Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

The Impacts of Increased Adverse Weather Events on Freight Movement

Project No. 19ITSUTA02

Lead University: University of Texas at Arlington

Final Report

August 2020

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16. Abstract

Freight transportation is a major economic backbone of the United States and is vital to sustaining the nation's economic growth. Ports, as one of the primary components of freight transportation and important means of integrating into the global economic system, have experienced significant growth and increased capacity during the past two decades. The study addresses an important national freight mobility goal to enhance the resilience of the port transportation operations in the event of extreme weather events. This study develops an adaptable resilience assessment framework that evaluates the impact of a disruptive event on transportation operations. The framework identifies dynamic performance levels over an extended period of an event including five distinct phases of responses- staging, reduction, peak, restoration, and overloading. This study applies the framework to the port complex in Houston, Texas, during a major hurricane event, Harvey, and two holiday events in 2017. The framework evaluates proactive and reactive responses of port truck activities during the disruptions and provides a comprehensive assessment of resilience and adaptability in port truck operations. Evaluating response systems and resilience of port truck activities during severe weather events such as Hurricane Harvey represents the first step for designing plans that support a fast system recovery that minimizes the economic, social, and human impacts.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

FAF	Freight Analysis Framework
GPS	Global Positioning System
MSA	Metropolitan Statistical Area
NFSP	National Freight Strategic Plan
OD	Origin-Destination
PHA	Port of Houston Authority

EXECUTIVE SUMMARY

This research seeks to understand the freight movements from the Port of Houston throughout the region and evaluate their response to adverse weather event such as Hurricane Harvey. The research focuses on identifying (i) truck activity from the port of Houston, (ii) capturing truck flow disruptions due to Hurricane Harvey, and (iii) identifying flow changes and recovery process during and immediately after the adverse events.

Specific research objectives include:

1) To develop a strategy for extracting and mining port truck travel patterns from large-sized GPS trajectories and transportation network of the region

2) To quantify travel behavior changes due to adverse weather events of Hurricane Harvey

3) To understand operational strategies to prepare for, adapt to, and recover from Hurricane events and estimate economic outputs by the types of strategies

This study develops an adaptable resilience assessment framework that evaluates the impact of a disruptive event on transportation operations. The framework identifies dynamic performance levels over an extended period of an event including five distinct phases of responses- staging, reduction, peak, restoration, and overloading.

This study applies the framework to the port complex in Houston, Texas, during a major hurricane event, Harvey, and two holiday events in 2017. The framework evaluates proactive and reactive responses of port truck activities during the disruptions and provides a comprehensive assessment of resilience and adaptability in port truck operations. Trucks serving local facilities show stable and shorter response phases while regional operations maintain a prolonged staging or overloading phases to handle the excess demands especially for significant multi-day disruptive events. Evaluating response systems and resilience of port truck activities during severe weather events such as Hurricane Harvey represents the first step for designing plans that support a fast system recovery that minimizes the economic, social, and human impacts. This study highlights the importance of staging and overloading phases since proactive or reactive responses during the phases describe the resilience and adaptability of the operation. The extent of flexibility in operational capacities such as instantaneous volume increases during a short period of staging phase or an extended overloading phase shows how much adaptable capacity and flexibility the system provides to recover from the disruption. An economic analysis using the resilience framework estimates economic gain or loss of each phase of the event periods based on the truck operations compared to normal performance level.

1. INTRODUCTION

According to the National Freight Strategic Plan (NFSP) (*1*), the US population will increase by 21% over the thirty years from 2015 to 2045 from 321 million to 389 million. At the same time, freight movements will increase at a faster rate and grow by 42 percent by 2040, which roughly equals a 1.3 percent increase per year. Among the various modes in freight transportation, trucks show the largest expected increase in flows from 46.5% in 2015 to 54.4% in 2040 since they handle the most ton-miles in the US (*2*). Comparing the increase in freight movement and population in a 30-year period, freight movement increases at a much faster rate (Figure 1).

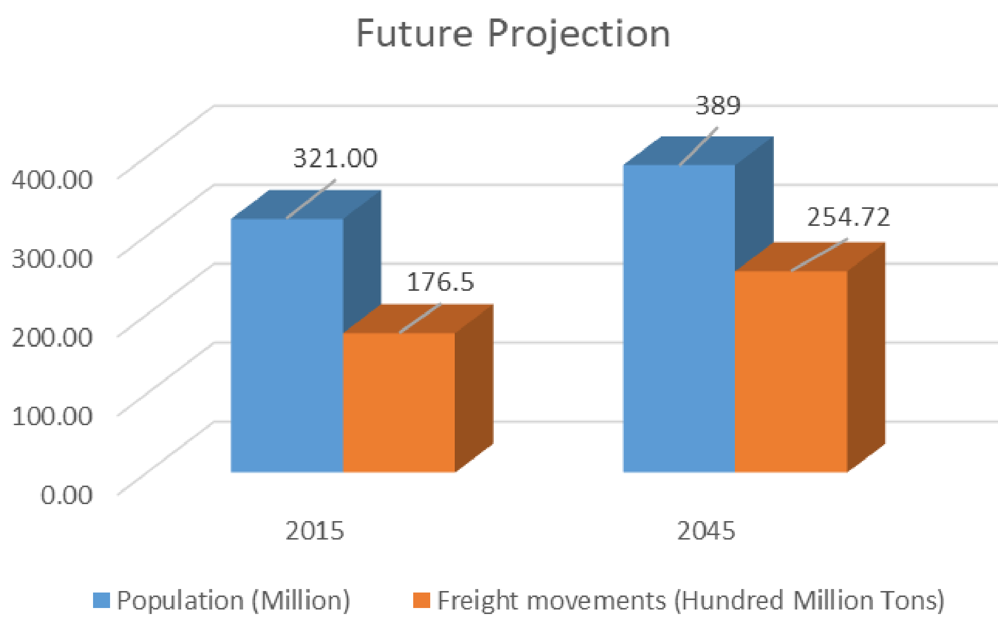


Figure 1. Population and freight movement growth from 2015 to 2045.

With significant increases in freight volumes, the economic and social impacts from severe weather events on port truck traffic represent significant concerns to local, regional, and state agencies. For example, the goals for freight transportation in Texas emphasize infrastructure maintenance and efficiency improvement by increasing the resilience of the freight transportation system to natural and man-made disasters (*3*). Many agencies prioritize enhancing the resilience of transportation system including highway, bridges, and operational infrastructure where resilience generally defines the ability of a system to keep or recover to a stable state after being affected by a disruptive event (*4*). As the resilience of the multimodal freight network remains a priority of many states containing an international port along the West, East, and Gulf Coasts in the US, they require regional strategies to minimize the short-term impacts on the multimodal freight network caused by frequent adverse weather events (*3*). Long-range regional priorities focus on designing cost-effective and reliable freight transportation operations. The short-term and long-term strategies both emphasize resilience and integration with emergency response plans that prioritizes critical lifelines.

Many studies developed strategic plans to optimize freight system performance by reducing direct impacts or damages from a disaster event and enhancing the system's overall resilience. Ta et al.

(*5*) created a set of actions for state DOTs focusing on organizational processes, information dissemination, and infrastructure improvements to enhance the resilience of freight transportation. Nair et al. (6) developed a similar framework for the application of resilience at the intermodal freight system level and produced the required steps to apply resilience to an existing port. Bekkem et al. (7) evaluated the resilience of a highway corridor and developed an analysis method to identify high-risk segments, which require improvements to ensure freight transportation operations. Miller-Hooks et al. (*8*) suggested actions to prepare and recover immediately after a disaster based on the maximum resilience of the freight transportation network obtained from a Monte Carlo simulation. Unfortunately, these strategies often relied on simple performance metrics that captured changes in physical functionality or performance levels before and after a disaster event. For example, researchers used the changes in operational metrics such as travel time or throughput during the disaster event to determine the vulnerability or resilience of the system (*9, 10*). Other studies directly translated physical damage to the built infrastructure into reductions in operations using a simulation or an optimization method (8). Topological measures characterizing the connectivity or accessibility of the network also commonly evaluated the robustness or vulnerability of the operational system and estimate the socioeconomic impact of disruptions (*11, 12*). These approaches adopted existing cross-sectional performance measures that failed to capture the dynamic characteristics of the entire event period.

The previous topological methods address the spatial qualities of resilience; however, resilience assessment requires a deliberate consideration of the stochastic temporal nature of disasters. Performance metrics that characterize disaster impacts must capture the variabilities in operations over time since the level of operation may change depending on the progress of the event and flexibility of the system to prepare, absorb, and recover from the disruption. This study develops an adaptable resilience assessment framework that evaluates the impact of a disruptive event by identifying varying performance levels over the entire period of the event including five distinct phases. A comprehensive analysis on the magnitude and depth of impacts develops more effective strategic plans for freight operations that remain resilient and adaptable to unexpected disruptions. This study applies the framework to the port complex in Houston, Texas, during a major hurricane event, Harvey, in 2017. Evaluating the proactive and reactive responses of port truck activities during severe weather events such as Hurricane Harvey represents the first step for designing plans that support a fast system recovery that minimizes the economic, social, and human impacts from disaster events.

2. OBJECTIVES

As Texas' population is projected to double by 2050, the freight transportation system, which currently moves more than 1 billion tons of freight, expects significant increases in port and intermodal facility demand. To better respond to this expanded demand, improvements to transportation infrastructure must be prioritized to ensure that the entire region has the ability to prosper and receive needed goods.

With significant increases in freight volumes, the impacts from severe weather events to port truck traffic may cause an economic loss in Texas and throughout the region. Although the adverse weather events significantly impact transportation infrastructure and networks, a lack of understanding on the scope and magnitude of a weather event's impact on freight movement persists. The knowledge of freight flows and their interaction with weather events provides a key input for developing operational strategies and identifying critical components in the port infrastructure and transportation network. The existing body of literature tends to rely on simple performance metrics that capture changes in physical functionality or performance levels before and after a disaster event. These simplified metrics directly translate physical damage to the built infrastructure into reductions in operations.

This project aims to characterize the port truck movements by identifying operational patterns by associated industry and service types and evaluate system response during adverse weather events. The research focuses on identifying (i) truck activity from the port of Houston, (ii) capturing truck flow disruptions due to Hurricane Harvey, and (iii) identifying flow changes and recovery process during and immediately after the adverse events. This study uses large-sized GPS data to represent individual trip characteristics such as travel time, origin-destination (OD), major route choice, and industry type. We apply the developed framework in Houston as the major destination (or origin) of freight or the intermodal point of the shipment. Identified truck flows categorized by their service (trip) type (i.e., intercity, first or last mile trip, or localized service) represents truck operation between the port and their final destinations. To understand the interactions of truck behavior to the flow disruptions due to flooding, we capture flow disruptions and activity changes before and after the Hurricane Harvey.

Understanding port trucks' operational strategies especially during the adverse events would be of importance in designing and operating transportation infrastructure, and developing neighborhood plans for coastal communities and hurricane-prone areas. With the knowledge of quantified interaction to the weather events, it becomes also possible to prioritize resources for decision-makers in freight infrastructure investments depending on the type of weather conditions. Moreover, knowledge of port traffic flows and behaviors by industry and service type would help developing long-term mobility, safety, and environmental plans.

3. BACKGROUND

3.1. Historical Disaster Events- Hurricane Harvey

Severe weather events impact port operations and port truck traffic and cause economic losses. Due to global climate change, adverse weather events, which include flash floods and hurricanes, continue to become more frequent and severe. A Category 4 storm, Hurricane Harvey, caused catastrophic flooding in the Houston area and inflicted $125 billion in damage according to the National Hurricane Center (Figure 2). In the first week, the storm directly affected nearly 10 percent of all US trucking and other transportation throughout the Texas coastal area due to flooded roadways and damaged infrastructure. While Hurricane Harvey was a significant hurricane in terms of its size and wind speed, ultimately, the storm caused extreme flooding in Houston and the surrounding areas. The storm caused two feet of rain in the first 24 hours and made landfall three times in six days. On September 1, 2017, one third of Houston was underwater (*13*). In 2017, above normal activity during the Atlantic hurricane season resulted in 17 storms and 10 hurricanes, including Harvey, Irma and Maria, which caused heavy damage and millions of dollars of losses (*14*). As inevitable consequences of climate change, natural disasters can lead to catastrophic and unexpected impacts on vulnerable areas.

Figure 2. Hurricane Harvey damages in Houston in 2017 (web sources[1] [2]).

[1] https://www.wsj.com/articles/judge-finds-u-s-liable-for-hurricane-harvey-damage-11576622542

[2] https://www.chron.com/news/houston-texas/houston/article/houston-apartments-damaged-hurricane-harvey-12270464.php

3.2. Port of Houston

Water is the leading transportation mode for international freight in the US. The Port of Houston, located in the fourth-largest city in the US and home of the busiest U.S. port in terms of foreign tonnage, and sixteenth-busiest in the world. The Port of Houston (PHA) consists of about 200 public and private terminals located along the 52-mile-long Houston Ship Channel extending inland from the Gulf of Mexico (*15*). The port includes eight public terminals that handle multiple cargo types and over 100 private terminals that handle bulk cargoes. Most of the Gulf Coast's container trade passes through the Barbours Cut and Bayport container terminals. Figure 3 shows the location of major container and cargo terminals as well as one of the biggest private terminals in Houston area.

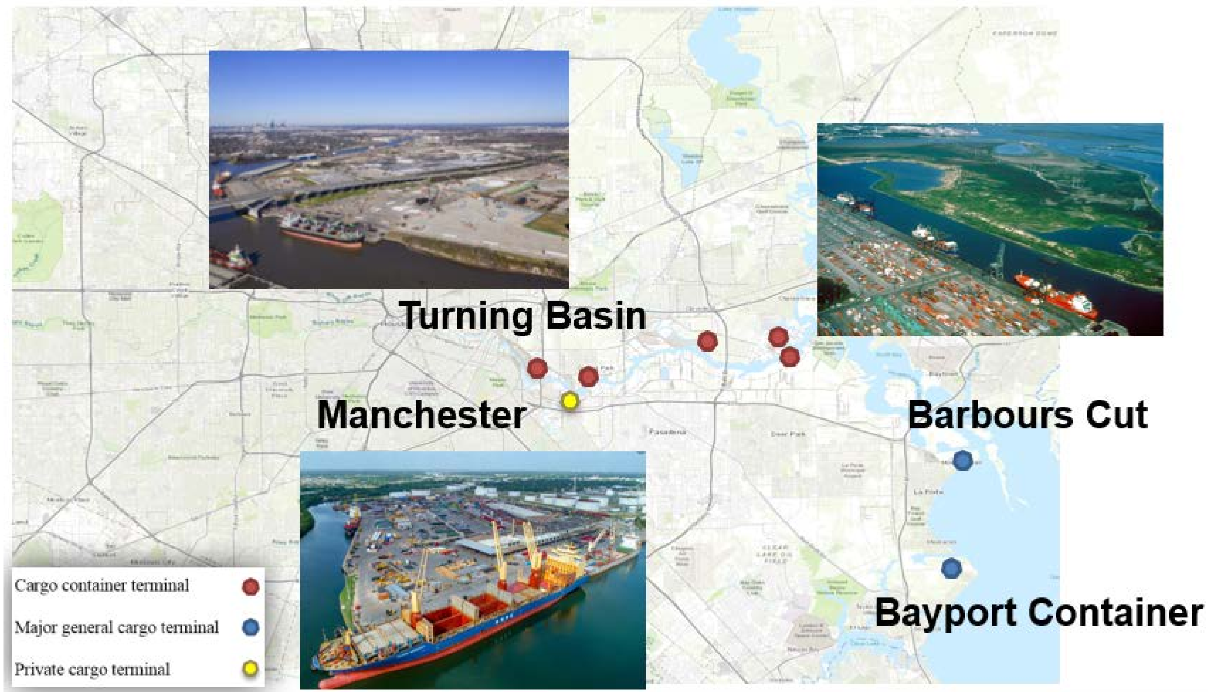


Figure 3. Location of major terminals in port of Houston.

Table 1 shows cargo tonnage changes in some of the busiest ports in the US from 2011 to 2016. The total tonnage throughput of Houston port complex was over 269 million in 2018, which is 3.4% and 8.5% higher than 2017 and 2016, respectively. The public terminals owned, operated, managed or leased by the PHA include the general cargo terminals at the Turning Basin, Care, Jacintoport, and Woodhouse besides the Barbours Cut and Bayport container terminals (refer to Appendix A for port operation records). This study uses the two largest container terminals, Bayport and Barbours Cut, and the largest cargo terminal, Turning Basin, in the Port of Houston complex for the analysis.

Table 1. Tonnage changes of the US busiest port *(15)*.

	2011	2012	2013	2014	2015	2016	11-16 CAGR%
Los Angeles/ Long Beach	29,973,261	27,059,059	27,886,875	28,071,297	23,672,299	28,929,355	-0.7%
Houston, TX	10,926,561	12,047,628	13,799,281	16,801,238	17,787,418	14,221,518	5.4%
Savannah, GA	14,351,476	12,518,824	11,939,780	12,463,801	11,769,924	12,062,782	-3.4%
New York/ New Jersey	11,402,486	10,309,642	9,639,822	9,224,426	9,439,392	8,499,078	-1.7%
Oakland, CA	7,793,629	7,278,709	7,260,225	7,075,258	6,540,280	6,346,060	0.1%

3.3. Port Truck Activity

Port trucks show unique and distinct travel patterns compared to domestic commercial vehicles. According to the NY & NJ Port Authority (*16*), most port trucks make short trips to local destinations within one hour although the majority completes their trips within 20 minutes to near- or off-dock facilities. The Metro transportation agency and Caltrans reported similar statistics for California and showed that only 5% of trucks originating in the San Pedro Ports travel beyond the Los Angeles County line (*17*). Over 95% of cargos imported to the Ports of Long Beach and Los Angeles have destinations at the near-doc facilities or intermodal yards near the port complex. Figure 4 shows how different types of on-road and rail transportation are used to move cargos from San Pedro Bay marine terminals to different destinations.

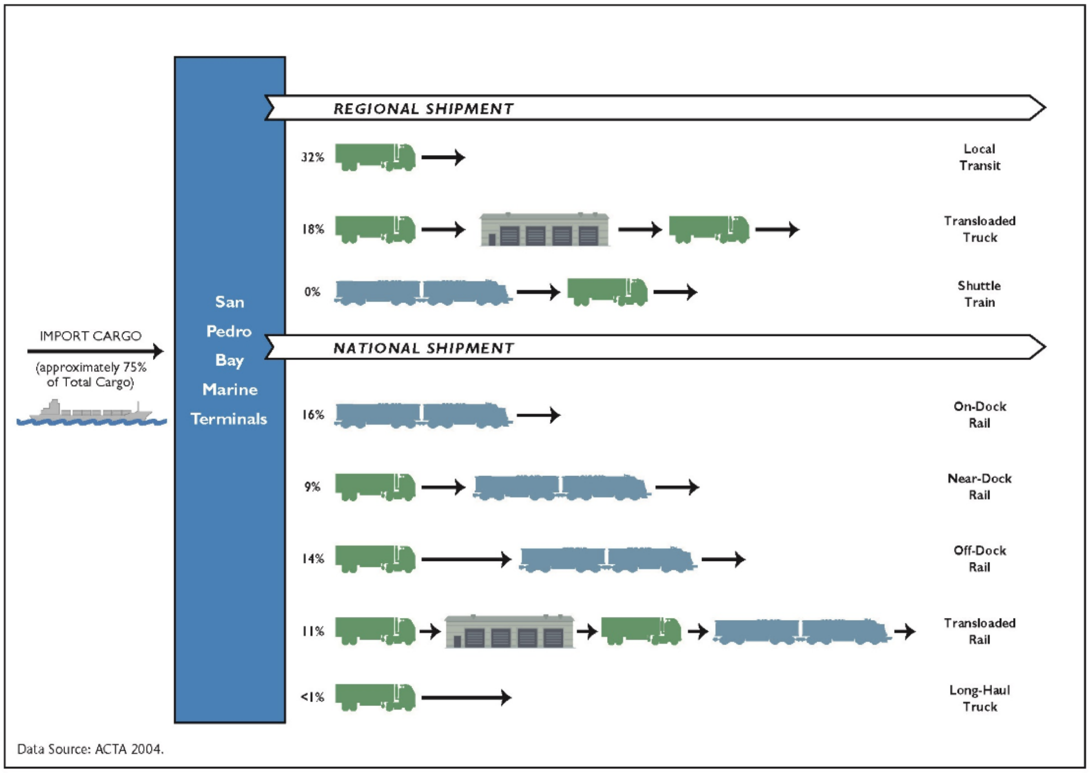


Figure 4. Rail and Truck Shipment (Port of Los Angeles)[3].

Port container trucks originated from the Port of Houston move their cargo to several local destinations for transloading, storage, and direct delivery. Figure 5 shows the locations of major local destinations including off-dock railroad terminals and depots. Rail yards generally attract manufacturing facilities adjacent to the yard to utilize the distribution capabilities of the area. Rail terminals also locate in proximity to facilities that handle bulk commodities. Rail terminals perform different functions for bulk, roll-on/roll-off, breakbulk, intermodal and shunting, which require different equipment and facilities by service/commodity types (e.g. grain, coal, cars, and containers) they handle. On the other hand, a depot serves as a central facility for container trucks to rearrange, sort, and consolidate multiple shipment.

[3] Source: http://www.freightworks.org/Documents/Port%20of%20Los%20Angeles%20Draft%20Rail%20Synopsis.pdf

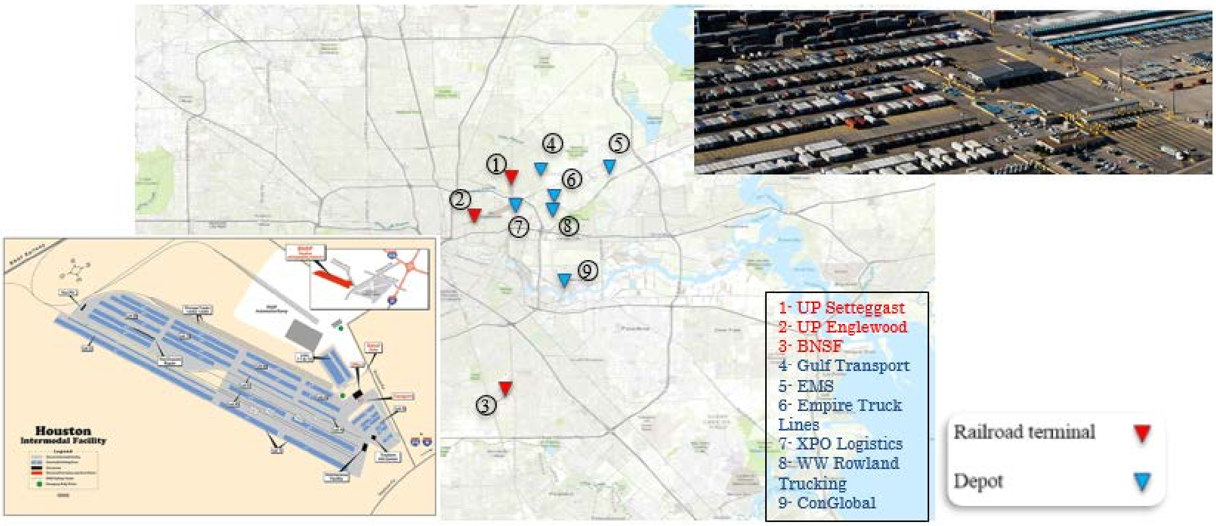


Figure 5. Location of some major railroad terminals and depots in Houston area.

4. LITERATURE REVIEW

4.1. Freight Activity in Disaster Events

Historically, adverse weather events interrupt the freight transportation network and infrastructure in different ways. Pavement damage, loss in freight infrastructure, and road or rail network closures represent the most common disruptions due to heavy storms and flooding (*18*). Shen and Aydin (*19*) used Hurricane Katrina to describe significant impacts on freight movement at the national level. Disruptions also change freight shipment schedules and locations, and impact safety of the transportation infrastructures (*20*). Fialkoff et al. (*21*) showed that Hurricane Sandy significantly affects the route choice of freight transportation from the Port of New York and New Jersey. Hernandez et al. (*22*) identified that flood events reduced 13% of daily truck traffic in Arkansas. Roh et al. (*23*) found some increases in truck volumes on higher functional road classes during snowfall events because trucks that used local arterials alter their routes to a higher functional road. Adams et al. (*9*) investigated network resiliency and truck responses during two weather events in Wisconsin and determined that the type and duration of the weather events affect the truck speed and volumes.

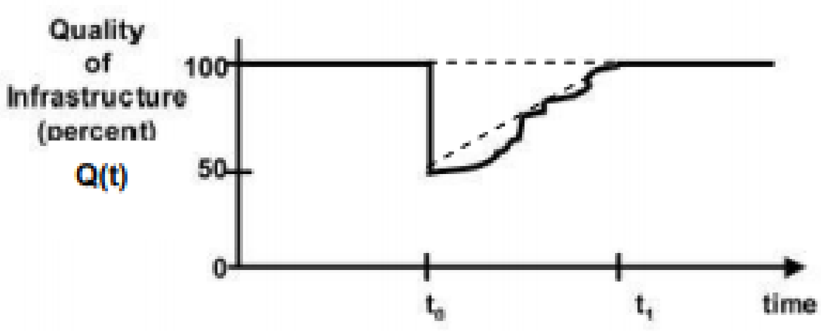
Several studies have analyzed the post disaster management strategies and disaster responses for freight transportation. Das et al. (*24*) used an ordered probit approach to identify the factors that affect freight flow during and after a natural disaster. Their model identified damaged severity of roadways, reduced performance of traffic control systems as the most significant variables that increase disruptions in freight flow. Nagurney (*25*) focused on humanitarian logistics to study freight service provision problems during disaster relief periods when different organizations transport relief supplies to demand points. The proposed algorithm solve for the network problem where the total cost functions of the disaster relief organization and the freight service providers are quadratic and separable. In a study on the impacts of natural disaster on ports, Hsieh (*26*) assessed the risks due to failure in port infrastructures and showed that port capacity and efficiency significantly affect port vulnerability. Beheshtian et al. (*27*) investigated the changes in routing assignment and cost of commodity flows as a result of climatic hazards by adopting interregional commodity flow model. They found that the vulnerability of the New York state's physical infrastructure play as a major bottleneck to commodity flow after disasters, which may result in as high as 20% reduction in nation-wide supply deficit.

Overall, most of the studies focus on measuring the vulnerability and resilience of the transportation network and providing recovery strategies to optimize the performance of the network during and after disruptive events. Moreover, the suggested approaches to increase the efficiency of disaster relief measures (*28, 29, 30, 31*). Disaster events definitively impact the freight transportation system; however, the spatial and temporal extent of these impacts vary by geographic locations and type of events. This uncertainty and variation require in-depth investigation and more effective resilience metrics to provide accurate estimates of impacts for practical applications.

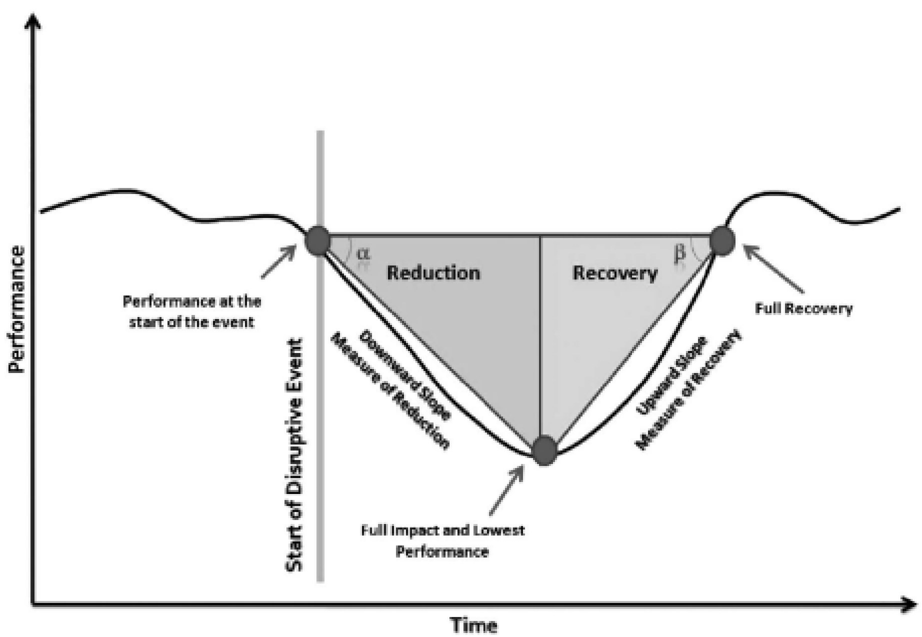
4.2. Resiliency Triangle for Seismic Systems

Disaster resilience originates from lifeline engineering to evaluate the performance of structures during and after seismic events. Bruneau et al. (*32*) introduced the resilience triangle to apply to disruptive impacts on seismic infrastructure to capture resilience (Figure 6 (a)). Later, many researchers (*33-35*) adopted the triangle method and expanded it to describe two dimensional responses of reduction and recovery (Figure 6 (b)). These triangles use two criteria to quantify resilience based on the magnitude and length of impacts. The quality of infrastructure, indicating a level of 100% before the event in figure 6 (a), sharply drops at time t_0 when a disaster event occurs. This creates the first edge of the triangle. The reduced quality of the system reaches the peak point – either the moment that the event occurred or with a lapse of time (Figure 6 (b)) – and increases until it recovers the same level of quality that it shows before the event. The process creates a triangle that represents a total loss of system resilience as defined as follows:

$$\mathrm{R} = \int_{t_0}^{t_1} [100 - Q(t)]\ dt \quad \text{[Zobel, 2010]} \qquad [1]$$



(a)



(b)

Figure 6. Resilience triangle: (a) Original resilience triangle (24) (b) Two conceptual measures of resilience triangle (9).

The resilience triangle represents a simple but powerful tool to evaluate the resilience of seismic infrastructure such as buildings or the road network. This concept has been used in many studies and specially to understand the impact on supply chain. For example, Bevilacqua et al. (*36*) used the resilience triangle framework to provide a comprehensive definition of supply chain resilience. In another study, they developed a modular structure of supply chain resilience components based on the resilience triangle tool (*37*). Xu et al. (*38*) proposed a model to measure supply chain resilience by adding a redundancy metric to the concept of disaster resilience triangle. In addition, Zobel (*39*) applied the resilience triangle concept to four interrelated dimensions including technical, organizational, social, and economic resilience. They extended the definition of disaster resilience using resilience triangle and suggested to analytically determine the relationships among disaster resilience measures including the initial impact of an event and the subsequent recovery period (*40*). This approach can help represent how a decision maker perceives the resilience value associated with these two measures.

However, previous studies fail to apply this measure to freight operations or the general traffic system since the metrics strictly rely on deterministic rules that define the functional failures. The two phases that the triangle depicts, reduction and recovery, may not always exist in freight or general traffic operations since the thresholds to determine each phase may not be stable over time due to inherent variabilities in travel behaviors while a physical structure may have well established safety or degradation thresholds.

4.3. Resiliency Assessment and Performance Metrics in Transportation Operations

Previous studies that investigate resilience in transportation operations use qualitative, quantitative, or combined approaches to define performance metrics. These methods are based on the resilience triangle or other performance measures such as vulnerability, reliability, robustness, flexibility, survivability, and resilience (*41*). Table 2 shows the definition of these measures and researchers who have used them in their studies.

Bruneau et al. (*32*) characterize robustness as the extent to resistance of the impact and rapidity that indicates the rate of recovery characterizes the overall disaster resilience. Snelder et al. (*42*) defined robustness as “the extent to which, under pre-specified circumstances, a network is able to maintain the function for which it was originally designed”. Opposite to robustness, vulnerability in the road transportation system is defined as a susceptibility to incidents which can lead to significant reductions in the serviceability of road network. This definition can be generalized for all modes of transport (*43*). Jenelius and Mattsson (*44*), on the other hand, relate vulnerability to the society’s risk of disruptions and degradations in the transportation system. Reliability is defined in many studies as the probability of a system to remain operative adequately under a disruptive event and it is important indicator of the quality and efficiency in transport systems (*45*, *46*). Morlok and Chang (*47*) showed that a system remains flexible in a disruptive event when it accommodates changes and maintains performances above a satisfactory level. Mead et al. (*48*) used the system capability to understand required performances during a disaster. Wang (*49*) stated that a system maintains survivability when it provides required services during disruptions and fully recovers in a timely manner.

Literature also introduces several modeling approaches and applications to adopt the performance metrics. Chang et al. (*50*) focused on immediate post-disaster responses from earthquake risk management, and Murray-Tuite and Fei (*51*) used probabilities of target–attack combinations to capture their interactions on the impacts of the transportation system and assess the risks within the network. Bell et al. (*52*) used game theory to analyze the vulnerability of a road network while Golroo et al. (*53*) applied a resource allocation optimization to maximize the network reliability. Other studies studied the robustness (Faturechi et al. (*54*); De-Los-Santos et al. (*55*)), flexibility (Chen and Kasikitwiwat (*56*)), and reliability (Bin et al. (*57*)) measures to assess the impact on transportation sectors and infrastructure including air, road and rail.

Most risk and resiliency assessments focus on functional measures such as travel time or volume, and network-based metrics. Travel flow or capacity measures represent the most common metrics to assess the resilience of infrastructure and economic loss (*7*, *9*, *54*, *58*). Travel time metrics characterize the reliability, vulnerability and robustness of the transportation network (*59*, *60*) while topological metrics describe network-based resiliency or connectivity (*61*, *62*).

Table 2. Performance measures commonly used in transportation (adopted from Faturechi, and Miller-Hooks (*41*)).

Measure	**Definition**	**Previous study**
Risk	Combination of probability of an event and its consequences in terms of system performance	Basoz and Kiremidjian (*63*), Chang et al. (*64*), Chang et al. (*50*), Dalziell and Nicholson (*65*), Kiremidjian et al. (*66*), Stergiou and Kiremidjian (*67*), Shiraki et al. (*68*), Werner et al. (*69*).
Vulnerability	Susceptibility of the system to threats and incidents causing operational degradation	Bell et al. (*52*), Jenelius et al. (*70*), Jenelius and Mattsson (*71*), Knoop et al. (*72*), Lownes et al. (*73*), Shimamoto et al. (*74*), Ukkusuri and Yushimito (*75*).
Reliability	Probability that a system remains operative at a satisfactory level post-disaster	Bell (*76*), Golroo et al. (*53*), Ibrahim et al. (*77*), Lam et al. (*78*), Sumalee and Watling (*79*), Szeto (*80*), Siu and Lo (*81*), Yin and Ieda (*82*).
Robustness	Ability to withstand or absorb disturbances and remain intact when exposed to disruptions	De-Los-Santos et al. (*55*), Morohosi (*83*), Nagurney and Qiang (*84*, *85*).
Flexibility	Ability to adapt and adjust to changes through contingency planning in the aftermath of disruptions	Morlok and Chang (*47*), Sun et al. (*86*).
Survivability	Ability to withstand sudden disturbances to functionality while meeting original demand	Grubesic and Murray (*87*), Matisziw and Murray (*88*).
Resilience	Ability to resist, absorb and adapt to disruptions and return to normal functionality	Adams et al. (*9*), Bekkem et al (*7*), Caplice et al. (*89*), Cox et al. (*90*), Liu and Murray-Tuite (*91*), Murray-Tuite (*92*), Vugrin et al. (*93*).

5. DATA

This research uses a metric-based GPS dataset collected by Streetlight to estimate the operational performance of trucks serving the PHA. Streetlight collects anonymized location records from smart phones and navigation devices equipped in vehicles and transforms the location data points to aggregated travel patterns. Streetlight reports to process over 12% of commercial vehicles nationally (*94*). The platform provides aggregated metrics such as travel volumes and travel times for spatial units (e.g. a parcel or a block) specified by users on the platform. The metric-based data maintains advantages that large-sized GPS data provide such as broader geographic coverages and granular aggregation levels (e.g., hourly or daily) but additionally offers accessible data structures, since the platform produces metrics (e.g. travel volume or time between any locations) without additional modeling processes such as spatial map-matching. Due to its ease of use, Streetlight is widely adopted in the US and Canada including all top 25 MSAs in the U.S. and top 15 MSAs in Canada (*95*). VDOT recently published guidelines for using Streetlight data based on data evaluations with ground truth sources such as count stations and toll transaction records. Streetlight appears to produce small errors in aggregated estimates; however, the metrics might become unstable when capturing low volume roadway segments (*96*). Figure 7 shows an analysis platform of Streetlight.

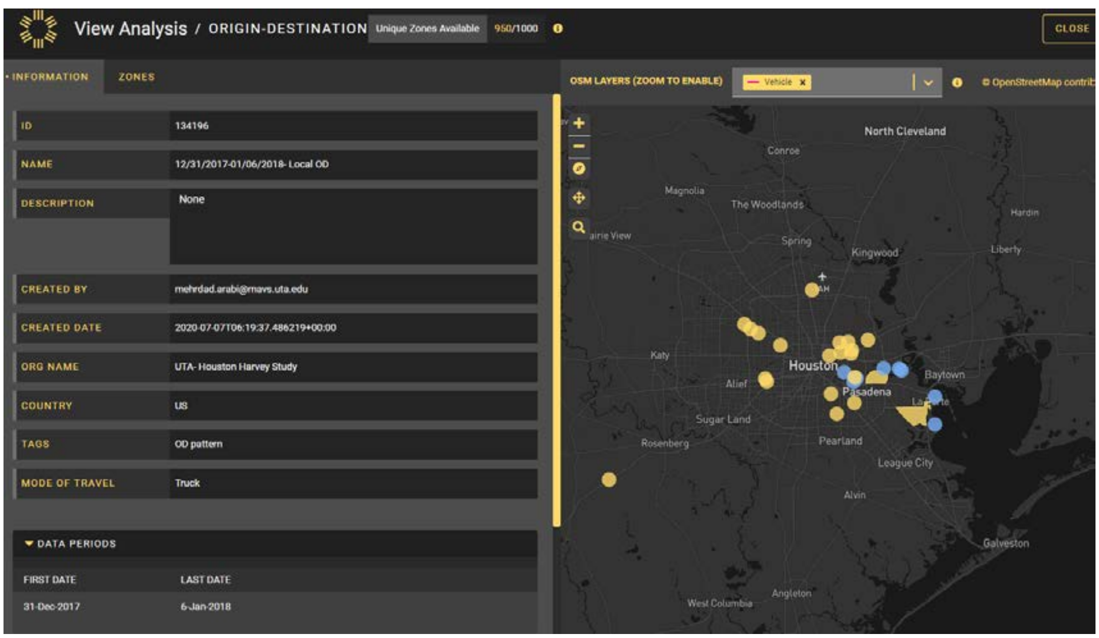


Figure 7. Streetlight Analysis Platform.

This study obtains 68 weeks of data including the four weeks of the Hurricane Harvey period (from August 18th to September 14th) and 64 weeks of preparation (normal) periods from May 1st to December 31st in 2017. This extended period includes major holidays such as July 4th and Thanksgiving. A total of 960 daily trip profiles (except weekends) extracted from Streetlight platform describes Houston and local truck operations originated from Bayport, Barbours Cut, and Turning Basin terminals in the port of Houston complex. Figure 8 shows basic metrics provided in an OD analysis platform in Streetlight.

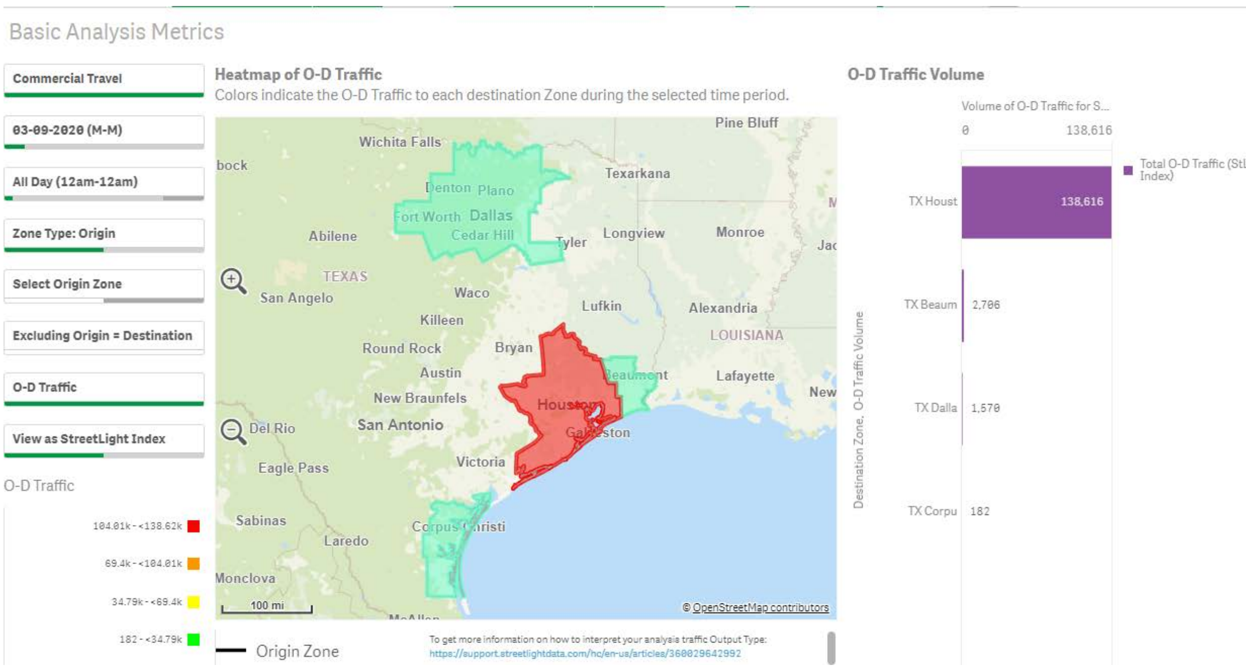


Figure 8. Streetlight OD Analysis Metrics.

Several warehouse and industrial areas are located near the PHA complex to process imported containers to local and regional destinations. Like the other ports in the US (Port of Los Angeles and Port of Ney York and New Jersey), these local facilities handle most non-petroleum cargos from PHA (*97, 98*). This study uses the Streetlight platform to assess the top destinations from Bayport, Barbours Cut, and Turning Basin terminals within Houston, and determines 21 local destinations as shown in Figure 9. Trucks from these three terminals made most of their trips to warehouses consisting 97% of daily trips among the local destinations, compared to 3% to depots and railyards. Since this study observes stable and consistent truck travel patterns among these three local facilities, we aggregated the daily volume metrics of local facilities to obtain sufficient sample sizes for analysis.

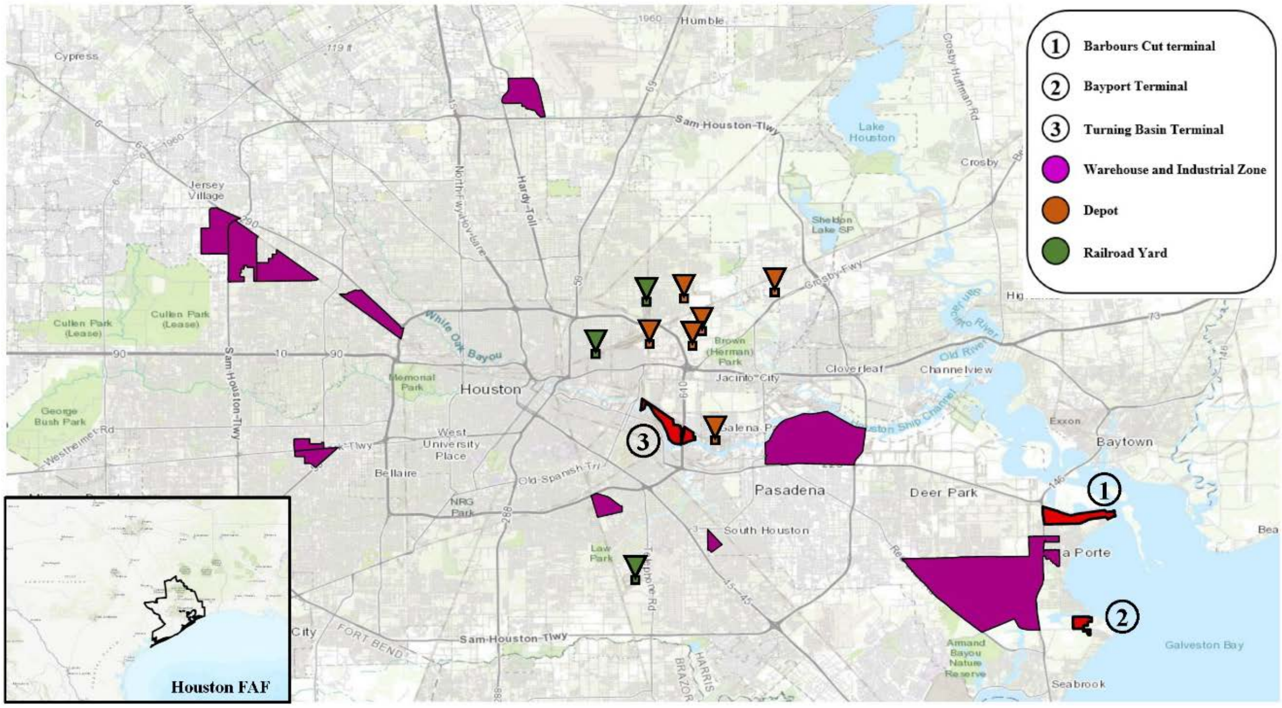


Figure 9. Location of major local destinations in Houston.

6. METHODOLOGY

6.1. Response Phase Identification

This study builds on the resilience triangle originally developed by Bruneau et al. (*24*). Performance metrics developed in this study assess operational resilience across different response phases during disruptive events, which create unique conditions and level of impacts over time. Compared to the previous approaches that declare predetermined performance thresholds (Figure 10) that may under- or over-estimate the transportation operational impacts, the developed measures are adaptable and flexible to the event type and magnitude.

Figure 10 shows a performance profile based on daily volume trends between an origin and a destination (OD). This framework can use any type of performance measures or ODs that provide continuous operational attributes such as travel time, speed, or performance index (e.g., volume/capacity). The performance measures capture behavioral or operation changes during a disaster event in comparison to preparation (normal) states, which determine the expected maximum and minimum operation performances. Based on these performance levels, six points of impact (A to E in Figure 10) determine five distinct response phases. Emergency management typically uses four cycles (preparedness, response, recovery, and mitigation) to develop standard structures of emergency responses (*99*). This paper largely follows the general terminology but expands the process to five phases to capture stochastic and dynamic characteristics in operational responses and characterize operational resilience and adaptability.

A preparation state corresponds with normal conditions. Disaster response starts with a staging phase that shows the extent of proactive operations using an increased operational capacity. A reduction phase follows and represents a direct performance impact from the disruption. During a peak phase, the level of performance remains lowest due to partial or completely terminated operations. Once the system resumes activity, a restoration phase begins and regains its operation capacity; however, backloads of demand may require an overloading phase to handle excess requests. The staging and overloading phases especially characterize an operational adaptability since they show how systems proactively or reactively prepare to and recover from a disruption. These two phases add important features of resilience framework to understand the system flexibility and adaptability beyond its normal functionality.

The six points of impacts (A to F) determines each phase as follows:

- *Staging phase* starts at point A and ends at B. Point A shows when an operation starts to exceed the maximum performance level (Figure 10) before an event. If operations immediately prior to a reduction phase do not exceed the maximum level, the staging phase starts when the operation level reaches a peak (highest point) before the reduction phase (Figure 11). This phase involves proactive responses to increase its capacity beyond their maximum expected performance.
- *Reduction phase* starts at point B and ends at C1. A reduction phase indicates the period when the operation level decreases below its minimum performance level. Point B displays when the system functionality drops below minimum level and starts to be significantly affected by the event.
- *Peak phase* lasts between C1 and C2. This phase indicates that the level of operation reaches the lowest performance due to the event. Compared to the original resilience

triangle, two points (C1 and C2) describe the peak phase since a significant disruption may affect the system for extended time periods.

- *Recovery phase* starts at C2 and ends at D. A recovery phase describes when an operation regains its functionality and recovers to the normal state. The end point of recovery phase (D) shows when an operation reaches back to the minimum performance level.
- *Overloading phase* starts at D and ends at E. If an operation level immediately after a recovery phase exceeds the maximum performance, E declares the last temporal point when the operation drops below the maximum threshold (Figure 10). If an operation level immediately after the recovery phase does not exceed the maximum performance, E indicates the highest peak point of the performance level after a recovery phase. This phase involves with reactive responses of operations that address backloads of demands.
-

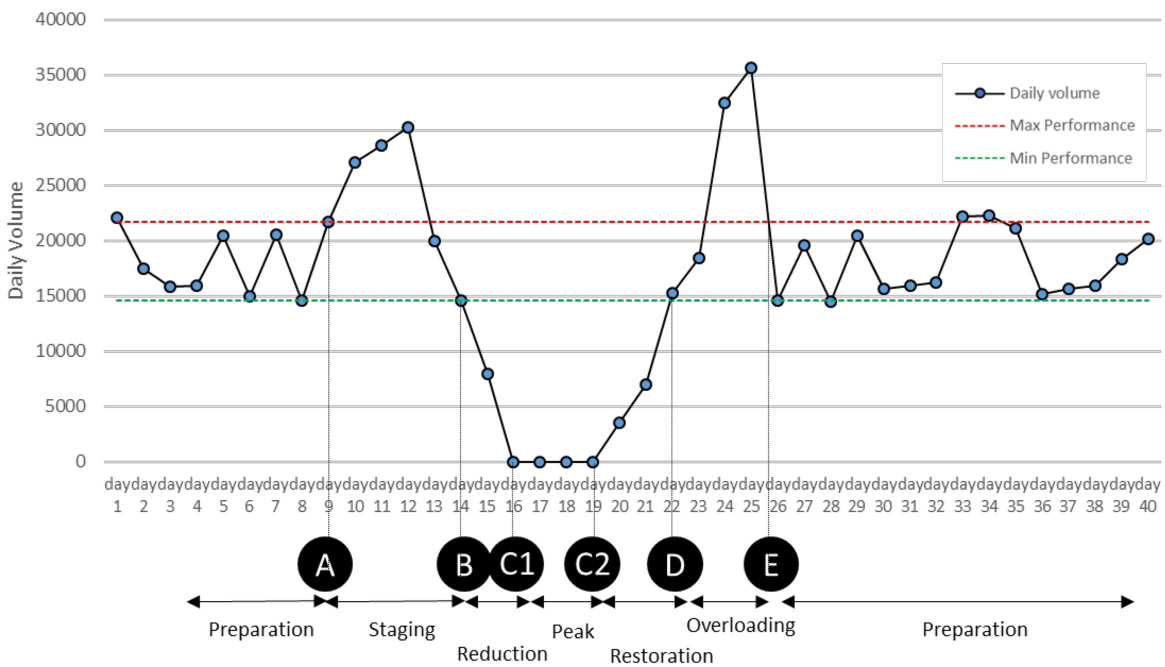


Figure 10. Performance profiles and phases (Case 1).

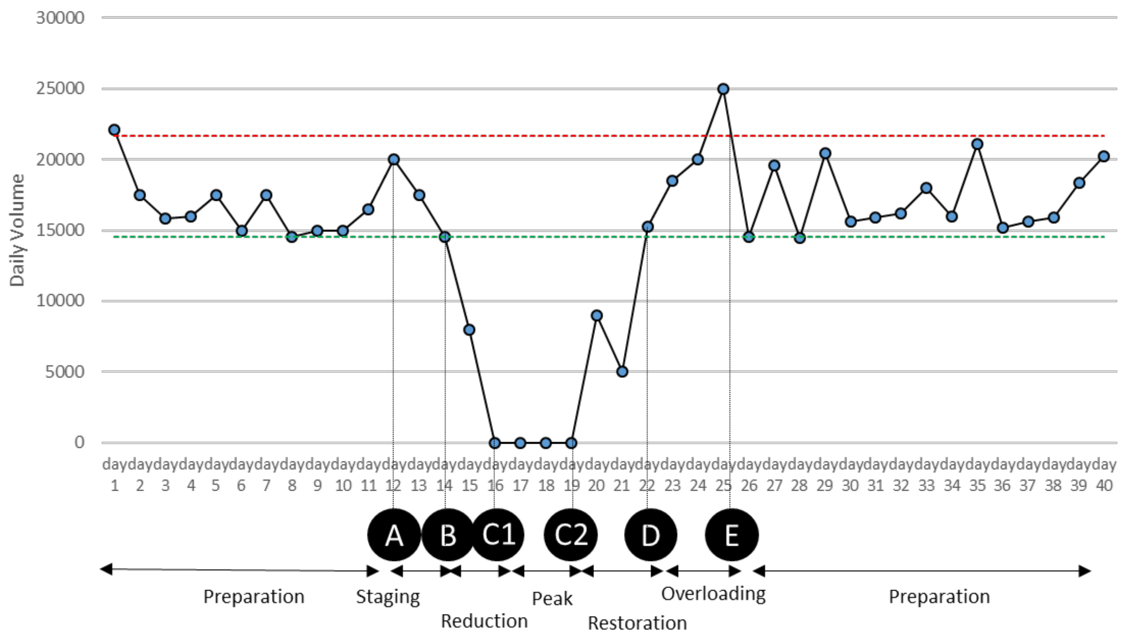


Figure 11. Performance profiles and phases (Case 2).

6.2. Metric Development

Based on the operational profiles and a set of rules that determines five disruption phases, this study develops performance metrics to evaluate the resilience and adaptability of freight operations. These developed metrics remain applicable to any type of transportation operations such as passenger traffic or rail service. Figure 12 illustrates a graphical representation of operational profiles.

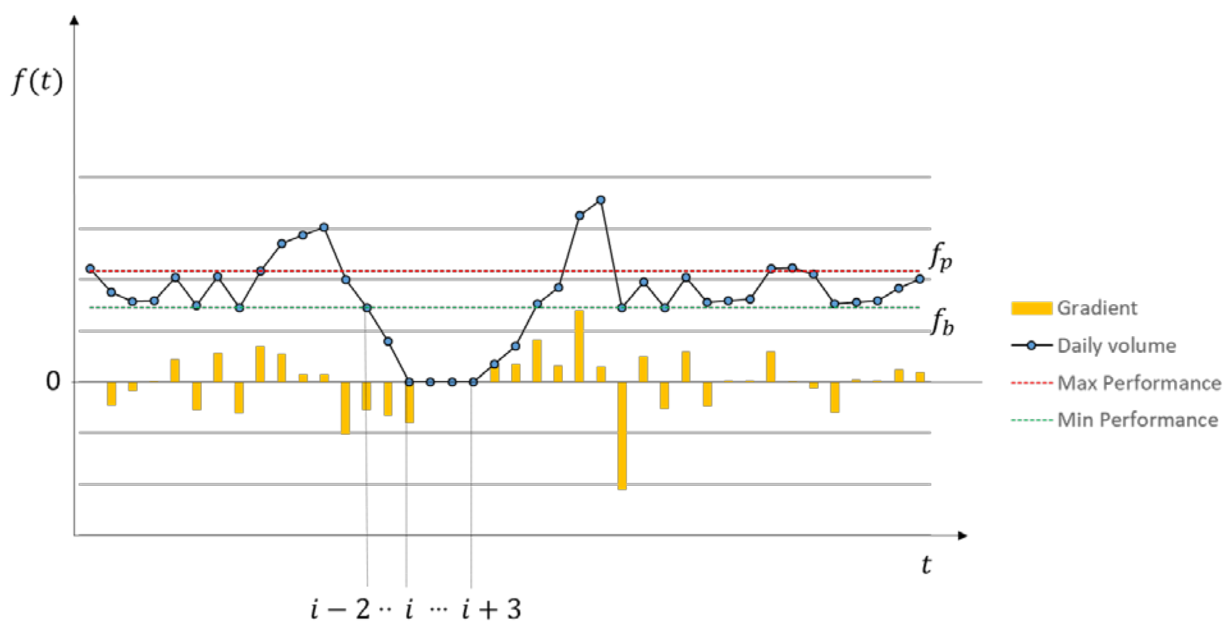


Figure 12. Graphical Representation of Operational Profiles.

The first performance metric captures a temporal duration, t, of each phase s :

$$\mathrm{t}^{s} = \mathrm{t}_{i}^{s} - \mathrm{t}_{j}^{s} \qquad [2]$$

Second, a set of measures characterizes the magnitude of impacts. A depth of impact, D^{s}, indicates a peak cross-sectional performance during the corresponding phase s compared to the normal state (f_b) as follows:

$$\mathrm{D}^{s} = f(t^{s}) - f_b \qquad [3]$$

A total impact, I, accounts for two dimensional responses – a temporal duration and depth – and calculates the area between the observed and baseline performances for reduction and restoration (direct impact) periods, ds, as follows:

$$\mathrm{I}^{ds} = \int f_b - f(t)\ \mathrm{dt} \qquad [4]$$

The staging and overloading (extended impact) periods, *es*, compare the operation levels between the observed and maximum performance to estimate the total impact.

$$\mathrm{I}^{es} = \int f(t) - f_p\ \mathrm{dt} \qquad [5]$$

In addition to the cross-sectional and temporal changes in operations, stability in each phase indicates the system efficiency of disaster responses. This study uses a gradient method to capture the performance stability. The gradient method defines the changes in operation level compared to the operation observed in the previous day.

$$g_t = \frac{f(t+k) - f(t)}{k} \qquad [6]$$

For example, if recovery shows steady gains in operations, the system appears stable during the phase as shown in figure 10. However, a recovery process experiences a few days of increases then decreases in service (Figure 11), the overall process remains unstable due to additional disruptions or operational malfunctions. Therefore, the patterns of gradient sign – either being positive or negative - are of interest rather than their absolute values since the operational performances may naturally vary day-by-day. The same sign of gradients simply represents the stability of the process such that the positive gradients reflect stable regaining during the recovery period.

7. ANALYSIS AND FINDINGS

7.1. Preliminary Findings

7.1.1. Port operation

Figures 13 and 14 show the overall truck activity profiles of Barbours Cut and Bayport Container terminals between August and September in 2017. This preliminary analysis shows how port activities changed when truck operators prepared for, adapted, and recovered from hurricane Harvey. The two graphs illustrate the daily truck volumes except weekends and the last of week of August (August 25th for August 31st) when the port of Houston was closed due to the hurricane. Both ports reduce activities prior to and during the event and considerably increase truck traffic from September 5th. Unlike Barbours Cut that quickly recovered from the hurricane and bounced back to normal operation, Bayport terminal shows slower reduction and recovery patterns over the extended period from the event.

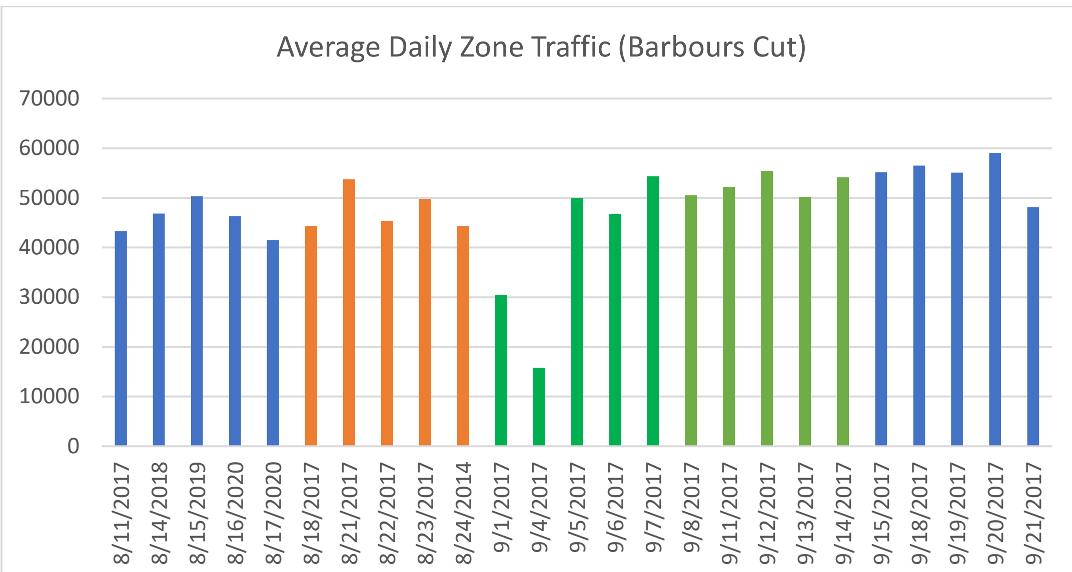


Figure 13. Overall daily zone traffic in Barbours Cut terminal.

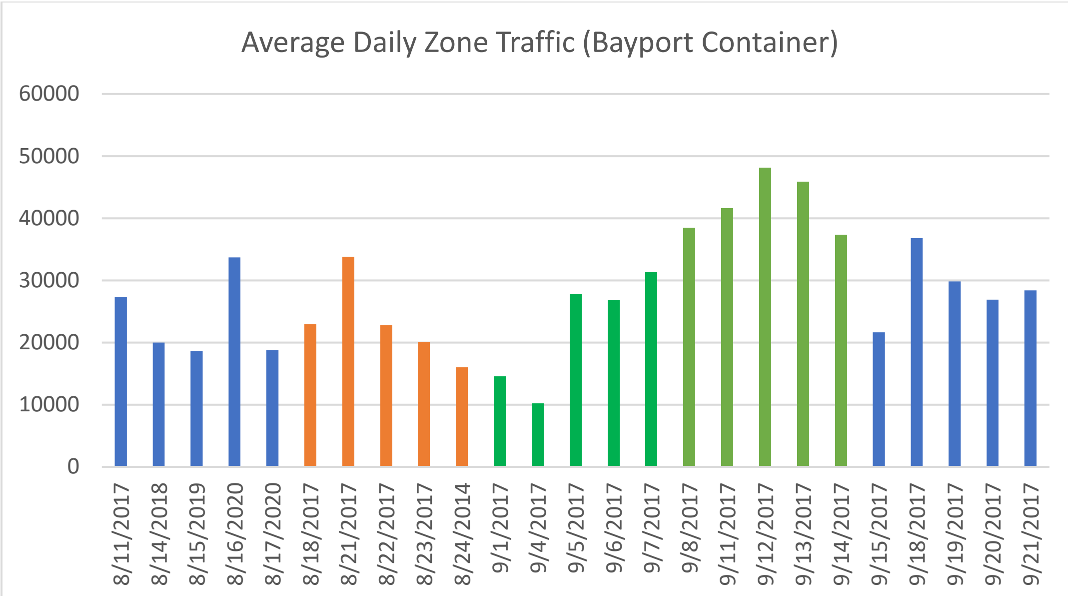


Figure 14. Overall daily zone traffic in Bayport Container terminal.

7.1.2. Route Choices

Figure 15 compares the average truck flow of major truck corridors of port trucks to access local and regional destinations. This study found a significant reduction in flow on most of the routes including I-10, I-45 and SH-225 since many freight facilities suspended their operation or have trucks re-route due to network closures during the Harvey period.

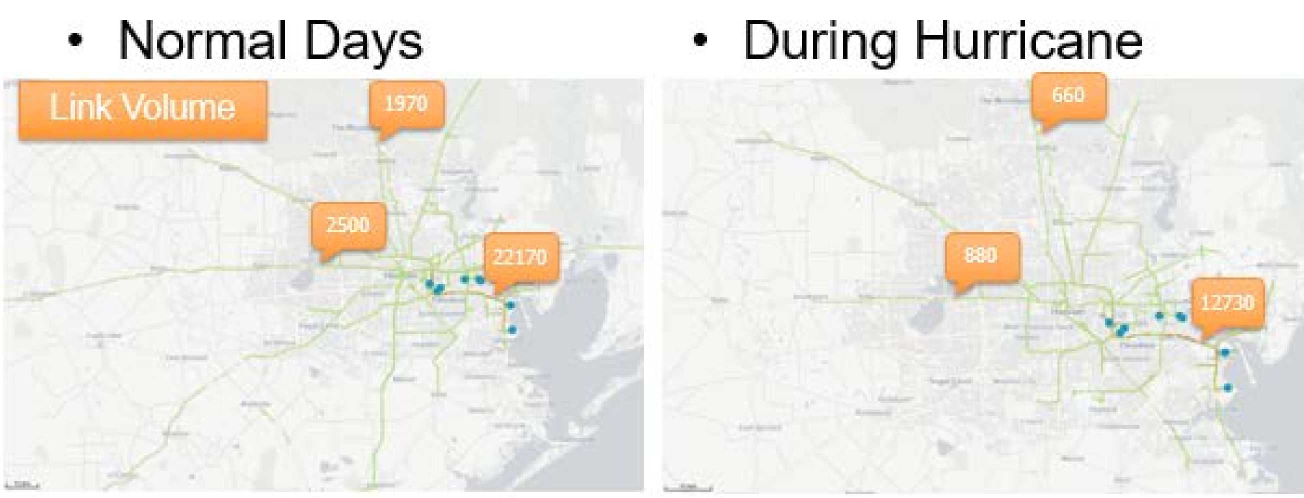


Figure 15. Changes in truck volume in major routes from port of Houston.

7.1.3. Regional movements (neighboring FAFs)

This study investigates the changes in regional movements as a result of Harvey. Figure 16 compares the daily truck volume from port of Houston to two major regional destinations including Houston and Beaumont FAFs. While the disrupted period clearly appears for both of the destinations, we found more significant impacts on the Beaumont FAF compared to the Houston

FAF. Results show that long-haul trips to Beaumont experienced significant decreases in trips during the peak period and slow recovery after the event periods.

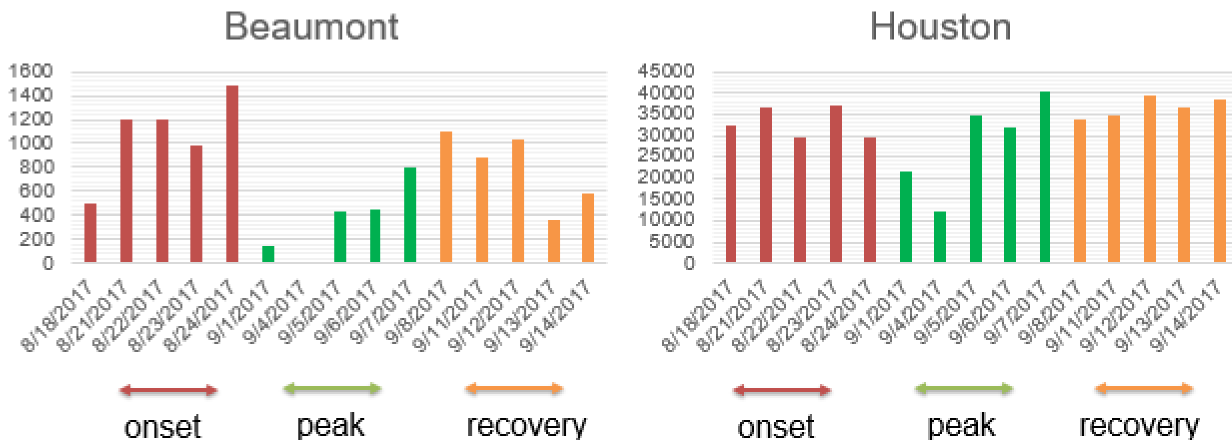


Figure 16. Daily regional truck trip volume to Beaumont and Houston FAFs.

7.1.4. Local movements

Figure 17 compares the average daily traffic from port of Houston to local destinations including major depots and railroad terminals for normal days and weeks prior to or during Hurricane Harvey. The hurricane considerably impacted truck trips to depot, while drayage trucks (i.e., trucks move cargo to railyards) maintain over 150 daily trips even during the event periods.

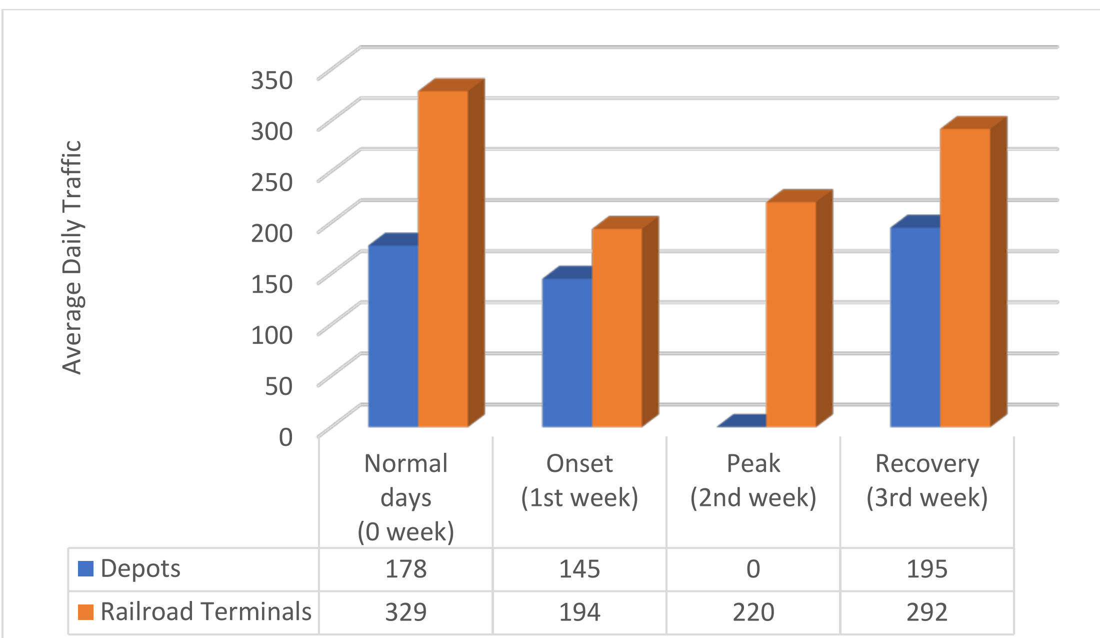


Figure 17. Average daily truck traffic from port of Houston to local destinations.

7.2. Framework Application

This study applies the developed metrics to truck operations serving PHA during the Hurricane Harvey period in 2017 as well as more common and expected disruptive events such as July 4th and Thanksgiving. This comparative analysis provides comprehensive understanding on how port trucks change their operations to prepare, respond, and recover from different types of disruptions.

This study evaluates 40ft container truck operations serving three ports in the PHA complex – Barbours Cut, Bayport and Turning Basin. Although these trucks handle imported goods from the ports, their operational behaviors may be different depending on their service facilities (*100*). Local operations to warehouses may be bound to daily or hourly delivery schedules due to their supply chain while regional operations may be more flexible due to their longer trips to destinations (*101*). This study categorizes the port truck operations to the regional Houston area and local destinations within 20 miles of the ports, and separately applies the framework. Daily volumes of previous three months from the event (May to July for Harvey cases) set a baseline performance level where the tenth and ninetieth percentiles of daily volumes determine the minimum and maximum operational thresholds.

7.2.1. Hurricane Harvey

Before the hurricane, port trucks completed 7,000 to 15,000 trips daily in the Houston area. Harvey substantially affected port truck operations including four days of full closure of the entire port complex between August 27th and August 31st. Figure 18 depicts regional movements from Bayport to Houston area between August 10th and September 20th. This study uses truck volume changes in each phase to show the intensity and the depth of impacts from the disruption, compared to a preparation (normal) state. For example, the baseline (minimum) performance between Bayport to Houston is 14,900 trips/day. During the staging phase, the maximum daily trips reaches 20,000, which is a 34% increase from the baseline. However, Bayport shows just one day of the staging phase while the overloading phase lasts for almost a week with substantial volume increases. The reduction and restoration phases are three days each, and both phases show relatively stable operations based on their gradients. In contrast, truck operations from Barbours Cut to local destinations show very short staging and overloading phases as shown in Figure 19. However, during the restoration phase, truck traffic significantly decreases just one day after the trucks resume their activity indicating substantial instability during the restoration phase. This may be because the operation remains disrupted by damaged transportation network or freight facilities.

Table 3 describes the overall impacts of four phases of responses except the peak phase that reports no activity. The level of impact is converted to percentages based on the baseline performance. In other words, a 34% increase in truck activities between Bayport and Houston during the staging phase indicates the cross-sectional impact (i.e. depth) is 34% of the baseline performance. The staging phase lasts for one day, which makes a total impact of this phase as 17% since the triangle between the operation level (daily trips) and the baseline performance determines the total impact. During the reduction phase, truck volumes drop to zero, which indicates that the event disrupts 100% of truck trips or 100% in depth.

Among the three ports, Barbours Cut presents the longest recovery period with a very short staging phase. As the busiest port in the PHA complex, Barbours Cut did not increase their truck volumes during the staging and overload phases. Instead, they spend five days during the restoration phase to build higher stability while regaining their functionality. They seem to successfully recover within the restoration phase, which allows them to minimize their activities during the overloading phase. On the other hand, Bayport shows the most reactive responses during the overloading period with 338% of total impact, which contrasts to their one-day staging phase with 17% of total impact. Bayport also shows the longest reduction phase over four days with substantial total impacts but a relatively shorter restoration phase. Stability measures during the reduction and restoration phases show distinct patterns across the ports and destinations. Reduction periods, regardless of the ports, show 100% stability, which indicates continuous reductions in volumes during the period. However, the stability varies for restoration phases.

Barbours Cut and Bayport terminals handle most local shipments and show similar patterns as their regional operations. Barbours Cut shows longer restoration and overloading phases while Bayport presents a longer proactive staging phase. However, compared to regional shipments, the impacts of local shipment seem lower with at most two days of staging or overloading phases with 30% to 54% volume increases.

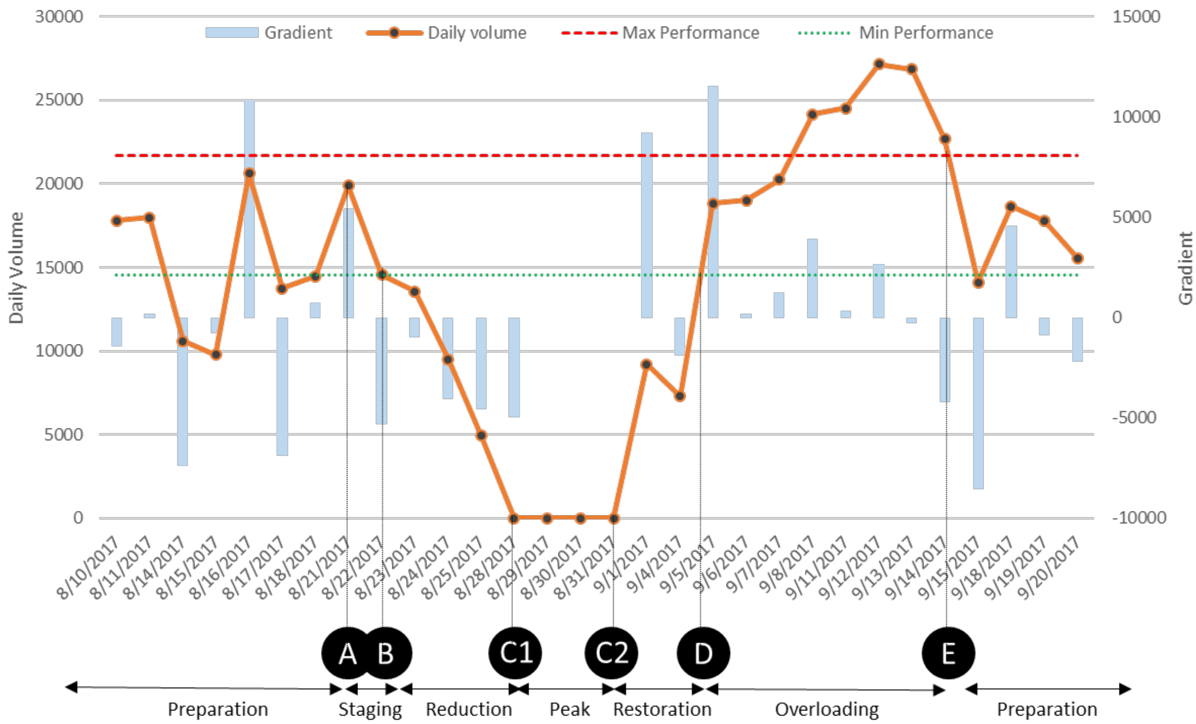


Figure 18. Performance profiles of Bayport terminal to Houston during Harvey.

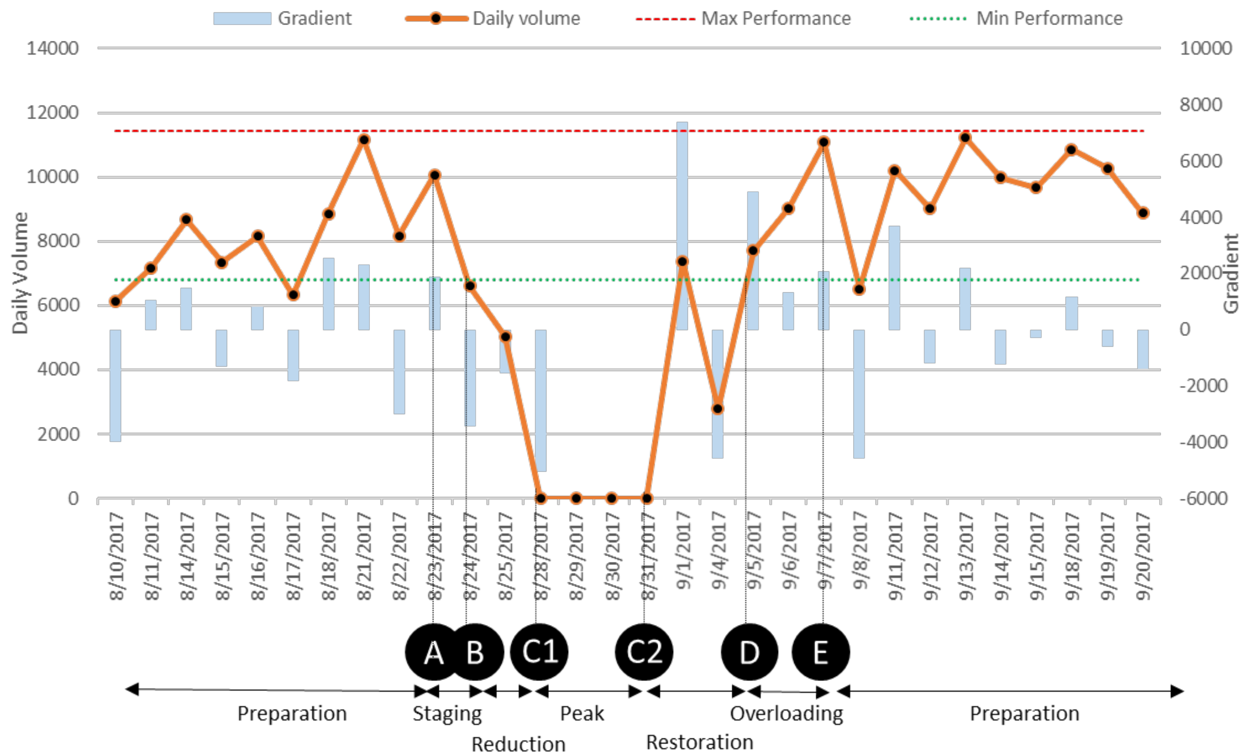


Figure 19. Performance profiles of Barbours Cut terminal to local facilities.

Table 3. Performance Metrics of Hurricane Harvey.

Phase	Metric	Houston FAF			Local	
		Barbours Cut	**Bayport**	**Turning Basin**	**Barbours Cut**	**Bayport**
Minimum (Baseline) Performance (trips/day)		31,200	14,800	8,400	6,700	3,600
Staging (Proactive Response)	Depth	14%	34%	71%	31%	54%
	Duration	1	1	3	1	2
	Total	7%	17%	98%	18%	54%
Reduction	Depth	100%	100%	100%	100%	100%
	Duration	2	4	1	2	3
	Total	150%	200%	50%	100%	150%
	Stability	100%	100%	100%	100%	150%
Recovery	Depth	100%	100%	100%	100%	100%
	Duration	5	3	3	5	3
	Total	250%	150%	150%	250%	150%
	Stability	80%	67%	67%	80%	80%
Overload (Reactive Response)	Depth	29%	72%	54%	44%	53%
	Duration	2	7	1	2	1
	Total	29%	338%	27%	44%	11%

7.2.2. Holiday Events

The performance profiles and metrics from holiday disruptions appear dissimilar from a major disruptive event, Harvey. A key difference is lower uncertainty in operation levels with facility schedules for temporary closures. Several years of experiences and historical data also allow operators to predict the overall impacts and service performances before and after the events.

This study uses two types of holiday events including July 4th and Thanksgiving, which represent single and multi-day disruptions, respectively. As shown in Figure 20, all the ports show less than two days of staging, reduction, restoration, and overloading phases with 100% stability for July 4th. None of the phases observe substantial increases in operations. These consistent and stable patterns across the ports and destinations indicate that a short disruption such as July 4th minimally impacts truck operations by processing shipments through a short period of staging or overloading phase. The Thanksgiving holiday however shows different patterns (Figure 21). Although Barbours Cut to Houston shows one day of staging and reduction phases, three days of overloading periods indicates that the disruption substantially impacts truck operations. Bayport to Houston shows more significant impacts including seven days of overloading and three days of staging. Turning basin to Houston also presents an extended period of staging despite the shortest overloading phase. Compared to July 4th, heavy loadings appear to show across the ports especially for regional movements (Table 4-5). Bayport shows 265% and 512% of total impacts during staging and overloading phases while Turning basin concentrates the shipments during the staging phase with 617% of total impact.

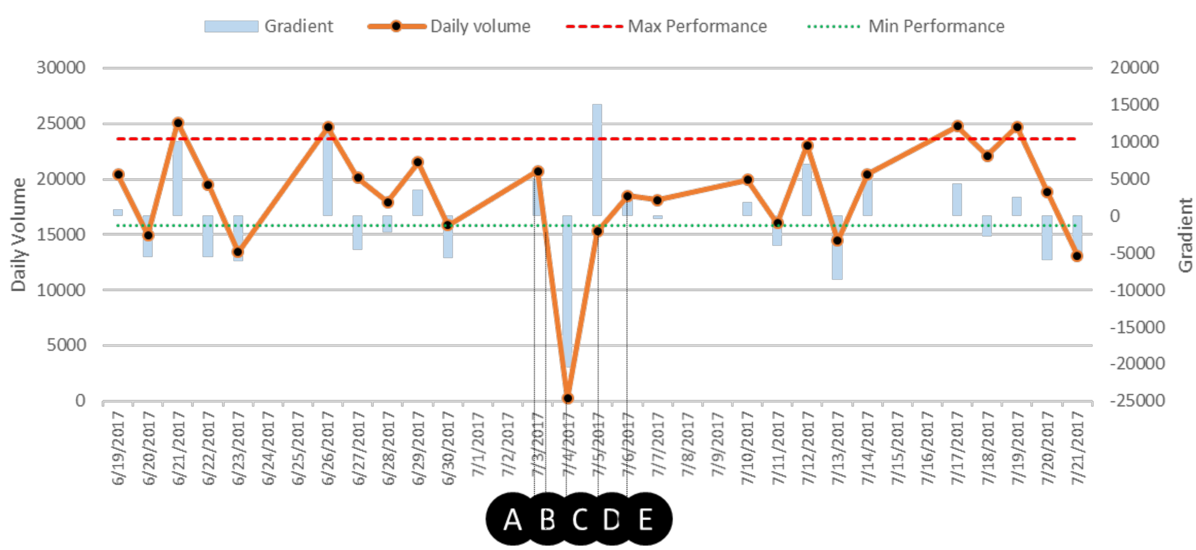


Figure 20. Performance profiles of Bayport terminal to Houston during July 4th.

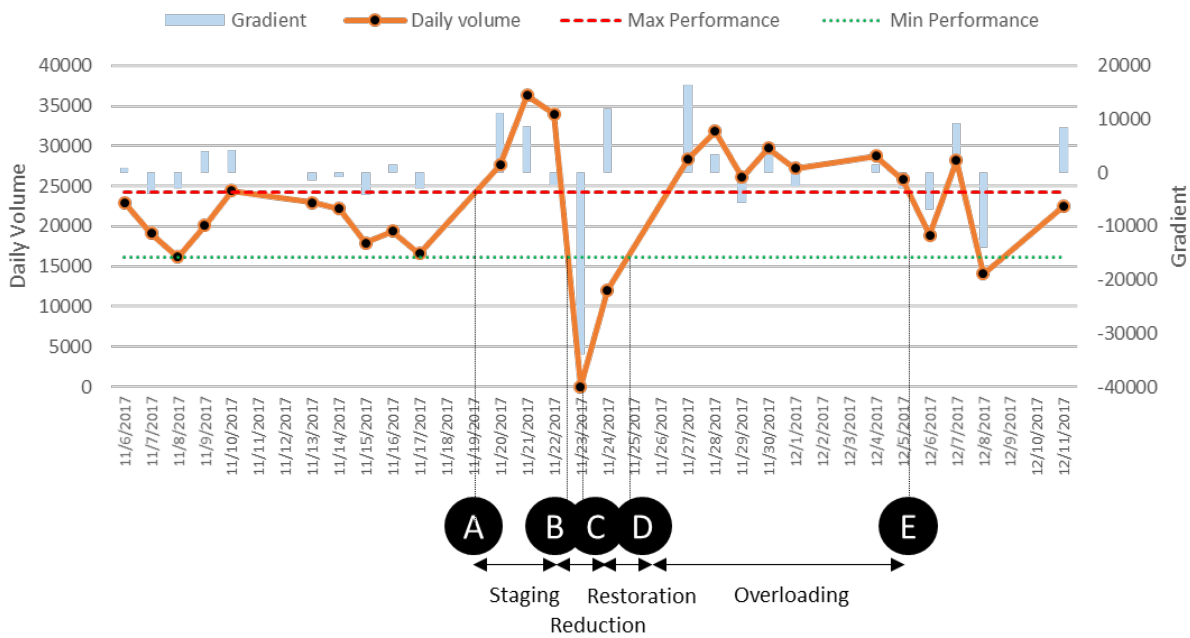


Figure 21. Performance profiles of Bayport terminal to Houston during Thanksgiving.

Table 4. Performance Metrics of July 4th.

Phase	Metric	Houston FAF			Local	
		Barbours Cut	Bayport	Turning Basin	Barbours Cut	Bayport
Minimum (Baseline) Performance (trips/day)		31,200	15,800	8,400	7,700	3,600
Staging (Proactive Response)	Depth	30%	32%	55%	70%	36%
	Duration	1	1	2	1	1
	Total	15%	4%	55%	35%	5%
Reduction	Depth	100%	100%	100%	100%	100%
	Duration	1	1	2	1	1
	Total	50%	38%	100%	50%	35%
	Stability	100%	100%	100%	100%	100%
Recovery	Depth	100%	100%	100%	100%	100%
	Duration	1	1	1	1	1
	Total	41%	50%	25%	43%	50%
	Stability	100%	100%	100%	100%	100%
Overload (Reactive Response)	Depth	23%	17%	116%	21%	88%
	Duration	1	1	2	1	1
	Total	2%	9%	120%	1%	44$

Table 5. Performance Metrics of Thanksgiving.

Phase	Metric	Houston FAF			Local	
		Barbours Cut	Bayport	Turning Basin	Barbours Cut	Bayport
Minimum (Baseline) Performance (trips/day)		31,200	15,800	8,400	7,700	3,600
Staging (Proactive Response)	Depth	39%	130%	232%	72%	105%
	Duration	1	3	7	1	3
	Total	5%	265%	617%	15%	266%
Reduction	Depth	100%	100%	100%	100%	100%
	Duration	1	1	1	1	1
	Total	38%	25%	50%	30%	25%
	Stability	100%	100%	100%	100%	100%
Recovery	Depth	100%	100%	100%	100%	100%
	Duration	2	2	2	2	1
	Total	80%	63%	100%	80%	50%
	Stability	100%	100%	100%	100%	100%
Overload (Reactive Response)	Depth	46%	102%	47%	52%	85%
	Duration	3	7	2	1	1
	Total	87%	512%	47%	10%	42%

7.3. Economic Analysis

As the US population is projected to grow by 79 million from about 326 million in 2019 to 404 million in 2060, the freight transportation system, which currently moves more than 5 billion ton-miles of freight in the US, expects significant increases in port and intermodal facility demand. The Texas Transportation Plan 2040 documents that "the transportation system must accommodate the growth" with strategic and long-range planning. The freight mobility plan seeks to reduce congestion and improve system efficiency by leveraging technology and effective operational management of the existing transportation system. As the current resources to evaluate the efficiency and reliability of freight transportation operation remain limited, decision-makers need a tool to better understand the freight transportation activities and behavior including industry types, service frequency, and operational strategies of major port trips. The freight mobility plan also emphasizes maintaining infrastructure and improving system efficiency by increasing the resiliency of the State's freight transportation system and effectively responding to natural and man-made disasters. A short-term regional plan requires strategies to minimize the impacts on the multimodal freight network caused by frequent adverse weather events while a long-range plan focuses on designing flexible and reliable freight transportation as a regional priority.

The port provides economic benefits to both local and larger megaregions. This study uses the resiliency framework to quantify the economic impacts from hurricane Harvey and directly translates the changes in truck activity (i.e., volumes) to economic outputs.

According to the latest report on the economic impact of marine cargo activity at the port of Houston (PHA) (*102*), port activity supports a total of 176,128 new direct and indirect jobs in 2018. The total economic value from the PHA and private terminals is $339 billion, which is almost 20.6% of state GDP. This study focuses on the economic outputs of three major ports of

PHA, Barbours Cut, Bayport, and Turning Basin and uses the revenue tonnage of these terminals to estimate their economic outputs as shown in Table 6 (*103*).

Table 6. Daily economic output of 3 PHA terminals.

Terminal	Revenue Tonnage (2018)	Share of Tonnage	Economic Output
Barbours Cut	10,738,674	21.5%	$145,714,960
Bayport	20,430,131	40.9%	$277,197,296
Turning Basin	5,527,888	11%	$74,551,840
All PHA terminals	49,989,913	-	-

The economic analysis uses performance profiles captured in the resilience framework for given OD locations e.g., a port and its local/regional destinations. We estimate the economic loss and gain for the five disaster phases including staging, reduction, inactivity, recovery, and overloading responses to understand the economic output changes before, during and after the disruption.

Figure 22 shows the important metrics used to estimate economic impacts. Three threshold values (three lines in red, green, and blue) determine the reference value for the analysis. The red and green lines show the average minimum and maximum OD volumes between a port and its destination based on a 3-month OD profiles, respectively. Again, these two lines correspond to the performance levels used for the resilience framework. The third performance reference (blue line) defines the average OD volumes for the previous 3-month period since the economic output of port should be based on the average performance rather than extreme boundaries such as maximum or minimum performances.

The five zones (1 to 5) in Figure 22 represent the stage of event progression. Zone 1 shows the economic impact during the staging phase. Since the performance level is below the average performance level, the staging phase yields a negative economic impact. Zones 2 and 4 show the economic impacts during the reduction and recovery phases, and both produced negative outputs. Zone 5, representing the overloading phase, shows the positive economic impact as its operation level exceeds the average reference. When the performance level reaches above the maximum level as Zone 6 shows, the operation yields a significant positive economic impact because of its substantial overloading activities to compensate for the loss of service during the disrupted period.

Table 7 shows the average economic outputs of three major port terminals to serve local and regional destinations.

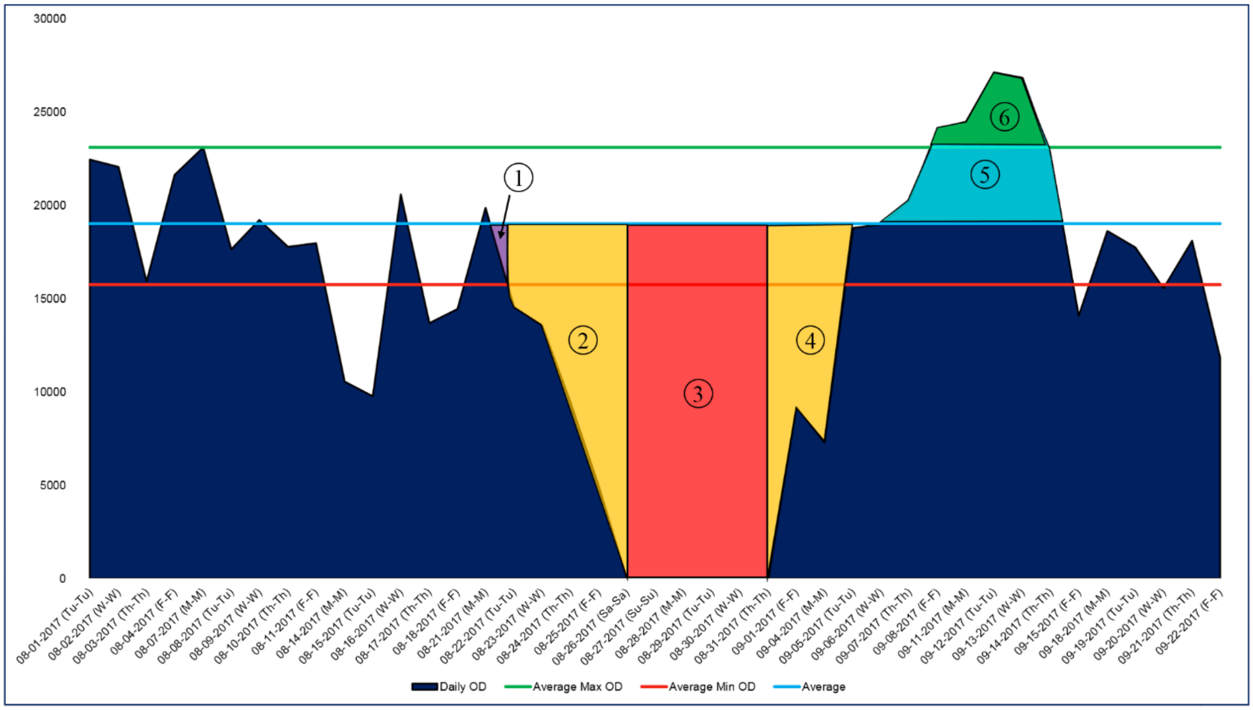


Figure 22. Different zones used to estimate the economic impacts during a disruption period.

Table 7. Daily economic output from 3 PHA terminals to different destinations.

Destination / Origin	Houston	Other FAFs	Local
Barbours Cut	$140.8 M	$4.95 M	$41.6
Bayport	$271.1 M	$6.08 M	$62.3 M
Turning Basin	$71.1 M	$3.43 M	$3.82 M

Table 8 summarizes the economic output analysis. Trucks serving Bayport terminal to Houston area show the highest economic loss during the staging and reduction periods due to its high daily truck operations. However, Bayport trucks serving Houston FAF show higher gain during the overloading phase due to their above-average operation level whereas Turning Basin trucks yield positive economic outputs during the staging phase. However, most of local operations show economic losses except for a1.4M gain during the overloading phase of Barbours Cut.

Table 8. Economic impact of PHA terminals.

Phase	Metric	Houston FAF			Local	
		Barbours Cut	Bayport	Turning Basin	Barbours Cut	Bayport
Daily Economic Output		$140.8 M	$271.1 M	$71.1 M	$41.6 M	$62.3 M
Staging (Proactive Response)	Duration	1	1	2	1	2
	Economic impact	-$8.7 M	-$23.2 M	+$25.9 M	-$4.3 M	-$6.9 M
	Economic impact at max performance	0	0	+$5.3 M	0	0
Reduction	Duration	2	4	1	2	3
	Economic impact	-$158.1 M	-$635. M	-$42.6 M	-$50.2 M	-$133.5 M
Inactive	Economic impact	-$422.3 M	-$1,355.6 M	-$355.6 M	-$124.7 M	-$311.5 M
Recovery	Duration	5	3	3	5	3
	Economic impact	-$395.2 M	-$476.4 M	-$155.3 M	-$117.6 M	-$126.3 M
Overload (Reactive Response)	Duration	2	7	1	2	1
	Economic impact	-$11.2 M	+$459.5 M	+$8.4 M	+$1.5 M	-$2.8 M
	Economic impact at max performance	0	+$138.0 M	0	0	0

8. CONCLUSIONS

The transportation systems serving ports represent a pivotal freight operation. Evaluating port truck activities during disruptive events such as Hurricane Harvey represents an important step for maintaining highway infrastructure and designing plans for a fast system recovery. This study develops an adaptable framework to evaluate resilience of freight operations during a disruptive event. The resilience metrics defines five distinct phases of disaster responses including staging, reduction, peak, restoration, and overloading phases. The performance of the reduction period shows vulnerability of a system while the restoration period reflects how fast the system regains capacity and rebounds to normal functionality. This study highlights the importance of staging and overloading phases since proactive or reactive responses during the phases describe resilience and adaptability of the operation. The extent of flexibility in operational capacities such as instantaneous volume increases during a short period of staging phase or an extended overloading phase shows how much adaptable capacity and flexibility the system provides to recover from the disruption.

The developed metrics assess resilience in transportation operations of PHA during Hurricane Harvey, and major holidays including July 4th and Thanksgiving in 2017. The framework quantifies cross-sectional and total impacts from disruptions by estimating performance changes across a different phase.

A major disruption such as a hurricane can significantly affect the local and regional economy in various scales. In order to minimize the impacts of adverse weather events on the multimodal freight network, we must understand how events impact economic outputs during the different stages of disruption. Using the resiliency framework developed in this study, we estimate the economic impacts of hurricane Harvey on port of Houston. This study uses the lost (or extra) service level of port trucks and turns it into the economic loss (or gain) of the port operation for the three major terminals of port of Houston.

This methodology allows agencies or freight industry to understand how well a system prepares for a disaster and responds to minimize the impacts from a disruptive event. This flexible structure allows the framework to be applicable to any disruptive events that cause significant operation changes for an extended period.

REFERENCES

1. U.S. Department of Transportation. (2015). National Freight Strategic Plan. Retrieved from https://www.transportation.gov/sites/dot.gov/files/docs/DRAFT_NFSP_for_Public_Comment_508_10%2015%2015%20v1.pdf.
2. Worth, Monica, Sebastian Guerrero, and Alan Meyers. 2016 Freight Quick Facts Report. No. FHWA-HOP-16-083. United States. Federal Highway Administration, 2016.
3. Texas Department of Transportation. (2016). Texas Freight Mobility Plan. Retrieved from http://ftp.dot.state.tx.us/pub/txdot/move-texas-freight/studies/freight-mobility/2016/summary.pdf.
4. Sun, Wenjuan, Paolo Bocchini, and Brian D. Davison. "Resilience metrics and measurement methods for transportation infrastructure: the state of the art." Sustainable and Resilient Infrastructure 5, no. 3 (2020): 168-199.
5. Ta, Chilan, Anne V. Goodchild, and Barbara Ivanov. "Building Resilience into Freight Transportation Systems: Actions for State Departments of Transportation." Transportation research record 2168, no. 1 (2010): 129-135.
6. Nair, Rahul, Hakob Avetisyan, and Elise Miller-Hooks. "Resilience framework for ports and other intermodal components." Transportation Research Record 2166, no. 1 (2010): 54-65.
7. Bekkem, Kaushik, Teresa M. Adams, and Vicki M. Bier. "Evaluating freight transportation resilience on a highway corridor." In Proceedings of the 90th Annual Meeting of Transportation Research Board, Washington DC., USA. 2011.
8. Miller-Hooks, Elise, Xiaodong Zhang, and Reza Faturechi. "Measuring and maximizing resilience of freight transportation networks." Computers & Operations Research 39, no. 7 (2012): 1633-1643.
9. Adams, Teresa M., Kaushik R. Bekkem, and Edwin J. Toledo-Durán. "Freight resilience measures." Journal of Transportation Engineering 138, no. 11 (2012): 1403-1409.
10. MAOH, Hanna, William ANDERSON, and Charles BURKE. "Modeling the resilience of surface freight transportation systems: an application to Ontario, Canada." In 47th Annual Conference of the Canadian Transportation Research Forum, Calgary, Alberta, Canada. 2012.
11. Berche, Bertrand, Christian Von Ferber, Taras Holovatch, and Yu Holovatch. "Resilience of public transport networks against attacks." The European Physical Journal B 71, no. 1 (2009): 125-137.
12. Osei-Asamoah, Abigail, and Nicholas E. Lownes. "Complex network method of evaluating resilience in surface transportation networks." Transportation Research Record 2467, no. 1 (2014): 120-128.
13. Amadeo, Kimberly. "Hurricane Harvey facts, damage and costs." The Balance. Retrieved from https://www. thebalance. com/hurricane-harvey-facts-damage-costs-4150087 (2018).
14. Trenberth, Kevin E., Lijing Cheng, Peter Jacobs, Yongxin Zhang, and John Fasullo. "Hurricane Harvey links to ocean heat content and climate change adaptation." Earth's Future 6, no. 5 (2018): 730-744.
15. Hu, Patricia S., Rolf R. Schmitt, Michael J. Sprung, Matthew Chambers, Daniel Friedman, Michelle M. Gilmore, Daniel Hackett, and Dan Smith. "Port Performance Freight Statistics in 2018: Annual Report to Congress 2019." (2020).
16. The Port Authority of NY & NJ. (2018). Truck Origin-Destination Data Analysis. Retrieved from https://www.panynj.gov/content/dam/port/customer-library-pdfs/truck-origin-destination-data-analysis.pdf.

17. Metro. (2018). Facts of Truck/Goods Movement in SR 710 North Study. Retrieved from http://media.metro.net/projects_studies/sr_710/images/sr_710_faqs_goods_movement.pdf.
18. Camp, Janey, Mark Abkowitz, George Hornberger, Laura Benneyworth, and James C. Banks. "Climate change and freight-transportation infrastructure: Current challenges for adaptation." Journal of Infrastructure Systems 19, no. 4 (2013): 363-370.
19. Shen, G., and S. G. Aydin. "Highway freight transportation disruptions under an extreme environmental event: the case of Hurricane Katrina." International Journal of Environmental Science and Technology 11, no. 8 (2014): 2387-2402.
20. Caldwell, Harry, Kate H. Quinn, Jacob Meunier, John Suhrbier, and Lance Grenzeback. "Potential impacts of climate change on freight transport." In The Potential Impacts of Climate Change on Transportation: Workshop Summary, US Dept. of Transportation, Workshop, pp. 1-2. 2002.
21. Fialkoff, Marc R., Olufemi A. Omitaomu, Steven K. Peterson, and Mark A. Tuttle. "Using geographic information science to evaluate legal restrictions on freight transportation routing in disruptive scenarios." International Journal of Critical Infrastructure Protection 17 (2017): 60-74.
22. Hernandez, Sarah, Taslima Akter, and Karla Diaz. The Effect of Weather Events on Truck Traffic Patterns Using Fixed and Mobile Traffic Sensors. No. SPTC 15.1-20-F. Southern Plains Transportation Center, 2017.
23. Roh, Hyuk-Jae, Satish Sharma, Prasanta K. Sahu, and Sandeep Datla. "Analysis and modeling of highway truck traffic volume variations during severe winter weather conditions in Canada." Journal of Modern Transportation 23, no. 3 (2015): 228-239.
24. Das, Tanmay, Ipshit Ibne Idris2 Bijoy Basak Nibas, and Apu4 Md Hadiuzzaman. "Key factors affecting highway freight transportation disruptions at post disaster phase." In Australasian Transport Research Forum (ATRF), 38th, 2016, Melbourne, Victoria, Australia. 2016.
25. Nagurney, Anna. "Freight service provision for disaster relief: A competitive network model with computations." In International Conference on Dynamics of Disasters, pp. 207-229. Springer, Cham, 2016.
26. Hsieh, Cheng-Hsien. "Disaster risk assessment of ports based on the perspective of vulnerability." Natural hazards 74, no. 2 (2014): 851-864.
27. Beheshtian, Arash, R. Richard Geddes, and Kieran P. Donaghy. "Modeling the Impacts of Climatic Extremes on Interregional Freight-Transportation System." Transportation Research Record 2672, no. 2 (2018): 33-43.
28. Zhang, Xiaodong, and Elise Miller-Hooks. "Scheduling short-term recovery activities to maximize transportation network resilience." Journal of Computing in Civil Engineering 29, no. 6 (2015): 04014087.
29. Gossler, Timo, Tina Wakolbinger, Anna Nagurney, and Patrizia Daniele. "How to increase the impact of disaster relief: A study of transportation rates, framework agreements and product distribution." European Journal of Operational Research 274, no. 1 (2019): 126-141.
30. Amdal, James R., and Stanley L. Swigart. "Resilient Transportation Systems in a Post-Disaster Environment: A Case Study of Opportunities Realized and Missed in the Greater New Orleans Region, 2010." (2010).
31. Cantillo, Victor, Luis F. Macea, and Miguel Jaller. "Assessing vulnerability of transportation networks for disaster response operations." Networks and Spatial Economics 19, no. 1 (2019): 243-273.

32. Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A. and Von Winterfeldt, D., 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake spectra, 19(4), pp.733-752.
33. Liao, Tsai-Yun, Ta-Yin Hu, and Yi-No Ko. "A resilience optimization model for transportation networks under disasters." Natural hazards 93, no. 1 (2018): 469-489.
34. Bevilacqua, M., F. E. Ciarapica, and G. Marcucci. "A modular analysis for the supply chain resilience triangle." IFAC-PapersOnLine 51, no. 11 (2018): 1528-1535.
35. D'Lima, Minette, and Francesca Medda. "A new measure of resilience: An application to the London Underground." Transportation Research Part A: Policy and Practice 81 (2015): 35-46.
36. Bevilacqua, M., F. E. Ciarapica, and G. Marcucci. "Supply chain resilience triangle: The study and development of a framework." International Journal of Economics and Management Engineering 11, no. 8 (2017): 2028-2035.
37. Bevilacqua, M., F. E. Ciarapica, and G. Marcucci. "A modular analysis for the supply chain resilience triangle." IFAC-PapersOnLine 51, no. 11 (2018): 1528-1535.
38. Xu, Mengjuan, Xinping Wang, and Lindu Zhao. "Predicted supply chain resilience based on structural evolution against random supply disruptions." International Journal of Systems Science: Operations & Logistics 1, no. 2 (2014): 105-117.
39. Zobel, Christopher W. "Representing the multi-dimensional nature of disaster resilience." In ISCRAM. 2011.
40. Zobel, Christopher W. "Representing perceived tradeoffs in defining disaster resilience." Decision Support Systems 50, no. 2 (2011): 394-403.
41. Faturechi, Reza, and Elise Miller-Hooks. "Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review." Journal of infrastructure systems 21, no. 1 (2015): 04014025.
42. Snelder, M., H. J. Van Zuylen, and L. H. Immers. "A framework for robustness analysis of road networks for short term variations in supply." Transportation Research Part A: Policy and Practice 46, no. 5 (2012): 828-842.
43. Berdica, Katja. "An introduction to road vulnerability: what has been done, is done and should be done." Transport policy 9, no. 2 (2002): 117-127.
44. Jenelius, Erik, and Lars-Göran Mattsson. "Road network vulnerability analysis: Conceptualization, implementation and application." Computers, Environment and Urban Systems 49 (2015): 136-147.
45. Billinton, Roy, and Ronald Norman Allan. Reliability evaluation of engineering systems. New York: Plenum press, 1992.
46. Tkhoruk, Yevhen, Olena Kucher, Mykola Holotiuk, Mykhailo Krystopchuk, and Oleg Tson. "Modeling of assessment of reliability transport systems." Матеріали Міжнародної науково-технічної конференції „Актуальні проблеми транспорту " (2019): 204-210.
47. Morlok, Edward K., and David J. Chang. "Measuring capacity flexibility of a transportation system." Transportation Research Part A: Policy and Practice 38, no. 6 (2004): 405-420.
48. Mead, Nancy R., Robert J. Ellison, Richard C. Linger, Thomas Longstaff, and John McHugh. Survivable network analysis method. No. CMU/SEI-2000-TR-013. CARNEGIE-MELLON UNIV PITTSBURGH PA SOFTWARE ENGINEERING INST, 2000.
49. Wang, Chunlei, Liang Ming, Jinjing Zhao, and Dongxia Wang. "A general framework for network survivability testing and evaluation." Journal of Networks 6, no. 6 (2011): 831.

50. Chang, Liang, Amr S. Elnashai, Billie F. Spencer, JunHo Song, and Yanfeng Ouyang. "Transportations Systems Modeling and Applications in Earthquake Engineering." (2010).
51. Murray-Tuite, Pamela M., and Xiang Fei. "A methodology for assessing transportation network terrorism risk with attacker and defender interactions." Computer-Aided Civil and Infrastructure Engineering 25, no. 6 (2010): 396-410.
52. Bell, Michael GH, U. Kanturska, J-D. Schmöcker, and Achille Fonzone. "Attacker–defender models and road network vulnerability." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 366, no. 1872 (2008): 1893-1906.
53. Golroo, Amir, Afshin Shariat Mohaymany, and Mahmoud Mesbah. "Reliability based investment prioritization in transportation networks." In Proceedings of the 89th annual meeting of the Transportation Research Board of the National Academies, pp. 10-14. 2010.
54. Faturechi, Reza, and Elise Miller-Hooks. "A mathematical framework for quantifying and optimizing protective actions for civil infrastructure systems." Computer-Aided Civil and Infrastructure Engineering 29, no. 8 (2014): 572-589.
55. De-Los-Santos, Alicia, Gilbert Laporte, Juan A. Mesa, and Federico Perea. "Evaluating passenger robustness in a rail transit network." Transportation Research Part C: Emerging Technologies 20, no. 1 (2012): 34-46.
56. Chen, Anthony, and Panatda Kasikitwiwat. "Modeling capacity flexibility of transportation networks." Transportation research part A: policy and practice 45, no. 2 (2011): 105-117.
57. Li, Bin, Xiaowei Hu, and Binglei Xie. "Transportation network reconstruction for natural disasters in the emergency phase based on connectivity reliability." In International Conference on Transportation Engineering 2009, pp. 2963-2968. 2009.
58. Chen, Richard Li-Yang, Amy Cohn, and Ali Pinar. "An implicit optimization approach for survivable network design." In 2011 IEEE Network Science Workshop, pp. 180-187. IEEE, 2011.
59. Luping, Y. A. N. G., and Q. I. A. N. Dalin. "Vulnerability analysis of road networks." Journal of Transportation Systems Engineering and Information Technology 12, no. 1 (2012): 105-110.
60. Freckleton, Derek, Kevin Heaslip, William Louisell, and John Collura. "Evaluation of resiliency of transportation networks after disasters." Transportation research record 2284, no. 1 (2012): 109-116.
61. Derrible, Sybil, and Christopher Kennedy. "The complexity and robustness of metro networks." Physica A: Statistical Mechanics and its Applications 389, no. 17 (2010): 3678-3691.
62. Lertworawanich, Ponlathep. "Highway network restoration after the great flood in Thailand." Natural hazards 64, no. 1 (2012): 873-886.
63. Basoz, N., and A. Kiremidjian. "Risk assessment for highway transportation systems, JA Blame Earthquake Engineering Center, Dept Civil Engineering." (1996).
64. Chang, Stephanie E., Masanobu Shinozuka, and James E. Moore. "Probabilistic earthquake scenarios: extending risk analysis methodologies to spatially distributed systems." Earthquake Spectra 16, no. 3 (2000): 557-572.
65. Dalziell, Erica, and Alan Nicholson. "Risk and impact of natural hazards on a road network." Journal of transportation engineering 127, no. 2 (2001): 159-166.
66. Kiremidjian, Anne, James Moore, Yue Yue Fan, Ozgur Yazlali, Nesrin Basoz, and Meredith Williams. "Seismic risk assessment of transportation network systems." Journal of Earthquake Engineering 11, no. 3 (2007): 371-382.

67. Stergiou, Evangelos C., and Anne S. Kiremidjian. "Risk assessment of transportation systems with network functionality losses." Structure and Infrastructure Engineering 6, no. 1-2 (2010): 111-125.
68. Shiraki, Nobuhiko, Masanobu Shinozuka, James E. Moore, Stephanie E. Chang, Hiroyuki Kameda, and Satoshi Tanaka. "System risk curves: probabilistic performance scenarios for highway networks subject to earthquake damage." Journal of Infrastructure Systems 13, no. 1 (2007): 43-54.
69. Werner, Stuart D., Craig E. Taylor, Sungbin Cho, Jean-Paul Lavoie, Charles K. Huyck, Chip Eitzel, Ronald T. Eguchi, and James E. Moore II. "New developments in seismic risk analysis of highway systems." In Proc., 13th World Conference on Earthquake Engineering, pp. 1-6. 2004.
70. Jenelius, Erik, Tom Petersen, and Lars-Göran Mattsson. "Importance and exposure in road network vulnerability analysis." Transportation Research Part A: Policy and Practice 40, no. 7 (2006): 537-560.
71. Jenelius, Erik, and Lars-Göran Mattsson. "Road network vulnerability analysis of area-covering disruptions: A grid-based approach with case study." Transportation research part A: policy and practice 46, no. 5 (2012): 746-760.
72. Knoop, Victor L., Maaike Snelder, Henk J. van Zuylen, and Serge P. Hoogendoorn. "Link-level vulnerability indicators for real-world networks." Transportation Research Part A: Policy and Practice 46, no. 5 (2012): 843-854.
73. Lownes, Nicholas E., Qixing Wang, Saleh Ibrahim, Reda A. Ammar, Sanguthevar Rajasekaran, and Dolly Sharma. "Many-to-many game-theoretic approach for the measurement of transportation network vulnerability." Transportation research record 2263, no. 1 (2011): 1-8.
74. Shimamoto, Hiroshi, Fumitaka Kurauchi, Jan-Dirk Schmöcker, and Michael GH Bell. "Evaluating critical lines and stations considering the impact of the consequence using transit assignment model-case study of London's underground network." Journal of advanced transportation 42, no. 3 (2008): 291-310.
75. Ukkusuri, Satish V., and Wilfredo F. Yushimito. "A methodology to assess the criticality of highway transportation networks." Journal of Transportation Security 2, no. 1-2 (2009): 29-46.
76. Bell, Michael GH. "A game theory approach to measuring the performance reliability of transport networks." Transportation Research Part B: Methodological 34, no. 6 (2000): 533-545.
77. Ibrahim, Saleh, Reda Ammar, Sanguthevar Rajasekaran, Nicholas Lownes, Qixing Wang, and Dolly Sharma. "An efficient heuristic for estimating transportation network vulnerability." In 2011 IEEE Symposium on Computers and Communications (ISCC), pp. 1092-1098. IEEE, 2011.
78. Lam, William HK, Hu Shao, and Agachai Sumalee. "Modeling impacts of adverse weather conditions on a road network with uncertainties in demand and supply." Transportation research part B: methodological 42, no. 10 (2008): 890-910.
79. Sumalee, Agachai, and David P. Watling. "Partition-based algorithm for estimating transportation network reliability with dependent link failures." Journal of Advanced Transportation 42, no. 3 (2008): 213-238.
80. Szeto, W. Y. "Cooperative game approaches to measuring network reliability considering paradoxes." Transportation Research Part C: Emerging Technologies 19, no. 2 (2011): 229-241.

81. Siu, Barbara WY, and Hong K. Lo. "Doubly uncertain transportation network: degradable capacity and stochastic demand." European Journal of Operational Research 191, no. 1 (2008): 166-181.
82. Yin, Yafeng, and Hitoshi Ieda. "Assessing performance reliability of road networks under nonrecurrent congestion." Transportation Research Record 1771, no. 1 (2001): 148-155.
83. Morohosi, Hozumi. "Measuring the network robustness by Monte Carlo estimation of shortest path length distribution." Mathematics and Computers in Simulation 81, no. 3 (2010): 551-559.
84. Nagurney, Anna, and Qiang Qiang. "Robustness of transportation networks subject to degradable links." EPL (Europhysics Letters) 80, no. 6 (2007): 68001.
85. Nagurney, Anna, and Qiang Qiang. "A relative total cost index for the evaluation of transportation network robustness in the presence of degradable links and alternative travel behavior." International Transactions in Operational Research 16, no. 1 (2009): 49-67.
86. Sun, Yao, Mark A. Turnquist, and Linda K. Nozick. "Estimating freight transportation system capacity, flexibility, and degraded-condition performance." Transportation research record 1966, no. 1 (2006): 80-87.
87. Grubesic, Tony H., and Alan T. Murray. "Vital nodes, interconnected infrastructures, and the geographies of network survivability." Annals of the Association of American Geographers 96, no. 1 (2006): 64-83.
88. Matisziw, Timothy C., and Alan T. Murray. "Modeling s–t path availability to support disaster vulnerability assessment of network infrastructure." Computers & Operations Research 36, no. 1 (2009): 16-26.
89. Caplice, Chris, James B. Rice Jr, Barbara Ivanov, and Elizabeth Stratton. "Development of a state wide freight system resiliency plan." Massachusetts Institute of Technology's Center for Transportation and Logistics for Washington State Dept. of Transportation, Cambridge, MA (2008).
90. Cox, Andrew, Fynnwin Prager, and Adam Rose. "Transportation security and the role of resilience: A foundation for operational metrics." Transport policy 18, no. 2 (2011): 307-317.
91. Murray-Tuite, Pamela. "Evaluation of strategies to increase transportation system resilience to congestion caused by incidents." Mid-Atlantic University Transportation Center (2008).
92. Murray-Tuite, Pamela M. "A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions." In Proceedings of the 2006 Winter Simulation Conference, pp. 1398-1405. IEEE, 2006.
93. Vugrin, Eric D., Drake E. Warren, and Mark A. Ehlen. "A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane." Process Safety Progress 30, no. 3 (2011): 280-290.
94. StreetLight Data. https://support.streetlightdata.com/hc/en-us/articles/360018848312-Location-Data-Sources-and-Probe-Technologies. Accessed July 10, 2020.
95. StreetLight Data. https://www.streetlightdata.com/accuracy-and-validation. Accessed July 10, 2020.
96. Yang, Hong, Mecit Cetin, and Qingyu Ma. Guidelines for Using StreetLight Data for Planning Tasks. No. FHWA/VTRC 20-R23. 2020.
97. Port of New York and New Jersey Statistics. https://www.panynj.gov/port/en/our-port/facts-and-figures.html. Accessed July 16, 2020.
98. The Journal of Commerce. https://www.joc.com/port-news/us-ports/la-lb-port-warehousing-nears-limits_20190201.html. Accessed July 16, 2020

99. Lindell, Michael K., ed. The routledge handbook of urban disaster resilience: integrating mitigation, preparedness, and recovery planning. Routledge, 2019.
100. Tok, Andre, Kyung Hyun, Sarah Hernandez, Kyungsoo Jeong, Yue Sun, Craig Rindt, and Stephen G. Ritchie. "Truck activity monitoring system for freight transportation analysis." Transportation Research Record 2610, no. 1 (2017): 97-107.
101. Economic Alliance Houston Port Region. (n.d). Retrieved from https://allianceportregion.com/research-2.
102. The Local and Regional Economic Impacts of the Port of Houston, prepared for the Port of Houston Authority, by Martin Associates, March 8, 2019.
103. General Statistical Data Packet. Prepared by Port of Houston Authority, December 2019.

APPENDIX A. SEASONAL TRAFFIC PATTERN

Table A.1. Average Daily Traffic of Barbours Cut Terminal.

Barbours Cut Terminal	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
36510	Winter 2017
46038	Spring 2017
42594	Summer 2017
35449	Fall 2017
45283	Winter 2018
44947	Spring 2018
54385	Summer 2018
58075	Fall 2018
41891	Winter 2019
40752	Spring 2019
45747	Summer 2019
59926	Fall 2019
Weekday (M-Th)	
44577	Winter 2017
61328	Spring 2017
54961	Summer 2017
43273	Fall 2017
57238	Winter 2018
60400	Spring 2018
69595	Summer 2018
72547	Fall 2018
53736	Winter 2019
53431	Spring 2019
59376	Summer 2019
77419	Fall 2019

Table A.2. Average Daily Traffic from Bayport Terminal.

Bayport Container Terminal	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
26357	Winter 2017
25360	Spring 2017
25316	Summer 2017
25619	Fall 2017
31822	Winter 2018
32890	Spring 2018
31855	Summer 2018
39951	Fall 2018
25988	Winter 2019
28809	Spring 2019
38609	Summer 2019
47372	Fall 2019
Weekday (M-Th)	
34447	Winter 2017
35720	Spring 2017
35105	Summer 2017
33915	Fall 2017
40807	Winter 2018
46476	Spring 2018
39849	Summer 2018
51998	Fall 2018
34853	Winter 2019
40882	Spring 2019
53450	Summer 2019
62054	Fall 2019

Table A.3. Average Daily Traffic from Bulk Materials Handling Plant.

Bulk Materials Handling Plant	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
837	Winter 2017
859	Spring 2017
225	Summer 2017
289	Fall 2017
442	Winter 2018
728	Spring 2018
1014	Summer 2018
1286	Fall 2018
1033	Winter 2019
956	Spring 2019
1111	Summer 2019
540	Fall 2019
Weekday (M-Th)	
1068	Winter 2017
942	Spring 2017
281	Summer 2017
410	Fall 2017
424	Winter 2018
731	Spring 2018
1174	Summer 2018
1928	Fall 2018
1223	Winter 2019
1052	Spring 2019
1751	Summer 2019
753	Fall 2019

Table A.4. Average Daily Traffic from Care Terminal.

Care	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
1875	Winter 2017
1822	Spring 2017
1181	Summer 2017
2028	Fall 2017
2482	Winter 2018
3802	Spring 2018
3582	Summer 2018
3329	Fall 2018
3480	Winter 2019
2207	Spring 2019
1495	Summer 2019
2682	Fall 2019
Weekday (M-Th)	
2047	Winter 2017
2750	Spring 2017
1614	Summer 2017
2357	Fall 2017
3162	Winter 2018
3582	Spring 2018
3195	Summer 2018
2673	Fall 2018
2855	Winter 2019
2590	Spring 2019
2009	Summer 2019
3363	Fall 2019

Table A.5. Average Daily Traffic of Jacintoport Terminal.

Jacintoport	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
14579	Winter 2017
6033	Spring 2017
5835	Summer 2017
5684	Fall 2017
7247	Winter 2018
7828	Spring 2018
6864	Summer 2018
6710	Fall 2018
6559	Winter 2019
5404	Spring 2019
6776	Summer 2019
6732	Fall 2019
Weekday (M-Th)	
17282	Winter 2017
7869	Spring 2017
7684	Summer 2017
7236	Fall 2017
9968	Winter 2018
11187	Spring 2018
9104	Summer 2018
8281	Fall 2018
9105	Winter 2019
7342	Spring 2019
9238	Summer 2019
8452	Fall 2019

Table A.6. Average Daily Traffic of Manchester Terminal.

Manchester Terminal	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
3900	Winter 2017
3615	Spring 2017
1727	Summer 2017
8479	Fall 2017
6474	Winter 2018
6986	Spring 2018
4641	Summer 2018
5710	Fall 2018
3733	Winter 2019
6825	Spring 2019
5508	Summer 2019
13831	Fall 2019
Weekday (M-Th)	
4800	Winter 2017
4093	Spring 2017
2234	Summer 2017
10250	Fall 2017
8094	Winter 2018
10070	Spring 2018
6474	Summer 2018
6140	Fall 2018
5301	Winter 2019
9084	Spring 2019
6136	Summer 2019
16962	Fall 2019

Table A.7. Average Daily Traffic of Turning Basin Terminal.

Turning Basin	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
13139	Winter 2017
16974	Spring 2017
23817	Summer 2017
17512	Fall 2017
17701	Winter 2018
22268	Spring 2018
17937	Summer 2018
20699	Fall 2018
15739	Winter 2019
16925	Spring 2019
15199	Summer 2019
10609	Fall 2019
Weekday (M-Th)	
15980	Winter 2017
20358	Spring 2017
30028	Summer 2017
23256	Fall 2017
22890	Winter 2018
29996	Spring 2018
23746	Summer 2018
25910	Fall 2018
19100	Winter 2019
22336	Spring 2019
17249	Summer 2019
13364	Fall 2019

Table A.8. Average Daily Traffic of Woodhouse Terminal.

Woodhouse	
All Days (M-Su)	
Average Daily Zone Traffic (StL Index)	Date
649	Winter 2017
3385	Spring 2017
2007	Summer 2017
862	Fall 2017
1929	Winter 2018
2718	Spring 2018
3919	Summer 2018
4867	Fall 2018
1847	Winter 2019
3455	Spring 2019
2340	Summer 2019
1216	Fall 2019
Weekday (M-Th)	
948	Winter 2017
4084	Spring 2017
2447	Summer 2017
955	Fall 2017
2153	Winter 2018
3228	Spring 2018
4349	Summer 2018
5978	Fall 2018
2308	Winter 2019
4245	Spring 2019
2517	Summer 2019
1712	Fall 2019

APPENDIX B. REGIONAL TRAFFIC PATTERN FROM PORT OF HOUSTON

Table B.1. Barbours Cut to neighboring FAFs.

	FAF			
	Beaumont	Corpus Christi	Dallas	Houston
Winter 2017	748	33	122	26059
Winter 2018	546	169	280	30950
Winter 2019	308	18	127	30790
Spring 2017	594	39	231	32511
Spring 2018	716	64	217	32811
Spring 2019	618	18	142	30385
Summer 2017	575	0	278	29818
Summer 2018	624	41	278	32847
Summer 2019	436	0	548	32706
Fall 2017	603	153	183	26119
Fall 2018	361	0	473	36100
Fall 2019	574	25	724	43330

Table B.2. Bayport to neighboring FAFs.

	FAF			
	Beaumont	Corpus Christi	Dallas	Houston
Winter 2017	89	0	0	18430
Winter 2018	136	0	39	19373
Winter 2019	163	0	0	19124
Spring 2017	117	0	0	15117
Spring 2018	149	21	55	18861
Spring 2019	37	0	37	21134
Summer 2017	257	0	61	15188
Summer 2018	165	0	77	19102
Summer 2019	304	0	94	28528
Fall 2017	0	15	92	16987
Fall 2018	173	0	30	24172
Fall 2019	115	37	50	34731

APPENDIX C. Daily OD Patterns during Harvey period

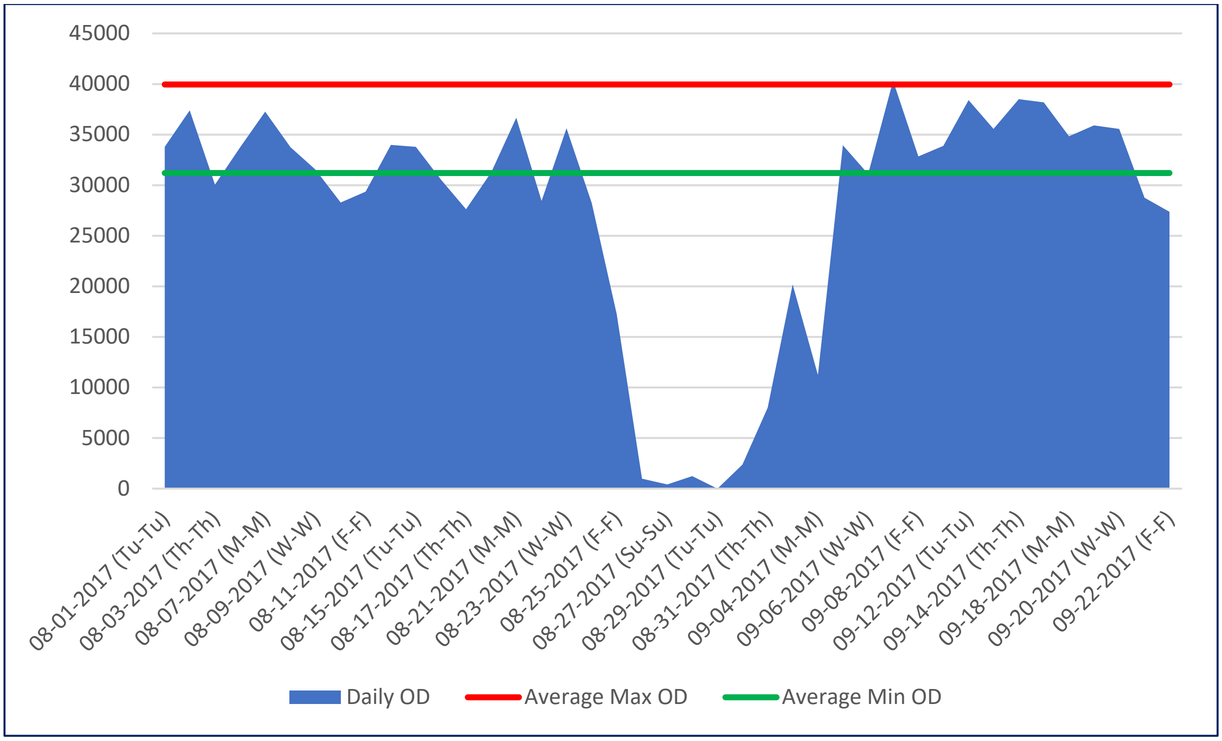


Figure C.1. Daily trips from Barbours Cut terminal to Houston area during Hurricane Harvey period.

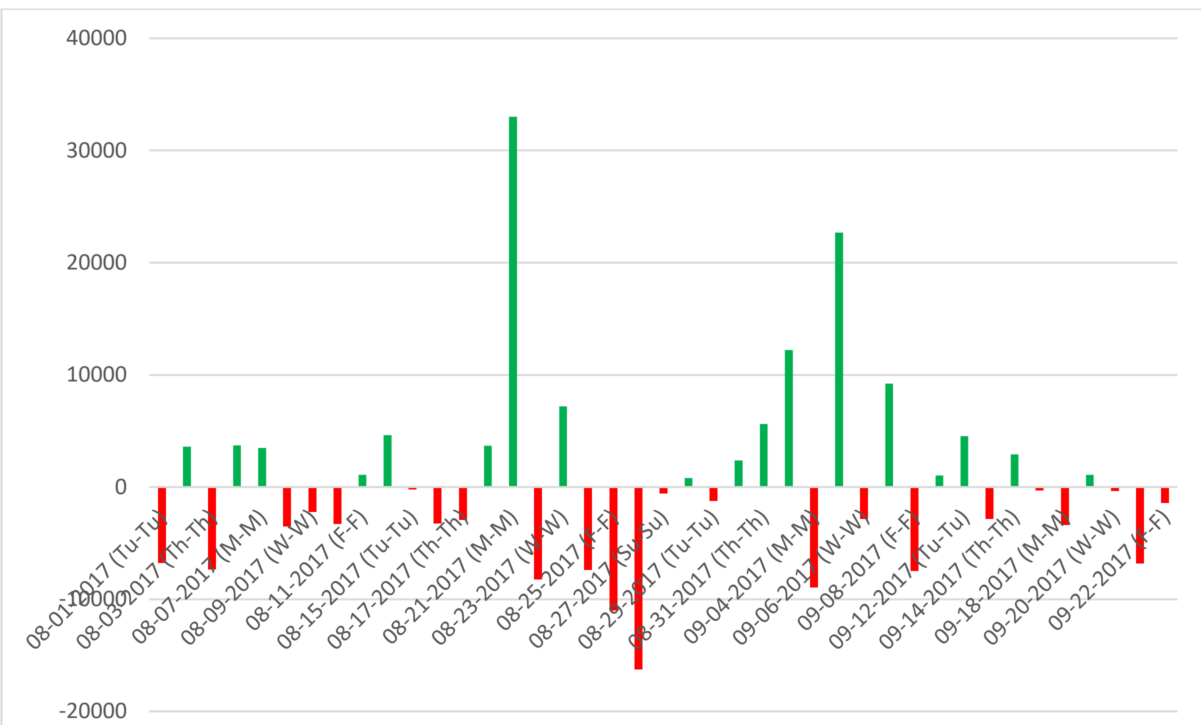


Figure C.2. Daily trip gradients from Barbours Cut to Houston area during Hurricane Harvey.

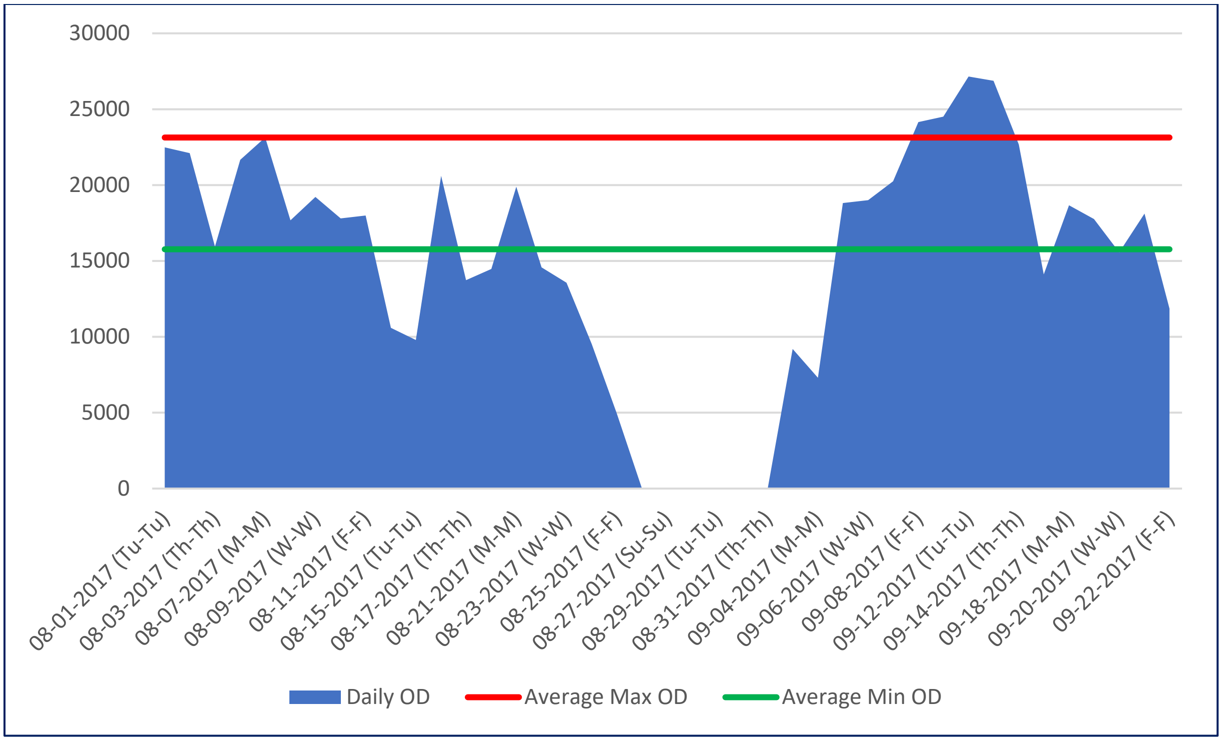


Figure C.3. Daily trips from Bayport terminal to Houston area during Hurricane Harvey period.

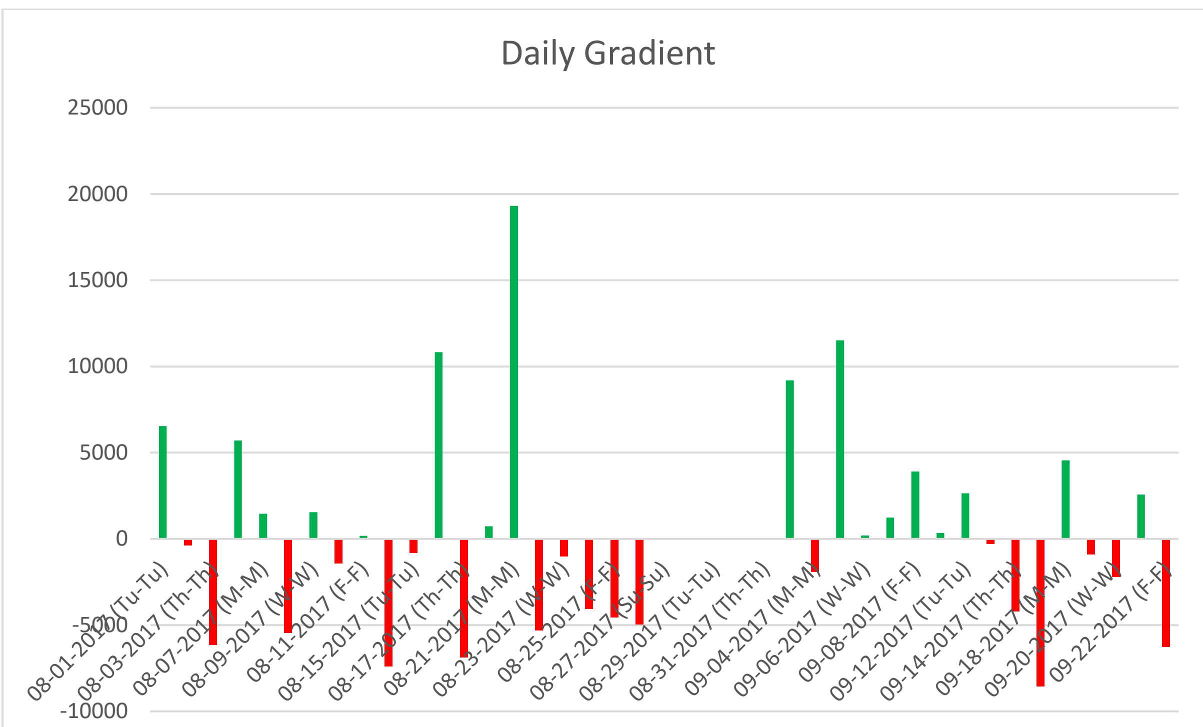


Figure C.4. Daily trip gradients from Bayport terminal to Houston area during Hurricane Harvey period.

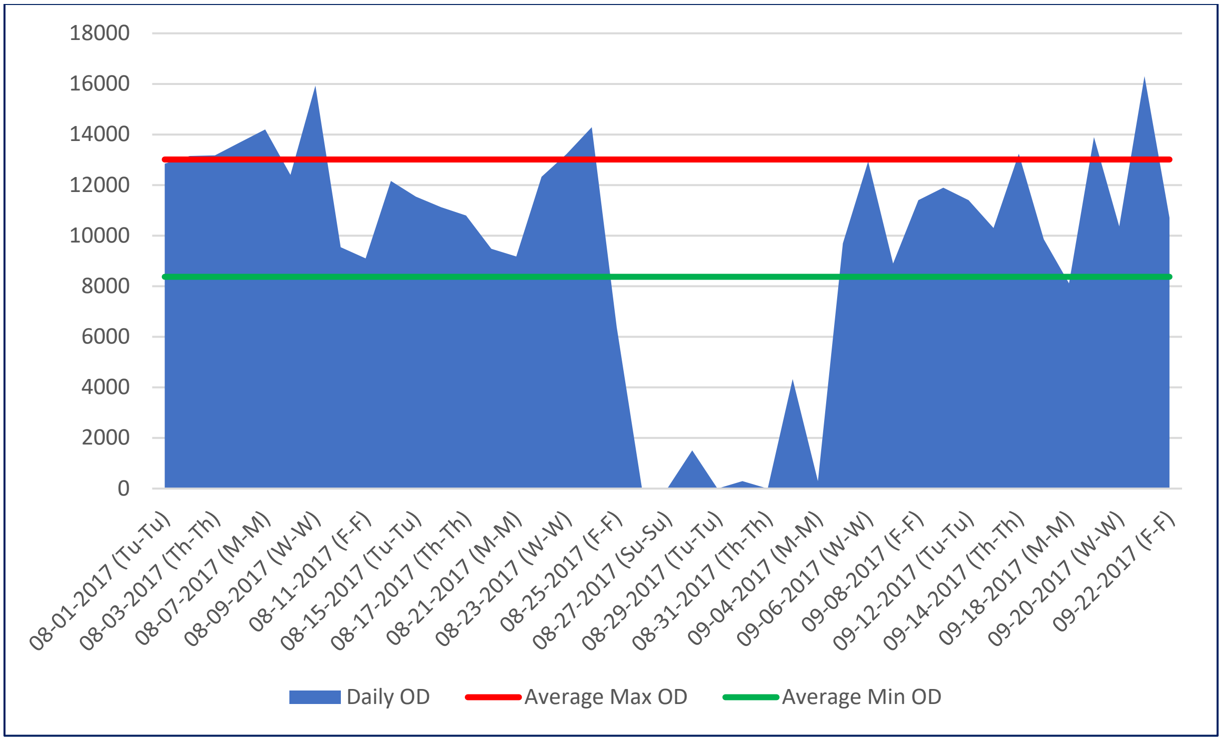


Figure C.5. Daily trips from Turning Basin terminal to Houston area during Hurricane Harvey period.

Figure C.6. Daily trip gradients from Turning Basin terminal to Houston area during Hurricane Harvey period.

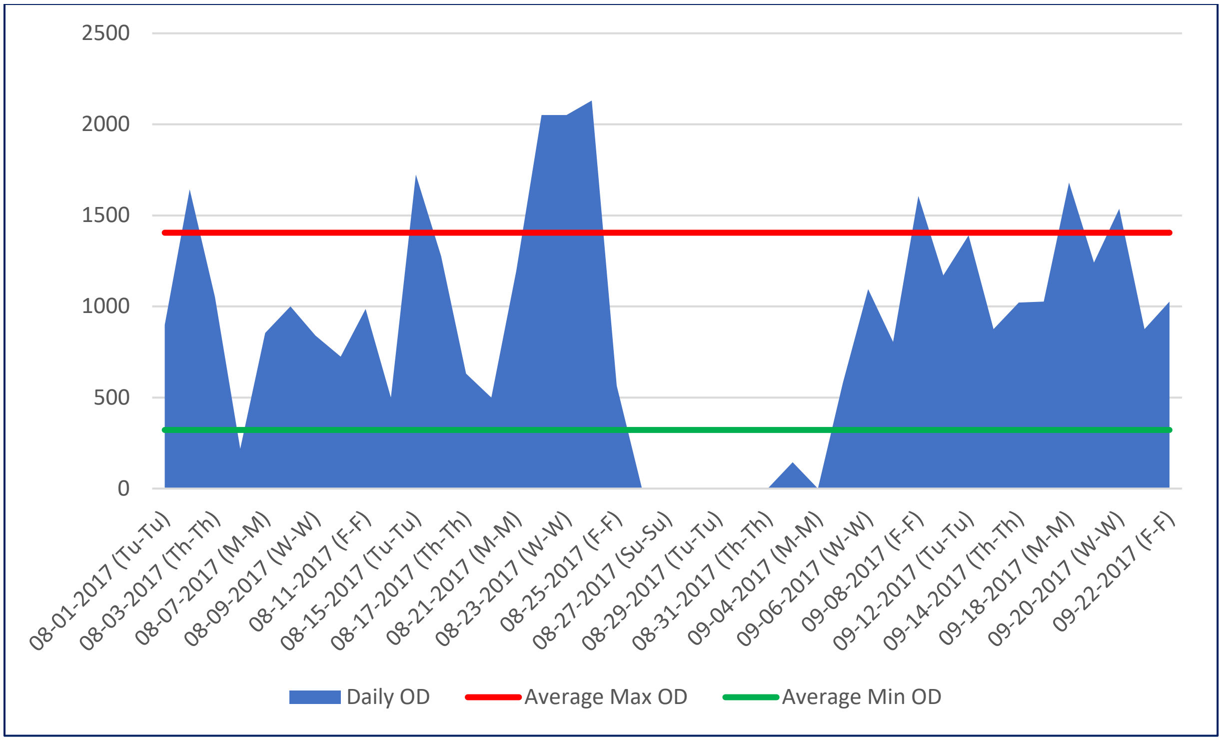


Figure C.7. Daily trips from Barbours Cut terminal to other regional destinations during Hurricane Harvey period.

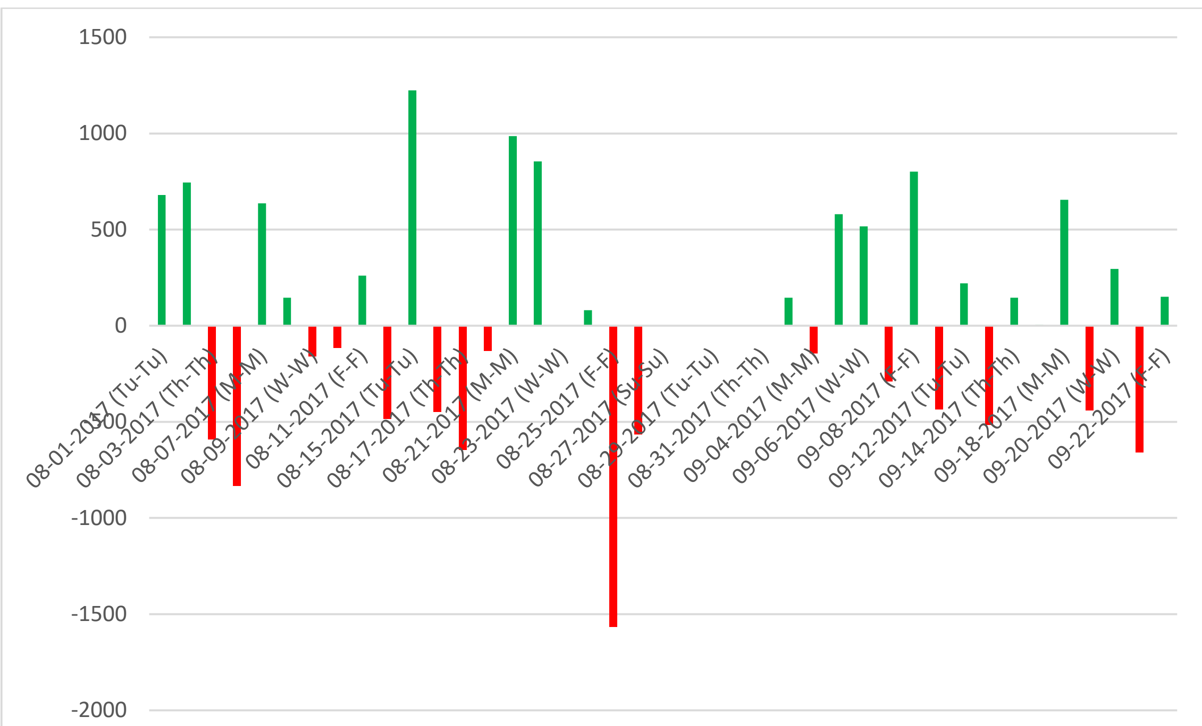


Figure C.8. Daily trip gradients from Barbours Cut terminal to other regional destinations during Hurricane Harvey period.

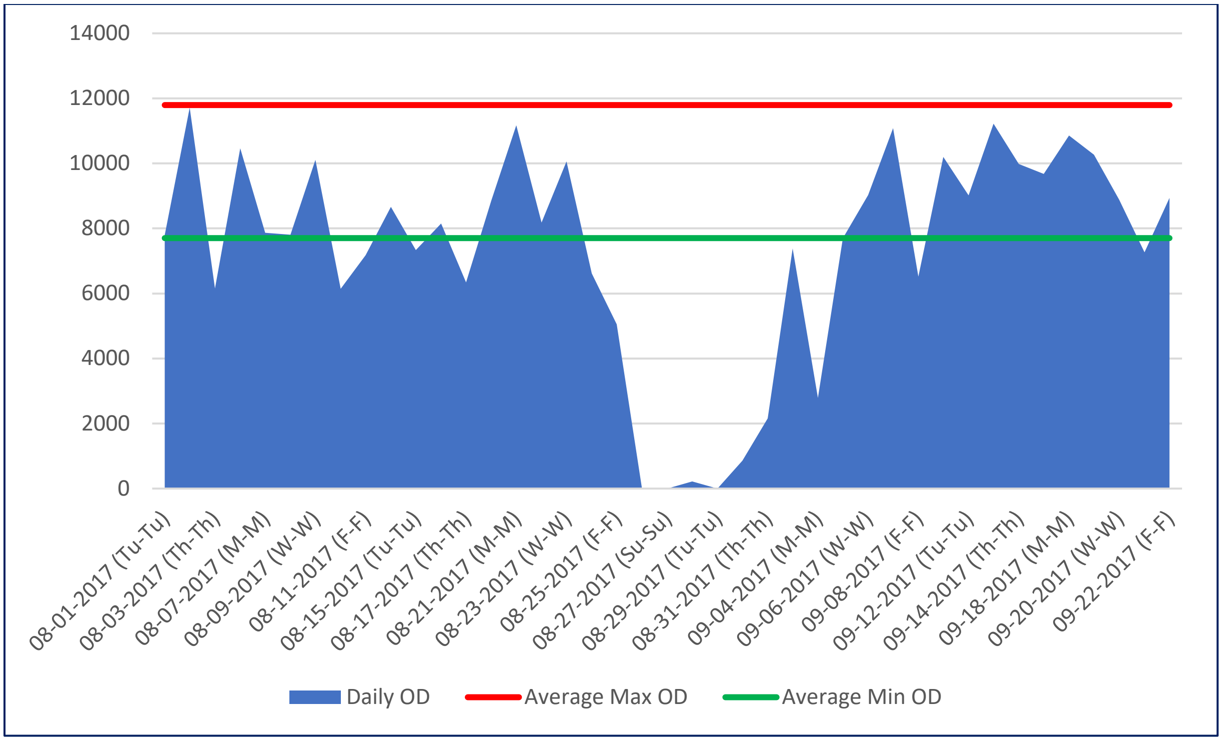


Figure C.9. Daily trips from Barbours Cut terminal to local destinations during Hurricane Harvey period.

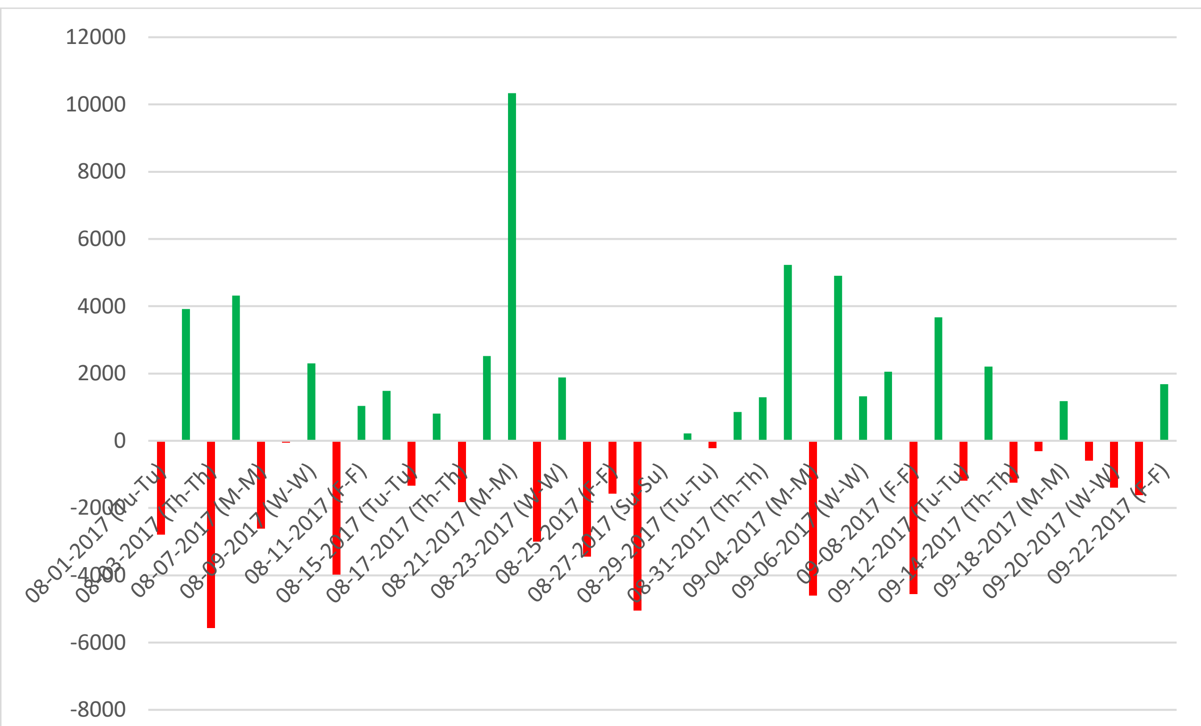


Figure C.10. Daily trip gradients from Barbours Cut terminal to local destinations during Hurricane Harvey period.

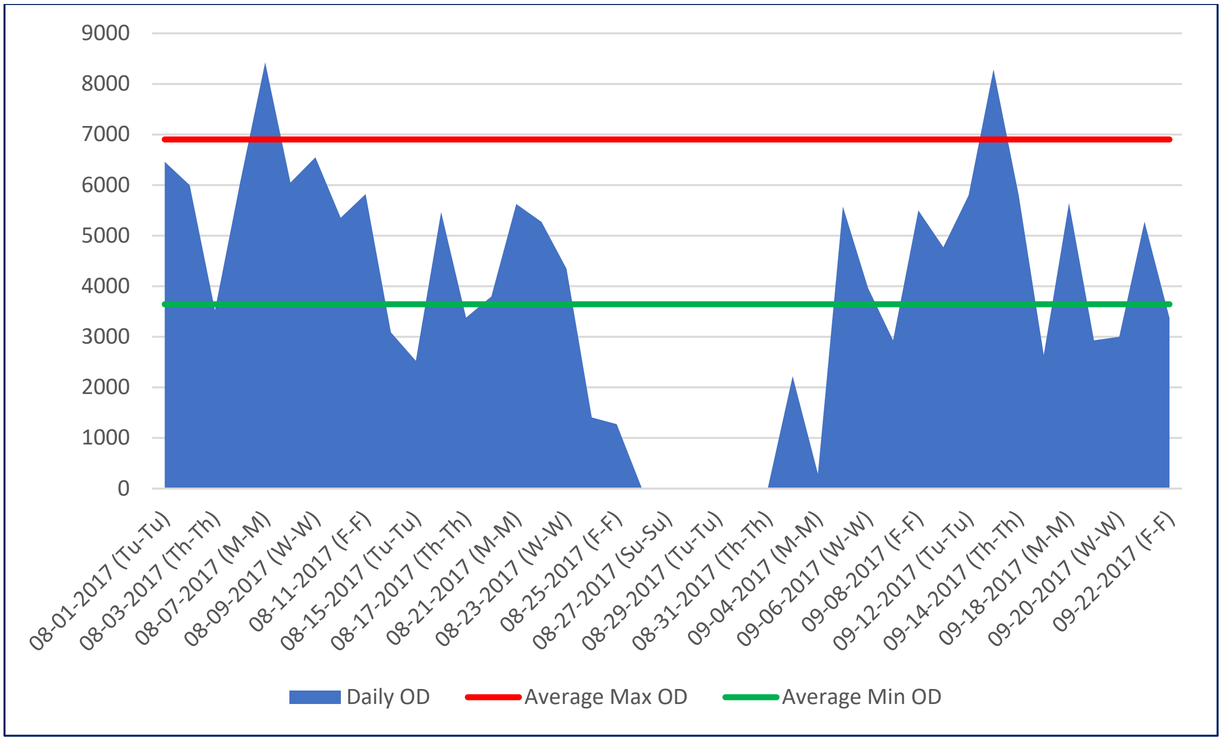


Figure C.11. Daily trips from Bayport terminal to local destinations during Hurricane Harvey period.

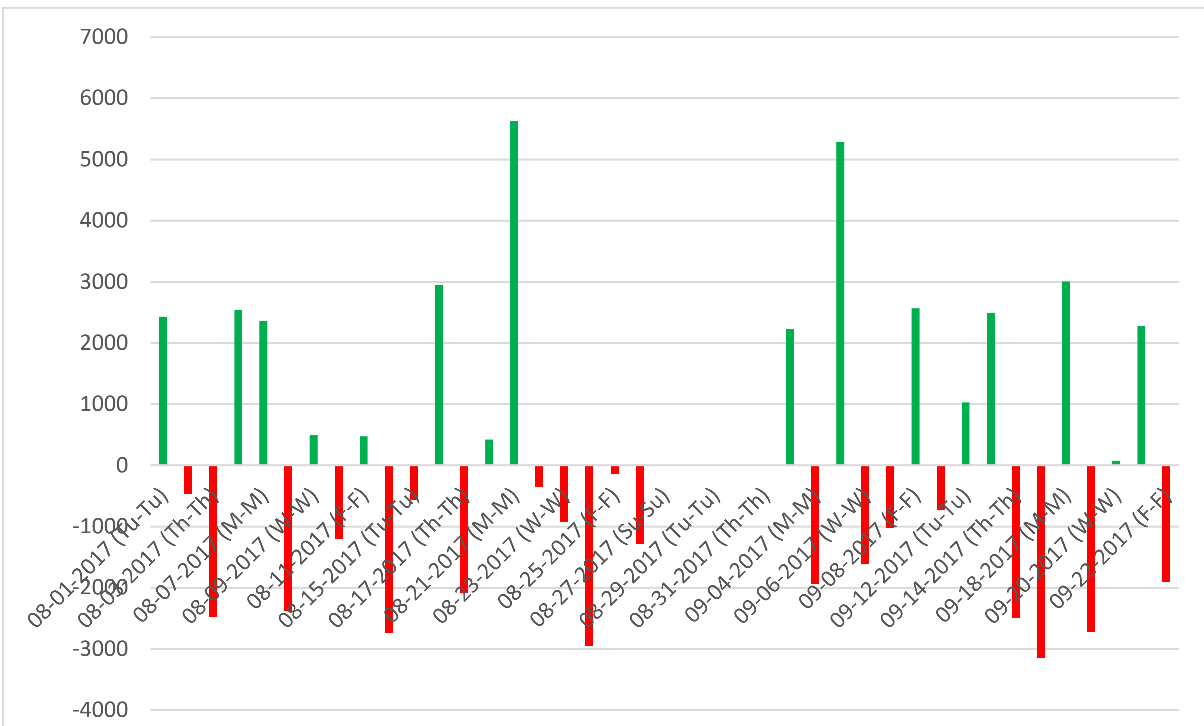


Figure C.12. Daily trip gradients from Bayport terminal to local destinations during Hurricane Harvey period.