A Resilience Assessment Framework for Infrastructure and Economic Systems: Quantitative and Qualitative Resilience Analysis of Petrochemical Supply Chains to a Hurricane

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Abstract

In recent years, the nation has recognized that critical infrastructure protection should consider not only the prevention of disruptive events, but also the processes that infrastructure systems undergo to maintain functionality following disruptions. This more comprehensive approach has been termed critical infrastructure resilience. Given the occurrence of a particular disruptive event, the resilience of a system to that event is the system's ability to efficiently reduce both the magnitude and duration of the deviation from targeted system performance levels. Under the direction of the U. S. Department of Homeland Security's Science and Technology Directorate, Sandia National Laboratories has developed a comprehensive resilience assessment framework for evaluating the resilience of infrastructure and economic systems. The framework includes a quantitative methodology that measures resilience costs that result from a disruption to infrastructure function. The framework also includes a qualitative analysis methodology that assesses system characteristics affecting resilience to provide insight and direction for potential improvements. This paper describes the resilience assessment framework and demonstrates the utility of the assessment framework through application to two hypothetical scenarios involving the disruption of a petrochemical supply chain by hurricanes.

1. Introduction

Historically, U.S. government policy toward critical infrastructure protection (CIP) has focused on physical protection and asset hardening (for examples, see [1], [2], [3], and [4]). Recently, the federal government has realized "protection, in isolation, is a brittle strategy" [5] and not all disruptive events, natural or manmade, can be prevented. Hence, national CIP policies must prepare the nation for unavoidable disruptive events.

With the formation of the Department of Homeland Security's (DHS's) Critical Infrastructure Task Force in 2005, this shift in policy 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 to ensure delivery of critical infrastructure services. As a result of this shift, the federal government has started a coordinated set of resilience initiatives to understand what features create resilience in critical infrastructures/key resources (CIKRs) and has initiated calls to agencies to start measuring the resilience of their infrastructure systems.

Private industry, including the chemical sector, would benefit through the inclusion of resilience concepts in business plans. By understanding how their businesses (and those that they depend upon) are affected by and recover from various types of disruptions, private industry can develop comprehensive emergency plans and evaluate the costs and benefits associated with various recovery strategies. Hence, the DHS Science and Technology Directorate has tasked Sandia to develop a resilience assessment methodology that can be applied to the chemical sector and other CIKR systems.

A uniform, methodical approach for assessing resilience of infrastructure systems is required to successfully incorporate resilience into CIP policies and business planning practices. This approach needs to be general enough to apply to all types of infrastructure systems to account for dependencies between different infrastructure types and establish standards across all infrastructure types. Furthermore, resilience assessment approaches should explicitly account for the costs of recovery processes in comprehensive disruption cost evaluations.

With these two requirements in mind, we have developed a novel framework for evaluating the resilience of infrastructure and economic systems [6]. The framework includes a new definition of resilience, a mathematical resilience cost measurement approach, and a qualitative analysis methodology that assesses system characteristics that affect resilience. This framework can be applied to studies of natural and manmade disruptions. This paper describes the three components of the resilience assessment framework in detail. Furthermore, we demonstrate the application of the framework through analysis of the resilience of the national petrochemical supply chain during two different hurricane disruption scenarios.

2. A Framework for Resilience Assessment

To define resilience, we identified the factors that determine resilience and need to be quantified when measuring resilience costs. We then described how these factors need to be combined to measure resilience costs and developed a mathematical algorithm for that purpose. We also developed a qualitative analysis approach to explain the system's resilience costs. Additionally, the qualitative approach can also be used to determine improvements needed to enhance the system's resilience. This section describes the individual framework components in greater detail.

2.1 A Definition of System Resilience

We define system resilience as follows:

> 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.

Elements of this definition can be further defined as follows:

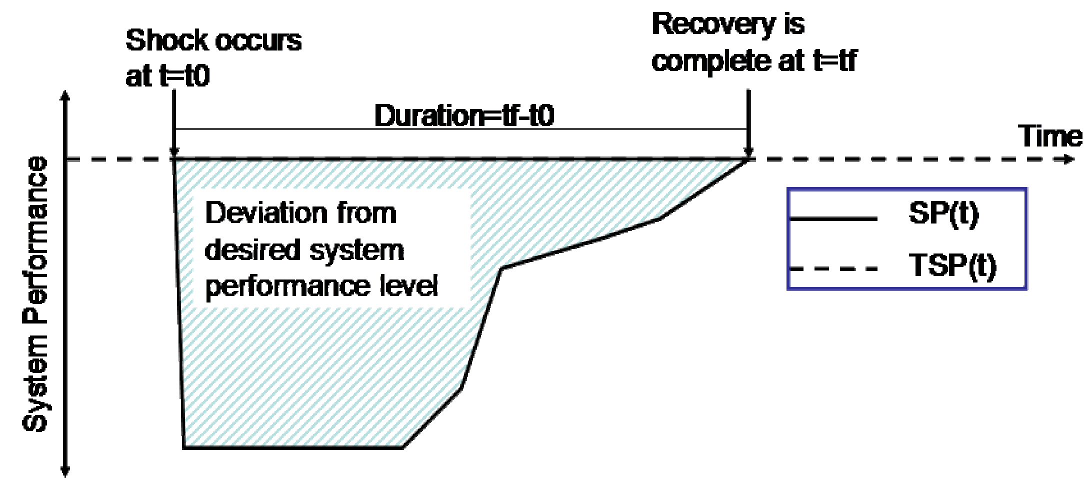
- Disruptive event - This definition considers resilience of a system to a specific disruption. Different disruptions may affect a system in different ways and, thus, necessitate different recovery processes. Hence, a system may have different levels of resilience to different disruptions.
- System performance - Given the flexibility of many systems to adjust and reconfigure to a disruptive event, maintaining system structure is not as important as maintaining system performance. Hence, measurement of resilience should evaluate how a disruption affects system performance and causes productivity to decrease relative to targeted system performance levels; i.e., how the system should behave during and after disruptive events.
- Efficiency - The term "efficiency" means using the lowest possible amount of resources during recovery processes; depending on the domain, these resources could be dollars, repair man-hours, infrastructure replacement assets, or time.

2.2 Calculation of Resilience Costs

We have developed a mathematical resilience costs measurement approach that can be used to objectively determine the impacts of disruptions on a system and the resilience costs associated with disruptions. The resilience cost measurement approach requires quantification of two key components of the definition of system resilience: systemic impact (*SI*) and total recovery effort (*TRE*). *SI* is the impact that a disruption has on system productivity and is measured by evaluating the difference between a targeted system performance (*TSP*) level and the actual system performance (*SP*) following the disruption. *TRE* refers to the efficiency with which the system recovers from a disruption and is measured by analyzing the amount of resources expended during the recovery process. The measurement of system resilience costs requires the quantification of both *SI* and *TRE*.

Figure 1 graphically represents systemic impact for a hypothetical system that has been disrupted. In this example, system performance decreases immediately following the disruption shock. With the onset of recovery actions, performance levels eventually increase and ultimately attain targeted system performance levels. At this point, recovery is considered complete. *SI* is quantified by calculating the area between the *TSP* and the actual *SP* curves in Figure 1. This area is calculated using the formula in Eq. 1.

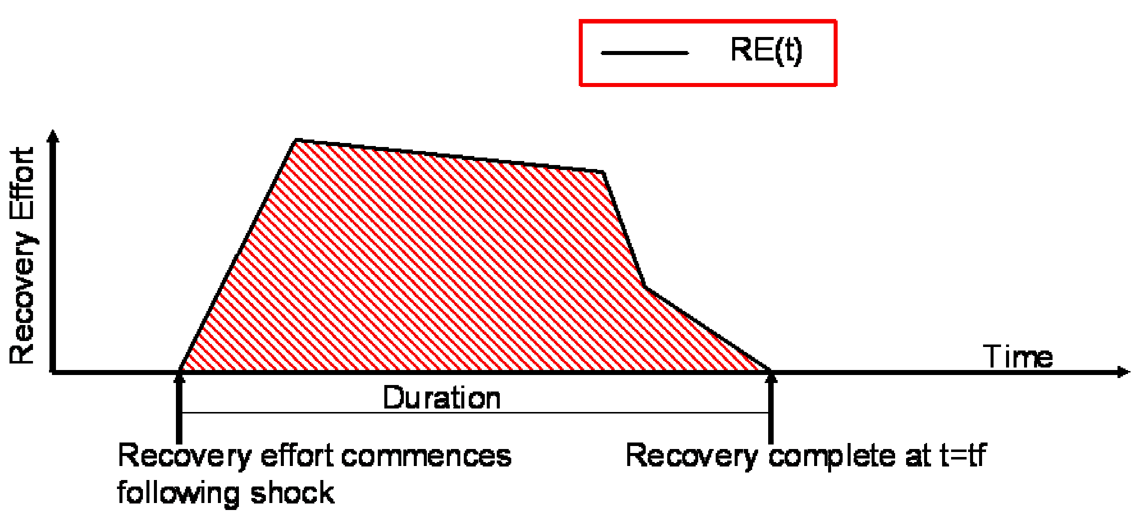
Figure 1: Systemic Impact



$$SI = \int_{t0}^{tf} \left[TSP(t) - SP(t) \right] dt \qquad \text{[Eq. 1]}$$

Figure 2 illustrates the recovery response for the system shown in Figure 1. After the disruption initiates, the recovery response begins and resources are expended in this effort. The *TRE* is the cumulative amount of resources expended during the recovery period and is represented by the area under the recovery effort (*RE*) curve in Figure 2. This area is calculated by Eq. 2.

Figure 2: Total Recovery Effort



$$TRE = \int_{t0}^{tf} \left[RE(t) \right] dt \qquad \text{[Eq. 2]}$$

The system performance is determined by the *RE*. That is, different *RE*s lead to different system performances. For example, if no *RE* is made following the disruption, the loss of system performance may be great. In contrast, if recovery resources are deployed shortly after the system shock, system performance may not be significantly affected, and SI may be small. The recognition that *SI* is implicitly determined by the selected recovery strategy leads to the development of two types of resilience cost measurements: optimal resilience (*OR*) costs and recovery-dependent resilience (*RDR*) costs. *OR* costs are the resilience costs for a system when the optimal recovery strategy, minimizing the combined *SI* and *TRE* costs, is employed. This calculation is beyond the scope of this paper. *RDR* costs are the resilience costs of a system under a particular recovery strategy and are calculated with Eq. 3.

$$RDR(RE) = \frac{\int_{t0}^{tf} \left[TSP(t) - SP(t) \right] dt + \alpha \times \int_{t0}^{tf} \left[RE(t) \right] dt}{\int_{t0}^{tf} \left| TSP(t) \right| dt} = \frac{SI + \alpha \times TRE}{\int_{t0}^{tf} \left| TSP(t) \right| dt} \qquad \text{[Eq. 3]}$$

RDR costs are linear combinations of *SI* and *TRE*. The denominators in Equation (3) are normalization factors that permit the comparison of the resilience of systems of different magnitudes. Because resilience represents a balancing of *SI* and *TRE* costs, the calculation of *RDR* costs includes the parameter α, which is a weighting factor that allows an analyst to assign the relative importance of the systemic impact and total recovery effort terms. Assigning a small positive value to α weighs the systemic impact more heavily; a large positive value for α weighs the cost of recovery more heavily. To equally weigh *SI* and *TRE*, α is set to 1.

Several things about this resilience measurement approach should be considered. First, smaller *RDR* costs indicate increasing resilience, with zero being the minimum possible value. Additionally, no finite *RDR* costs correspond with the concept of a minimally "resilient" system. Also, the approach for measuring system resilience is neither model- nor domain-specific. It only requires time series data (either historical or from a model) that represent system output and recovery efforts. However, the summation of the *SI* and $\alpha \times TRE$ terms in Eq. 3 requires either that the *SI* and *TRE* be measured in the same units and α be a dimensionless constant or that α be assigned units that are appropriate for converting *TRE* to the same units as *SI*.

Because the *RDR* costs 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. The system that has lower resilience costs will be the more resilient system. *RDR* values can also be used to compare the resilience of the same system to different types of disruptions. The system is more resilient to the disruption that results in smaller *RDR* values. Moreover, they can be used to compare the resilience of a system to a disruption under different recovery strategies. Each different recovery strategy will result in different *SI* and *TRE* values. The recovery strategy that results in the smallest *RDR* values will provide maximal resilience for the system.

2.3 Qualitative Resilience Analysis

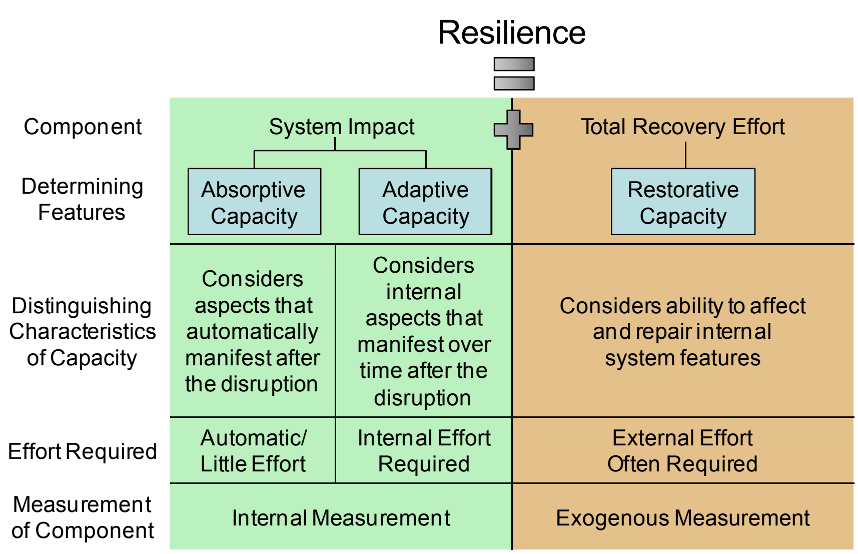
Joseph Fiksel [7] suggests that "it is important to assess not only performance outcomes but also the intrinsic characteristics that contribute to system resilience." Consequently, the framework described in this paper features a qualitative analysis component that can be used to explain the results of quantitative measurements or can take the place of quantitative results when no data are available. This analysis is done through consideration of system structures, characteristics, and features.

This portion of the framework uses three fundamental system capacities (*absorptive capacity, adaptive capacity, and restorative capacity*) to formulate how properties of a system can determine system resilience, specifically by reducing *SI* and *TRE*.[1]

These capacities are affected by resilience enhancement features; that is, the features of the system that are in place before a disruption and that affect one or more of the system's capacities. Identifying resilience enhancement features enables a better understanding of fundamental characteristics that contribute to resilience. Most importantly, pre-disruption preparatory actions can target these resilience enhancement features to increase the resilience of the system.

The following subsections describe the characteristics of resilience capacities and related resilience enhancement features and provide examples of each. Figure 3 summarizes the distinguishing characteristics of the capacities.

Figure 3: Resilience Capacities



[1] These capacities are similar to the abilities to "absorb, recover from, or successfully adapt to adversity or a change in conditions" in the official Department of Homeland Security definition of resilience (U.S. Department of Homeland Security Risk Steering Committee 2008), but do not include that definition's ability to resist.

2.3.1 Absorptive Capacity

Absorptive capacity is the degree to which a system can automatically absorb the impacts of system perturbations and minimize consequences with little effort. The absorptive capacity is an endogenous feature of the system.

For example, storage can enhance the absorptive capacity; if a chemical plant is disabled but a large amount of collocated storage of its product is undamaged, customers can continue to be supplied by the stored quantities, with little cost to the producer or customer, while the plant is repaired.

Other examples of absorptive capacity resilience enhancement features include the system robustness and redundancy. System robustness decreases *SI* through the strength of individual connections in the system. Levees that prevent hurricane storm surges from damaging a chemical facility are an example of system robustness within the chemical sector. System redundancy decreases *SI* through providing alternate pathways for the system mechanics to operate. A specific example of system redundancy in the chemical sector is purchasing inputs from multiple, geographically-dispersed suppliers.

2.3.2 Adaptive Capacity

Adaptive capacity is the degree to which the system is capable of self-organization for recovery of system performance levels. It is a set of properties that reflect actions that result from ingenuity or extra effort over time, often in response to a crisis situation. It reflects the ability of the system to change endogenously during the recovery period.

Consider the scenario in which a hurricane destroys many high voltage power lines, leaving many customers without electricity. Customers with emergency generators enhance system adaptive capacity because the system can be changed (customers adapt to the disruptive event by generating power from a fuel source such as gasoline rather than connecting to the electric grid) so that some portion of system performance is regained at a relatively low amount of effort.

Substitutability, the ability to replace one system component or input with another, is a resilience enhancement feature that can affect adaptive capacities. Chemical production processes can sometimes substitute inputs or use alternate technologies. Economic systems with a high adaptive capacity can easily adjust to shocks through ordinary means such as input substitution, which can occur in situations where an input is scarce. Other resilience enhancement features that increase adaptive capacity tend to be more difficult to identify because they often rely upon the ingenuity of people faced with adversity.

2.3.3 Restorative Capacity

Restorative capacity is the ability of a system to be repaired easily, and these repairs are considered to be dynamic. In the case of massive catastrophic events, systems may not be able to repair themselves or they may not be able to do so rapidly enough to prevent unacceptably large consequences. In these circumstances, repairs may be performed by entities external to the system. In the context of infrastructure policies, the government can be an external, enabling or repairing entity. The government agencies may not directly perform the repairs, but may serve as a lead restoration planner or restoration planning coordinator. These repairs usually restore the system to near its original preevent state, but can also restore the system to a completely new state or regime that anticipates future system requirements. Therefore, the repairs are a form of investment.

An infrastructure owner, such as a corporation, may also take action, often by drawing on external resources such as other units of the corporation or by outsourcing. Businesses may be able to perform repairs using their own local resources (such as custodial staff), but in most cases these repairs could be better described as maintenance. However, a business with a high degree of restorative capacity may be able to eliminate the need for repairs by an external entity.

Restorative capacity directly affects the *TRE*, although repairs to the system enabled by the system's restorative capacity also increase the system performance and may reduce recovery duration, thereby reducing *SI*. Whereas adaptive capacity reflects the ability of a system to be changed endogenously, restorative capacity reflects the ability to be repaired. Most importantly, adaptive capacity involves changes that can radically alter the structure of the system to restore system performance, while restorative capacity most often involves repairs that are implemented with the goal of returning a system to something near its original structure. For example, the electric power grid has monitoring systems that can automatically detect when and where a break in the grid emerges. Such technologies enhance the restorative capacity of the power grid because repair crews can be sent to the location of the break. These technologies result in a shorter disruption that is easier to repair (in terms of cost and time) than it would be if crews had to search large portions of the grid to find the break before repairing it.

Another differentiation between adaptive capacity and restorative capacity is that restorative capacity may affect a system's ability to be permanently changed (an investment decision) while adaptive capacity is primarily concerned with features that are temporary. The restorative period provides an opportunity to remake the system. For example, a chemical plant using an inefficient technology may decide to invest in a superior, more efficient technology during restoration. The restoration period is also an opportunity to modify the system to increase resilience to future events. Therefore, a system with a greater restorative capacity may indirectly have higher absorptive and adaptive capacity. Systems with a greater ability to be upgraded during the restoration period will have a greater restorative capacity.

3. Application to the National Petrochemical Sector

This section describes an application of the framework to a petrochemical supply chain model to demonstrate the utility of the resilience assessment. Specifically, the framework was used to compare the resilience of the national petrochemical supply chain to two hurricane scenarios. To perform this analysis, we used an agent-based simulation to simulate the effects of a hurricane disruption on the national petrochemical supply chain. The model reported economic data representing system performance and recovery processes, and these data were then processed, using the resilience assessment framework

3.1 Chemical and Economic Models

To perform the comparative analysis, we used the National Infrastructure and Simulation Analysis Center (NISAC) Petrochemical Supply Chain Model (version #1, 2007) that Sandia developed as a part of NISAC. This NISAC petrochemical supply chain 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 4,000 domestic and foreign consumers and producers of 63 commodity petrochemicals. Each of the firms in the CDM makes a primary feedstock petrochemical (benzene, toluene, ethylene, propylene, xylene, o-xylene, or 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 among these chemicals.

Sandia uses the petrochemical CDM in conjunction with the NISAC Agent-Based Laboratory for Economics (N-ABLE™) microeconomics simulation tool [8] to simulate disruptions to the petrochemical sector from various types of disturbances. N-ABLE™ is a collection of tools that Sandia has developed to perform supply-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.

In N-ABLE™, 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. Firms representing the range of economic activity in a supply chain (such as manufacturing, transportation, and consumption) are 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, independent of input costs. The production manager adapts 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 supply chains are constructed from collections of firms, based on this enterprise design, with each participating firm interacting with others through markets and physical infrastructure.

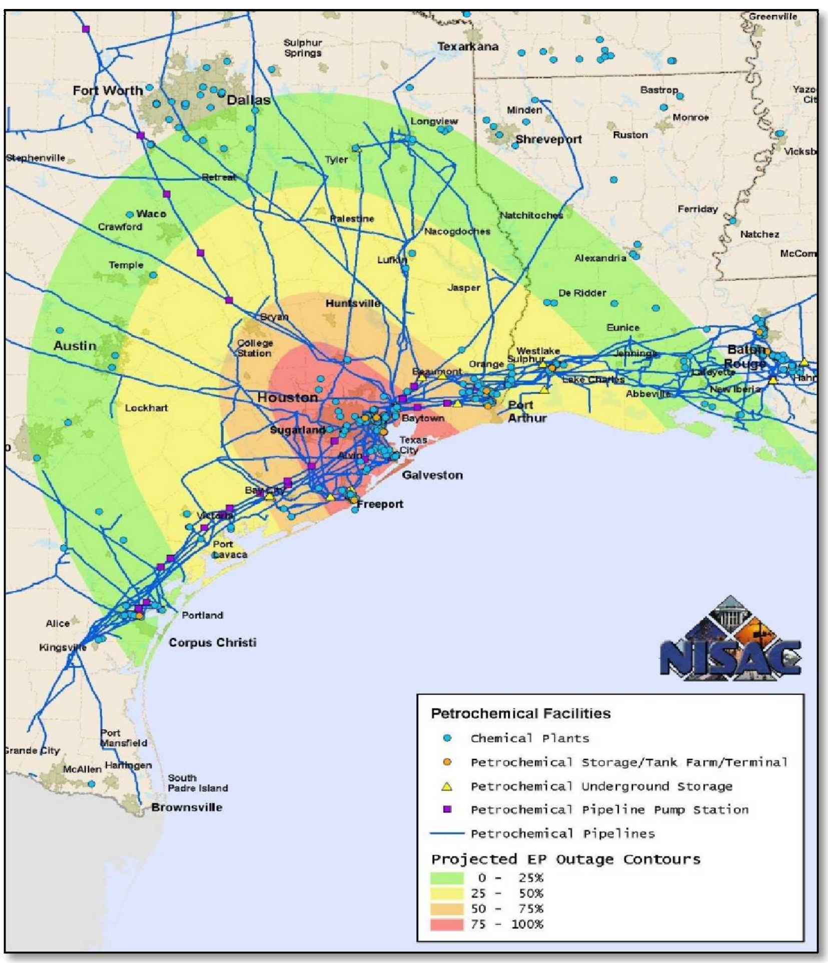
When applied to the petrochemical CDM, N-ABLE™ simulations can provide quantitative and qualitative information necessary for resilience analyses. For example, if a hurricane temporarily shuts down a set of chemical production facilities, N-ABLE™ can estimate economic impacts resulting from a decreased chemical supply to downstream facilities (e.g., customers of the closed facilities, the customers of the customers, etc.). N-ABLE™ can also predict losses resulting from decreased demand of input chemicals used by the closed production plants to upstream facilities (e.g., suppliers to the closed plants, suppliers of the suppliers, etc.). These economic impact and loss estimates can be used to measure the *SI*s to the petrochemical supply chain from a hurricane.

In addition, N-ABLE™ can predict how the petrochemical sector will adapt to and recover from a disruption. The tool has the capability to estimate production curtailments by the customers of the closed plants who cannot find new suppliers, the higher transportation costs associated with new suppliers, the use of chemical substitutes, and the implementation of different production technologies and recipes to adapt to a disruption. The cost estimates associated with the recovery and adaptation processes are crucial to calculating the *TRE* in a resilience analysis.

3.2 Analysis Methodology

In this analysis, we consider the resilience of the national petrochemical sector to two different hurricane scenarios. In the first scenario, a Category 2 hurricane makes landfall in the Houston, Texas, area (Figure 4). It is common practice for Gulf Coast petrochemical 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 a few weeks. Production at these facilities will not likely be restored immediately following restoration of power. Following a plant shutdown, petrochemical facilities often require additional startup time to perform system checks, such as purging lines and vessels with inert gases such as nitrogen, to ensure the unit's operability. Hence, to simulate the cumulative effects of the electric power outage on production levels at the affected petrochemical facilities, it is also assumed that all petrochemical facilities within the outage contours are shut down for 25 days.

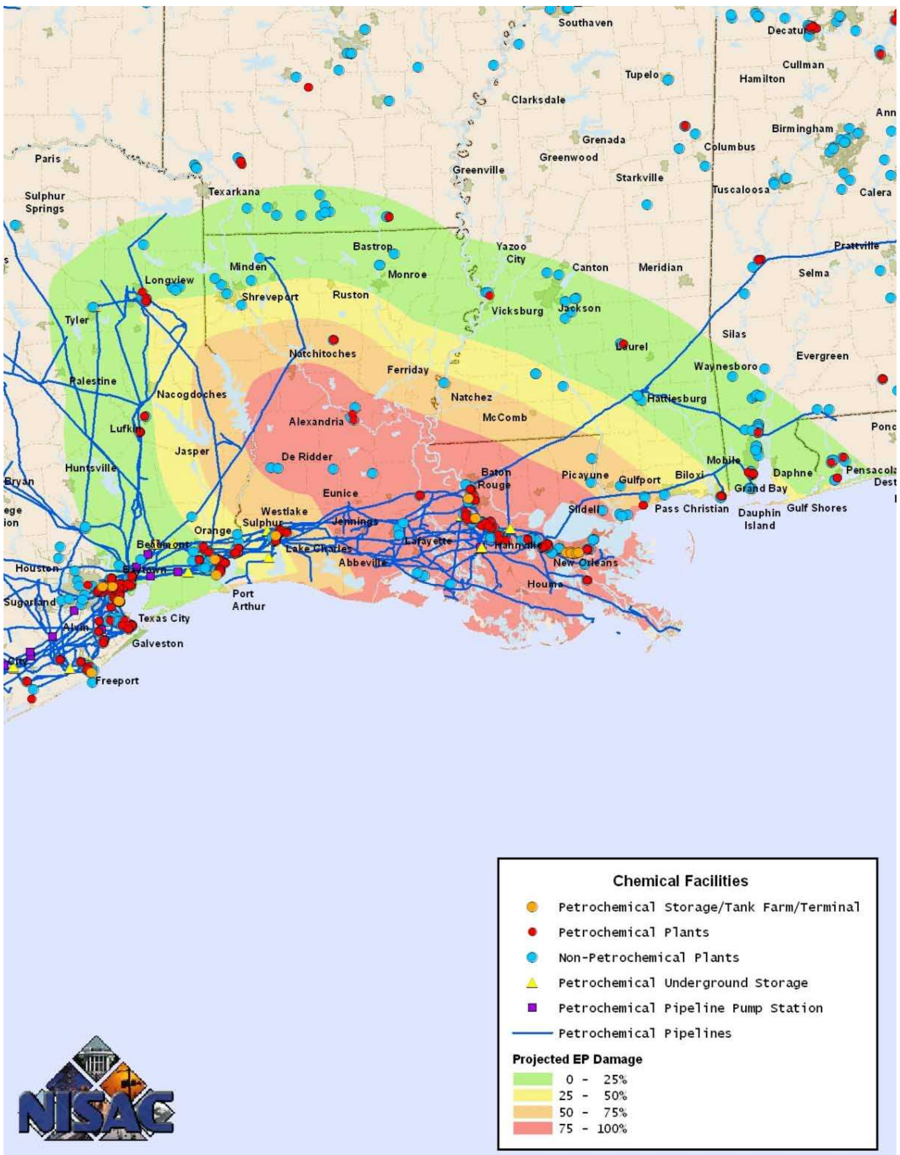
Figure 4: Electric Power Outages: Houston Scenario



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).

In the second scenario, a Category 2 hurricane makes landfall near New Orleans, Louisiana (Figure 5). It is assumed that all petrochemical facilities that lie within the outage contours will be shut down for 25 days.

Figure 5: Electric Power Outages: New Orleans Scenario



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). Some of the same petrochemical facilities are affected in both the Houston and New Orleans scenarios.

It is projected 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). Second, 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, unmet demand is expected to be higher in this scenario, and more consumers will be expending more resources to receive their necessary products, thereby driving up recovery costs in an attempt to limit system impacts.

To quantitatively evaluate the resilience of the petrochemical supply chain, we ran three sets of N-ABLE™ simulations. In the baseline scenario, we assumed no disruptions. In the Houston disruption scenario, we assumed that a hurricane is projected to make landfall on day 202 of the simulation and the electric power outage shown in Figure 4 is expected to occur. On day 200, all petrochemical facilities within the contours shut down in anticipation of the storm. 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.

The market value of production (*MVP*) is the metric used to measure system performance. *MVP* captures total "street value" of every step of production. It is similar to the sale value of end products, but it counts production at every stage in the production process, whereas the sale value only counts chemicals that are sold on the merchant market. *MVP* equals sale value of end products if there is absolutely no vertical integration; i.e., outputs of every stage of the production process are sold on the merchant market

For this analysis, two factors are considered in the recovery effort variable: additional aggregate transportation costs (*TC*) and additional aggregate market costs (*MC*). When a disruption decreases the supply of available chemicals, consumers of those chemicals will seek new suppliers. These suppliers will likely be farther from the consumers than the original suppliers, so the cost of transporting chemicals from the new suppliers will likely be greater due to the increased transportation distances. 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. Unmet demand will generally be low during baseline conditions, when long-term, supply-demand ratios and relationships ensure that most buyers can find product most of the time, but generally higher during the disruption, when these buyers must try to find product from alternative sources. These market search costs will increase if buyers are unable to find product, either due to lack of supply or lack of sufficient time to find suppliers.

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 caused by winds and/or flooding, startup costs, etc. However, for the sake of simplicity, we only consider the *TC*s and *MC*s when calculating the *TRE* for this example. To calculate *RDR* costs, we set α to 1 in Eq. 3 and we approximate the integral with 1-day time-step intervals because N-ABLE™ reports data on a daily basis.

3.3 Simulation Results

Figures 6 and 7 show the *MVP*s and recovery costs for all scenarios. *MVP* is immediately affected by the disruptions in each scenario. The initial *MVP* decrease is less than the fraction of shut-down production capacity because the system uses stored inventories of chemicals and seeks new suppliers from further distances. However, inventories start to deplete near the end of the shutdown 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 full production capacity is restored, *MVP* levels for the disruption scenarios actually exceed baseline levels, initially (days 240 to 275), because the plants have ramped up production levels to meet not only previously unmet demand but also to restore inventory levels. After day 275, no consistent differences are observed between the baseline and disruption *MVP* levels; differences between the *MVP* levels are attributed to the stochastic nature of the supply chain model.

Figure 6: Simulated Market Values of Production

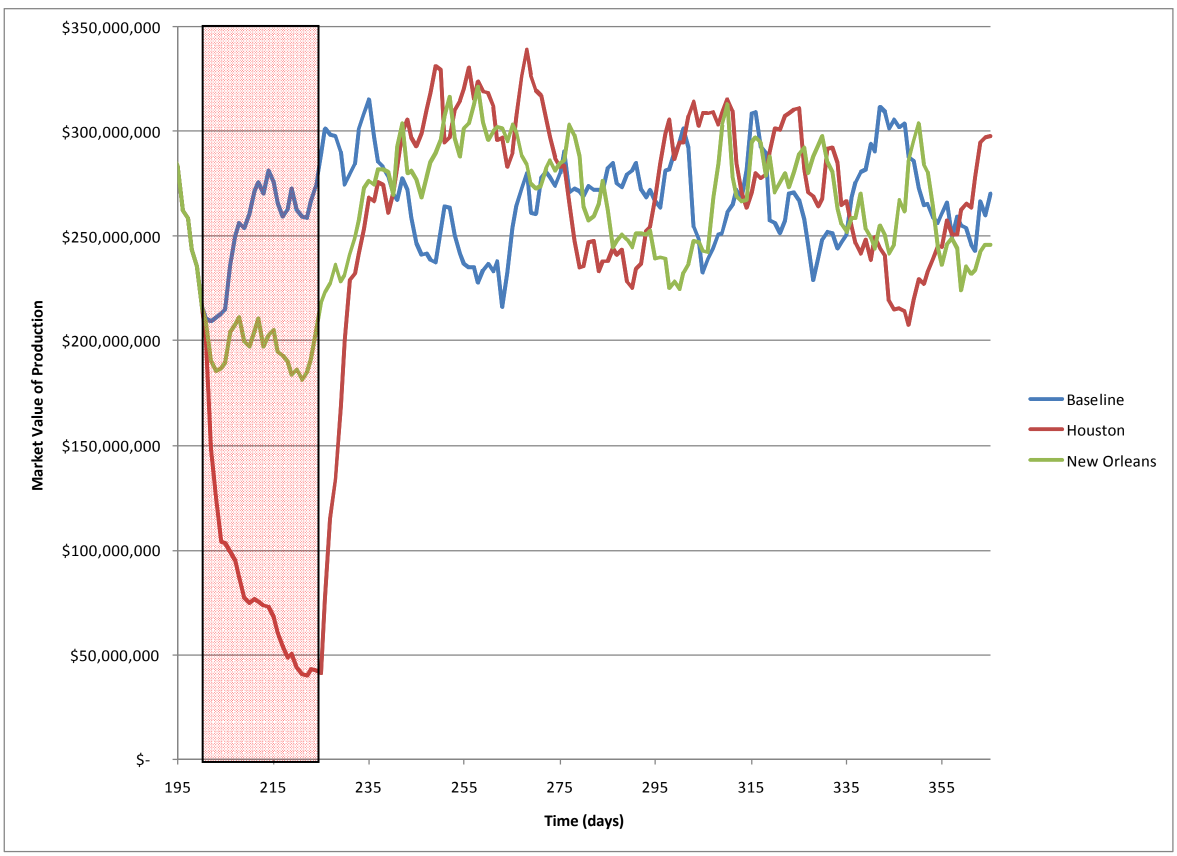


Figure 7: Recovery Costs

Figure 7a: Additional Market Costs

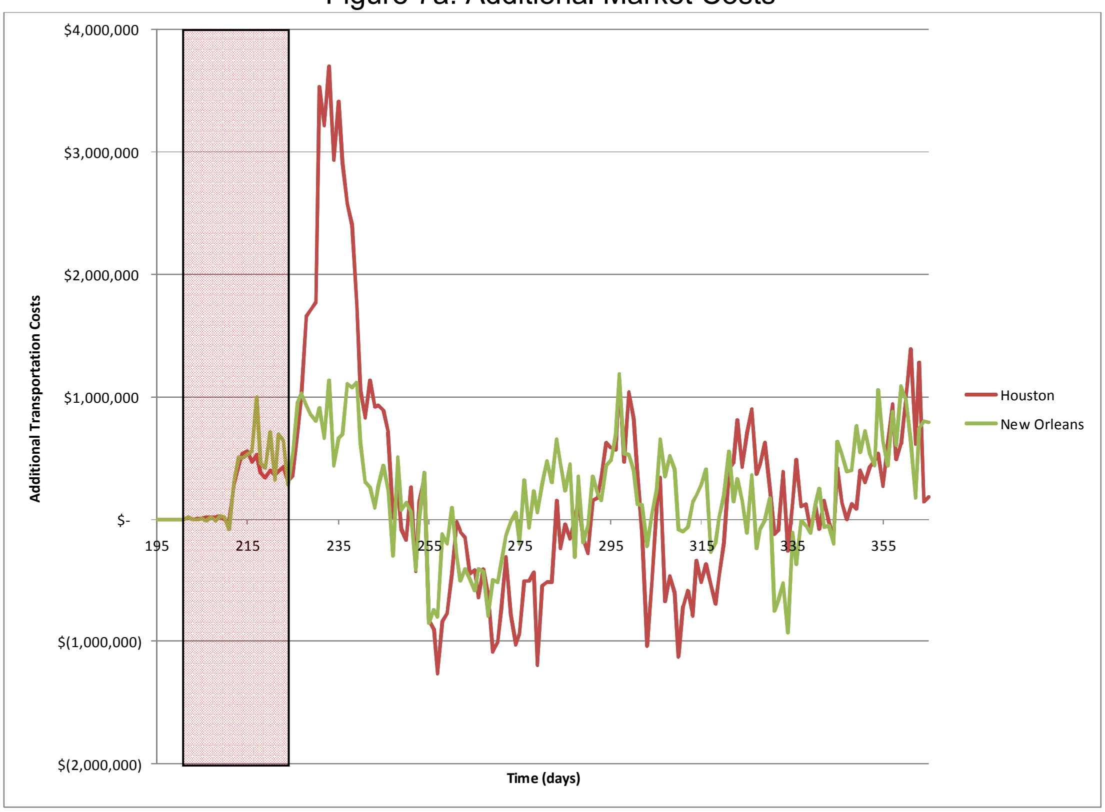


Figure 7b: Additional Transportation Costs

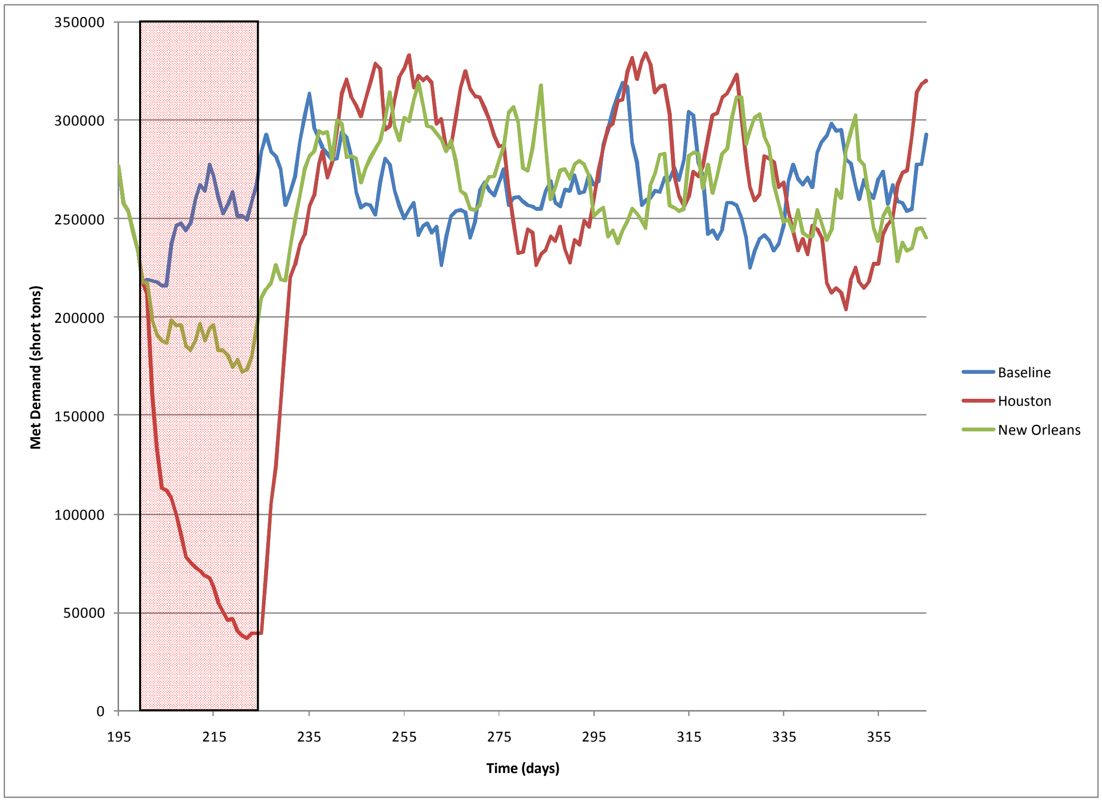


Figure 7c: Unmet Demand

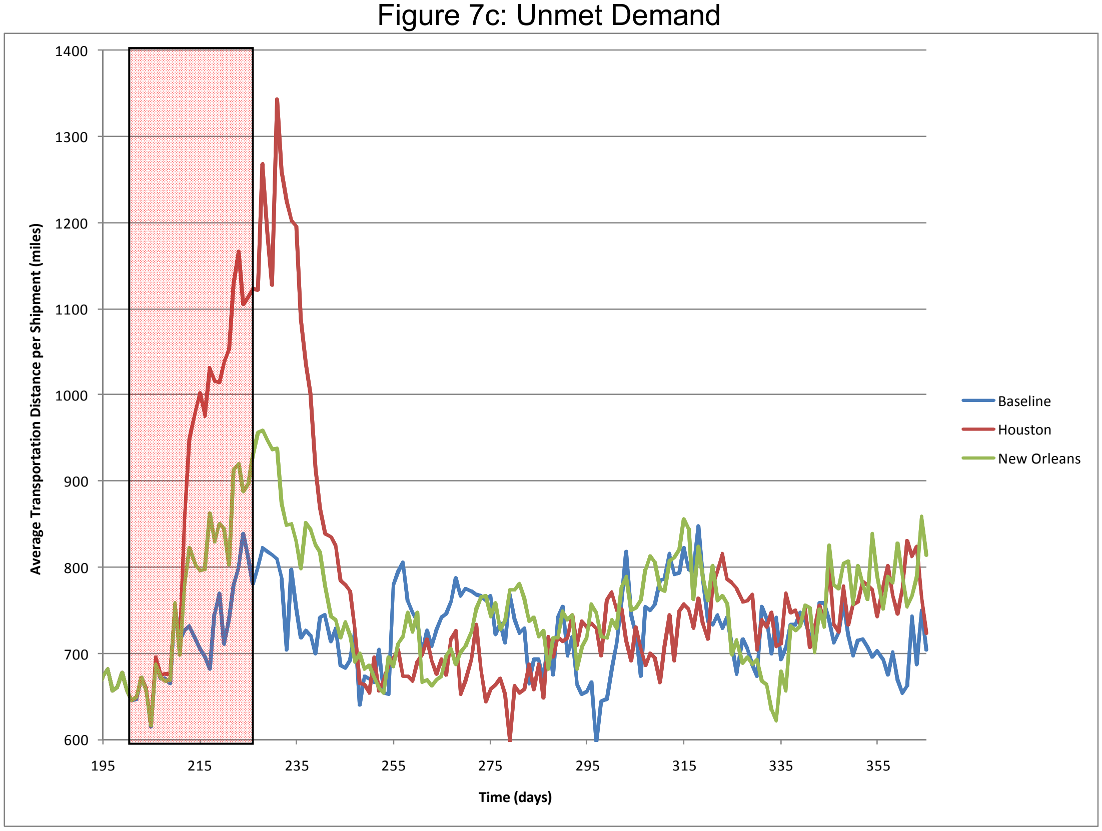


Figure 7d: Average Transportation Distance

Additional transportation costs are determined by two factors: average distance travelled by a chemical shipment and met demand. Travel distances for the disruption scenarios start to exceed baseline distances around day 210 (Figure 7d). 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 7c). This decrease in met demand and, consequently, the number of chemical shipments 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 this period, disruption scenario travel distances decrease and become similar to baseline levels. Differences between the disruption scenarios and baseline scenario are attributed primarily to the stochastic nature of the supply chain model.

In this analysis, differences between disruption and baseline *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, recovery is considered complete at this time.

3.4 Resilience Assessment

Table 1 lists the systemic impact, recovery efforts, and resilience costs for both disruption scenarios. The resilience costs for the Houston scenario are higher than the New Orleans scenario, so the petrochemical sector is more resilient to the New Orleans hurricane scenario than the Houston hurricane scenario. Furthermore, resilience costs are primarily determined by systemic impact as recovery costs are two orders of magnitude less than systemic impacts.

Table 1. Resilience Costs (unitless)

Measure	Houston Hurricane	New Orleans Hurricane
Target Market Value of Production ($M)	20,000	20,000
Systemic Impact ($M)	3,600	600
Recovery Effort: Market ($M)	23	3.9
Recovery Effort: Transportation ($M)	32	14
Resilience Cost	0.19	0.03

Resilience cost is calculated according to Eq. 3; i.e.,

$$\text{Resilience Cost} = \frac{\text{Systemic Impact} + \text{Market Recovery Effort} + \text{Transportation Recovery Effort}}{\text{Target Market Value of Production}}$$

The resilience framework allows qualitative assessment of attributes that enhance the supply chain's absorptive, adaptive, and restorative capacities. In this analysis, the supply chain is more resilient to the New Orleans hurricane because, when compared with the Houston hurricane, a larger fraction of the overall supply chain is unaffected, giving the entire supply chain greater ability to keep chemical production running. Thus, the diversity in location increases the system's absorptive capacity and *SI*s are lower for the New Orleans scenario.

Recovery costs are relatively small when compared with *SI*. This result suggests two resilience enhancement strategies. First, companies or policymakers could seek ways of enhancing the robustness of petrochemical supply chains to decrease *SI*. Alternatively, they could try more aggressive recovery strategies that may be more costly than current recovery processes but are still relatively low cost when compared to *SI*.

This example illustrates some general and important considerations when computing *TRE*. The calculation of *TRE* ideally should account for all costs associated with the supply chain's recovery to targeted system performance levels. While this example only considered transportation and market costs in the estimation of *TRE*, we recognize that recovery costs in actuality would be more extensive and include additional expenses such as repair of damage caused by winds and/or flooding, startup costs, etc. More work is needed to identify and estimate a complete set of variables that contribute to recovery costs (in addition to those listed in Table 1) so that better estimates of *TRE* can be calculated.

4. Summary

The resilience assessment framework presented herein consists of three primary components. First, our definition of system resilience indicates what factors need to be considered when assessing the resilience of a system. Second, we quantitatively evaluate these factors using our resilience cost measurement methodology. Third, we use the qualitative analysis component to examine resilience capacities and resilience enhancement features of the system, to explain or replace quantitative results.

The chemical sector (and other industries) must make cost-benefit decisions on a regular basis, and the resilience cost measurement approach described in this paper provides a structured, quantitative means for conducting those cost-benefit studies. For example, the resilience framework separates resilience costs into two categories: costs resulting from decreased system productivity (*SI*) and costs attributed to recovery activities (*TRE*). This information provides firms with a strategy for decreasing resilience costs by measuring tradeoffs between *SI* and *TRE*. If the *SI* far outweighs total recovery effort, a firm may want to focus on approaches for decreasing *SIs* (perhaps by increasing inventories, adding redundancy, etc.) without significantly increasing *TRE*. If *TRE* outweighs *SI*, a firm may want to focus on developing cheaper, more efficient strategies for recovery that do not drastically increase *SI*. Additionally, if the resilience costs for a sector 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. The framework can also be used to choose recovery strategies by comparing the resilience costs under different recovery strategies. Thorough application of this resilience assessment framework can result in a comprehensive evaluation of a system's resilience and provide information about how to further enhance system resilience.

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