# Integrated Stochastic Inventory and Input-Output Models for Enhancing Disaster Preparedness of Disrupted Interdependent Sectors

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## ABSTRACT

Natural and man-induced disasters have been found to categorically disrupt the vital functions of several infrastructure and economic sectors that produce commodities and provide services indispensable for any given region to thrive. The intrinsic interdependencies linking these sectors exacerbate the disaster consequences as exemplified by a wider range of inoperability across interdependent sectors. The unavailability of the required production input resulting from non-operational sector sources amplifies economic losses. However, inventory levels during a disruptive event influence sector capability to absorb these input requirements while in an inoperable state. Hence, disaster preparedness may be improved by a thorough implementation of inventory-enhanced policies to target critically disrupted interdependent sectors. This research investigates the reliability of economic loss estimates and sector recovery analysis as influenced by the inherent stochastic behavior of inventory. Inventory modeling is incorporated into a dynamic cross prioritization plot (DCPP) that merges the risk assessment metrics, namely, economic loss and inoperability into a decision support tool that prioritizes the critical sectors for inventory enhancement. Risk assessment models without factoring inventory at the time of disastrous events were found to have overestimated total economic loss by approximately 22% relative to simulated inventory values derived from empirical cumulative distribution functions of individual economic sectors. Furthermore, the critical sectors found by implementing the DCPP varied significantly between the deterministic and stochastic models of inventory for average and extreme-event scenarios. Hence, the inclusion of inventory modeling reflects a more realistic system representation and strengthens the basis of the decision support tool in selecting the critical sectors. While the study focuses on enhancing preparedness through stochastic modeling of inventory, complementary analysis is recommended to manage the resilience of the service sectors.

# 1. INTRODUCTION

## 1.1. Preface

Recent debilitating disasters like hurricanes Katrina and Irene, the earthquake in Haiti, the September 11 attack, and the 9.0 magnitude earthquake in Japan have brought significant losses to the economy and left vivid and life-changing experiences to the society. These natural and man-made disasters present tremendous amounts of challenges affecting regional productivity in intricately interdependent systems. For example, hurricanes have been known to greatly affect physical infrastructures that, in turn, disrupt the production of goods (i.e. damaged power and communication lines) and its distribution (i.e. transportation systems). The disruption of such functions can easily propagate the disaster consequences to other sectors that are heavily dependent on these products and services for their operations especially when the levels of inventory are at their minimum. As indirectly hit sectors are unable to receive their production input requirements from the disrupted sectors and no material inventory on hand, they also become inoperable. As a result, an entire region experiences greater economic loss and a wider scope of inoperability.

In fact, intrinsic interdependencies are a characteristic of today's large and complex infrastructure and economic systems. And in the aftermath of natural and man-made disasters, the physical, economic, and logical connections facilitate the propagation of initial disruptions across the sectors of a given region.[1] This is apart from observed significant consumption pattern changes and production output adjustments over disaster recovery periods.[2]

A holistic and immediate recovery management of systems disrupted by disastrous events must be achieved. Disaster preparedness plans should be formulated such that the recovery of disrupted critical economic sectors and infrastructure systems are prioritized in order to counter the ripple effect of disaster consequences across the region. Risk assessment and appropriate inventory management policies must be developed to help suppress the proliferation of inoperability and minimize the losses across the disrupted interdependent sectors. However, although interdependencies between sectors are increasingly becoming more pervasive, significant gaps still remain in the area of coordinated disaster policy making and risk analysis.

The principal concept of this research is that maintaining higher levels of inventory increases a region's capacity to provide the production input requirements while some sectors remain inoperable. System recovery may be improved and economic losses reduced through the implementation of inventory-enhanced policies to critically disrupted sectors. However, resources for supporting these inventory-enhanced policies are finite and may not be available completely or simultaneously as needed within the recovery period. Hence, prioritization of identified critical economic and infrastructure systems with respect to the allocation of these resources must be made. The use of these resources translates into an increase in the capacity of manufacturing sectors (a subset of *critical* sectors) to deliver their expected production output even when they are in a disrupted state thus, deterring the proliferation of inoperability across the economic region. Prioritization also allows enhancement of inventory in the earlier stages of recovery which decreases the chance of further propagation of disaster consequences across the region.

The significant contribution of this research is the integration of a stochastic input-output model of interdependent inventory into a Dynamic Cross Prioritization Plot (DCPP)—an interactive graphical critical sector selection tool developed by Resurreccion and Santos [41]. The research will investigate the capacity of current levels of inventory of manufacturing systems to absorb the input requirements of a region undergoing disaster recovery and formulate a decision support system to help generate cost effective inventory enhanced policies that will improve regional disaster preparedness. Various stakeholders, domain experts, and policy makers whose preferences would affect this decision process as well as budget allocations will be incorporated into the decision support system.

### 1.2. Scope

The Homeland security policy makers have deliberately included hurricanes in its fifteen planning scenarios.(3) Hurricanes can damage physical infrastructure systems, disrupt the flow of traffic, and can cause substantial productivity losses. The Commonwealth of Virginia belongs to the top ten states that have experienced the most number of hurricane events on recorded history (4) incurring $625 million worth of damages from hurricane Isabel in 2003.(5,6) To generate significant insights on Virginia's disaster preparedness and recovery policies, a case study implementing the DCPP is presented to identify and prioritize the critical sectors in the region. More importantly is designing this prioritization process in allocating the finite resources to strengthen Virginia's overall disaster preparedness capability. Hence, the inventory enhancement plans to be formulated and evaluated in this research will be based on the production output and inventory levels of the economic and infrastructure systems of Virginia.

The purpose of this research is to formulate a stochastic model of inventory that provides more reliable estimates for the risk analysis metrics, namely, economic losses and sector inoperability. There may be other sources of uncertainty but the focus of this endeavor is to characterize inventory uncertainty in relation to risks. Utilizing principles of risk analysis, the research will analyze the impacts of inventory enhanced policies on the recovery behavior of interdependent sectors during a disaster. Inventory enhanced scenarios will be generated by integrating stochastic inventory modeling into the DCPP. The efficacy of these policies that allocate resources to the most critical economic sectors will be assessed based on dynamic inoperability input–output models (DIIM). In particular, the contributions of this research are as follows:

(i) Expand the DCPP sector selection tool to integrate the stochastic behavior of inventory in manufacturing sectors.
(ii) Design a structured process for identifying and quantifying disaster perturbation scenarios associated with the inoperability and recovery parameters of the interdependent sectors.
(iii) Formulate measures of performance for evaluating the efficacy of inventory enhanced policies for different clusters of economic sectors.
(iv) Formulate generalizations on the adequacy of (or the lack thereof) current inventory levels to absorb production input requirements under extreme event scenarios.
(v) Provide recommendations to prioritize critical sectors and identify areas for broader preparedness applications.

The research involves a comparison of a prioritization model that does not factor inherent stochastic inventory behavior (e.g. scenario 0) with a model that incorporates the uncertainty of interdependent inventory in estimating risk analysis metrics (e.g. scenario 1). The baseline case from which generated inventory enhanced scenarios (scenarios 2 to 5) are evaluated is anchored on scenario 1 as the absence of uncertainty in inventory modeling overestimates economic losses and is not reflective of real system behavior.(42) Without loss of generality, these case studies serve as a repeatable methodology that can be extended to other disasters that directly affect different sets of initially disrupted sectors.

The decision support system with an integrated stochastic inventory model developed in this research features a front-end graphical user interface (GUI). The support system is capable of identifying different portfolios of critical sectors for inventory enhancement, given different combinations of priority levels across inoperability and economic loss minimization objectives, and various levels of resource availability.

## 2. REVIEW OF LITERATURE

### 2.1. Modeling Disrupted Interdependent Systems

Hurricane consequences are well documented in the literature. Blake *et al*.[4] provide a list of destructive hurricanes in terms of intensities, as well as the resulting economic losses and human casualties. Hurricane Katrina's landfall in 2005 unleashed a devastating $96 billion worth of damages to the Gulf Coast region affecting 138 counties—making it the most destructive hurricane on record in terms of economic losses.[7] Other relatively less intense hurricanes can also bring significant regional losses. A case in point, Hurricane Isabel in 2003 brought massive flooding and destruction to the Hampton Roads region of Virginia. The Commonwealth sustained $625 million of damage[6] and a death toll of 36 people.[5] The flooding of a bridge-tunnel in Virginia, which lasted for nearly a month, is one of the many examples of how an infrastructure failure can impair regional mobility and productivity.[8]

Risk assessment and management have paved the direction for minimizing the impact of disruptive events such as hurricanes. Typically the process is guided by the triplet of questions in risk assessment: (i) What can go wrong? (ii) What is the likelihood? and (iii) What are the consequences?[9] In risk management, we ask another set of triplet questions: (i) What can be done and what options are available? (ii) What are the tradeoffs in terms of all costs, benefits, and risks? and (iii) What are the impacts of current decision on future options?[10]

Inventory management concepts, typically used in enhancing the efficiency of manufacturing systems, have also gained growing importance in the domain of disaster preparedness.[11,12] With the just-in-time (JIT) philosophy driving today's supply chain-oriented systems, it has been observed that quite a lot of these systems are unprepared for "low probability, high-impact disruptive events."[11] Chopra and Sodhi[13] identify two mitigation strategies for the management of risks resulting from disruptive events: (i) increasing inventory and (ii) providing redundant suppliers. However, the impact of disruptive events may be great enough that even the essential set of suppliers become unavailable when these events occur. Hence, a balance has to be made between allocating some resources to keep a level of inventory as buffer and the cost of inoperability. As to the level of inventory required to reduce risks from disruptive events, Barker and Santos[11] evaluated the impact of incorporating inventory policies in the DIIM on the resilience of disrupted systems. They discussed how most of the key inventory control approaches found in practice and in literature are in conflict with the notion of preparedness and investigated tradeoffs between multiple objectives given various inventory policies.

This research acknowledges the importance of inventory or the provision of buffer in addressing disaster preparedness. Inventories are a form of resilience adjustment that functions as temporary sources of production requirements while the actual sector provider is inoperable. As raised by Rose and Liao, system losses are underestimated by individual sector resilience where the use of inventories, among other measures, becomes an adaptive response of economic sectors to avoid incurring maximum potential losses.[42] Hence, a manufacturing sector's level of inventory at the occurrence of a disastrous event is a significant factor that can be associated with its resilience. And as this level involves uncertainty, investigating resilience enhancement from inventory requires stochastic modeling. This has been the motivation to incorporate inventory uncertainty in a critical sector selection tool that helps generate inventory enhancement policies to improve sector preparedness.

The economic impacts of devastation from natural disasters and recent man-caused attacks have already impelled further research on disaster preparedness and management policies. Recent works on disaster risk analysis have extensively explored the areas of infrastructure renewal involving interdependencies and preparedness strategy development using extensions of the input–output (I-O) model.

Chandana and Leung[14] emphasized that the effectiveness of the infrastructure renewal process involves consideration of system requirements, processes, and interdependencies in disaster situation management. Arboleda *et al*.[15] analyzed interdependencies between infrastructure systems and the operational vulnerability of health care facilities. Chang *et al*.[16] presented a conceptual framework for investigating infrastructure failure interdependencies focusing on power outage consequences. Although these models integrate interdependencies to disaster management, a more holistic and quantitative approach for accounting economic loss and recovery capability of disrupted interdependent sectors has been provided by using I–O models.

## 2.2. I–O Model and Extensions

The following sections provide an overview of the classic Leontief I–O model and progressively discuss the formulations of the IIM and its dynamic extension.

### *2.2.1. Leontief's I–O Model*

The I–O modeling views the economy as a set of interconnected sectors, which both produces and consumes goods in the process of production.[17] The Leontief model, which describes the output of each sector as a combination of intermediate consumption and final demands, has proven to be a useful model for evaluating impacts of economic disruptions across multiple sectors of a regional economy.[18,19] The National Cooperative Highway Research Program[20] recognizes the I–O method in its guidebook for assessing the social and economic factors in infrastructure management domain. Extensions and current frontiers on I–O analysis can be found in Dietzenbacher and Lahr.[21] The availability of high-resolution economic data and social accounting matrices enables the application of I–O model and its hybrids for analysis of relatively small regions (e.g., analysis of infrastructure disruptions in Portland[22]).

From the general representation of interindustry flows of goods[23] and the I–O economics first discussed by Leontief,[17] "individual industry sectors are interconnected with commodity transactions." Hence, total production output includes commodity flows among interdependent sectors in addition to the output intended to satisfy final demand. In Leontief's model, Equation (1), the total production output or the expected output, $x$, of a sector is the sum of what it provides as input to other sectors and its output for the final consumption of end-users. This relationship for all the sectors involved is summarized in (1)

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{c}, \qquad (1)$$

where $\mathbf{x}$ is the output vector, $\mathbf{c}$ is the consumption vector, and $\mathbf{A}$ is the interdependency matrix. Given $n$ sectors, $\mathbf{x}$ and $\mathbf{c}$ are column vectors with $n$ elements each and $\mathbf{A}$ is an $n \times n$ matrix of technical coefficients.

Each element, $x_i$, of $\mathbf{x}$ represents the total production output of an industry sector $i$. Each technical coefficient, $a_{ij}$, of the interdependency matrix $\mathbf{A}$ indicates the proportion of the total production requirement of sector $j$ that is provided by the production output of sector $i$. The collection of elements under a column $j$ of $\mathbf{A}$ corresponds to the distribution of inputs from the row sectors as proportions of the total input requirements of sector $j$. Finally, each element, $c_i$, of the consumption column vector $\mathbf{c}$ is the final demand for sector $i$ by the end users.

*2.2.2. IIM*

Initially intended for analyzing changes in consumption, the I–O model has been extended into an IIM by Haimes and Jiang[24] and Santos and Haimes[23] to investigate losses brought about by cascading effects of disruptive events to interdependent sectors. Of particular interest is the quantification of the economic loss and inoperability of a sector arising from (i) disruptions to the sector itself and (ii) failure to receive the expected production requirements from other disrupted sectors.[23]

The IIM has been featured in several applications. Examples include modeling of infrastructure interdependencies and risks of terrorism,[25,26] regional electric power blackouts,[27] and inventory management.[11] The IIM was also applied to problems with sequential decisions and multiple objectives, such as the biofuel subsidy analysis explored by Santos *et al*.[28] Crowther *et al*.[29] have demonstrated the decision-making capability of the IIM for developing multiregional disaster preparedness policies for hurricane events, which can complement geospatial analysis.[30] Santos *et al*.[31] have also formulated a conceptual framework for bridging IIM analysis with agent-based simulation for interdependent infrastructure systems.

The IIM assumes that the interdependency matrix in Equation (1) remains invariant to changes in output and consumption levels of a system in disrupted state. The I–O model becomes

$$\tilde{\mathbf{x}} = \mathbf{A}\tilde{\mathbf{x}} + \tilde{\mathbf{c}}, \qquad (2)$$

where $\tilde{\mathbf{x}}$ is the output vector in disrupted state and $\tilde{\mathbf{c}}$ is the consumption vector in disrupted state.

The economic loss realized from changes in final consumption, $\mathbf{c}$, and reduction of production output, $\mathbf{x}$, of disrupted sectors. It is given in (3) and is obtained from the difference between the expected output (1), and the disrupted state output (2),

$$\mathbf{x} - \tilde{\mathbf{x}} = \mathbf{A}(\mathbf{x} - \tilde{\mathbf{x}}) + (\mathbf{c} - \tilde{\mathbf{c}}). \qquad (3)$$

Manipulating (3), the economic loss relationship is

$$(\mathbf{x} - \tilde{\mathbf{x}}) = (\mathbf{I} - \mathbf{A})-1(\mathbf{c} - \tilde{\mathbf{c}}). \qquad (4)$$

This has been one of the metrics used by Santos and Haimes[23] in analyzing the impacts of sector perturbation. The metric helps identify the highly affected sectors in terms of the associated monetary value that is lost as a result of not being able to deliver completely its expected output, $\mathbf{x}$, during and after a disruption. Collectively, the total economic impact can be based on the sum of the economic losses from each of the $n$ sectors of the given system. Thus, it is of essence that the sectors with the highest economic losses be identified as a set of "critical sectors" as they contribute largest to the total economic loss of the system. Moreover, these unrealized expected outputs propagate the inoperability in the other sectors relying on these outputs for their own recovery.

Inoperability is associated with the inability of a sector to function at its "as planned" performance level due to internal or external disruptions. The inoperability, $q_i$, is expressed as the fraction of the unrealized output of a sector over its expected output

$$q_i = \frac{x_i - \tilde{x}_i}{x_i} \qquad (5)$$

The inoperability shown in Equation (5) is the normalized economic loss from (4). The inoperability, *qi* has a value of 1 for a completely inoperable sector and an ideal value of 0 as the sector returns to its intended performance level. Santos and Haimes[23] extended the I–O relationships from (1) and (4) into the IIM formulation as follows

$$\mathbf{q} = (\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{c}^* , \qquad (6)$$

where **q** is the inoperability vector, **c*** is the perturbation vector, and **A*** is the interdependency matrix.

Each element, $q_i$, of the vector **q** represents the inoperability of a sector *i*. Each element, $a^*_{ij}$, of the interdependency matrix **A*** represents the inoperability contribution of sector *i* to sector *j*. Finally, each element, $c^*_i$, of the perturbation vector **c** is the normalized changes in final consumption for sector *i*,

$$c^*i = \frac{c_i - \tilde{c}_i}{x_i} \qquad (7)$$

*2.2.3. DIIM*

Building on the IIM, Lian and Haimes[32] developed DIIM to take into account the temporal evolution of inoperability among interdependent sectors during the recovery process. Lian *et al.*[2] proposed an extreme event analysis extension to investigate significant consumption pattern changes and production output adjustments after extreme events. Barker and Haimes[33] introduced an uncertainty index to evaluate the impact of the sensitivity of interdependency parameters on economic loss. Kujawski[34] developed a multiperiod model to decompose disaster recovery into two phases, namely (i) the period when the active perturbation affects the sector interdependencies and (ii) the period that it takes for the sectors to achieve a postdisaster equilibrium state. The same paper criticized the DIIM shortcomings particularly with the use of I-O data. Nevertheless, such shortcomings have been addressed with recent DIIM applications. In particular, DIIM extensions have been formulated to study preparedness strategies to address cyber-security scenarios involving oil and gas sectors,[31] transient production levels in the aftermath of disasters,[33] and workforce inoperability for pandemic recovery analysis.[35]

The DIIM formulates the variability of **q** over time. A sector is assumed to recover from an initial disruption at time zero with inoperability $q_i(0) > 0$, to some inoperability, $q_i(T_i) > 0$ at a known time $T_i$. The recursive form of the DIIM[32] is

$$\mathbf{q}(t + 1) = \mathbf{q}(t) + \mathbf{K}[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)], \qquad (8)$$

where $\mathbf{q}(t)$, $\mathbf{q}(t + 1)$ is the inoperability vectors at times *t* and *t* + 1, respectively, **K** is the resilience matrix, and $\mathbf{c}^*(t)$ is the perturbation vector at time *t*.

Observe that **A*** of Equation (8) is the same as the matrix from an IIM and that at a steady state (e.g., the disruption levels for all sectors have reached equilibria), $\mathbf{q}(t + 1) = \mathbf{q}(t)$. Further, a sector in the recovery process has $\mathbf{q}(t + 1) < \mathbf{q}(t)$ where **q** takes only nonnegative values as defined from Equation (5). In this case, the second term of Equation (8) yields only negative values. Therefore, to hasten the recovery of a system to the near-ideal state, the inoperability, **q**, and the contribution of the second term in Equation (8) must be kept at their minima. From Equation (5), lower values of $q_i$ reflect higher proportions of satisfied output requirements, which is either an indication of a low impact disturbance or a high level of preparedness to absorb disruption consequences.

The resilience matrix, **K**, is a diagonal matrix that reflects the collection of resilience coefficients, *ki*, which represent the recovery capability of a sector *i* from a disruptive event. From Equation (8), lower values of $k_i$ suggest closer values between $\mathbf{q}(t + 1)$ and $\mathbf{q}(t)$ as this intend to decrease the contribution of the second term to the equation. From the published results,[32] sector resilience is given by

$$k_i = \frac{\ln[q_i(0)/q_i(T_i)]}{T_i} \, (1/(1\text{-}a^*ii)) \qquad (9)$$

Although the significance of economic loss directly shows the monetary equivalent of disaster impacts on the individual sectors and the system as a whole, the objective of reducing inoperability and using $q_i$ as a metric for evaluating the importance of deciding an inventory enhancement for sector *i* has its own implication. For example, a sector, regardless of the underlying disaster intensity, could still exhibit a high economic loss due to the significance of its total output. It is probable that such particular sector will experience a higher economic loss but its inoperability (or the production loss normalized with respect to total output) will remain insignificant relative to other sectors. This sector's corresponding resilience coefficient (see Equation (9)) will be low enough such that the benefit of an additional inventory enhancement could be marginal in reducing its high economic loss. In addition, as Equation (8) demonstrates inoperability as a component for eventually reaching the desired ideal state over some period, *T*, inoperability is an also an excellent metric to evaluate the preparedness capability of a sector in terms of the period of recovery from disruptive events. Hence, the objectives of minimizing economic loss and inoperability are both important in achieving preparedness among interdependent sectors.

### 2.3. Critical Asset Prioritization

With the resources essential for acquiring inventory often being finite, prioritization is needed to allow only the most "critical" sectors to receive inventory enhancement. Through the proper allocation of these resources, the underlying objectives of hastening recovery through the reduction of inoperability and minimizing overall system losses can be achieved.

The following presents the development of selection mechanisms to prioritize elements based on multi-objective problems.

Gokey *et al.*[36] developed a prioritization methodology to help the decision makers from the Virginia Department of Transportation allocate their limited budget effectively with respect to bridge maintenance. Separate lists of the most critical bridges (each arranged in decreasing order of importance) were found according to two perspectives, economic and maintenance. Hence, a multi-objective approach was presented by integrating the ordinal ranking of the critical bridges based on these two important perspectives.

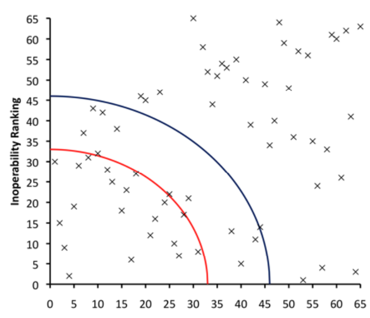



**Fig. 1.** Equally preferred inoperability and economic loss.

Each point in the graph developed by Gokey *et al.*[36] represented the relative position of a bridge in terms of its ordinal ranks, with 1 being the highest or most important with respect to a perspective. A bridge's economic rank and maintenance rank corresponded to the *x* and *y* coordinates of the point representing the bridge, respectively. Thus, the points closest to the origin are given priority to receive funding for bridge maintenance because they are the most important based on the two perspectives. The use of quarter circles illustrated how the points closest to the origin are enclosed and captured for the identification of a single list of the most critical bridges for the multi-objective problem. This is based on the assumption that the circular regions represent two perspectives having equal importance or weights.

This critical asset prioritization methodology, similar to the chart depicted in Fig. 1, had very limited capability in terms of handling user specifications.[37] It applies only to two objectives with equal preferences. It presents a static visualization of the critical region by arbitrarily varying the size of the quarter circle and manually counting the final number of enclosed critical assets. The graph is not supported by analytical formulations that explicitly relate the preference structure for the different objectives.

Resurreccion and Santos [37,41] explored the use of generalizable regions (in contrast to fixed circular regions) to gain more flexibility in capturing critical sectors for varying preferences on two given objectives. That is, possibly adapting an arc orientation that captures more points closer to the *x*-axis (*y*-axis) to highlight the higher preference for the inoperability (economic loss) objective over the economic loss (inoperability) objective. Figures 2 and 3 reflect these resulting arbitrary curves (represented as ellipses) with higher preference on the inoperability and economic loss objectives, respectively. The user-specified values required to define these curves are prioritization scope and *EL*preference.

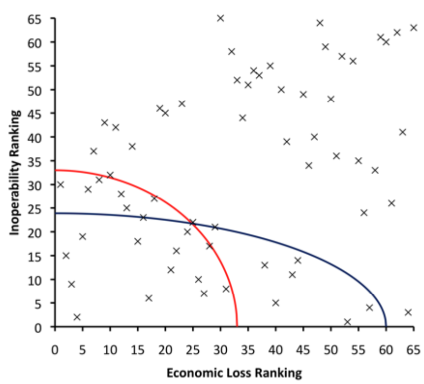



**Fig. 2.** DCPP with more importance to inoperability.

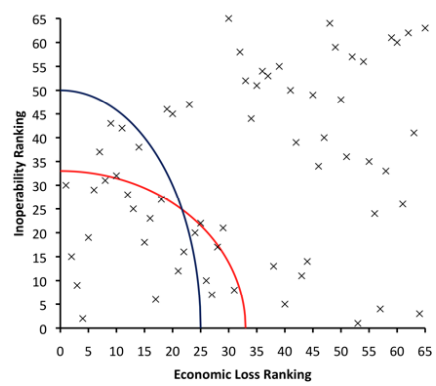



**Fig. 3.** DCPP with more importance to economic loss.

*Prioritization scope* is the maximum permissible rank of a sector with respect to a preferred objective for which decision makers no longer consider such sector to be critical. That is, only sectors having ranks for the preferred objective that are better than the prioritization scope value (1 being the best rank value) can be enclosed in the ellipse. This also represents the distance of a co-vertex from the major axis of the ellipse whereas the preferred objective lies along its minor axis. This parameter allows the region enclosed by the ellipse to be increased to include more critical sectors should resource allocation fund also increase.

The second user-specified value, *EL*preference, determines the weights associated with the importance of meeting each objective. As there are only two objectives, they should add up to unity and the weight of one could be expressed in terms of the other. In the graphical user interface, only the *EL*preference weight associated with the economic loss objective is user-specified and *Q*preference, the weight associated with the inoperability objective is just 1 - *EL*preference. Table 1 summarizes the user-specified parameters associated with the DCPP model. (41) includes a detailed derivation and further explanation of the DCPP.

**Table 1. Preference cases and values of ratio and prioritization scope**

| Objective Preferred | EL preference | Ratio | *a* | *B* |
|---|---|---|---|---|
| Equal preference | 0.5 | 1 | Prioritization scope | Prioritization scope |
| Economic loss | > 0.5 and ≤ 1.0 | < 1 | Prioritization scope | *a* / ratio |
| Inoperability | ≥ 0 and < 0.5 | > 1 | *b* * ratio | Prioritization scope |

## 3. METHODOLOGY

### 3.1. Determination of Sector Ranks

#### *3.1.1. Data*

Regional productivity data for the 65 sectors coded according to the North American Industry Classification System (NAICS) are adapted as the set of economic and infrastructure systems forming a region. Published data of industry-by-industry total requirements for 2009 between the 65 infrastructure and economic sectors for the United States from the Bureau Economic Analysis (BEA) are used to build the interdependency matrix. The expected output requirements and interdependency represented by this data are under normal operating conditions. Additional production output requirements arising from disastrous events will be an area for future research work.

Data from the Regional Economic Information System are taken to customize the interdependency matrix for the Commonwealth of Virginia. [(38)] To complete entries for Equation (1), the gross domestic product by state from the BEA website is used for the consumption vector **c**.

Finally, monthly inventory to sales ratio data from BEA with a 14-year span and 168 observations are utilized to generate empirical cumulative distributions for each of the 21 manufacturing and retail and trade sectors to model inventory uncertainty. The resulting empirical cumulative distributions are depicted in Figure 4.

#### *3.1.2. DIIM Implementation*

Equations (8) and (9) are implemented over a simulated period with one day time intervals for **q** values to generate the daily inoperability of the 65 sectors over the simulated recovery period. The initial inoperability (at day 0) is assumed to be proportional of each sector's expected output, which has a resulting total economic loss comparable to what the state of Virginia experienced from hurricane Isabel in 2003. The resilience coefficients used are assessed based on the initial inoperability value. For the purpose of investigation, fully recovered state is assumed to be when a sector has regained an operability equivalent to 99.9% of its expected output prior to the disruption.

From the computed daily inoperability values, Equation (5) gives the daily economic losses for each sector. The 65 sectors are then ranked according to their cumulative economic losses over an arbitrarily selected horizon that exceeds the maximum period of all predetermined sector recovery periods (i.e., the $T_i$ term in Equation (9)). If it were a single objective of minimizing economic loss, this ranking would give top priority to the sector with the highest possible cumulative economic loss.

As for the inoperability metric, the effective inoperability is obtained by manipulating Equation 5 using published data of yearly expected output against the obtained cumulative economic losses over the study period. The sectors are ranked in the order of decreasing effective inoperability. The most critical sectors based solely on this metric are those that have the highest effective inoperability values. This completes the two separate lists of rankings for the multi-objective inventory preparedness problem.

## 3.2. Inventory Model

### *3.2.1. Inventory Cumulative Functions*

The processing of monthly inventory to sales ratio data from BEA resulted in the individual empirical cumulative probability distributions (CDFs) of each of the 21 manufacturing and retail and trade sectors. Sample CDFs are presented in Fig. 4. Each of the 65 sectors are coded as S1, S2, …, S65. A complete list and description of the sector coding system used in the case studies are found in the appendix of this paper.

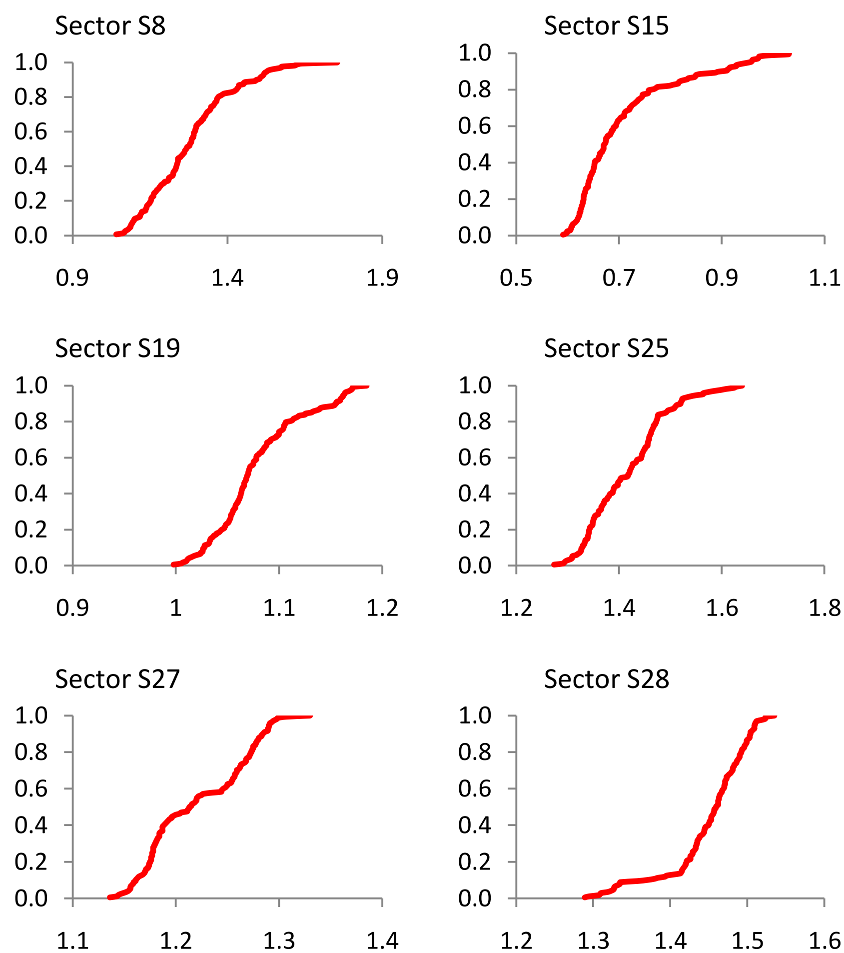



**Fig. 4** Empirical Cumulative Distribution Functions

*3.2.2. Inventory Scenarios*

Two scenarios to investigate the impact of using stochastic inventory models are defined as Scenario 0, a DIIM that does not take into account the uncertainty in inventory level behavior and Scenario 1, a DIIM that incorporates uncertainty in the inventory levels. These scenarios are developed to serve the purpose of validating how individual sectors may use portions of their inventory levels as an adaptive response to counter threats of inoperability as a consequence of disrupted sector sources.[(42)]

Since the composition of critical sectors may vary depending on the decision-maker's objective preferences[(41)], three additional scenarios are evaluated for different *EL*preference values to determine the impact of enhancing the level of inventory in critical manufacturing sectors. The baseline for comparison for the last three scenarios is scenario 1 which assumes that a "no inventory enhancement policy" is equivalent to the current levels of inventories in the economic sectors. Its purpose is to provide a reference for the evaluation of the performance of applied inventory-enhanced policies for the stochastic inventory model. The resulting inoperability of each sector is obtained as a proportion of the sector's expected output before the disruption and matches the resulting total regional economic loss brought about by hurricane Isabel to the state of Virginia in 2003. Further, the study assumes that complete recovery is when sector inoperability has been reduced back to an acceptable level of recovery (or when inoperability asymptotically reaches 0).

In summary, the five scenarios evaluated are:

- *Scenario 0 - No Inventory Model Scenario*
- *Scenario 1 – Current Inventory Scenario (Baseline Scenario)*
- *Scenario 2 – Enhanced Inventory at ELpreference=0.2 (Reduction of inoperability is preferred over economic loss)*
- *Scenario 3 – Enhanced Inventory at ELpreference=0.5 (Reduction of inoperability and economic loss are equally preferred)*
- *Scenario 4 – Enhanced Inventory at ELpreference=0.8 (Reduction of economic loss is preferred over inoperability)*

Simulation of the above scenarios and discussion of associated results are found in subsequent sections of this paper.

*3.2.3. Simulation*

The DIIM computer code was ran in Matlab and the random number generator in it was adapted for the simulation of inventory levels. A simulation run is a 20-level, 10 replications per level design to specifically store the maximum economic loss incurred for every replication. This is to capture upper 10 percentile for an extreme-event analysis. The program was run to account for 5000 replications for every defined stochastic inventory scenario.

## 4. RESULTS AND DISCUSSION

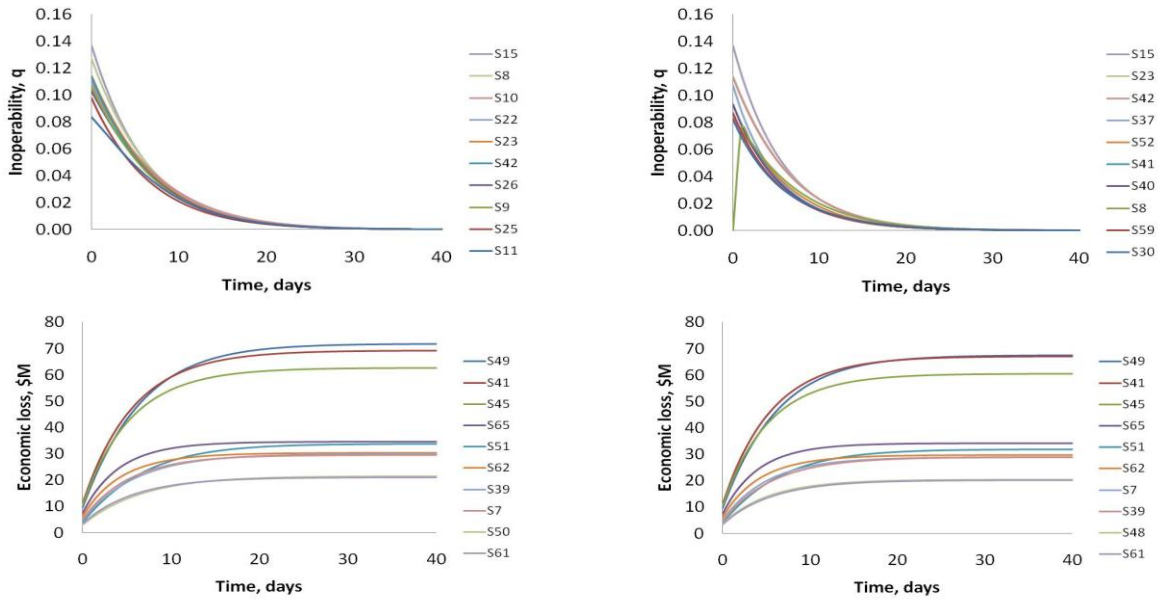
### 4.1. Stochastic Inventory Model

Results (fig. 5) show that scenarios 0 and 1 differ in the sets of the 10 most critical sectors for each objective. There is evidence that shows the significance of incorporating uncertainty in inventory as it affect economic losses and sector inoperability. Consistent with previous findings[(41)], more manufacturing sectors experience the highest inoperability values than service and infrastructure systems.

However, by incorporating the stochastic behavior of inventory, even at the current level data, the capacity of inventories to increase disaster preparedness is supported by the drastic reduction in the number of critical manufacturing sector from scenario 0 (e.g. 90% in the top ten are from manufacturing sectors) into only 3 after considering current inventory levels. Also, there is a significant from \$760M to \$623M in total regional economic loss between the two scenarios. The cushioning effect of inventory is evident from the inoperability curve for S8 for scenario 1. It had the 2nd highest initial inoperability of almost 13% in scenario 0 but was not inoperable at the time that the simulated disaster struck from scenario 1. S8 experienced an inoperability level of no more than 8% throughout the recovery period. Finally, for the worst ten % of the cases based on the sample, extreme-event average economic loss rises to \$635M from \$623M.

**DIIM w/out Stochastic Inventory Model (Scenario 0)**

**DIIM w/ Stochastic Inventory Model (Scenario 1)**




**Total economic loss = \$760M**

**Average total economic loss = \$623M**
**Extreme-event average economic loss = \$635M**

**Fig. 5.** Inoperability and Economic Loss Behavior w/out and w/ Stochastic Inventory Model

### 4.2. Enhanced Inventory Scenarios

Applying the DCPP to the rankings resulting from part 4.1 for scenario 1, table 2 summarizes the critical manufacturing and retail and trade sectors identified for the chosen enhanced inventory scenarios.

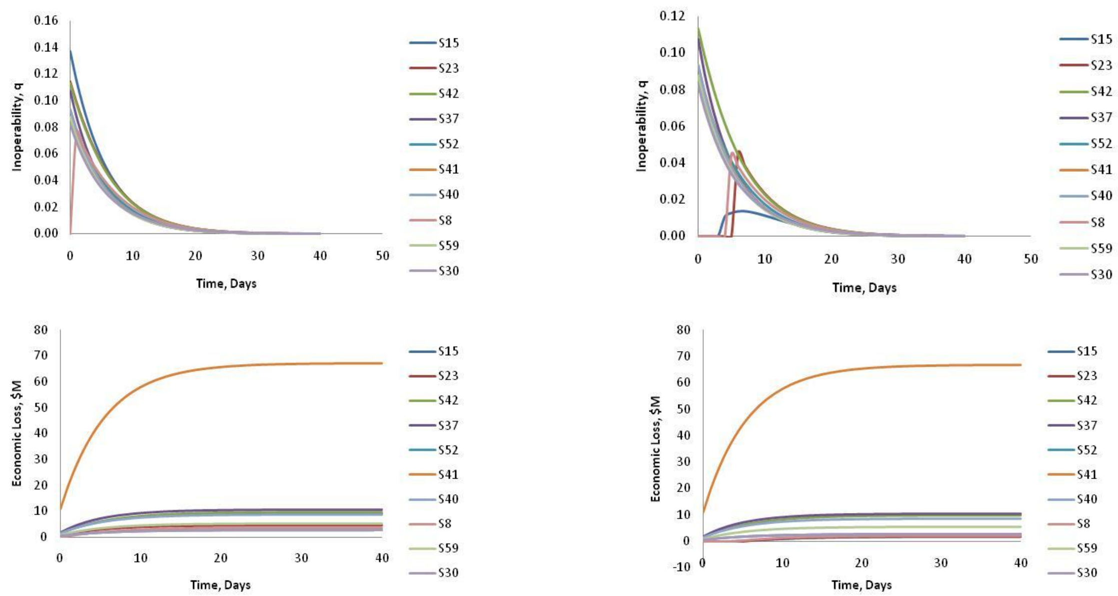
**Table 2.** Scenario Description

| | ELpreference value | Critical manufacturing sectors |
|---|---|---|
| Scenario 2 | 0.2 | S8, S15, S23 |
| Scenario 3 | 0.5 | S8, S15, S19 |
| Scenario 4 | 0.8 | S19, S25, S27, S28 |

*4.2.1. Scenario 2 – Enhanced Inventory at ELpreference=0.2*

Among the enhanced inventory scenarios considered, scenario 2 exhibited the least reduction in expected economic losses as well as having the highest extreme-event mean for economic loss. A probable cause would be the lower ELpreference specification set for this the scenario as compared to scenarios 3 and 4. However, no similar pattern follows with respect to sector inoperability. What can be said is that there is evident improvement in the individual inoperability behavior of the critical manufacturing sectors and an average improvement of 2% functionality (e.g. a drop of .02 inoperbliity to individual sectors as a result of interdependence (fig. 6).

**ELpreference=0.2 w/out Inventory Enhancement** **ELpreference=0.2 w/ Inventory Enhancement**




**Average total economic loss = $623M**
**Extreme-event average economic loss = $635M**

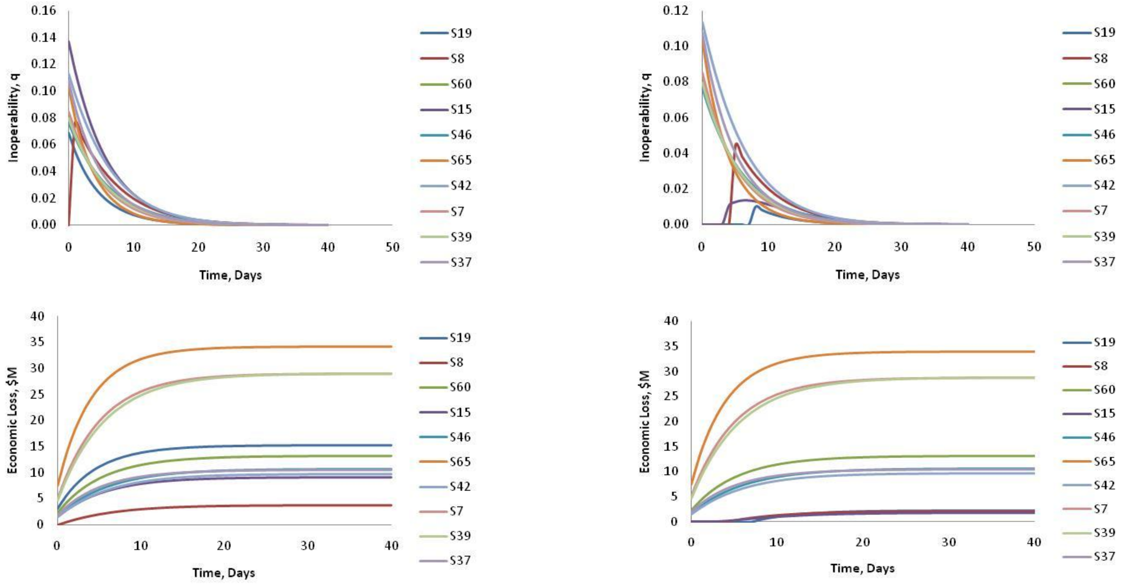
**Average economic loss = $607M**
**Extreme-event average economic loss =$618M**

**Fig 6.** Inoperability and Economic Loss Behavior w/ Stochastic Inventory Model (ELpreference=0.2)

*4.2.2. Scenario 3 – Enhanced Inventory at ELpreference=0.5*

Similar to scenario 2, there were also three critical manufacturing sectors found for scenario 3 but enhancing the inventory level of sector S19 instead of S23 has reduced economic losses by at least $16M more. The variability of individual sector inoperability has been reduced but, in general, the scenario did not have the same effect on the mean which remained about the 10% level.

**ELpreference=0.5 w/out Inventory Enhancement** **ELpreference=0.5 w/ Inventory Enhancement**




**Average total economic loss = $623M**
**Extreme-event average economic loss = $635M**

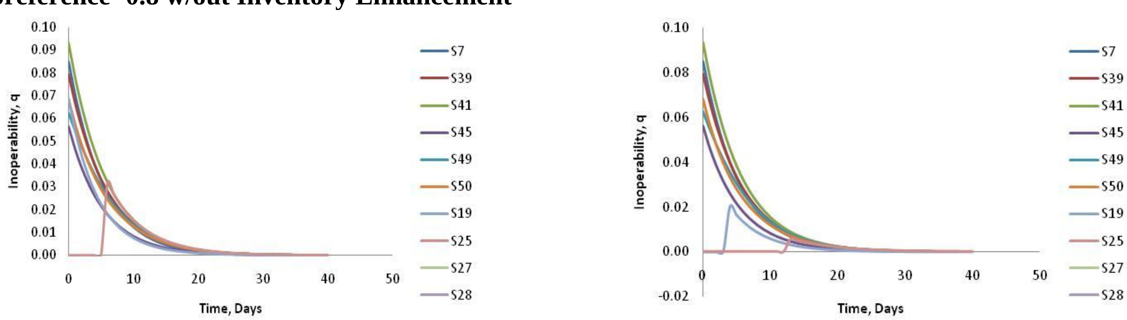
**Average economic loss = $602M**
**Extreme-event average economic loss = $605M**

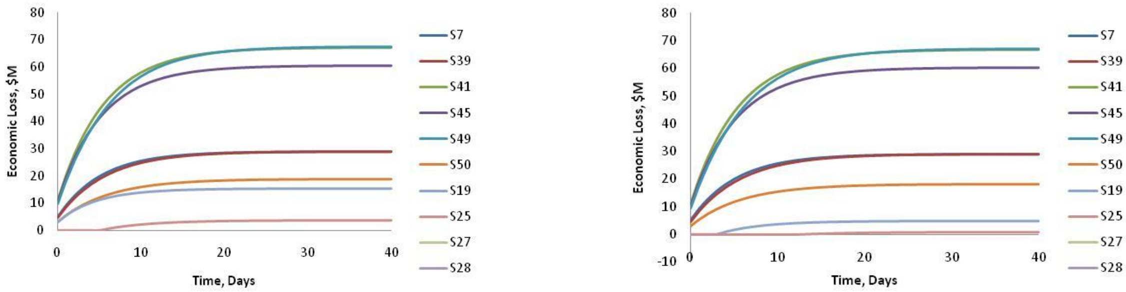
**Fig. 7.** Inoperability and Economic Loss Behavior w/ Stochastic Inventory Model (ELpreference=0.5)

*4.2.3. Scenario 4 – Enhanced Inventory at ELpreference=0.8*

It is important to note that in all the enhanced inventory scenarios considered, the critical manufacturing sectors experienced a delay in the spike of inoperability since the sectors were able to use their current inventory to remain in operation. The interdependency took its toll when the inoperability levels rise as a result of the diminishing supply of inventory and the directly hit sectors remain inoperable. It also can be observed that there is a unified direction for individual sector inoperability as the curves (figs. 6, 7 and 8) almost coincide as the sectors move towards recovery. For this particular scenario, it has a comparably low total economic loss indicating that the minimization objective at an ELpreference of 0.8 has been met. This can only be possible as the sectors attain earlier recovery which is supported by the lowest range of inoperability even when the objective preference if for the minimization of economic loss.

**ELpreference=0.8 w/out Inventory Enhancement** **ELpreference=0.8 w/ Inventory Enhancement**






**Average total economic loss = $623M**
**Extreme-event average economic loss = $635M**

**Average economic loss = $609M**
**Extreme-event average economic loss = $611M**

**Fig. 8.** Inoperability and Economic Loss Behavior w/ Stochastic Inventory Model (ELpreference=0.8)

## 5. CONCLUSIONS AND AREAS FOR FUTURE RESEARCH

In this research, we integrated a stochastic inventory model to interdependency analysis and critical sector prioritization. In particular, we derived empirical cumulative distribution functions to model the inventory levels of manufacturing and retail and trade sectors. We investigated how inventory serves as resiliency adjustment medium that delays the propagation of disaster consequences while certain sectors of an economic region remain inoperable. We generated and evaluated inventory enhancement policies by revisiting the DIIM and the DCPP. With the inclusion of published inventory levels for estimating disaster scenario parameters and user-elicited preference structure pertaining to the DIIM objectives (i.e., inoperability and economic loss), we obtained a closer replica of actual regional sector relationships.

In anticipation of disasters, such as hurricanes, results from the scenarios reveal that maintaining enhanced levels of inventories can significantly reduce associated losses and expedite recovery. Although inventory minimization in the context of JIT has proven to be cost-effective for “as-planned” scenarios, prudence in its implementation must be exercised particularly in times of disasters (despite their seemingly low likelihoods). More so, caution must be taken as extreme-event conditions prove to be more costly even with enhanced levels of inventory.

The hurricane-based scenarios performed in this research have exposed a host of other potential contributions in the area of disaster preparedness and recovery. Although the focus of the current application is on enhancing inventory levels in Virginia’s manufacturing sectors, a complementary analysis is needed to manage the resilience of workforce sectors—particularly those involved in the provision of essential services to further expedite recovery. Sensitivity analysis of inoperability and loss reduction objectives with respect to recovery assumptions can be performed to generate robust resource allocation policies. Finally, the flexibility and scalability of the current methodology and resulting decision support system can also be extended to accommodate analysis of other regions and other disaster scenarios.(40)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# APPENDIX. Sector Classification Codes Used in the Case Studies

**Table 1. Sector Classification**

| Sector | Description |
|---|---|
| S1 | Farms |
| S2 | Forestry, fishing, and related activities |
| S3 | Oil and gas extraction |
| S4 | Mining, except oil and gas |
| S5 | Support activities for mining |
| S6 | Utilities |
| S7 | Construction |
| S8 | Wood products |
| S9 | Nonmetallic mineral products |
| S10 | Primary metals |
| S11 | Fabricated metal products |
| S12 | Machinery |
| S13 | Computer and electronic products |
| S14 | Electrical equipment, appliances, and components |
| S15 | Motor vehicles, bodies and trailers, and parts |
| S16 | Other transportation equipment |
| S17 | Furniture and related products |
| S18 | Miscellaneous manufacturing |
| S19 | Food and beverage and tobacco products |
| S20 | Textile mills and textile product mills |
| S21 | Apparel and leather and allied products |
| S22 | Paper products |
| S23 | Printing and related support activities |
| S24 | Petroleum and coal products |
| S25 | Chemical products |
| S26 | Plastics and rubber products |
| S27 | Wholesale trade |
| S28 | Retail trade |
| S29 | Air transportation |
| S30 | Rail transportation |
| S31 | Water transportation |
| S32 | Truck transportation |
| S33 | Transit and ground passenger transportation |
| S34 | Pipeline transportation |
| S35 | Other transportation and support activities |
| S36 | Warehousing and storage |
| S37 | Publishing industries (includes software) |
| S38 | Motion picture and sound recording industries |
| S39 | Broadcasting and telecommunications |
| S40 | Information and data processing services |
| S41 | Federal Reserve banks, credit intermediation, and related activities |
| S42 | Securities, commodity contracts, and investments |
| S43 | Insurance carriers and related activities |
| S44 | Funds, trusts, and other financial vehicles |
| S45 | Real estate |
| S46 | Rental and leasing services and lessors of intangible assets |
| S47 | Legal services |
| S48 | Computer systems design and related services |
| S49 | Miscellaneous professional, scientific, and technical services |
| S50 | Management of companies and enterprises |
| S51 | Administrative and support services |
| S52 | Waste management and remediation services |
| S53 | Educational services |
| S54 | Ambulatory health care services |
| S55 | Hospitals and nursing and residential care facilities |
| S56 | Social assistance |
| S57 | Performing arts, spectator sports, museums, and related activities |
| S58 | Amusements, gambling, and recreation industries |
| S59 | Accommodation |
| S60 | Food services and drinking places |
| S61 | Other services, except government |
| S62 | Federal general government |
| S63 | Federal government enterprises |
| S64 | State and local general government |
| S65 | State and local government enterprises |
| Source: | Bureau of Economic Analysis |