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Managing Physical and Economic Risk for Systems with Multidirectional Network Interdependencies

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Critical infrastructure networks, such as transportation and supply chains, are becoming increasingly interdependent. As the operability of network nodes relies on the operability of connected nodes, network disruptions have the potential to spread across entire networks, having catastrophic consequences in the realms of physical network performance and also economic performance. While risk-informed physical network models and economic models have been well-studied in the literature, there is limited study of how physical features of network performance interact with sector-specific economic performance, particularly as these physical networks recover from disruptions of varying durations. In this article, we create a generalizable framework for integrating Functional Dependency Network Analysis (FDNA) and Dynamic Inoperability Input–Output Models (DIIM), to assess the extent to which disruptions to critical infrastructure could degrade its functionality over a period of time. We demonstrate the framework using disruptive scenarios for a critical transportation network in Virginia, USA. We consider scenarios involving: (a) mild case that is relatively more frequent such as recurring traffic conditions; (b) moderate case involving an incident with a multihour delay, and (c) severe case that is relatively less frequent such as evacuation after a major hurricane. The results will be useful for network managers, policymakers, and stakeholders who are seeking to invest in risk mitigation for network functionality and economic activity.

KEY WORDS: Critical Infrastructure; disaster risk management; functional dependency network analysis; inoperability input–output model; transportation network

1. INTRODUCTION

The functionality of critical infrastructures, such as transportation, energy, and supply chains, is vital for health, safety, security, and economic activity. Because these infrastructure systems have a massive footprint on global activities, disruptions can have disastrous consequences that encompass both physical and economic dimensions. For example, the recent COVID-19/SARS-CoV-2 pandemic has caused major adverse impacts on the movement of goods and services (Ivanov, 2020), and has debilitated a myriad of industry and government sectors in global economies. Similarly, consider the February 2021 winter storm in Texas, which resulted in over four million customers without power, at least 57 deaths that were primarily related to complications from the energy loss (Sparber, 2021), and subsequent disruptions to dependent infrastructures. In addition to the humanitarian crisis arising from the energy failure combined with freezing temperatures, the event leads to $80–$130 billion in direct and indirect

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economic losses (Golding, Kumar, & Martens, 2021). As widespread disasters continue to occur, it is imperative for research to better understand the relationship between physical infrastructure systems and broader economic behavior.

Critical infrastructure systems are increasingly being modeled as networks, recognizing the interdependencies among their nodes. Disruptions in single nodes can potentially have widespread repercussions throughout the network. While these repercussions are typically studied by modeling degradation to network performance and functionality, there remain challenges for modeling and decision making when considering how these disruptions can potentially spread to other types of critical activities. More specifically, there is an urgent need to understand how disruptions to physical flows on these infrastructure networks impact sector-specific economic activity. As an added challenge, the role of time needs to be better understood, recognizing that the duration of various disruptions to physical flows can influence economic behavior. Finally, there is a need to leverage insights from physical and economic disaster models to understand the risk-based policy implications for infrastructure safety, functionality, and economic health.

To address the challenges described above, we create a generalizable framework for integrating Functional Dependency Network Analysis (FDNA) and Dynamic Inoperability Input–Output Models (DIIM) to assess the extent to which disruptions to critical infrastructure could degrade its functionality over a period of time. There are several contributions of this work. This article is one of the few recent works that explicitly address how physical network models can be integrated with economic models, in the context of disaster risk management. The novelty of this article is the development of a framework for utilizing network models to assess the extent to which disruptions to critical infrastructure could degrade its functionality over a period of time. Although the integrated model can be generalized for a variety of infrastructure systems, the focus of the application is on highway transportation systems with scenarios describing: (i) a mild case but relatively more frequent such as recurring traffic conditions; (ii) a moderate case of infrequent, yet severe, traffic disruptions; and (iii) a severe case but relatively less frequent such as evacuation after a major hurricane.

The organization of this article is as follows: Section 2 provides a background on risk principles, critical infrastructure, and case examples describing the use of FDNA and DIIM for infrastructure applications. Section 3 explains the framework of the article, describing the integration of FDNA with DIIM. Section 4 demonstrates the methods of the article on a transportation network in Virginia, USA. Finally, Section 5 provides conclusions and opportunities for future work.

2. BACKGROUND

This section describes relevant research relating to network modeling of disruptions. Section 2.1 describes general principles for risk-based analysis and decision making. Section 2.2 describes the need for greater understanding of risk for network-based infrastructure. Section 2.3 describes the role of FDNA and DIIM for assessing risk for critical infrastructure systems.

2.1. General Principles for Risk-Based Infrastructure Protection

The Society for Risk Analysis (2015) glossary refers to risk as in reference to:

> *"... a future activity [interpreted in a wide sense to also cover, for example, natural phenomena], for example the operation of a system, and define risk in relation to the consequences (effects, implications) of this activity with respect to something that humans value. The consequences are often seen in relation to some reference values (planned values, objectives, etc.), and the focus is often on negative, undesirable consequences. There is always at least one outcome that is considered as negative or undesirable."*

The Society for Risk Analysis glossary describes several qualitative definitions, including the ISO 31000 (International Organization for Standardization, 2018) definition, which suggests that risk relates to study of uncertainty on objectives. These definitions imply that analysts cannot anticipate every possible scenario, but can instead prioritize based on uncertainties. Decision making can instead study the most influential assumptions and uncertainties (Thekdi & Lambert, 2012).

There is also an emphasis on resilience for risk applications. It is particularly relevant to describe resilience in the context of this research since it is one of the parameters used in the infrastructure recovery model and case study explored in subsequent sections of this article. The Society for Risk Analysis (2015) presents a definition of resilience (among many) as: "Resilience is the ability of a system to reduce the initial adverse effects (absorptive capability) of a disruptive event (stressor) and the time/speed and costs at which it is able to return to an appropriate functionality/equilibrium (adaptive and restorative capability).” Therefore, risk-based investments must not only consider uncertainties in decision making but also investigate how to promote reduced losses and more effective recovery.

Managing risk associated with critical infrastructure is a major priority for nations and regions. The United States National Infrastructure Protection Plan includes initiatives for reduction of risk to national critical functions; and promoting security and resilience (Department of Homeland Security, 2018). Similarly, the European Programme for Critical Infrastructure Protection emphasizes the importance of protecting critical infrastructure, including the assessment of interdependencies that may be geographic or sectoral (European Union, 2020). In the United States, the Department of Homeland Security (2020) identifies 16 critical infrastructure sectors, including commercial facilities, communications, critical manufacturing, energy, water and wastewater systems, and transportation systems. Many of these types of infrastructure sectors can be viewed as a network consisting of nodes and edges. Flows on these networks often include physical resources. For example, transportation system network models may consider vehicle movement as a flow through the network. As a result of the network structure, interdependencies become an important factor in the modeling of these networks.

The current condition of these network-based critical infrastructures has been widely studied. The American Society of Civil Engineers (2016) estimates that deficiencies in the current condition of infrastructure have a major economic impact of \$3.9 trillion in losses to the U.S. GDP by 2025. Thus, infrastructure that has not been adequately maintained prompts even greater concern over the vulnerability to disasters, and also the capability of these systems to effectively recover following a disaster.

This article focuses on critical transportation infrastructure that is essential for conveying resources and sustaining the productivity of the economy. It is central to providing mobility for people and commodities; and is arguably critical in implementing disaster response logistics. A myriad of government policy directives has explicitly included transportation as a critical lifeline infrastructure. Hence, a reduced level in the capacity or functionality of the transportation infrastructure can have profound impacts not only on the mobility of the workforce but also in the shipment of resources that are crucial in the operation of practically all sectors of the economy. With the vulnerability of the transportation infrastructure to disruptions that recur on a regular basis (e.g., accidents and peak congestions), as well as catastrophic events (e.g., disasters such as hurricanes and earthquakes), government and private agencies need to create contingency plans to minimize the impact of such disruptions.

2.2. Interdependency Modeling for Network Risk

Critical infrastructure systems are ubiquitous, and their interdependencies have vital importance to the wellbeing of society. The interdependencies among critical infrastructures, which can be expressed as a supplier–receiver relationship, require close attention to understand the potential losses if degradation of one or more of these critical infrastructures occurs. Operability loss of a supplier system has the potential to cause cascading impacts over various critical infrastructure systems, including other sectors.

FDNA, a graph-based methodology, is used to assess the cascading effects of such interruptions by modeling the impact propagation among supplier receiver relationships. In other words, FDNA focuses on how the operability loss of a supplier causes cascading effects on its receiver systems (Garvey & Pinto, 2009). FDNA has been applied in various domains including space infrastructure (Guariniello & DeLaurentis, 2013), the security of Global Navigation Satellite Systems (Wang, Zhang, & Li, 2014), data dependency modeling (Cole, 2017), cyberspace (Servi & Garvey, 2017), power systems (Garvey, Pinto, & Santos, 2014), and finance (e.g., interbank lending) (Costa, McShane, & Pinto, 2015).

2.3. Economic Modeling for Network Risk

Several analytical models are available to assess the ripple effects of infrastructure disruptions across multiple interdependent sectors of the economy. One notable example is Leontief’s economic input–output (IO) model (Leontief, 1936), which will be used in this article to assess the direct losses attributable to the reduction in functionality of transportation, as well as the indirect effects due to sector interdependencies. Miller and Blair (2009) is the primary book that encompasses the theory behind the IO model, and also provides extensions and applications mostly in the domain of economics. Nonetheless, there has been a recent surge in the use of IO model extensions in other domains, such as in reliability and disaster risk management. Examples of recent IO-based articles on disaster risk management include COVID-19 modeling (Santos, 2020; Yu, Aviso, Santos, & Tan, 2020), water service disruptions (Pagsuyoin & Santos, 2021), and electric power disruptions (Lee, Park, Lee, & Ham, 2020), among others. Many nations in the world publish IO data since they are invaluable in understanding the key sectors in the economy. Key sector evaluation could be based on the magnitude of a sector's contribution to the gross domestic product, as well as the extent to which a sector is intertwined with others in its role as a supplier or as a consumer. Along with allied models like the computable general equilibrium, the IO model has been used recently in analyzing the impact of resilience in the context of disaster risk management of interdependent economic and infrastructure systems (see, for example, Rose & Liao, 2005).

The following section will provide a framework to integrate both physical and economic infrastructure risk models.

3. FRAMEWORK

3.1. Modeling Operability Loss Using FDNA

In this study, FDNA is employed to evaluate how the cascading impact of disruption propagates within the transportation network. The transportation network is modeled as a directed graph to reveal possible cascading effects caused by degradation occurred in one or multiple parts of a system. A dependency in FDNA topology is represented as a directed, acyclic graph, meaning that no cycles are allowed. Two functional nodes do not depend on each other. If needed, the only way of representing such dependency is granulation, to decompose the nodes to more specific functionalities so that the cycle between two nodes is converted into two separate dependency relationships among more specific dependency nodes. Garvey and Pinto proposed the constituent node concept to make the cyclic dependency decomposition process analytical (Pinto & Garvey, 2012).

In FDNA terminology, the operability of a node, also known as its measure of effectiveness, stands for the level of performance the node functions. Operability[1] has a value in a range from 0 to 1 (or similarly 0 to 100, when the operability level is expressed as a percentage) according to the utility the node yields. For example, the performance of a machine can be measured based on the number of its outputs, while its operability level concerns the performance. However, it is not required to have a linear relationship among the amount of the output and the operability value. Operability is determined based on the utility of the system; in other words, the total worth it provides to the system. If a node in an FDNA graph is fully operable (i.e., operability level is 100), it means that the relevant system completely satisfies the user's expectations. Contrarily, if a node is wholly inoperable (i.e., operability level is zero), it means that the relevant system dissatisfies the expectations.

In the Garvey's original FDNA, the operability level of a receiver node only depends on the operability level of its feeder nodes. However, this representation is insufficient in addressing the cases in which a receiver node degrades while all of its supplier nodes are fully operable. Tatar (2019) introduced the self-efficiency of an FDNA node, which is a multiplier to its operability value that reflects the operability degradation even if all of the feeder nodes are fully operable. self-efficiency is defined in the interval [0,1] and can have values lower than one if the node has an inherent issue that causes its performance to diminish. For operability calculations, self-efficiency value is inserted as a multiplier to the original FDNA equations.

The relationships among feeder and receiver nodes are represented by Strength of Dependency (SOD) and Criticality of Dependency (COD) relations. Baseline Operability Level (BOL) is defined as the operability level that a node operates without considering the contribution of its feeder nodes. The SOD relationship indicates how much a feeder node contributes a receiver node to increase the BOL of the receiver node. On the other hand, the COD relationship suggests how much a receiver node degrades from its BOL if its feeder node becomes inoperable for an extended period. For the sample FDNA graph in Fig. 1, the SOD relationship between a feeder node N_i and a receiver node N_j is governed by SOD

[1] For consistency with the supporting literature, we will use the term *operability* in the discussions associated with the FDNA model, and retain the term *inoperability* for the DIIM. Operability is the complement of inoperability (i.e., operability loss). Although they are both dimensionless numbers between 0 and 1, they have opposite interpretations are (i.e., the ideal case for operability is 1, while the ideal case for inoperability is 0).

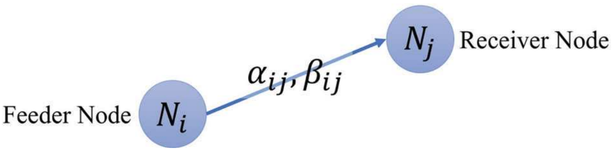


Fig 1. Sample FDNA graph with two nodes

fraction, α_{ij} that can have values from zero to one. On the other hand, the COD relationship is adjusted using COD constraint, β_{ij} that can have a range of values from zero to 100.

Operability of the receiver node (P_j) is determined based on the weakest link rule. According to this rule, the minimum value that comes from SOD and COD is used for calculating P_j. Eqn (1) relates the operability values of a feeder and receiver node.

$$P_j = SE_j * \text{Min}\left(\alpha_{ij}P_i + 100\left(1 - \alpha_{ij}\right), P_i + \beta_{ij}\right), \quad (1)$$

$$0 \leq P_i, P_j \leq 100, \; 0 \leq \text{SE}_\text{j} \leq 100,$$
$$0 \leq \alpha_{ij} \leq 1, \; 0 \leq \beta_{ij} \leq 100,$$

where P_i is the operability of the feeder node, P_j is the operability of the receiver node, SE_j is the self-efficiency of the receiver node, α_{ij} is the SOD fraction, β_{ij} is the COD constraint, and $100(1 - \alpha_{ij})$ stands for the BOL.

In the case that there are more than one feeder nodes of a receiver node, SOD relationships are aggregated by taking the average of their alpha values; however, COD relationships are taken into consideration separately based on the weakest link rule. Operability of N_j with n feeder nodes is calculated using Eqn (2).

$$P_j = \text{SE}_j * \text{Min}(\text{Average}(\text{SOD}P_{1j}, \text{SOD}P_{2j}, \ldots, \text{SOD}P_{nj}), \text{COD}P_{1j}, \text{COD}P_{2j}, \ldots, \text{COD}P_{nj}) \quad (2)$$

$$P_j = \text{SE}_j * \text{Min}\left(\frac{1}{n}\sum_{i=1}^{n}\alpha_{ij}P_i + 100\left(1 - \frac{1}{n}\sum_{i=1}^{n}\alpha_{ij}\right), P_i + \beta_{1j}, P_i + \beta_{2j}, \ldots, P_i + \beta_{nj}\right)$$

$$P_j = \text{SE}_j * \text{Min}\left(\frac{\alpha_{1j}P_1 + \alpha_{2j}P_2 + \cdots + \alpha_{nj}P_n}{n} + 100\left(1 - \frac{\alpha_{1j} + \alpha_{2j} + \cdots + \alpha_{nj}}{n}\right), P_i + \beta_{1j}, P_i + \beta_{2j}, \ldots, P_i + \beta_{nj}\right),$$

Operability values for each node of an FDNA graph is calculated by starting from the feeder nodes at the bottom of the hierarchy. The process ends on the receiver nodes at the top of the hierarchy. The cascading effects of the failure of a node are explored using this modeling approach.

3.2. Modeling Sector Interdependencies Using IO Models

This section will focus on the inoperability extension to the IO model. The term inoperability is akin to the concept of "unreliability" and as such its value ranges between 0 and 1 (Santos & Haimes, 2004). Hence, a value of 0 is the ideal case corresponding to a sector's "business as usual" mode of operation. Conversely, a value of 1 implies that the sector is completely dysfunctional or inoperable. The dynamic inoperability IO model, or DIIM in short, has been applied in diverse types of disaster scenarios, such as terrorist attacks (Santos & Haimes, 2004), hurricanes (Haggerty, Santos, & Haimes, 2008), electric power blackout (Anderson, Santos, & Haimes, 2007), droughts (Pagsuyoin, Santos, Salcedo, & Yip, 2020), COVID-19 pandemic (Santos, 2020), and several others. The formulation of the DIIM is shown below. The formulation comprises of the following terms: $\mathbf{q}(t+1)$ and $\mathbf{q}(t)$ correspond to the inoperability vector at time $t+1$ and t, respectively; $\mathbf{K}$ is the resilience matrix[2] that describes the rate with which the sectors are expected to recover to the "business as usual" levels; $\mathbf{A}^*$ is the interdependency matrix that describes the degree of interdependency across the sectors; and $\mathbf{c}^*(t)$ is the demand perturbation at time t.

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}\left|\mathbf{A} * \mathbf{q}(t) + \mathbf{c} * (t) - \mathbf{q}(t)\right|. \quad (3)$$

The concept of infrastructure inoperability in the context of IO modeling is not new. Nonetheless,

[2]The resilience matrix in the DIIM formulation is consistent with the definition of resilience in the SRA glossary, which was provided in the introduction section of this article.

linking it with the FDNA model discussed in the previous section is one of the novelties of this article. In addition, the "supply use tables" or SUT[3] that are published as a component of IO data sets could facilitate the assessment of the extent to which each sector is dependent upon a particular infrastructure, such as transportation. The transportation sector is comprised of various modes such as highway, rail, water, and air. This article will model, in particular, the impact of disruptive events on highway transportation. When the highway transportation is subjected to a disruption that adversely affects its capacity or operability for a certain period of time, sectors that are dependent upon it will be directly affected due to the delay of shipment of goods as well as degradation in the mobility of the workforce. Given the total production output of a sector (x_i) and its dependence on an infrastructure (w_i), one can estimate a dimensionless ratio w_i/x_i that essentially describes the weight of an infrastructure's contribution per unit output of a sector.

The SUT data described above could be leveraged to generate the "infrastructure-use" data to eventually calculate the ratio of an infrastructure's contribution to a particular sector (which we denote by w_i/x_i). In addition, suppose that we use the notation $d(t)$ to assess the percentage disruption to an infrastructure at time t (e.g., if the highway transportation were only operating at 80% capacity at time t, then $d\ (t) = 0.2$). Hence, the ideal case would correspond to a disruption of 0, and oppositely, a value of 1 would imply the infrastructure is in a complete failure state. We assume that the ratio w_i/x_i is constant, but when multiplied with $d(t)$ will generate the time-varying sector inoperability that is needed in Eqn (1). Hence, the inoperability of sector i at time t can be computed as shown below:

$$q_i\ (t) = (w_i/x_i)\ d\ (t)\,, \tag{4}$$

Using matrix notation, we can write the above equation into the following equivalent formulation, where: $d(t)$ is the infrastructure disruption at time t; diag($\mathbf{x}$) is the diagonalized form of the vector of production output $\mathbf{x}$ for the economic sectors; and finally $\mathbf{w}$ is the vector form of the numerator in the infrastructure-use balance ratio w_i/x_i.

$$\mathbf{q}\ (t) = \ d\ (t) * (\text{diag}\ (\mathbf{x}))^{-1}\mathbf{w} \tag{5}$$

Substituting the sector inoperability derived from Eqn (5) to (3) generates the updated inoperability of each sector at the subsequent time step $t+1$ taking into account the interdependencies amongst the sectors. After the determination of the updated inoperability, the corresponding economic losses can be computed via multiplication with the production output. Given a particular scenario, the aim of the study is to apply the FDNA to simulate the disruption to the transportation network and compute a system-wide inoperability and associated duration. FDNA results are then used to generate the disruption factor $d(t)$ for the DIIM to compute the value of inoperability at various increments of t until the sectors achieve recovery.

3.3. Integrated Framework for using Network Analysis to Assess System Recovery

This section will illustrate the integrated framework for assessing system recovery, as shown in Fig. 2. The methods first characterize the system, defining the relevant geographic area, nodes, edges, and metrics to model. Then, disruptive scenarios are developed to test various levels of system disruptions. FDNA is then applied to simulate the set of disruptive scenarios, resulting in a system-wide inoperability value, referred to as a disruption factor $d(t)$. Operability is determined based on the utility of the system; in other words, the total worth it provides to the system. The operability level of a node, which is in the interval [0,100], is used to measure how much the node meets its performance requirements. Then, the DIIM model uses the operability values computed from FDNA to compute the value of inoperability at various increments of t until the sectors achieve recovery. Finally, the results of the DIIM are used to evaluate implications for risk-based planning and investment.

The next section will describe the application of the integrated FDNA and DIIM framework for a critical infrastructure system.

4. APPLICATION AND RESULTS

This section provides a demonstration of the methods described above for a critical transportation network in Virginia, USA. Section 4.1 will describe

[3]Many national statistical agencies across the globe publish their IO data on a regular basis. In the United States, the Bureau of Economic Analysis publishes annual IO data in multiple formats. For example, the supply use tables are referred to as *make* table (row industries that produce the column commodities), as well as *use* table (row commodities that are consumed by the column industries).

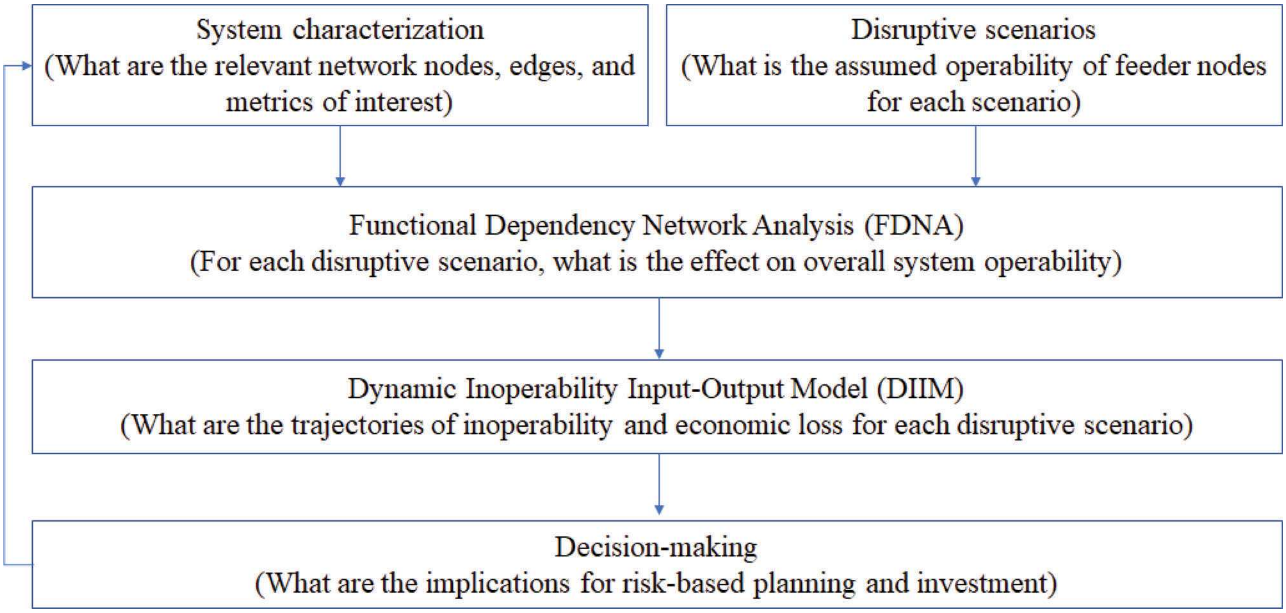


Fig 2. Overview of the integrated framework for modeling disruptions to infrastructure systems

the scope of the analysis. Section 4.2 will describe the application of FDNA for the case study. Section 4.3 will provide the application of DIIM for the case study. Section 4.4 will discuss the main findings and implications for decision-making.

4.1. Scope for Demonstration of Methods: Critical Transportation Network in Virginia, USA

The methods of this article will be demonstrated on a critical transportation infrastructure network in the Hampton Roads region of Virginia, USA. This region includes 16 cities and counties, including Virginia Beach, Norfolk, and Newport News. The Virginia Beach-Norfolk-Newport News Metropolitan Statistical Area accounted for over $100 billion GDP in 2018 (Bureau of Economic Analysis, 2020), which largely resulted from economic activity related to defense, port operations, and tourism. The Port of Hampton Roads is the third largest port in the country when measured by 20-foot equivalent units (Port of Virginia, 2020). The region also hosts military activities, including a strong naval presence (US Navy, 2020) and related private industries. The area is also known for tourism, hosting 19 million visitors annually (City of Virginia Beach, 2020).

The Hampton Roads region includes critical transportation connections for the state, including the Hampton Roads Bridges and Tunnels. The Hampton Roads Bridge-Tunnel (Interstate 64) connecting Hampton and Newport News to Norfolk and Virginia Beach, is particularly of high importance as it is used by over 100,000 vehicles per day during high-tourist seasons. The Monitor-Merrimac Memorial Bridge-Tunnel (Interstate 664) has a lower capacity but also serves critical importance for the region as it connects Newport News and Hampton to Suffolk and Chesapeake. The Berkley Bridge (Interstate 264) allows traffic from I-464 in Chesapeake to merge with I-264 traffic in Norfolk (Virginia Department of Transportation, 2020a).

Disruptions to the critical transportation network of the Hampton Roads region can potentially greatly reduce the mobility within the region and throughout the state. Minor disruptions can severely limit daily economic activity. Major disruptions, such as natural disasters, can potentially cause severe physical and economic consequences. Fig. 3 shows that the region contains critical hurricane evacuation routes, denoted by arrows. The shading of the figure also shows hurricane evacuation zones, with darker colors denoting types of evacuation zones. Evacuation patterns are particularly complicated for the region due to the reliance on tunnels and bridges that are vulnerable to weather conditions. For example, during Hurricane Dorian in 2019, it was warned that the Hampton Roads Bridge-Tunnel may close temporarily, halting evacuation efforts. Additionally,

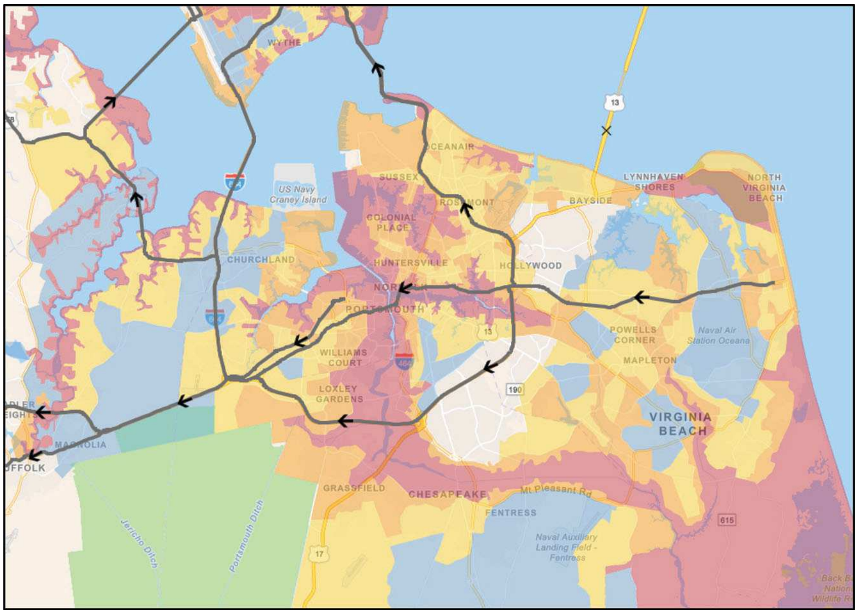


Fig 3. Evacuation zones in the Hampton Roads region of Virginia, USA. The arrows denote critical hurricane evacuation routes. Source: Virginia Department of Emergency Management (2020)

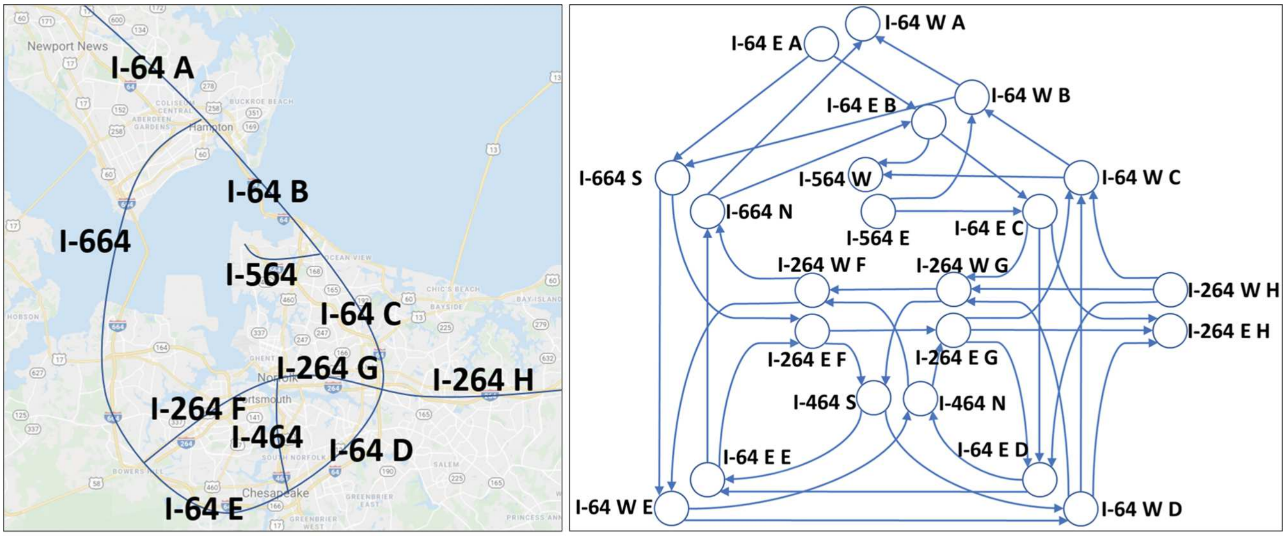
routes operated at wind restrictions and reduced speed limits (Pilot, 2019). These types of changes can be particularly concerning for residents with delayed evacuation (Florido, 2018).

Mobility for this region is also important because of the large propensity for hurricane and tropical storm activity. For example, the 1999 Hurricane Floyd resulted in one of the largest United States peacetime evacuations (National Weather Service, 2020). The region is also vulnerable to other types of natural and human-induced disasters. For example, the region is associated with a relatively high sea-level rise (Bekaert, Hamlington, Buzzanga, & Jones, 2017). Additionally, there is concern over local traffic and congestion impacting the mission and performance of military installations (Hampton Roads Transportation Planning Organization, 2011).

The demonstration of methods studies four scenarios. Scenario 1 involves a mild incident involving disabled vehicles or accidents on I-264 toward Virginia Beach, which would lead to a backup on eastbound I-264 and connected roadways (duration of 3 hours). Scenario 2 involves a moderate incident with a bridge tunnel closure that causes a major backup in both directions along I-64 Hampton Roads Bridge Tunnel and connected roadways (duration of six hours). Scenario 3a involves a major hurricane incident with evacuation, that assumes hurricane evacuation routes are operating at capacity with designated lane reversals in place. This scenario assumes a relatively extended evacuation process with a duration of two days, which is consistent with patterns suggesting evacuations begin two days prior to landfall (Dow & Cutter, 2002). Scenario 3b studies a major incident with evacuation due to a hurricane, which focuses on the post-evacuation, representing the time between the evacuation and when residents are permitted to return. This scenario models the underutilization of the roads, assuming that the bridge tunnels are operating at a reduced capacity due to reduced speed limits and demand, with a duration of one day. Traffic is assumed to primarily include emergency personnel and late evacuees.

4.2. Application of the FDNA on Transportation Infrastructure of Hampton Roads

The transportation infrastructure of Hampton Roads is analyzed by converting the interstate road network into a functional dependency graph and employing FDNA algebra. Interstate road network is divided into road segments, as shown in Fig. 4(a). Both directions for these road segments are converted into the nodes of the FDNA graph, as shown in Fig. 4(b). In this Fig., the edges represent the traffic flow directions at each ramp of all intersections among these road segments.



(a) (b)

Fig 4. (a) Interstate road network of Hampton Roads area (b) FDNA nodes and traffic flow

4.2.1. Operability of Road Segments and Transportation

The average daily traffic (ADT) data for each road segment (Virginia Department of Transportation, 2020) indicates that the regular number of vehicles for the relevant road segment is expected to handle. For this simulation, it is assumed that if this amount is met, it means the operability for the road segment is 100. The operability value of a road segment is calculated by the dividing number of daily vehicles by average daily number of vehicles. If the total number is less than the average daily number of vehicles for a given day, it means that the road segment has not met the expectation, hence the operability is less than 100. On the other hand, if more vehicles than average travel within a day, the road can supply this demand until it reaches its capacity. Within this range, operability is considered 100, even if it is numerically higher.

The overall operability level of transportation is a measure that indicates the performance of the whole interstate road network of the Hampton Roads area. It is equal to the weighted sums of all road segments in the network where weights are calculated based on each road segment's ADT value. This value is the main output of the FDNA model for each scenario that is eventually used as an input for the DIIM model.

4.2.2. Capacity

In order to conduct evacuation scenarios, the capacity of multilane interstate roads should be calculated. Base Capacity equation (Margiotta & Wasburn, 2017) is as follows:

$$\text{Base Capacity} = 100 + 20 * \text{Speed (mph) for Speed} \leq 60;\ 2,200 \text{ otherwise}$$

In order to use in the simulation scenarios, average capacity is approximated as 50,400 vehicles per lane per day by taking the average of base capacity values for speed values of 45, 50, 55, 60, 65, and 70, using the base capacity equation.

4.2.3. SOD for Transportation

Since the interstate roads are limited-access roads, each road segment is mostly fed by the preceding road segments. The SOD relationship among the road segments depends on the ADT travel through the ramps connecting each pair of road segments. The relevant alpha values are determined by approximation of the actual ADT values provided by VDOT. The direction of the SOD relationship is the inverse of the traffic flow direction since a traffic jam in the following road segments causes lines at the preceding road segments. Since each scenario has a different traffic jam location, the specific road segments

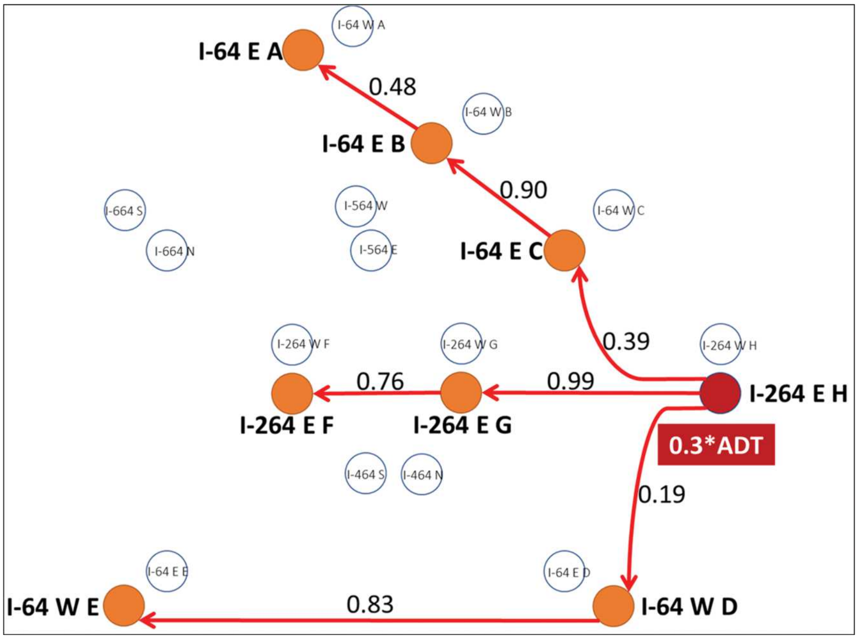


Fig 5. Dependency structure for scenario 1

and dependency relationships under focus change for each scenario.

Since the COD relationship is not relevant for the transportation case, it is not included in the analyses.

4.2.4. *Simulation Scenarios*

In this section, the loss of operability is in Hampton Roads transportation network is analyzed based on four scenarios. Each scenario is taken into consideration from the functional dependency perspective, and the operability values of dependent nodes are calculated using FDNA algebra. At the end of the process of calculating individual operability values for each road segment, the operability of transportation is calculated as a weighted sum.

Figs. 5, 6, 7, and 8 present the dependency structure for each simulation scenario. Red nodes are the road segments that initial traffic jam occurs. Orange nodes are affected by the operability loss of these road segments. Yellow nodes represent the road segments that operate at full capacity. Red arrows show the dependency direction during a traffic jam (i.e., operability loss) while yellow arrows depict the dependency direction at full capacity (i.e., overloaded traffic). Thin blue lines show the traffic flow direction. Alpha values (i.e., the strength of dependency fraction) are shown for the relevant dependency relationships.

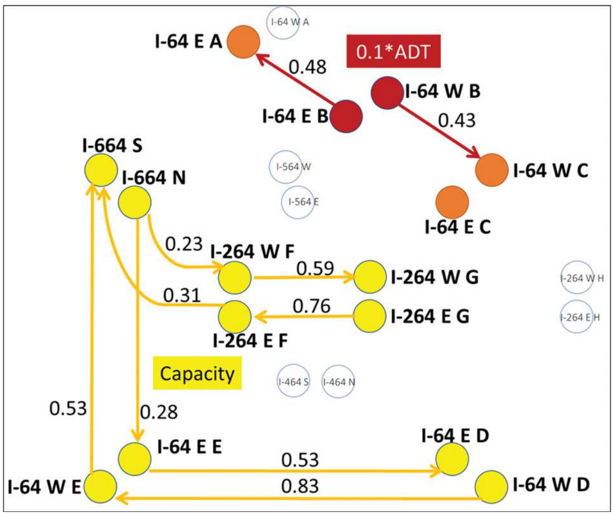


Fig 6. Dependency structure for scenario 2

Scenario 1: Mild incident. Disabled vehicles cause a major backup in eastbound Interstate (I) 264 toward the beach (node I-264 E H) with a flow rate decrease from ADT to 0.3*ADT for 3 hours. This causes a backup on I-64 eastbound (and westbound after I-264 junction) and I-264 eastbound (See Fig. 5). Although this is a minor incident, it is interesting that only one initially blocked segment can cause seven other road segments to get jammed.

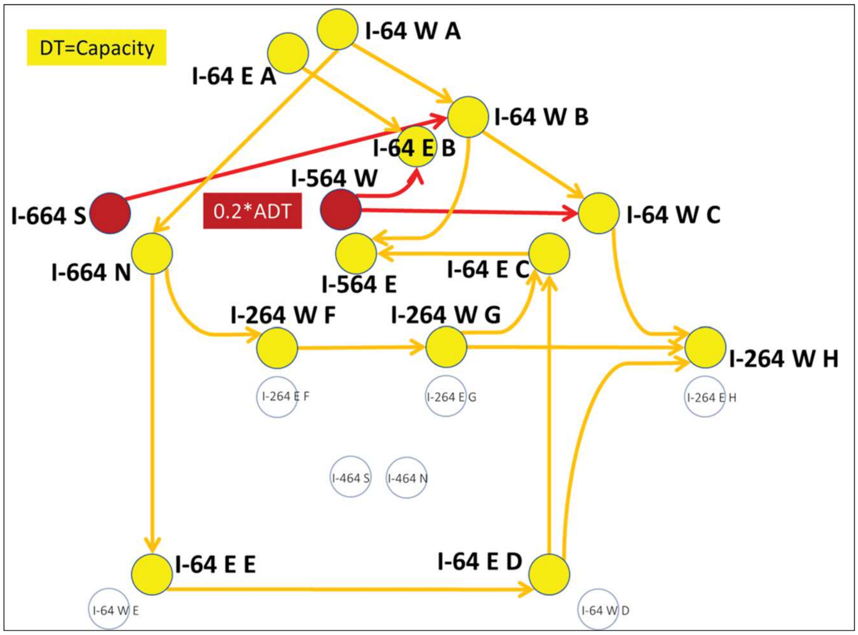


Fig 7. Dependency structure for scenario 3a

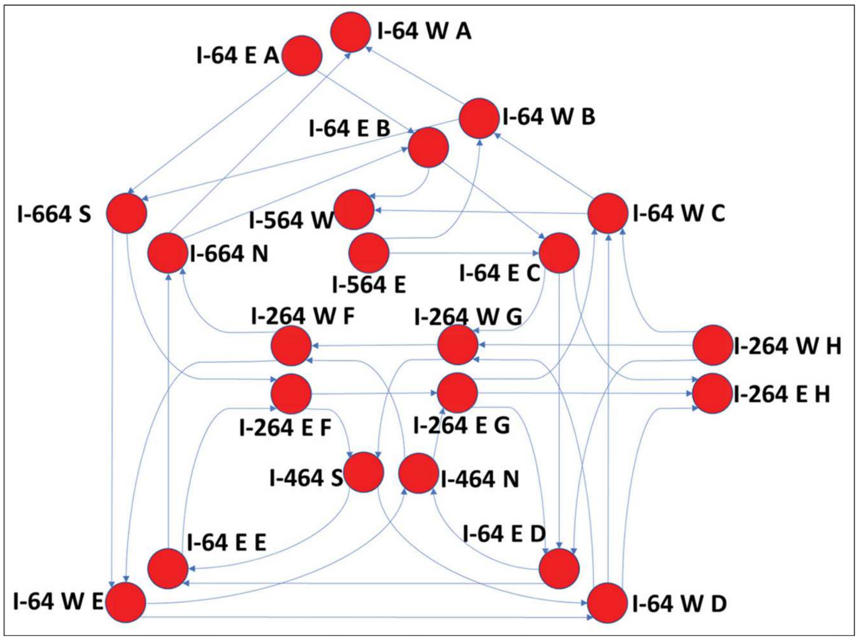


Fig 8. Dependency structure for scenario 3b

Scenario 2: Moderate incident. Major backup in both directions along I-64 Hampton Roads Bridge-Tunnel (I-64 E B & I-64 W B) with a flow rate decreases from ADT to 0.1*ADT for 6 hours, causing jam on I-64 E A and I-64 W C and redirecting traffic to the other bridge-tunnel (I-664 N & I-664 S) and eventually to I-264 (nodes G and F), I-64 (nodes D and E) is simulated. Here, I-64 E C is not affected much since this road segment is east of the tunnel (See Fig. 6). Therefore, its lower operability value is not because of congestion, but merely because of less traffic. Similarly, I-64 W A is also located east of the tunnel. The impact on this road segment is much lower since the traffic redirected to the other tunnel would eventually feed it up to a normal level. This scenario shows the importance of the existence of a redundant bridge-tunnel.

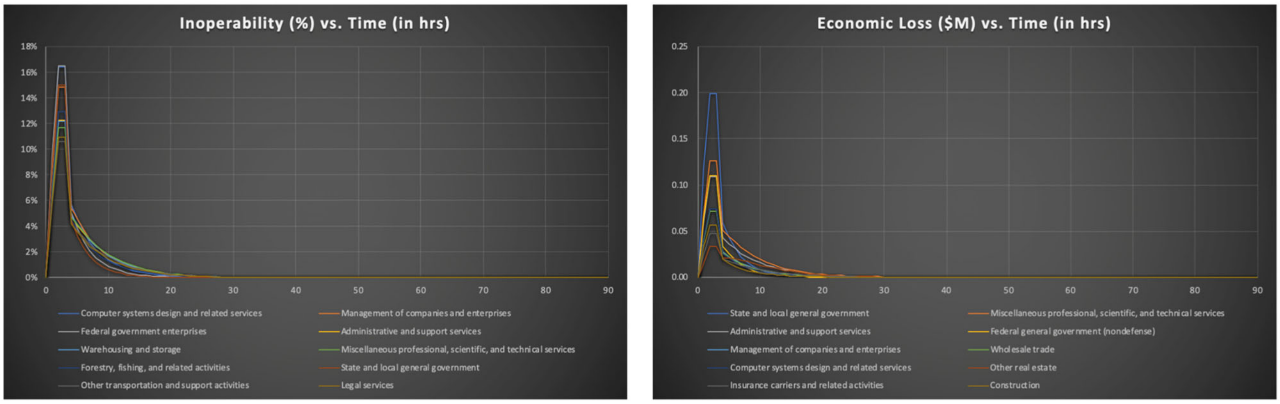


Fig 9. Inoperability versus time and economic loss versus time for scenario 1

Scenario 3a: Major incident (during evacuation). A major incident is simulated for two days when the Governor orders lane reversal on I-64 (E A and E B), evacuation routes operate at full capacity, and other nodes are at low numbers. This scenario provides a representation of a rare evacuation case, serving as a simulation that would not be possible to test on real roads (See Fig. 7).

Scenario 3b: Major incident (after the evacuation, before evacuees are permitted to return). Rather than a wide impact traffic jam, the traffic is significantly lower than the usual due to reduced demand. This scenario only considers the demand by emergency personnel and late evacuees. Since there is no jam, no road segments cause a jam on another segment; hence, there is no dependency relationship in this scenario. Therefore, there are no red or yellow arrows, which are used to show dependency directions, in Fig. 8, but blue arrows to show the traffic direction. The simulation is conducted for one day. The utility of all road segments is very low because of the ongoing hurricane threat. This is the scenario that has the lowest overall operability value since the demand is low. It is inevitable to observe the economic consequences of this situation when it is integrated into DIIM.

The final output of FDNA analyses, the operability values of transportation for the scenarios 1,2,3a, and 3b are 84.68, 86.10, 95.15, and 15.22, respectively.

4.3. Application of the Dynamic Inoperability IO Model

In this section, results from the DIIM model are presented. The approach is to extract the outputs from the FDNA simulation, notably the highway network inoperability and recovery duration for the scenarios considered in this study. The trajectories of inoperability and economic loss are presented for each of the scenarios as depicted in subsequent discussions.

Scenario 1: Mild incident

In the mild incident scenario, we considered a 15.32% inoperability to the transportation network with a duration of 3 hours. In terms of inoperability, Fig. 9 shows the ten most affected economic sectors as follows: (1) *Computer systems design and related services;* (2) *management of companies and enterprises;* (3) *federal government enterprises;* (4) *administrative and support services;* (5) *warehousing and storage;* (6) *miscellaneous professional, scientific, and technical services;* (7) *forestry, fishing, and related activities;* (8) *state and local general government;* (9) *other transportation and support activities;* and (10) *legal services*.

In contrast, the top 10 sectors in terms of economic losses are: (1) *State and local general government;* (2) *miscellaneous professional, scientific, and technical services;* (3) *administrative and support services;* (4) *federal general government (nondefense);* (5) *management of companies and enterprises;* (6) *wholesale trade*; (7) *computer systems design and related services;* (8) *other real estate;* (9) *insurance carriers and related activities;* and (10) *construction*.

Clearly, the rankings generated using the inoperability measure are different from those generated using the economic loss measure. Sectors that suffer significant economic losses are typically those that contribute more to the regional GDP (e.g., state

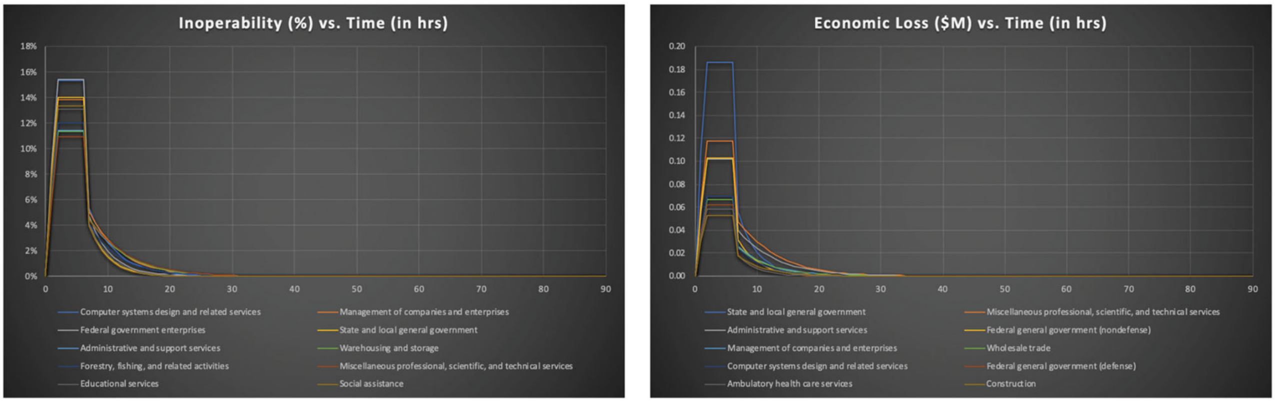


Fig 10. Inoperability versus time and economic loss versus time for scenario 1

and local government sector, which is highly visible and active in the region). Conversely, sectors such as warehousing and storage, as well as forestry, fishing, and related activities have been included in the inoperability ranking despite their absence in the economic loss top ten ranking. Policymakers need to recognize both inoperability (i.e., the extent to which a sector is "damaged") and economic loss (i.e., monetary value associated with the loss of operability) when making resource optimization decisions associated with disaster risk management.

Scenario 2: Moderate incident

In the moderate incident scenario, we considered a 13.90% inoperability to the transportation network with a duration of 6 hours. In terms of inoperability, Fig. 10 shows the 10 most affected economic sectors as follows: (1) *Computer systems design and related services;* (2) *management of companies and enterprises;* (3) *federal government enterprises;* (4) *state and local general government;* (5) *administrative and support services;* (6) *warehousing and storage;* (7) *forestry, fishing, and related activities;* (8) *miscellaneous professional, scientific, and technical services;* (9) *educational services;* and (10) *social Assistance*.

In contrast, the top 10 sectors in terms of economic losses are: (1) State and local general government; (2) miscellaneous professional, scientific, and technical services; (3) administrative and support services; (4) federal general government (nondefense); (5) management of companies and enterprises; (6) wholesale trade; (7) computer systems design and related services; (8) federal general government (nondefense); (9) ambulatory healthcare services; and (10) construction.

As with the previous scenario, the rankings for inoperability and economic loss are different. Also unique in this scenario are sectors that were not previously included within the inoperability top 10 ranking, such as educational services and social assistance. Furthermore, the ambulatory health care services sector is now included within the economic loss top 10 ranking, which is intuitive given the existence of major hospitals in the region (e.g., Sentara).

Scenario 3a: Major incident (during evacuation)

In this scenario, we consider the evacuation due to a hurricane incident, particularly during the evacuation timeline itself. This scenario is designed to be an extreme but plausible case in which a massive evacuation takes place over multiple days. We considered a 4.85% inoperability to the transportation network with a duration of 2 days. In terms of inoperability, Fig. 11 shows the ten most affected economic sectors as follows: (1) *Computer systems design and related services;* (2) *Federal government enterprises;* (3) *Management of companies and enterprises;* (4) *State and local general government;* (5) *Social assistance;* (6) *Educational services;* (7) *Nursing and residential care facilities;* (8) *Ambulatory health care services;* (9) *Forestry, fishing, and related activities;* and (10) *Administrative and support services*.

In contrast, the top 10 sectors in terms of economic losses are: (1) State and local general government; (2) Miscellaneous professional, scientific, and technical services; (3) Administrative and support services; (4) Federal general government (nondefense); (5) Management of companies and enterprises; (6) Computer systems design and related services; (7) Wholesale trade; (8) Federal

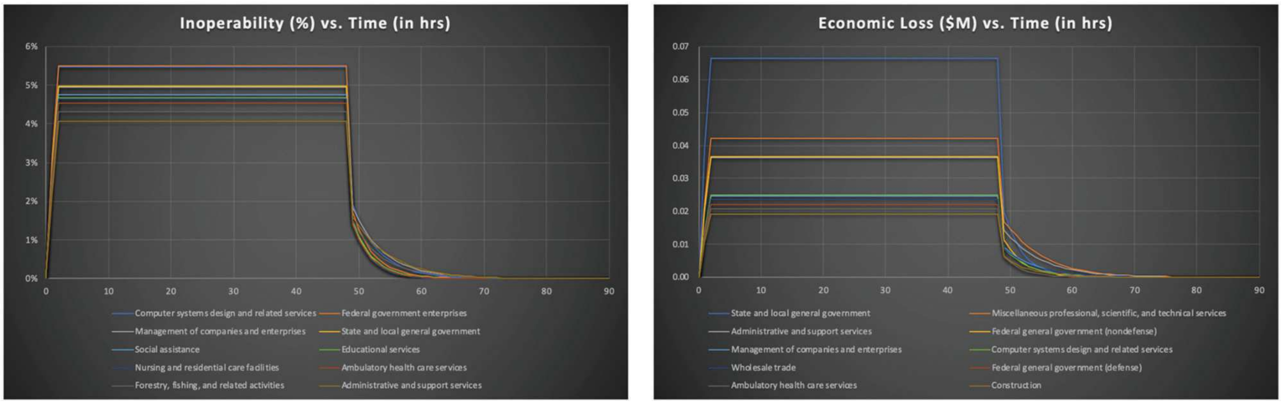


Fig 11. Inoperability versus time and economic loss versus time for scenario 1

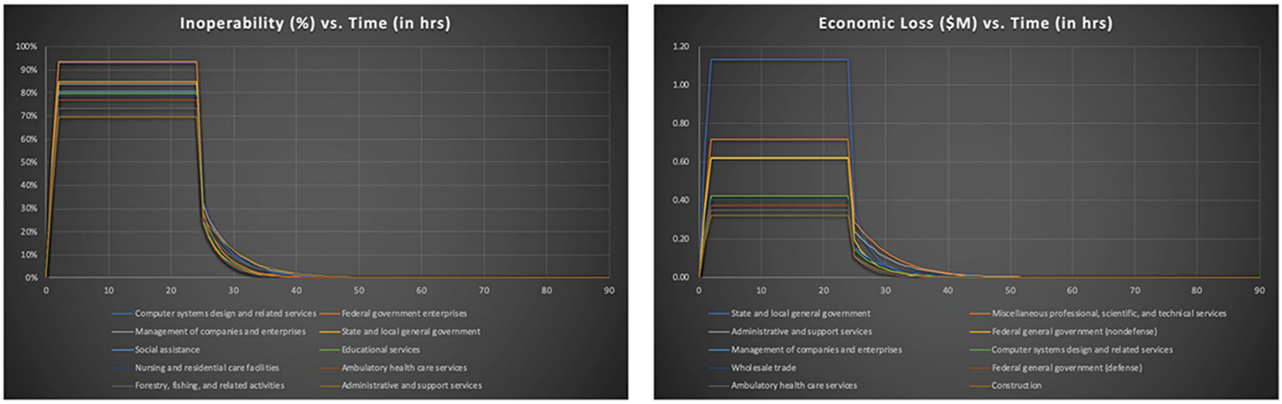


Fig 12. Inoperability versus time and economic loss versus time for scenario 1

general government (nondefense); (9) Ambulatory healthcare services; and (10) Construction.

Relative to the previous scenario, the economic loss ranking is practically the same with a few shuffling. The major change was in the inoperability ranking where we now see the prevalence of sectors that are actively engaged in disaster risk management such as: social assistance; nursing and residential care facilities; and ambulatory health care services.

Scenario 3b: Major incident (after the evacuation, before evacuees are permitted to return)

In this scenario, we consider a hurricane incident, but the focus is on the time period directly after the evacuation but prior to the return of the evacuees to the region. We considered an 84.78% inoperability to the transportation network with a duration of 1 day. In terms of inoperability, Fig. 12 shows the 10 most affected economic sectors as follows: (1) Computer systems design and related services; (2) Federal government enterprises; (3) Management of companies and enterprises; (4) State and local general government; (5) Social assistance; (6) Educational services; (7) Nursing and residential care facilities; (8) Ambulatory health care services; (9) Forestry, fishing, and related activities; and (10) Administrative and support services.

In contrast, the top 10 sectors in terms of economic losses are: (1) State and local general government; (2) Miscellaneous professional, scientific, and technical services; (3) Administrative and support services; (4) Federal general government (nondefense); (5) Management of companies and enterprises; (6) Computer systems design and related services; (7) Wholesale trade; (8) Federal general government (nondefense); (9) Ambulatory healthcare services; and (10) Construction.

Comparing scenarios 3a and 3b, the rankings are identical since these scenarios have relatively longer

Table I. Summary of DIIM Results for Different Case Study Scenarios

Scenario #	Scenario Title	Operability Level (%)	Inoperability Level (%)	Duration	Loss ($M)
1	Scenario 1: Mild incident	84.68	15.32	3 hours(0.125 days)	8.07
2	Scenario 2: Moderate incident	86.10	13.90	6 hours(0.25 days)	12.49
3a	Scenario 3a: Major incident (during evacuation)	95.15	4.85	2 days	29.25
3b	Scenario 3b: Major incident (after)	15.22	84.78	1 day	256.42

durations and are more severe than those of the first two scenarios. Nonetheless, the overall loss for Scenario 3b is much higher than that of Scenario 3a. This is because the inoperability level for the transportation network is much higher for Scenario 3b compared to that of Scenario 3a.

The results for the four scenarios are summarized in Table I. The table shows the inoperability and duration parameters for each scenario, which were used as the inputs for the DIIM. The last column of the table shows the economic loss for each scenario, which was aggregated for all the economic sectors in the affected region. The dynamic trajectories of the economic loss for each of the top 10 most affected sectors are shown in Figs. 9–12. From Table I, we can draw the following conclusions. The economic loss for the mild scenario (Scenario 1) has been found to be $8.07 million, in contrast to the $12.49 million loss incurred in the moderate scenario (Scenario 2). Considering that both the foregoing scenarios only lasted for fractions of a day, these losses are deemed to be quite significant.

For relatively longer durations of inoperability, the losses are expected to be higher. For example, in Scenario 3a, the economic loss has been found to be $29.25 million. In contrast, the loss incurred in Scenario 3b is much higher at $256.42 million since the prespecified inoperability disruption is also markedly higher compared to Scenario 3a (i.e., 84.78% versus 4.85%, respectively). Note that Scenario 3b does not at all correspond to the evacuation return. It is the period after evacuation and prior to the evacuation return. During this period, the roads are assumed to be significantly underutilized, and the losses can be assessed based on the reduced levels of economic activities relative to the "normal" use of the roads by the workforce, business sectors, and more notably, trade and tourism. Furthermore, inoperability is interpreted either as exceeding the capacity due to the incident (Scenario 3a) or underutilized capacity due to aberrant low road activity (Scenario 3b). Note that Scenarios 3a and Scenario 3b are not mutually exclusive. As a matter of fact, the losses for Scenarios 3a and 3b of $29.25 and 256.42 million, respectively, can be combined to get an overall loss for a major hurricane incident. In summary, the magnitude of losses for each of the four scenarios can be used to inform and justify the need for preparedness investments.

4.4. Findings and Implications for Decisionmakers

Evaluating risk for this case study involves exploring the impact of uncertainties on objectives, as framed by the International Organization for Standardization (2018) and others (Thekdi & Lambert, 2015). Here, the uncertainties can be understood using the studied scenarios, assumptions, and resulting model outputs. We pose several questions that can guide decision making:

Which uncertainties matter the most? Some scenarios result in higher levels of severity. In the case study, Scenario 3b, evacuation due to a hurricane incident, particularly after the evacuation but prior to the return of the evacuees to the region, resulted in the highest loss. From a decision-making perspective, there may be a need to further study this scenario using additional iterations of the model. Additional iterations could involve using more specific scenario designs that are able to capture a wider variety of storm conditions, evacuation policies, and assumptions about human behavior models during evacuation.

Which sectors matter the most? Some sectors were highly impacted across all studied scenarios. For example, in all four of the studied scenarios, the topmost affected sector for inoperability was the *Computer systems design and related services* sector. Additionally, sectors including *Management of companies and enterprises; Federal government enterprises;* and *State and local general government* were found in the top 10 affected sectors for inoperability. Similarly, in all four studied scenarios, the topmost affected sector for economic losses was *State and local general government*. Additionally, sectors including *Miscellaneous professional, scientific, and technical services; Administrative and support services;* and *Federal general government (nondefense)* were found in the top 10 affected sectors for economic losses. This multidimensional information provided by the inoperability and economic loss measures can guide policymaking by directing mitigation activities toward these particular sectors.

What is the knowledge basis for assumptions? Some assumptions may require further study in later iterations of the model. For example, assumptions about ADT and the most appropriate multiplication factors were used. While ADT was based on known and publicly available data, there may be issues with spatiotemporal accuracy, future projections, and relevance. However, these types of assumption issues would be consistent across the studied scenarios, therefore, would not favor or disfavor any particular scenario. In stages of planning for system investment and further study, it may be necessary to further address issues of assumptions.

What types of uncertainties matter the most? We pose the question: From a policymaking and investment perspective, should minor and recurring scenarios be prioritized above extreme event or disaster scenarios? This is a policy question that involves decisionmakers and public health values that would require extensive further study.

How should the reiteration of the model be conducted? It may be necessary to reiterate the methods of the article to address a wider variety of influential scenarios to perform a more granular analysis. For example, analysts may choose to model additional hurricane types and additional evacuation assumptions concurrently in a more refined analysis. Additionally, decisionmakers may choose to concurrently study only those scenarios that share a similar severity profile. For example, they may choose to only evaluate hurricane-related scenarios concurrently. There may also be a need to perform weighting on particular model outputs in order to capture the relative importance of scenarios that can be due to: (i) likelihood of scenarios, (ii) relevance for decision making, or (iii) varying amounts of uncertainty. Finally, the integrated FDNA-DIIM framework—which in this article was applied to a highway transportation network—can be used for modeling disruptions in maritime networks and other modes of transportation. For example, opportunities exist to apply the FDNA-DIIM framework to model the ripple effects of the six-day closure of the Suez Canal due to a large container vessel that blocked this vital commerce channel on March 23, 2021. Nonetheless, as with any case studies, constraints in data availability may pose as a challenge with the formulation and application of the FDNA-DIIM framework. It highly hinges on the availability and accuracy of traffic and other relevant volume occupancy data, as well as economic IO data. For a transportation network that is situated near the boundaries of several nations (such as the Suez Canal), a multicountry model is warranted, which in turn requires temporally and spatially accurate IO data for the affected countries.

5. CONCLUSIONS

This article has presented an integrated framework for modeling the relationship between disruptions to infrastructure networks and economic activity. This work is one of the few recent attempts to study the relationship between physical network models and economic assessment of network recovery that considers time as a factor in the degradation of functionality. In particular, this article is the first to operationalize the integration of the FDNA and DIIM to form a cohesive risk-based model of critical infrastructure that can be used to guide risk-based decision-making and investment[4].

The methods of the article were demonstrated using disruptive scenarios for a critical transportation network in the Hampton Roads region of Virginia, USA. We studied scenarios involving a mild incident, moderate incident, and two scenarios involving a severe incident. The results found several policy-related implications, including both sectors and uncertainties that were particularly influential in decision making for various infrastructure interventions. The results will be useful for critical infrastructure managers who seek to prioritize investments in network reinforcements, with a broader goal of promoting and security infrastructure functionality and economic activity. Moreover, calculating the economic impact of disruptive scenarios will improve risk communication for the public. While the methods were applied to a transportation network, they are generalizable for a variety of networked

[4]The conceptual model developed by Garvey, Pinto, and Santos (2014) is limited only to the FDNA and the static version of the inoperability model. Furthermore, the case study presented in the current paper utilizes actual traffic data (e.g., ADT) and region-specific IO data; hence achieving a more seamless integration between FDNA and DIIM.

infrastructure systems. Significant opportunities remain in specializing the integrated FDNA-DIIM framework for other networked systems (e.g., air and water transportation modes, electric power grids, oil and gas pipelines, and supply chains).

There are several opportunities for additional study. First, there is an opportunity to further understand how specific investments can be prioritized across competing nodes. For example, a logical next step would be to understand the impact of reinforcing specific nodes on economic loss and recovery duration. Second, there is an opportunity for further study on how to approach a sensitivity analysis of the model results, taking into consideration the complex mathematical relationships represented in the FDNA and DIIM. Sensitivity analysis, for example, can be performed to assess the volatility of the model results due to single and simultaneous changes in variables (e.g., infrastructure demand, available capacity, severity of scenario, and time), as well as parameters that were assumed to be fixed due to limitations in data resolution (e.g., average daily traffic, vehicle type and occupancy, and annualized production output data for various economic sectors, among others). While the authors believe that the integration of the physical and economic models is in itself is a novel contribution of this article, opportunities exist to integrate social and human decision-making models to more accurately simulate evacuation choices and behaviors. Finally, opportunities exist to use the work of this article for modeling and decision making for resilient architecture design that applies to a variety of networked infrastructure types.

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