Measurement of System Resilience: Application to Chemical Supply Chains

Eric D. Vugrin R. Chris Camphouse P. Sue Downes Mark A. Ehlen
Drake E. Warren*

Abstract
Within the context of infrastructure and economic systems analysis, we define resilience as follows: given the occurrence of a particular disruptive event, the resilience of a system to that event is the ability to efficiently reduce both the magnitude and duration of the deviation from targeted system performance levels. We propose a new methodology, originating from optimal control applications, for measuring system resilience. The approach is demonstrated through application to a national petrochemical supply chain model.

1 Introduction.

Historically, U. S. Federal Government policy towards critical infrastructure protection (CIP) has focused on physical protection and asset hardening (for examples, see [1], [2], [3], [4]). This approach to CIP has sometimes been termed the "3G" approach since it is often used to determine how to allocate "guns, gates, and guards" in order to decrease vulnerabilities and to lessen the probability of a successful attack on an asset. Recently, the federal government has realized that "protection, in isolation, is a brittle strategy" [5] and that not all disruptive events, natural or man-made, can be prevented. Hence, national CIP policies must also prepare the nation for situations in which disruptive events occur.

With the formation of the Department of Homeland Security's (DHS) Critical Infrastructure Task Force in 2005, this realization become a national priority as the task force made critical infrastructure resilience (CIR) its top-level strategic objective. CIR is the concept concerned with how critical infrastructures absorb, adapt, and recover from the effects of a disruptive event in order to ensure the optimal delivery of critical infrastructure services in an all hazards environment. Following this shift to include CIR in national CIP policies, the federal government has started a coordinated set of government resilience initiatives, begun the process of understanding what features create resilience in critical infrastructure systems, and initiated calls to agencies to start measuring the resilience of their infrastructure systems.

*Sandia National Laboratories.

Many challenges, including the lack of a standardized methodology for evaluating CIR , must be overcome to successfully integrate CIR concepts into national CIP policies. A single, unifying approach that is general enough to perform CIR assessments for all of DHS's eighteen critical infrastructure and key resource (CIKR) system types is needed to address DHS's CIR focus. It is with this goal in mind that we have formulated a new resilience assessment framework, including a definition of resilience and system performance metrics and measurement methodologies, that can be applied to studies of natural and man-made disruptive events. This paper describes the framework's resilience costs measurement methodology for critical infrastructure systems and industries.

National CIR depends on the resilience of the private industries that operate and support critical infrastructure systems. Much of the nation's critical infrastructure systems is privately owned. For example, the chemical sector is almost exclusively owned and operated by private industry and provides the nation with chemicals that are essential to the nation's public health, national security, and economy. Because of the highly connected nature of chemical supply chains, the profitability of individual firms is dependent upon its resilience and the resilient the chemical industry. As a demonstration of our resilience assessment framework, we apply it to a case study in chemical supply chains.

2 Past Resilience Measurement Approaches.

Holling [6] provided the first systems level definition of resilience more than 30 years ago. Since that initial definition, many different definitions of resilience have been proposed (for examples, see [7], [8], and [9]). These definitions all include some aspect of a system withstanding change due to a disruption or disturbance, whether by reducing the impact of the change, adapting to the change, or recovering from the change. However, many of the definitions are domain-specific and, thus, vary according to the discipline in which they are considered. Fewer methods have been proposed for measuring or quantifying resilience of infrastructure or economic systems (for examples, see [7], [8], and [9]). However, each of these approaches only consider the impact that a disturbance has on the state of the system or system outputs. They do not consider the cost of the recovery effort required to restore system output levels.

The recovery effort that commences following a system disruption is a foundational component of resilience; hence, we assert that the resilience assessment approaches should explicitly consider the costs associated with system recovery. With this consideration in mind, we propose a new definition of system resilience for use in CIR analysis.

DEFINITION 2.1 Given the occurrence of a particular, disruptive event (or set of events), the resilience of a system to that event (or events) is the ability to efficiently reduce both the magnitude and duration of the deviation from targeted system performance levels.

According to this definition, systemic impact is measured as the difference between targeted system output levels and actual system output levels following a disturbance. The magnitude and duration of this disturbance are factors to be considered when quantifying systemic impact. The system's ability to efficiently return to targeted performance levels refers to the cost of system recovery, or what we define as the total recovery effort. This resilience definition provides the basis for a new resilience measurement methodology, as described in the following section.

3 Measurement of System Resilience Costs.

Whereas previous quantitative resilience assessment methods have proposed to measure resilience directly, we propose a method that calculates the costs related to the resilience of a system to a particular disturbance. We assert that decreasing resilience costs imply increased resilience to a disturbance.

Consider a dynamic system with time-dependent output of the form:

$$y(t) = f\left(x(u(t), d(t), t)\right), \tag{3.1}$$

where

- x is a state vector and a function of the recovery effort u and the disturbance d.
- u is a time-dependent vector representing the means by which the system recovers, i.e., the recovery effort.
- d represents a time-dependent, piece-wise continuous, disturbance forcing term.
- y is the vector of system outputs under the disturbance d and is obtained by calculation of the function f.

Let $y_{ref}(t)$ be an exogenous reference signal that represents the time-dependent, targeted system performance level. If $t_0 \geq 0$ is the first time at which d is nonzero, i.e., the disturbance initiates, and $t_1 > t_0$ is the final time for the period over which one considers the resilience of the system, then we define TRE, the total recovery effort, as

$$TRE = \int_{t_0}^{t_1} w_T^T(t)\, u(t) \; dt, \tag{3.2}$$

Generally, the time t_1 is the time at which recovery is considered complete, and $w_T(t)$ is a time-dependent vector of weighting terms used to calculate the costs of the recovery terms. If the recovery occurs over a long time period (e.g., several years), $w_T(t)$ can be used to discount future costs since future dollars are generally worth less than current dollars. In general, the type of disturbance will dictate the recovery strategy so TRE is a function of d and u. We define SI, the systemic impact, as

$$SI = \int_{t_0}^{t_1} w_S^T(t)\left[y_{ref}(t) - y(t)\right] dt. \tag{3.3}$$

The vector $w_S(t)$ includes a set of time-dependent weighting terms that are used to calculate the costs of decreased system productivity.

Then we define recovery dependent resilience costs, RDR, of x to d under u as

$$RDR\left(x(t_0), u, d\right) = \frac{SI + \alpha \times TRE}{\int_{t_0}^{t_1} |w_R^T(t)\, y_{ref}(t)| dt} \tag{3.4}$$

The denominator in (3.4) is a normalizing term that permits comparison of RDR values for systems of varying magnitudes. The term $w_R^T(t)$ is a time-dependent vector of weighting terms used to measure the magnitude of targeted system performance, and α is a weighting constant that resilience analysts can use to assign the importance of system impacts relative to recovery costs. When they exist, we define the optimal resilience costs, OR, of system x to disturbance d as

$$OR\left(x(t_0), d\right) = \min_u \frac{SI + \alpha \times TRE}{\int_{t_0}^{t_1} |w_R^T(t)\, y_{ref}(t)| dt}. \tag{3.5}$$

We note the following considerations for this approach to measuring resilience costs:

- Decreasing RDR and OR values imply increasing resilience.
- This resilience evaluation approach is neither model- nor domain-specific. One simply needs time

series data representing system output and recovery effort data to calculate the resilience costs. Explicit knowledge of a model used to generate the data is not necessary.

- Since the RDR and OR values are dimensionless quantities, they are most informative when used in a comparative manner. For example, they can be used to compare the resilience of different systems to the same disruption or to compare the resilience of the same system to different types of disruptions. Moreover, they can be used to compare the resilience of a system to a disruption under different recovery strategies.

4 A Resilience Case Study.

To demonstrate the utility of the resilience cost measurement approach, we apply it to a model of the national petrochemical supply chain.

4.1 A Petrochemical Supply Chain Model. As a part of the National Infrastructure Simulation and Analysis Center (NISAC), Sandia National Laboratories (Sandia) has developed the NISAC Petrochemical Supply Chain Model. This model consists of two primary components. The first component, the chemical data model (CDM), is a database of domestic and foreign chemical plants, chemical productions, commodity flows, and chemical infrastructure (for example, pipelines, rail networks, and water-transport networks). The version of the CDM used for this analysis contains data for almost 4000 domestic and foreign consumers and producers of 63 commodity petrochemicals. Each of the firms in the CDM either makes a primary feedstock petrochemical (benzene, toluene, ethylene, propylene, xylene, o-xylene, p-xylene), converts these chemicals into other petrochemicals, or produces other chemical and non-chemical products based on these chemicals. Using the stoichiometric (chemistry-based) and other production "recipes" for each chemical, the CDM can identify the basic relationships between these chemicals.

Sandia uses the petrochemical CDM in conjunction with the N-ABLE^{TM} agent-based, microeconomics simulation tool [10] to simulate disruptions to the petrochemical sector from various types of disturbances. N-ABLE^{TM} is a collection of tools that Sandia has developed to perform value-chain analysis, the analysis of ways individual firms within multi-tiered, multi-product economic systems purchase input goods, produce products, sell them in markets, and ship them via different modes of transportation.

The actions of individual plants are the primary units of analyses in N-ABLE^{TM}. Each agent-based enterprise firm is composed of buyers, production workers, supervisors, sellers, and strategic planners who conduct their real-world analog tasks within the enterprise and among enterprises (Figure 1). Using a generic data-driven object structure, firms representing the range of economic activity in a value chain (such as manufacturing, transportation, and consumption) can be modeled by specifying such things as particular production functions, buying and selling behaviors, inventory capacities, and long-term strategic planning. Production decisions are made by a production manager, independently of input costs. The production manager adjusts production based on the inventory of finished goods and the presence of market signals (orders). Every day, the plant orders enough to raise its inventory position to a predetermined level, taking into account expected usage patterns and historic averages of delivery times. Entire value chains are constructed from collections of firms, based on this enterprise design, with each participating firm interacting with others through markets and physical infrastructure.

When applied to the petrochemical CDM, N-ABLE^{TM} simulations can provide dynamic information about how disruptions affect the petrochemical sector. For example, if a hurricane temporarily shuts down a set of chemical production facilities, N-ABLE^{TM} can estimate economic impacts resulting from a decreased chemical supply to downstream facilities (i.e., customers of the closed facilities, the customers of the customers, etc.). N-ABLE^{TM} can also predict losses resulting from decreased demand of input chemicals used by the closed production plants to upstream facilities (i.e., suppliers to the closed plants, suppliers of the suppliers, etc.). N-ABLE^{TM} can also predict how the petrochemical sector will adapt to and recover from a disruption. The tool has the capability to describe how customers of the closed plants will find new suppliers, the higher transportation costs associated with those suppliers, the use of chemical substitutes, and the implementation of different production technologies and recipes to adapt to a disruption. N-ABLE^{TM}'s ability to predict consequences of disruptions and ways firms adapt to and recover from these disruptions make it an ideal tool for assessing the resilience of the petrochemical sector to hurricane events.

4.2 Methodology. In this analysis we consider the resilience of the national petrochemical sector to two different hurricane scenarios. In the first scenario we consider a category 2 hurricane that makes landfall in the Houston, TX, area. Figure 2 shows expected electric power outage contours for this scenario. It

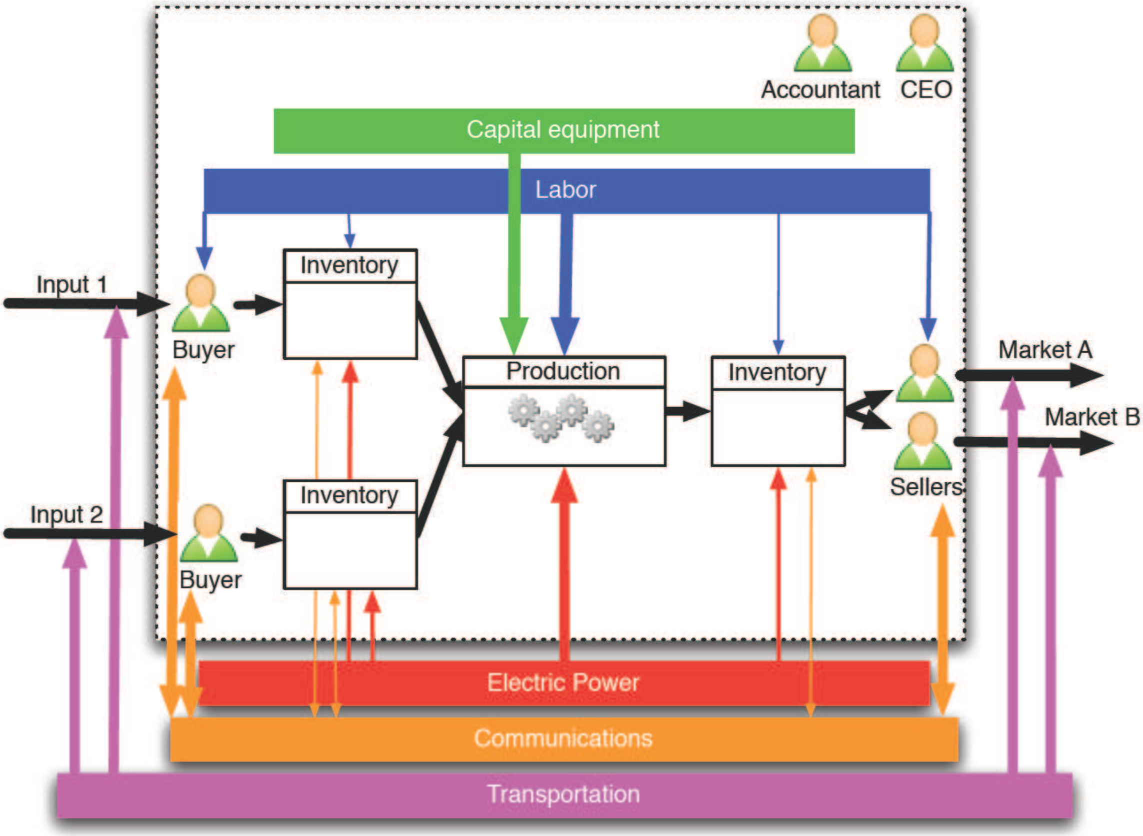

Figure 1: An N-ABLE^{TM} Enterprise Firm

is common practice for Gulf Coast petrochemic al production facilities in the projected path of a hurricane to shut down operations 48 hours prior to hurricane landfall. On average, the petrochemical facilities within the electric power outage contours will be without power for an additional 23 days. Hence, to simulate the effects of the electric power outage, we assume that all petrochemical facilities within the outage contours are shut down for 25 days.

The second scenario involves a category 2 hurricane that makes landfall near New Orleans, LA (Figure 3). We also assume that all petrochemical facilities that lie within the outage contours will be shutdown for 25 days.

For the Houston hurricane scenario, 1,390 chemical firms (36-percent of all firms in the model) will be affected. These firms represent 570,000 daily short tons of product supply (81-percent of production capacity for the entire petrochemical sector) and 349,000 daily short tons of product demand (53-percent of the sum of all demand for the particular chemicals if and when these firms are running at full capacity).

For the New Orleans scenario, 886 chemical firms (23-percent of all firms in the model) will be affected. These firms represent 475,000 daily short tons of product supply (68-percent of production capacity for the entire petrochemical sector) and 493,000 daily short tons of product demand (75-percent of the sum of all demand for the particular chemicals if and when these firms are running at full capacity). It should be noted that some petrochemical facilities are affected in both facilities.

We expect that the petrochemical sector will be less resilient to the Houston hurricane scenario for two reasons. First, a greater fraction of production capacity is shut down in the Houston hurricane scenario than the New Orleans scenario (81-percent versus 68-percent). Secondly, the product demand affected in the New Orleans scenario is larger than that of the Houston scenario (75-percent versus 53-percent). That is, more product consumers and, thus, a greater fraction of product demand will still be in operation during the Houston scenario. Thus, more consumers will be expending more resources to receive their necessary products.

To quantitatively evaluate the resilience of the petrochemical supply chain, we ran three sets of N-ABLE^{TM} simulations. In the baseline scenario, we as-

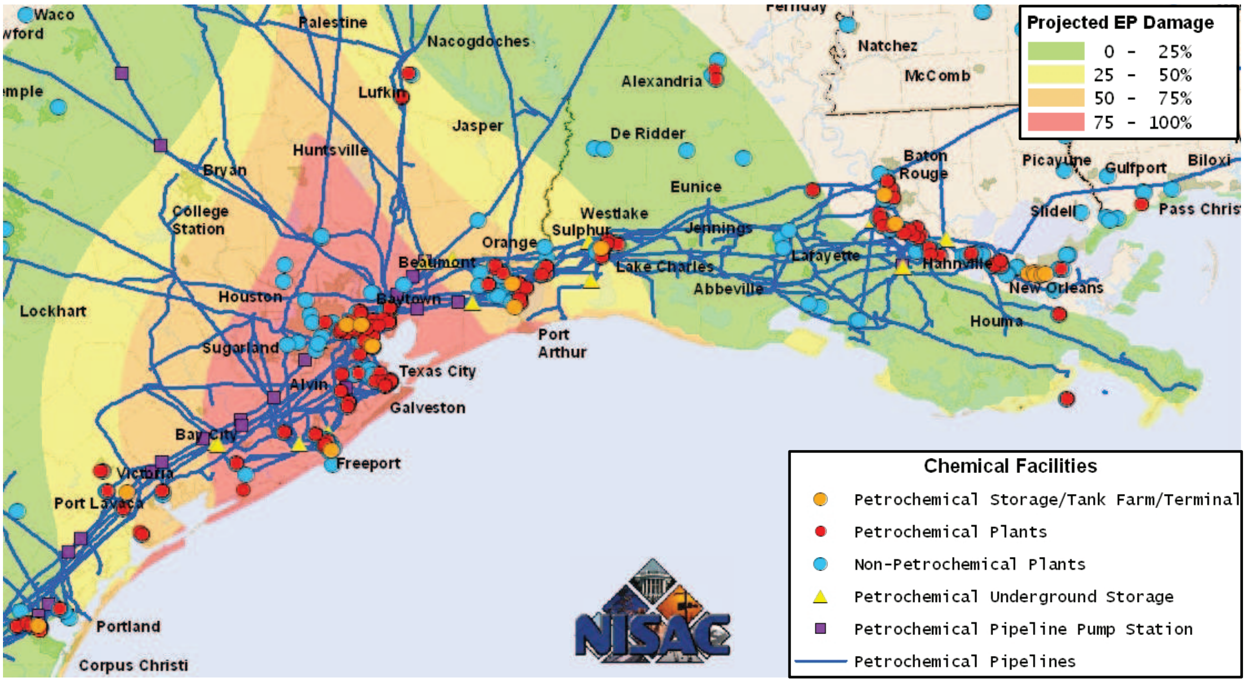

Figure 2: Electric Power Outage Contours for the Houston Hurricane Scenario

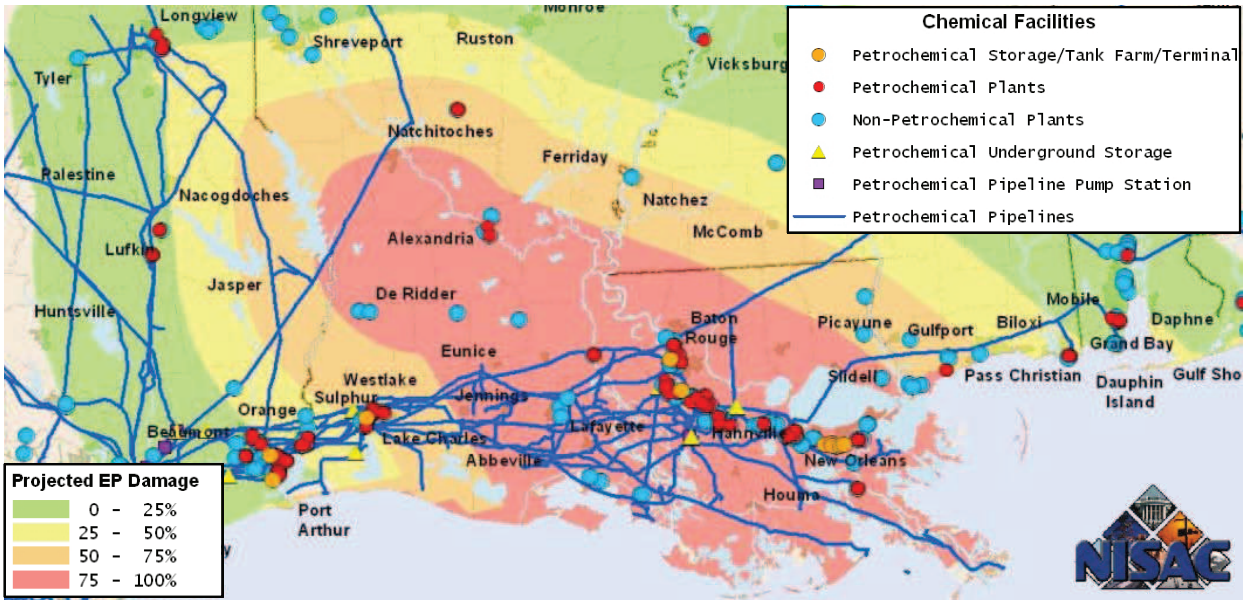

Figure 3: Electric Power Outage Contours for the New Orleans Hurricane Scenario

sume no disruptions. In the Houston disruption scenario, we assume that a hurricane is projected to make landfall on day 202 of the simulation and the electric power outage shown in Figure 2 is expected to occur. All petrochemical facilities within the contours shut down in anticipation of the storm on day 200. Normal production capabilities are assumed to return on day 225 of the simulation. The New Orleans disruption is identical to the Houston disruption scenario with the exception that different petrochemical facilities are affected.

For this analysis, market value of production (MVP) for the baseline scenario represents targeted system performance, $y_{ref}(t)$ in (3.3), for the petrochemical supply chain. MVP captures the total "street value" of production in the petrochemical supply chain and is equal to the sale value of chemical end products produced if there were no vertical integration, i.e., outputs of every production stage are assumed to be sold on the merchant market. During the scenario disruptions, MVP will decrease because of decreased levels of chemical production. Disrupted MVP values represent disrupted system performance levels, $y(t)$ in (3.3), for the petrochemical supply chain.

For this analysis, we consider two factors that contribute to the cost of recovery for the petrochemical supply chain: the onsite transportation costs (TC) and marketing costs (MC). When a disruption decreases the supply of available chemicals, consumers of those chemicals will seek new suppliers. These suppliers will likely be a further distance from the consumers than the original suppliers, so the cost of transporting chemicals from the new suppliers will likely be higher. Marketing costs are the costs associated with the process that a buyer uses to find a supplier. These costs are expected to increase in times of shortages.

We recognize that in the event of an actual hurricane, recovery of individual chemical plants and the entire supply chain could involve additional expenses, including repair of damage to facilities caused by winds and/or flooding, the expense associated with labor and materials required to restore electric power, etc. However, for the sake of simplicity, we only consider the transportation and marketing costs when calculating the total recovery effort for this example.

The recovery vector u in (3.2) is taken to be the difference between these baseline costs and the disrupted scenario costs. That is, if TC and MC denote that aggregate transportation and marketing costs, respectively, across all petrochemical firms, recovery costs are calculated according to (3.2) where

$$u = [TC_d(t) - TC_b(t)] + [MC_d(t) - MC_b(t)] \tag{4.6}$$

(The subscripts b and d in (4.6) refer to the baseline

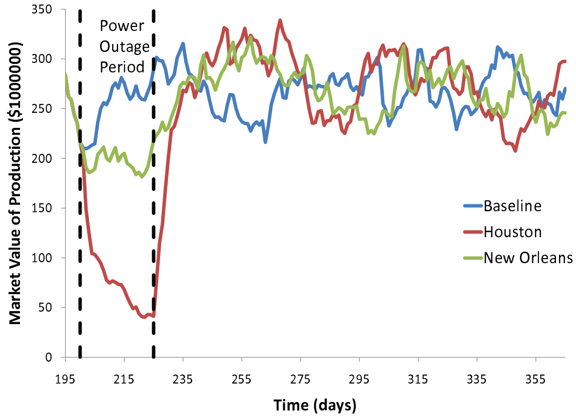

Figure 4: Market Value of Production

and disruption scenarios, respectively.) To calculate recovery dependent resilience costs, we set w_T, w_S, and α each to 1 in (3.2), (3.3), and (3.4), respectively, and approximate the integral with one-day time-step intervals since N-ABLE^{TM} reports data on a daily basis.

4.3 Results. The primary goal of this test case is to demonstrate the application of the resilience assessment framework. Hence, for the sake of simplicity, this paper presents results for a single N-ABLE^{TM} simulation realization for each hurricane scenario. Statistical analysis of uncertainty estimates are not provided.

Figures 4, 5, and 6 show the MVPs, marketing recovery costs, and transportation recovery costs for all scenarios, respectively. MVP is immediately impacted by the disruptions in each scenario. The initial MVP decrease is less than the fraction of shut down production capacity since the system utilizes stored inventories of chemicals. However, inventories start to deplete near the end of the outage period, and MVP decreases by more than 80-percent for the Houston scenario. Maximum MVP reductions for the New Orleans scenario are more modest, representing an approximate 30-percent reduction. When the power outage ends and production capacity is restored, MVP levels for the disruption scenarios actually exceed baseline levels, initially (days 240 to 275), since the plants have ramped up production levels to meet not only previously unmet demand but also to restore inventory levels. After day 275, differences between the MVP levels are attributed to the stochastic nature of the supply chain model

Marketing costs actually decrease during the production shutdown period. This decrease is primarily attributed to the fact that a large percentage (53-percent and 75-percent for the Houston and New Orleans sce-

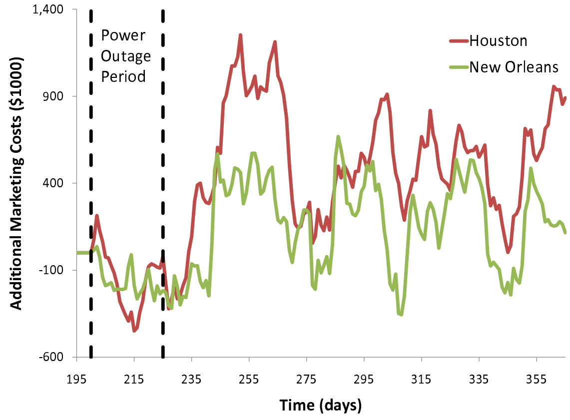

Figure 5: Marketing Recovery Costs

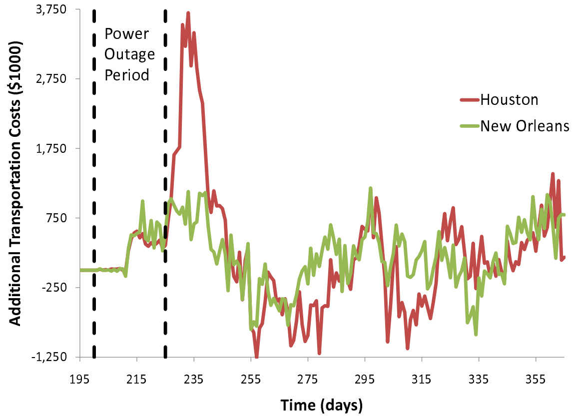

Figure 6: Transportation Recovery Costs

narios, respectively) of product demand is shut down during the hurricane disruption. Thus, even though production capacity is reduced, unmet demand initially decreases because overall demand decreases as well. As production capacity returns online, market costs increase as scarcity of petrochemicals is realized, and the additional marketing costs peak between days 240 and 270. Marketing costs are generally higher for the Houston scenario than the New Orleans scenario. After that period, these values oscillate, but generally remain positive; i.e., marketing costs for the disruption scenarios generally remain higher than those for the baseline scenario.

Additional transportation costs are determined by two factors: average distance traveled by a chemical shipment and met demand. Travel distances for the disruption scenarios start to exceed baseline distances around day 210 (Figure 7). Travel distances are highest for the Houston scenario, with average travel distances peaking above 1,300 miles per shipment (a 70-percent increase over baseline distances) around day 230. Average distances for the New Orleans scenario peak around 950 miles per shipment (approximately a 20-percent increase) during the same period of time. However, met demand decreases dramatically during the shutdown period (Figure 8). This decrease in met demand offsets the increase in transportation distances, keeping increases in transportation costs relatively moderate. However, after production capacity is restored, met demand increases at the same time that travel distances are highest, and additional transportation costs peak during this period (near day 230). After day 240, disruption scenario travel distances decrease and become similar to baseline levels. Differences between the disruption scenarios and baseline scenario are attributed primarily to

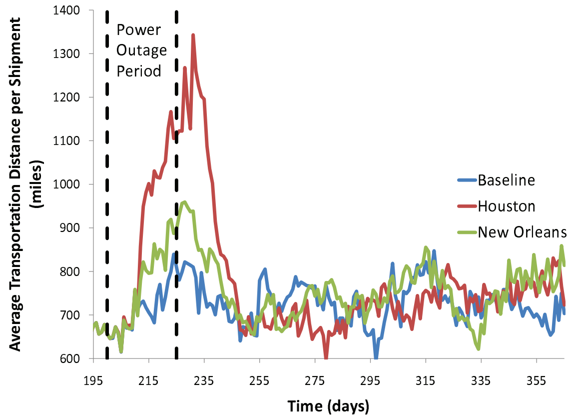

Figure 7: Average Travel Distances for Chemical Shipments

the stochastic nature of the supply chain model

Calculation of resilience costs requires selecting the times t_0 and t_1 in (3.2), (3.3), and (3.4). The onset of the disruption establishes the beginning of both periods, i.e., $t_0 = 200$. Completion of recovery can be defined in several different ways. Recovery is often considered complete when system performance under the disruption first achieves targeted system performance levels. For this example, MVP levels for the Houston and New Orleans scenarios equal or exceed baseline MVP levels for the first time on day 240. Some infrastructure analysts consider recovery to be complete only after system production levels have returned to baseline levels, stored inventory levels are restored, and recovery processes have ended. In this analysis, differences between disruption and baseline

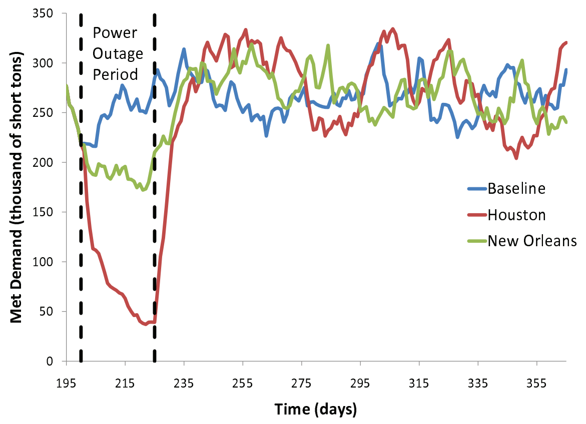

Figure 8: Met Demand

Table 1: Resilience Costs: $t_1 = 240$

Measure	Houston	New Orleans
Target MVP ($M)	10000	10000
System Impact ($M)	5500	2000
Marketing Cost ($M)	-4.0	-6.8
Transportation Costs ($M)	39	20
Resilience Costs	**0.53**	**0.19**

MVP levels and transportation costs after day 275 appear to be primarily due to the stochastic nature of the supply chain model; they do not appear to be caused by production shutdown. Hence, we calculate resilience costs for two different periods of analysis. In both periods, we assign a value of 200 days to t_0. For one period, we assign t_1 a value of 240 days and in the other period we assign t_1 a value of 275 days.

Tables 1 and 2 list the system impacts, total recovery efforts, and resilience costs for $t_1 = 240$ and $t_1 = 275$, respectively. For both time periods of analysis, systemic impact dominates recovery costs in both analyses. Systemic impact is significantly smaller for the New Orleans scenario, resulting in lower resilience costs. Hence, for both time periods, the petrochemical sector is more resilient to the New Orleans hurricane scenario. Recovery costs are also larger for the Houston scenario, but the differences in recovery costs do not significantly contribute to the difference in resilience costs because systemic impacts are so much larger than the recovery costs.

Table 2: Resilience Costs: $t_1 = 275$

Measure	Houston	New Orleans
Target MVP ($M)	20000	20000
System Impact ($M)	3600	600
Marketing Cost ($M)	23	3.9
Transportation Costs ($M)	32	14
Resilience Costs	**0.19**	**0.03**

5 Summary.

This paper presents a new quantitative approach to measuring resilience costs. This approach enables individual firms, industries, and infrastructure managers to better understand the resilience of their respective systems. The methodology considers both costs resulting from decreased system productivity and costs attributed to recovery activities. This approach improves on previous resilience measurement methods in that it explicitly considers costs for recovery from disruptions and it is general enough to be applied broadly across different industries, infrastructure systems, and economic systems. To our knowledge, this approach is the only quantitative resilience assessment methodology that currently addresses both issues.

Individual firms and industries make cost-benefit decisions on a daily basis, and the resilience cost measurement approach described herein provides a structured, quantitative approach for conducting those cost-benefit studies. For example, by separating resilience costs into the two cost categories (systemic impact and total recovery effort), companies can understand the primary source of disruption costs. This information can provide the firms with a strategy for decreasing resilience costs. If the system impacts far outweigh the recovery costs, the firm may want to focus on approaches for decreasing system impacts (perhaps by increasing inventories, adding redundancy, etc.) without significantly increasing recovery costs. If recovery costs outweigh system impacts, the firm may want to focus on developing cheaper, more efficient strategies for recovery that do not drastically increase system impacts.

Furthermore, if the resilience costs for a company or supply chain are calculated before and after resilience enhancements are made, the framework can be used to compare benefits of the decreased resilience costs with costs of making the system modifications. Additionally, the framework can be used to help select preferable recovery strategies by comparing the resilience costs under different recovery strategies.

We demonstrated the utility of the resilience cost measurement approach by applying it to a model of the national petrochemical supply chain. The model included nearly 4000 domestic and foreign producers of 63 commodity petrochemicals, and we analyzed the resilience of the supply chain to two different hurricane disruptions.

For this paper, we focused on measuring the resilience costs associated with a particular recovery strategy, i.e., the recovery dependent resilience costs; we did not attempt to calculate the minimal resilience costs under an optimal recovery strategy. That calculation requires a more complex theory and set of techniques than considered in this paper, but we note that research opportunities exist for development of optimal resilience cost measurement methods.

Recall that the quantitative resilience methodology is based on two key measurable components: systemic impact and total recovery effort. The systemic impact is a measurement of the difference between a targeted system performance level and the actual performance level following a disruption. The total recovery effort is a measurement of the efficiency in which the system recovers from disruption and is determined through an analysis of resource amounts expended to restore system output levels to their target values. These considerations lend themselves nicely to mathematical formulations utilized for the development of optimal feedback control laws. When applied to a system, feedback controllers utilize measured system outputs to regulate system behaviors to target conditions while simultaneously providing a measure of the cost in doing so. Feedback control has been successfully utilized in a wide variety of settings and applications, from simple household temperature thermostats to more complicated applications such as the mitigation of aero-acoustic noise in supersonic jets. Incorporating feedback control in the quantitative description of resilience enables automatic system recovery from disruption and provides predictions of recovery cost.

In the context of feedback control design, numerous formulations are currently available that allow for systematic development of optimal control laws, and we note that the total recovery effort and system impacts (as defined in (3.2) and (3.3)) have some similarities to components in the cost function for the linear quadratic regulator (LQR) tracking problem (5.7).

$$(5.7)\ J\left(u, x(0)\right) = \int_{t_0}^{t_1} \left[y_{ref} - y\right]^T Q \left[y_{ref} - y\right] \quad dt + \int_{t_0}^{t_1} u^T R u \quad dt.$$

The variables y_{ref}, y, and u are defined as in Section 3, and Q and R are appropriately sized positive semi-definite and positive definite matrices, respectively. Controls (or recovery strategies to use the terminology established in this paper) developed with this formulation are able to drive system outputs to target values and have built-in robustness to system disturbances. We propose that future resilience measurement research efforts should consider the development of optimal resilience costs measurement through LQR and other optimal feedback control methods.

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