demonstrate that system robustness cannot be described by single trajectories or point estimates, even when the hazard scenario is fixed. From a reliability engineering perspective, robustness assessment should therefore be ensemble-based, focusing on overall trends, variability and emergent behavior rather than nominal values.

A key result relates to the interpretation of counterintuitive robustness signals. The temporary increases in global efficiency during a disruption do not indicate improved performance. They result from structural contraction after node failures. As inoperable nodes are removed from the functional network, the remaining network may briefly show shorter average path lengths and higher efficiency values, even though redundancy and service capacity are reduced. For this reason, *efficiency spikes* should be interpreted as signals of structural stress and network reconfiguration, not as positive performance outcomes. Their consistent appearance under the flooding scenario, and their absence in the reference case, suggests that such anomalies may act as early-warning signals of impending systemic degradation.

These results have clear implications for engineering practice, regulation, and infrastructure operation. For regulators and infrastructure owners, they highlight the limits of compliance frameworks and stress tests based only on deterministic worst-case scenarios or static robustness metrics. System-level resilience cannot be reliably inferred from single-event analyses. Stress-testing approaches should instead include stochastic, multi-scenario evaluations that reveal variability, tipping points and non-linear responses. In particular, the identification of thresholds beyond which small additional disruptions cause abrupt network fragmentation indicates that regulatory stress tests should explicitly consider correlated failure scenarios, not only isolated component losses.

For infrastructure operators, the dynamic behavior of robustness metrics offers practical support for real-time monitoring and decision-making. Sudden changes or unusual trends in indicators such as global efficiency or connected component size may signal rapid shifts in network configuration that precede major performance losses. These signals can support early intervention actions, such as adaptive traffic management, load shedding or targeted deployment of resources, before cascading effects fully develop.

Overall, this discussion reinforces the need to move beyond deterministic robustness assessments toward uncertainty-aware, dynamic analyses that better reflect how interdependent infrastructure systems operate in practice. By combining stochastic functional simulation with network-based robustness indicators, the proposed approach provides a more realistic basis for stress testing, regulatory evaluation and operational preparedness under multi-hazard conditions. The results demonstrate that robustness is best understood as an evolving property shaped by uncertainty, interdependencies, and time-dependent responses.

7. Conclusions

This paper presented a stochastic, system-level robustness assessment of interdependent critical infrastructures using Robustness Network Analysis (RNA) within the S-DMCI-e framework. By integrating dynamic functional simulation with network-based robustness metrics, the approach enables the evaluation of how infrastructure systems evolve under multi-node, spatially correlated disruptions. Applied to a multi-layer transportation network in the Milan Metropolitan Area and a representative flood scenario, the analysis revealed non-linear degradation patterns, significant variability across simulations, and emergent behaviors that are not captured by deterministic robustness assessments.

Several limitations of the present study should be acknowledged. The robustness analysis models flooding impacts through probabilistic cluster-based failures, not through detailed physical hazard modelling. Moreover, adaptive human and institutional responses are represented implicitly through recovery dynamics rather than explicitly modelled. Despite these limitations, the proposed approach captures essential features of systemic risk in interdependent infrastructures and provides a scalable framework for exploring robustness under uncertainty.

From a risk and reliability engineering perspective, the results underscore the limitations of static and deterministic robustness metrics when applied to interdependent infrastructure systems exposed to multi-hazard events. The tipping points and anomalous efficiency increases demonstrate that system performance may exhibit counterintuitive behavior under stress, complicating interpretation and decision-making. By explicitly accounting for uncertainty and temporal dynamics, the proposed approach supports more realistic stress testing, enhances situational awareness and provides a richer basis for evaluating systemic risk in complex infrastructure networks.

The proposed methodology provides a flexible foundation for advancing robustness assessment in interdependent CI. Future research may extend the approach by integrating higher-resolution hazard models, real-time monitoring data, and explicit representations of human and organizational response. Such developments would enable the exploration of adaptive behaviors and the operationalization of dynamic robustness indicators as part of early-warning and decision-support systems. As infrastructure systems face increasingly complex and uncertain risk environments, stochastic and dynamic robustness analysis will play a crucial role in supporting resilient design and operation.

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