MODELING THE PETROLEUM SUPPLY CHAIN: MULTIMODAL TRANSPORTATION, DISRUPTIONS AND MITIGATION STRATEGIES

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Yasaman Kazemi

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Title

MODELING THE PETROLEUM SUPPLY CHAIN: ANALYSIS OF RANDOM AND ANTICIPATED DISRUPTIONS AND MITIGATION STRATEGIES

By

Yasaman Kazemi

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

SUPERVISORY COMMITTEE:

Dr. Joseph Szmerekovsky
Chair

Dr. Kambiz Farahmand

Dr. Rodney Traub

Dr. Eunsu Lee

Approved:

9/12/16
Date

Dr. Denver Tolliver
Department Chair

ABSTRACT

The petroleum industry has one of the most complex supply chains in the world. A unique characteristic of Petroleum Supply Chain (PSC) is the high degree of uncertainty which propagates through the network. Therefore, it is necessary to develop quantitative models aiming at optimizing the network and managing logistics operations.

This work proposes a deterministic Mixed Integer Linear Program (MILP) model for downstream PSC to determine the optimal distribution center (DC) locations, capacities, transportation modes, and transfer volumes. Three products are considered in this study: gasoline, diesel, and jet fuel. The model minimizes multi-echelon multi-product cost along the refineries, distribution centers, transportation modes and demand nodes. The relationship between strategic planning and multimodal transportation is further elucidated.

Furthermore, this work proposes a two stage Stochastic Mixed Integer Linear Program (SMILP) models with recourse for PSC under the risk of random disruptions, and a two stage Stochastic Linear Program (SLP) model with recourse under the risk of anticipated disruptions, namely hurricanes. Two separate types of mitigation strategies – proactive and reactive – are proposed in each model based on the type of disruption. The SMILP model determines optimal DC locations and capacities in the first stage and utilizes multimode transportation as the reactive mitigation strategy in the second stage to allocate transfer volumes. The SLP model uses proactive mitigation strategies in the first stage and employs multimode transportation as the reactive mitigation strategy. The goal of both stochastic models is to minimize the expected total supply chain costs under uncertainty.

The proposed models are tested with real data from two sections of the U.S. petroleum industry, PADD 3 and PADD 1, and transportation networks within Geographic Information

System (GIS). It involves supply at the existing refineries, proposed DCs and demand nodes. GIS is used to analyze spatial data and to map refineries, DCs and demand nodes to visualize the process.

Sensitivity analysis is conducted to asses supply chain performance in response to changes in key parameters of proposed models to provide insights on PSC decisions, and to demonstrate the impact of key parameters on PSC decisions and total cost.

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DEDICATION

This dissertation is dedicated to my mom, Maryam Kazemi, for all of the sacrifices she made for me to reach my dreams.

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LIST OF ABBREVIATIONS

PSC ....Petroleum Supply Chain

EIA..Energy Information Administration

DC..Distribution Center

PADD..Petroleum Administration for Defense District

MILP...Mixed Integer Linear Programming

SMILP...Stochastic Mixed Integer Linear Programming

SLP..Stochastic Linear Programming

GIS..Geographic Information System

1. INTRODUCTION

1.1. The Petroleum Industry Supply Chain

The petroleum industry includes the global process of exploration, production, refining, and marketing of oil and petroleum products. Oil accounts for a large percentage of the world's energy consumption and is vital to many industries. In 2008, 34% of the world's energy needs were provided by oil [1]. The importance of oil in industrial civilization and our everyday lives makes it a critical concern for many nations.

The oil industry dates back hundreds of years. Its importance evolved slowly with the whale oil used for lighting in the 19th century, which led to an increase in demand for whale oil. After the industrial revolution, the need for energy and petroleum products to use for light or heating increased dramatically and by the twentieth century oil became the most valuable commodity traded on the world market [2].

Today, the oil industry has one of the most complex and advanced supply chains around the world. It is supplying about 39% of total U.S. energy demand and 97% of transportation fuels [3]. The petroleum industry can be characterized as a typical supply chain, which is defined as a complex structure of supply facilities linked together in order to serve end customers [4]. The oil supply chain is vertically integrated, covering activities from exploration to transformation in refineries and product distribution with a large logistic network. The whole supply chain is divided into upstream, midstream and downstream.

The upstream activities include exploration and production of crude oil. Exploration includes seismic, geographical and geological operations. The midstream segment consists of infrastructure and modes used to transport crude oil by pipeline, tankers or rail depending on the distance, the nature of the product and, the demand volumes to various refineries and storage tanks [1] . The downstream consists of refining, transportation, marketing and distribution of petroleum products.

The PSC network is presented in Figure 1. As can be seen from the figure, downstream section represents a very important economic segment which delivers products to the final customers cost effectively [5]. Products generated at the refineries are sent to distribution centers primarily via a network of underground pipelines. They mostly carry gasoline, diesel fuel, home heating oil and kerosene (jet fuel). Pipelines are the safest, cheapest and most reliable transporter of energy in the United States. The downstream segment has two different customers: wholesale customers such as power plants, some manufacturing plants, airlines, shipping companies, etc.; and retail customers who use the fuels for heating and transportation.

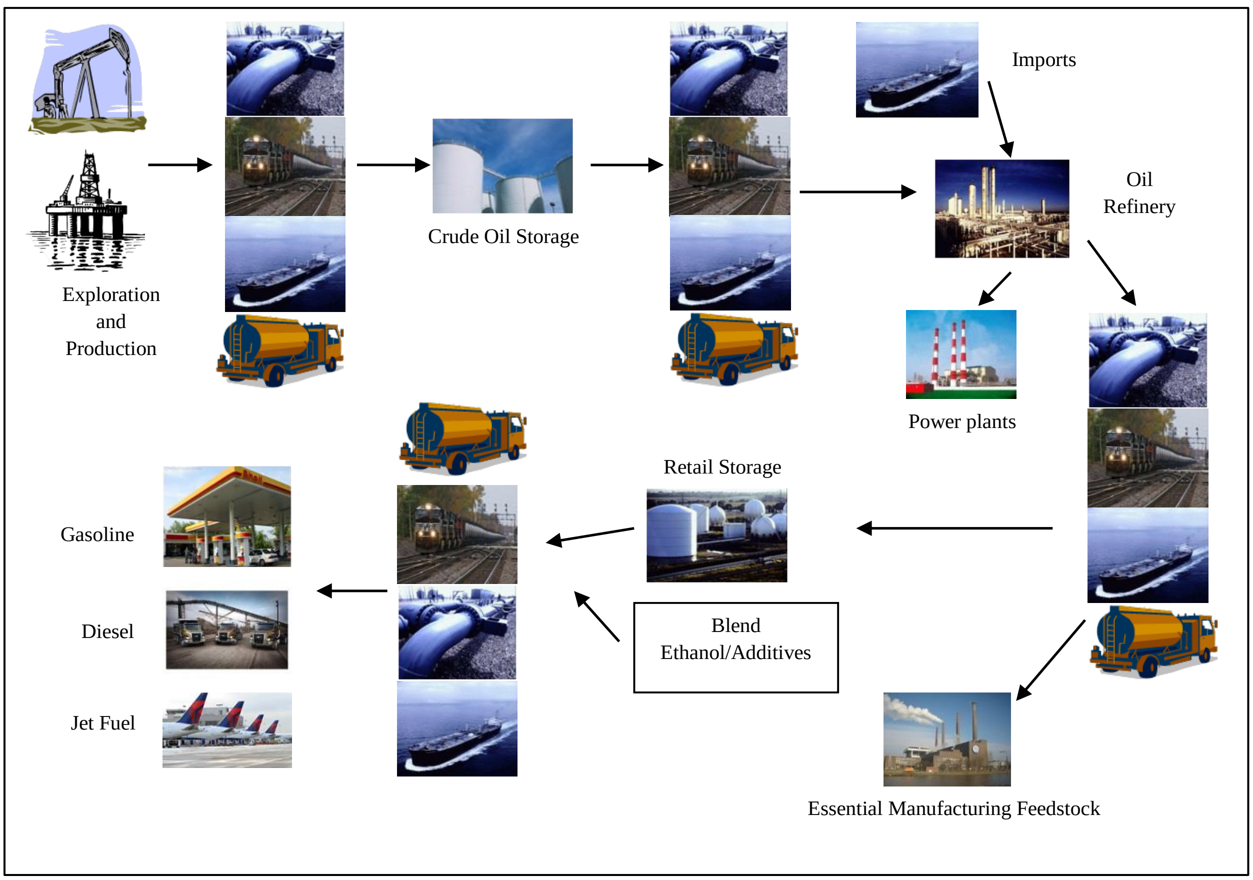


Figure 1. The Structure of the Petroleum Supply Chain.

The main objective of any petroleum supply chain is to deliver crude oil and refined products safely and economically [6]. With growing demand, rising freight costs and unexpected volatility, the petroleum supply chain faces major challenges and therefore, is developing a comprehensive strategy and efficient supply networks have become important to meet the varied demands of global customers while maintaining desirable profit margins. As noted in Chima [7] the need is to ensure that the supply chain can respond quickly to the customers, and protect itself and its operations from the uncertainties in supply and demand. This explains the continuing interest in studies related to different aspects of the oil industry supply chain and the uncertainties involved.

1.2. An Overview of the U.S. Petroleum Supply Chain

The U.S. oil supply chain is a vertically integrated complex network which is composed of many activities, infrastructures and the involvement of several stakeholder [6]. Pipelines are the primary transport mode of crude oil and refined products. They are the safest, cheapest and most reliable transporter of energy in the United States. In 2013, approximately 63,500 miles of refined product pipeline linked the nation, reaching almost every state in the United States [8]. Nearly two thirds of crude oil and petroleum products are transported via pipelines annually. Interstate pipelines deliver more than 11.3 billion barrels of petroleum each year. About 52% of the petroleum transported by pipelines is crude oil and 47% is in the form of refined petroleum products [9]. Rail and trucks move a small portion since they are costlier and therefore, they are only used in short haul shipments. Water carriers transport the remaining portion wherever the marine shipments are available. Figure 2 shows the network of crude oil and petroleum products pipeline in the United States.

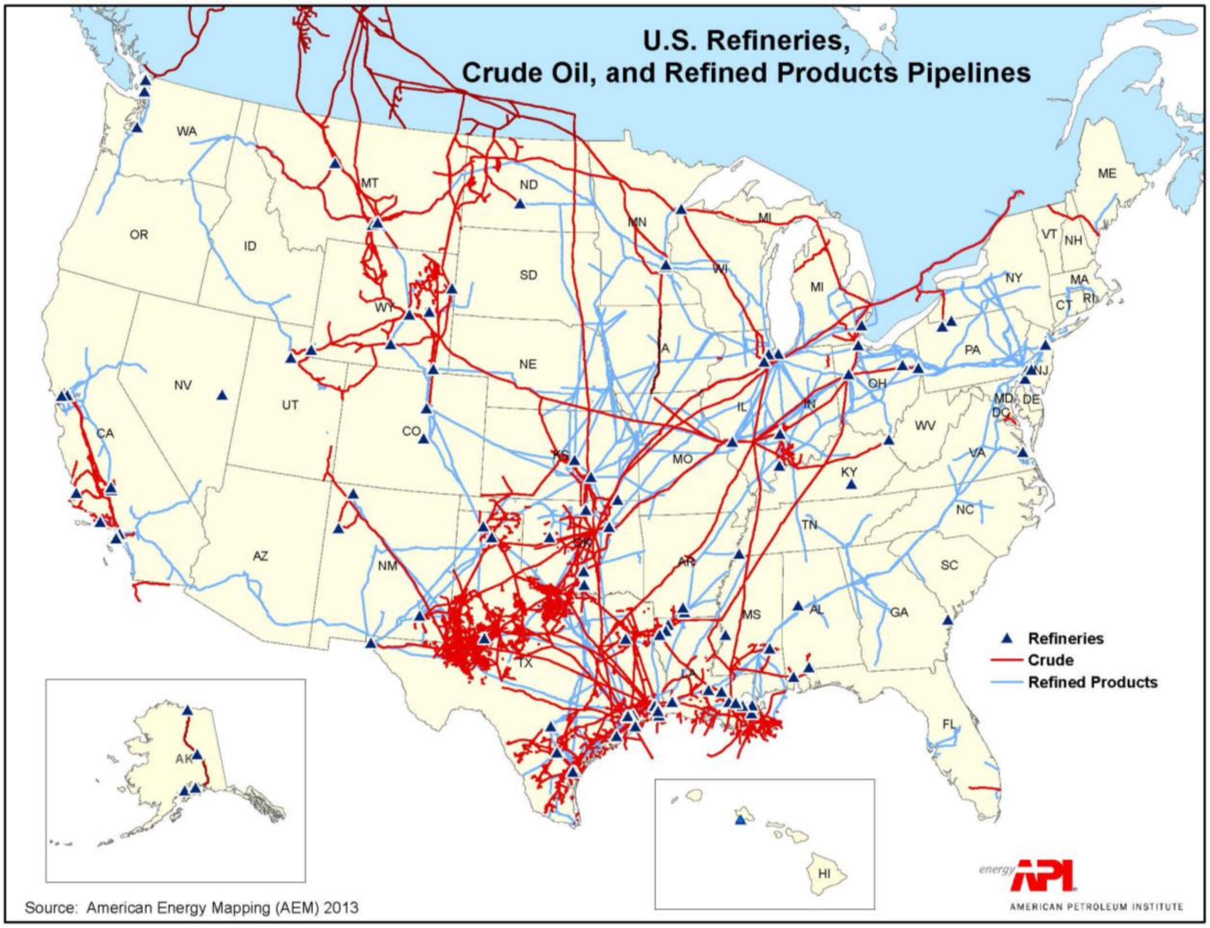


Figure 2. United States Refineries, Crude oil and Refined Products Pipeline.

Approximately, 55% of crude oil and petroleum products are produced inside the United States. Crude oil is produced in 31 states and U.S. coastal waters, however, the top crude oil producing states, which account for 56% of U.S. crude oil production, are Texas, North Dakota, California, Alaska and Oklahoma [10]. The other 45% is imported from foreign countries such as Canada, Saudi Arabia, Mexico, Venezuela and other small producers. Figure 3 represents the U.S. crude oil imports to the United States using the data from Energy Information Administration (EIA) [11].

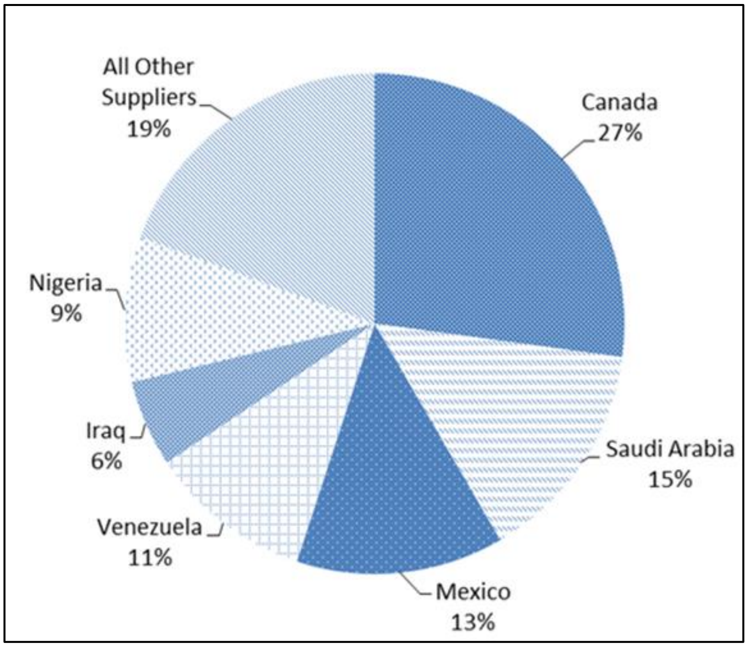


Figure 3. U.S. Crude Oil Imports.

The petroleum supply chain consists of five administrative districts as shown in Figure 4. The PADDs help users of petroleum data assess regional petroleum product suppliers [12]. The study area is limited to the Gulf Coast and East Coast regions.

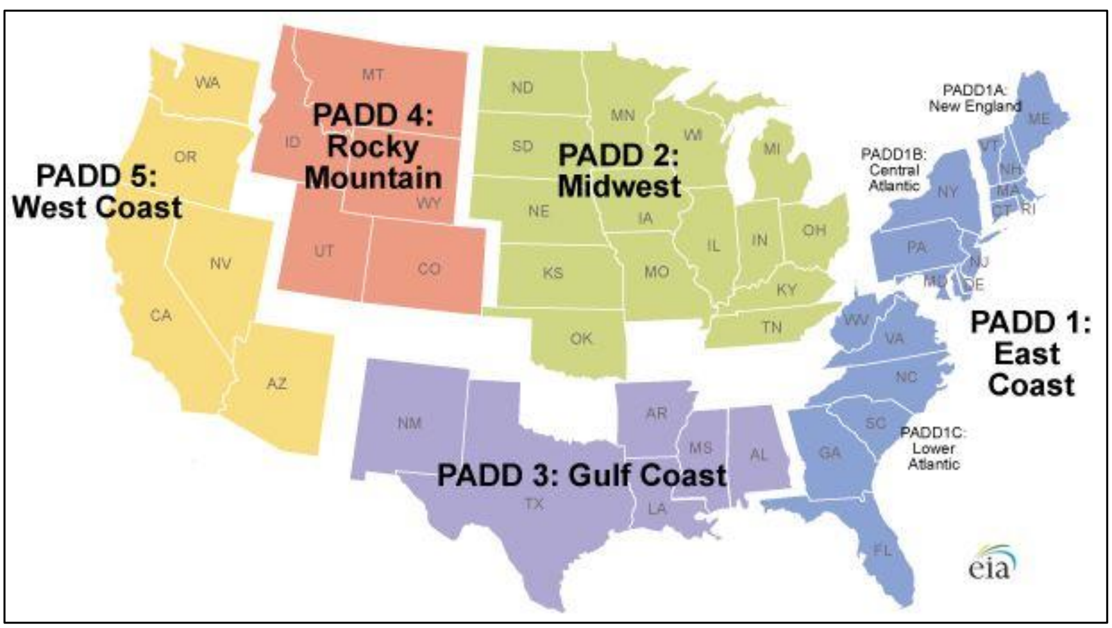


Figure 4. Petroleum Administration for Defense Districts (PADDs) [12].

PADD 3 (Gulf Coast) is the core of the U.S. petroleum supply chain and the major supply area (80% of the refined product shipments) [13]. Gasoline and other finished petroleum products are shipped from PADD 3 to all of the other PADDs; however, PADD 1 receives its largest portion via the Colonial and Plantation pipelines and, to a lesser extent, via barge (Figure 5). In 2012, over a million barrels of petroleum products were shipped from PADD 3 to PADD 1. With the highest refining capacity in the United States and providing the largest portion of fuel supply in the East Coast, the Gulf Coast area is a critical region in the domestic petroleum supply chain.

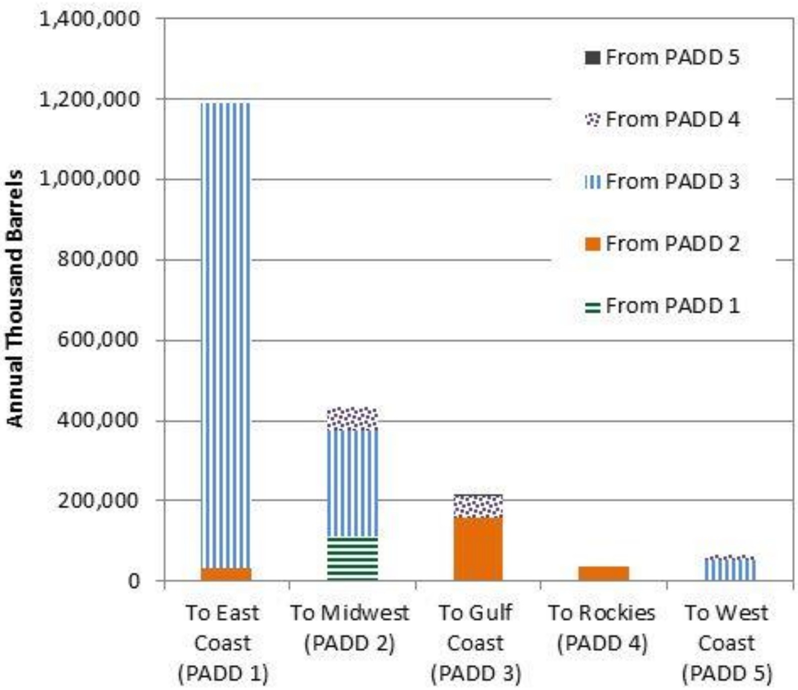


Figure 5. Petroleum Products Movement between U.S. Regions, 2013 [14].

On the other hand, the East coast is the largest consumer of fuel in the United States because of the highest population density. According to Table 1, in 2013, the East coast produced only 19% of the petroleum products in the U.S, but consumed 31% of them.

Table 1. U.S. Petroleum Products Production and Consumption by PADD, 2013 [15].

	PADD 1	PADD 2	PADD 3	PADD 4	PADD 5
Petroleum Products Production	19.3%	22.3%	38.7%	3.4%	16%
Petroleum Products Consumption	30.7%	27.3%	21.2%	4%	17%

Although PADD 1 has refining capacity, it is not enough to satisfy all demand with its own resources. The net refinery production of PADD 1 is less than the consumption of petroleum products; therefore, PADD 1 relies on receipts from other regions which include primarily PADD 3 and imports. Since the proportion of PADD 1 receipts from other PADDs to demand is less than 1% and the proportion of products moved to other PADDs from PADD 1 to production is less than 1%, we did not consider the trade between other PADDs and PADD 1. In order to use imports in the analysis, we assumed a physical location such as a petroleum refinery to store imports and considered it as the capacity for that supply point (refinery) in the analysis.

1.3. Supply Chain Disruption and the Petroleum Industry

In today's highly unstable and vulnerable world, disruptions are becoming more important than ever. A supply chain disruption can be defined as a random event with high impact that can happen in any part of the supply chain and that causes a supplier or any other element to stop functioning partially or completely for a random amount of time [16]. Sources of disruption risk can be divided into two main categories: *random disruption risks* which may occur at any point of the supply chain, and *premeditated disruption risks* that are intentionally planned to interfere with performance to cause maximum damage [17]. Random disruptions include fire, leaks, explosions, unpredictable natural disasters, and supplier failure. Hurricanes Katrina and Rita in 2005, for example, severely affected the oil production and refining processes in the Gulf Coast area and brought the largest monetary loss in history to the core of

U.S. oil industry region. These weather-related disruptive events can be categorized as a special case of random disruptions as they can be anticipated in advance. Premeditated disruptions include labor union strikes or other intentional acts on the critical components of the oil supply chain such as pipelines. In this study, we focus on random and anticipated disruptions affecting refineries.

Relying on common trends such as just-in-time logistics, efficient production, outsourcing, globalization and reducing other costs in business has resulted in supply chains that are effective in normal situations, but vulnerable to disruptions [18]. In addition, tightly coupled infrastructures and interconnected networks, such as the petroleum supply chain, are highly vulnerable, and therefore, damage to one part of the system may lead to a failure in another that eventually propagates throughout the whole value chain [19]. Although supply chain disruptions are unavoidable and costly, the structure of the supply chain affects the influence of disruption risks significantly [17]. Consequently, developing appropriate strategic plans to improve the supply chain in order to mitigate the risks becomes a priority [17]. The recent surge in interest and academic publications related to supply chain disruption and risk mitigation emphasizes the destructive and costly effects of disruptions.

The petroleum industry is highly automated, capital intensive and has a tightly coupled network; therefore, disruptions might propagate through the network, causes immense financial losses and environmental or nation-wide crisis [19, 20]. In addition, as petroleum supply chains become more efficient, they have also become more vulnerable to different disruptions. In order to face these challenges, oil companies have put significant effort in risk management; however, disruptions in petroleum supply chains remain a critical issue and must be pursued further in the research. According to Cigolini and Rossi [21], Wagner et al. [19], An et al. [22] and Fernandes et al. [20] there is still a strong need for quantitative modeling in this area which contributes not only to the literature, but also helps managers better understand and deal with disruptions in the petroleum supply chain.

In the following sections, we explain different types of disruption and their effects on the petroleum supply chain in more detail.

1.3.1.1. Random disruptions, natural disasters and other incidents

Unanticipated random events such as earthquakes or other incidents such as fires, leaks, explosions and unscheduled maintenance can potentially harm the petroleum industry supply chain. Because these disruptive events are not known in advance, there will not be any preparation procedures, and therefore, the damage can have lengthy consequences. For example, if gasoline or crude oil terminals lose power, pipelines and barges cannot load or discharge products, and therefore, the supply chain may become disrupted in the corresponding segment.

Another example of the damaging effects of disruptions in petroleum supply chains is an unexpected gas price hike in the Midwest during April-May 2013 as a result of unplanned refinery maintenance in Minnesota and Illinois. Since refineries in the Midwest do not typically produce enough gasoline to meet demand and need shipments from the Gulf Coast region, during the disruption the inventories went lower and pushed the gas prices higher.

In order to handle these disruptions it is necessary to identify potential disruptions and also recognize/invest in resources in order to manage them in advance of the disruptive event. In addition, using coping strategies and available resources to manage disruptions when they happen is crucial to overcoming the adverse effects of disruptions in the supply chain.

1.3.1.2. Hurricanes, storms, and tornados

Weather related disruptive events are a special case of random disruptions, because they can be anticipated in advance. Storms, tornados and hurricanes are examples of anticipated disruptions. Hurricanes originate over the warm waters of the North Atlantic Ocean, Caribbean Sea, Gulf of Mexico, Central, Eastern and South Pacific Oceans [23]. Hurricanes are classified using the Saffir/Simpson Scale. According to this scale, there are 5 categories for a hurricane, based on the wind speed and the damage. Category 1 sustained winds speed ranges from 74 to 95 mph which is very dangerous and capable of producing some damage, while a Category 5 can cause catastrophic damage with winds of 157 mph or higher. A similar scale, the Enhanced Fujita scale (EF scale) rates tornados from EF 0 to EF 5 based on the damage they can cause [23].

A major hurricane or storm rarely happens, but it can be disastrous. The Gulf of Mexico, unlike any other major oil producing region in the U.S., is regularly exposed to hurricanes. 53 hurricanes have been recorded in this region from 1950 to 2011. Although the majority of the hurricanes in this period were a category 1, 42% of them had a category 3 or higher which results in devastating damage.

Hurricane Katrina and Rita are characterized as the deadliest and most catastrophic hurricanes in U.S. history. Hurricane Rita made landfall in September 2005, the refining operations along the Texas coast, which produced 4.8 million barrels per day, were shut down and an additional 900,000 million barrels remained shut down because of Hurricane Katrina [24]. 91% of the offshore crude oil production and 83% of daily gasoline production were lost in 2005 [25]. According to Yeletasi [6], 113 offshore oil platforms were destroyed during Hurricanes Katrina and Rita and 52 were extensively damaged. Therefore, at one time, around one third of the U.S. refining capacity was shut down and it took several months to be restored [24]. These two hurricanes were not the only costly ones that happened in the region. Chevron company, the third largest producer in the region, reported an estimated loss of $400 million resulting from damages to the facilities in the Gulf Coast caused by hurricanes Gustav and Ike in 2008 [19].

During hurricanes Katrina and Rita, in addition to the refineries and oil platforms, product terminals, ports, and other underground pipelines were not operating at full capacity because of lack of input, damage and electricity problems. The Colonial and Capline Pipelines which are major oil carriers to PADD 1 and PADD 2 (East Coast and Midwest) were shut down or operated at a very low capacity and the tight supply of gasoline and other fuel products created a major price hike in the market [24]. The recovery from such disasters depends heavily upon the ability to respond quickly to the product demands, transport the petroleum products to the markets and resume operations at the production sites.

1.3.1.3. Premeditated disruptions

Disruptions that are caused intentionally or as a premeditated act, such as labor strikes, wars, and civil unrest, can put the petroleum supply chain at risk. Pipelines and other refineries are critical components of the oil industry and therefore if they get disrupted, it would be extremely costly and damaging to the economy. It is noteworthy that in some cases a strike can be anticipated. The main reason is probably that the unions in some certain regions are more active than others, and sometimes the historical events can be a measure to predict that the strike would be more likely to take place in a critical or other certain port rather than a larger region. However, most of the times the approaches to handling the premeditated disruptions are mainly game theoretic, which is out of the scope of this work.

1.4. Problem Statement

Considering the importance of the oil industry and the great need for the development of risk and disruption analysis in the oil supply chain, this area of research requires further attention in order to contribute to the body of knowledge and to help managers in the area to be able to make robust decisions based on quantitative methods. Therefore, in this study, we consider an integrated distribution network design, DC location and product allocation under a multi-product, multi-echelon and multi-mode setting, arising in the context of transportation planning of petroleum products distribution over a large, yet specific geographic area.

The downstream sector of the petroleum supply chain is defined as a complex network encompassing refineries, distribution centers, demand nodes, and transportation modes which coordinate to satisfy the demand for petroleum products. Planning activities in the downstream sector involve both strategic and tactical decisions. Strategic decisions include determining the location and capacities for distribution centers, while decisions regarding tactical planning involve flow allocation and modes of transportation. In order to distribute the fuel products from refineries to distribution centers in a cost effective manner, the firm has to select the geographic location, number and capacity of the DCs to serve demand nodes and it is important to efficiently manage the flow of materials along the supply chain.

Based on the identified and relevant logistics aspects from the downstream petroleum supply chain models, this study proposes MILP models that minimize the entire petroleum supply chain cost. The models include refineries, distribution centers, demand nodes and the transportation modes (pipeline, waterway carriers, rail and truck) in the supply chain in order to analyze the importance of using different modes on supply chain design and performance measures. The focus of this research is on the three most common fuel products, gasoline, diesel and jet fuel, which are transferred from refineries to distribution centers in the primary transportation and from there to demand nodes in the secondary transportation.

Furthermore, this research introduces new decision metrics to quantify the petroleum supply chain disruptions and mitigation strategies using the proposed models. To fill the gaps in the existing literature, the scope of this study is to explore the effects of random and anticipated (weather-related) disruption risks on downstream PSC design, and to propose both proactive and reactive mitigation strategies based on the type of disruptions to not only operate efficiently in normal conditions, but also to provide appropriate strategies to minimize cost increase and adverse impacts under disruptions. We specifically focus on disruptions affecting refineries (supply) in the downstream PSC, and develop two stage multi-echelon stochastic programing models with recourse in order to optimize the location of distribution centers and to transport petroleum products from refineries to DCs in primary transportation and to the demand nodes in secondary transportation under uncertain conditions. The first stage decisions, which are related to DC locations (i.e. strategic decisions) and proactive mitigation strategies, must be made before the realization of disruptions. The second stage (i.e. recourse) decisions which are reactive mitigation strategies are taken once the uncertainty is unveiled. Based on the type of disruption, the impacts on PSC decisions are determined and appropriate mitigation strategies are incorporated into the model.

Finally, in this study, GIS will be applied to the ground networks, waterway networks, rail and pipeline based on an impedance factor (distance) and shortest path algorithms. Only a limited number of studies can be found in the literature that focus on integrating GIS-based approaches in petroleum product supply chain design while considering detailed decisions on planning levels. GIS will be used as a first step for selecting potential distribution center locations for the PSC system and locating other supply chain entities such as refineries and demand nodes. Then the optimization model assigns transfer volumes to the transportation networks and locates the optimal facility locations to solve the problem.

1.5. Research Objectives

The first objective of this study is to develop optimization models for the downstream petroleum supply chain for multi-echelon, multi-product and multi-mode network design, and to investigate the importance of using multimodal transportation on supply chain configuration and performance measures in a deterministic setting. Therefore, a comparison between the proposed multimode model and the pipeline-based strategically planned model is conducted to demonstrate the importance of considering multimodal transportation when designing the supply chain from the strategic point of view. The goal of the supply chain models is to minimize the total fixed costs and distributing costs associated with all three decision components: DC locations and capacities, transfer volumes and transportation mode selection.

The second objective of this study is to develop stochastic optimization models for the downstream petroleum supply chain to study the effects of random and anticipated disruptions on refineries (supplies), and to propose both proactive and reactive mitigation strategies based on the type of disruption. The goal is to minimize the total cost of the supply chain by considering a different model and mitigation strategies for each type of disruption to distinguish between the appropriate strategies needed for each disruption type. As a result, the supply chain can respond to various disruptions more effectively, while minimizing the excess cost caused by the disruptive event. Since the problem is modeled as a two stage stochastic program, the objective is to choose the first stage decision variables in such a way that the expected value of the objective function, which is the expected total cost of the downstream PSC, is minimized over all the scenarios. The first stage decisions are related to DC locations and proactive mitigation strategies which are taken before the realization of disruptions. The second stage decisions which are reactive mitigation strategies are taken once the uncertainty is unveiled.

1.6. Significance of the Study

Our research contributes to petroleum supply chain management, strategic and operations management, and disruption management within the oil industry literature in six important areas:

- The proposed models exclusively consider multiple modes of transportation when designing the supply chain strategically. This decision is often not considered or was considered in a simplified manner in previous studies. In addition, we incorporate the use of multiple transportation modes at any point along the supply chain, relaxing the assumption of utilizing a primary or a single mode of transport in a specific echelon or when developing the strategic planning.
- Unlike the previous literature which dealt with profit maximization when designing PSC from a strategic point of view (e.g. [5] and [26]), our study contains MILP and SMILP models which minimize the total cost of the PSC from refining to distribution and to the final demand by considering the impact of different transportation modes on transferring three types of fuel products (i.e. gasoline, diesel and jet fuel) to satisfy the demand. In addition, we obtained important managerial implications related to the optimization of logistics operations given the relationship between refining and distribution and transportation in the supply chain.
- In the proposed mathematical framework, we also integrate the benefits of using GIS to locate the refineries, potential DC locations and demand nodes, obtain realistic transportation data, and use mapping tools in order to better visualize the process. IT

driven models, in particular, GIS, are the new trend in planning and management within specific types of supply chains such as PSC [22]. There is an abundant amount of studies which utilized GIS to make decisions and/or to develop mathematical models in the biofuel based supply chains (e.g. [27-30]); however, GIS application in the oil industry is still in its beginning when it comes to supply chain optimization. As a result, this study uniquely contributes to the state of the art by incorporating the use of GIS techniques to provide high quality results and effective application of the model.

- In addition to the development of MILP models, we present a case study that involves real data from the U.S. petroleum supply chain. This study focuses on validating the model, demonstrating the features and indicating how the proposed model can be used to benefit petroleum companies.
- Preliminary work on PSC under uncertainty did not consider facility disruptions and their effects on the PSC decisions or performance measures. Moreover, studies that focused on disruptions in supply chains in general, did not separate their models nor develop mitigation strategies based on different types of disruptions. In addition, according to Stecke [18] there is still a lack of quantitative methods to address these strategies to reduce disruption effects on supply chains. Therefore this research introduces new decision metrics to quantify the supply chain disruption mitigation strategies using the proposed model.
- Unlike most of the prior research which assumes that the disrupted facility loses all of its capacity (see Snyder et al. [16]), we calculated the lost capacity depending on the

severity of disruption in each scenario. In other words, in any scenario where disruption occurs, some refineries may still run at a fraction of the normal capacity.

1.7. Organization

The remainder of this dissertation is organized as follows. Chapter 2 presents an extensive review of relevant literature on petroleum supply chain models, disruption and uncertainty modeling within the petroleum industry. Chapter 3 outlines the background and detailed explanation for model development and structure. The deterministic or base optimization models are developed, followed by the description of both types of disruptions and stochastic models. In addition, model parameter estimation and assumptions are elaborated in this chapter.

Chapter 4 contains the case study and the parameters set up. The petroleum supply chain network, including refineries, DCs, demand nodes and the transportation network (in GIS) is explained in detail. The data acquired for parameters in the study region are elaborated further in the chapter. We also explain the detailed process of scenario construction for each type of disruption, along with the approaches taken to derive random variables for stochastic models.

Chapter 5 includes the detailed solution procedures and numerical case study results for both deterministic and stochastic models. The results are elaborated and presented in detail. We conducted a comparison between two deterministic models and obtained important conclusions about the efficiency of the models. In addition, we compared the stochastic models to deterministic models to verify the efficiency of the proposed stochastic models against the deterministic models under uncertainty. Finally, we further emphasized separating the mitigation strategies based on the type of disruption in the stochastic models.

Chapter 6 focuses on sensitivity analysis conducted on the key parameters of both deterministic and stochastic models to study their impacts on PSC performance and costs. Managerial insights were given based on the results of the sensitivity analyses.

Finally, chapter 7 presents concluding remarks of the research and future direction of the study. It includes major findings of the results, novel features of the models and the contribution to the literature. Future directions include potential subjects worth pursuing beyond completion of this thesis.

2. LITERATURE REVIEW

The following literature review includes an extensive study of past work done in the fields of facility disruption, petroleum supply chain, and geographic information system (GIS). The emphasis of the literature review is to capture the influential literature in each of the domains and publications that took multi-disciplinary approaches combining the main topics of research relevant to this study. Therefore, different aspects and contributions of a publication may be discussed in multiple sections and interactions of different publications may be explored. The literature review concludes with a discussion which describes the current standing of research and identifies research gaps, some which of are filled by this research.

2.1. Petroleum Supply Chain

Since the petroleum industry is characterized as highly capital intensive, considerable financial commitment, time and effort have been devoted to develop mathematical programming tools to support decision making in the planning process [31, 32]. The petroleum supply chain has been addressed in the literature based on the decision levels as well as the section of the supply chain.

Mathematical programming applications in the oil industry dates back to the 1950s [33]. In the upstream section, the majority of the models support decision making that includes the selection of oil wells to be drilled and operational decisions such as crude oil transportation, scheduling and platform production. Aronofksy and Williams [34] developed a multi period linear programming model for oil well production. Decision variables include production rates for oil wells, the number of wells drilled, the number of rigs purchased, and the number of rigs in operation. Similarly, Kosmidis et al. [35] developed a mixed integer optimization formulation for the well allocation/operation of integrated oil/gas production systems. Iyer et al. [36] developed a multi-period MILP for planning and scheduling the infrastructure and operations in offshore oil fields' facilities. A sequential decomposition strategy followed by successive disaggregation was proposed to solve the problem. Van den Heever and Grossmann [37] proposed a multi period nonlinear model for oilfield infrastructure planning which involved continuous and discrete decisions. In addition, Ierapetritou et al. [38] studied the problem of selecting the optimal vertical well locations by formulating a large scale MILP and solving by a decomposition technique based on applying quality cut constraints. Crude oil transportation was addressed by several authors. Mas and Pinto [39] addressed oil scheduling in a distribution complex which is composed of marine terminals, storage tanks, and pipelines with an MILP model. Material flow of crude oil from port to refinery tanks and distillation units is modeled by Chryssolouris et al. [40].

In the midstream sector, substantial work in the literature has been devoted to the decisions related to the processes inside the refinery such as refinery production planning and scheduling. Decisions related to the supply for process units, production and refinery optimization have been addressed in several studies. For example, Lee et al. [41] focused on scheduling of crude oil supply in the short term for a single refinery. A short term refinery scheduling problem was addressed by Yuzgec [42]. They presented a model predictive control (MPC) strategy to determine the optimal control decisions in a short term refinery scheduling problem. Three different case studies with several disturbance scenarios regarding oil demands were studied to demonstrate the performance of the proposed control strategy. Pinto et al. [43] addressed production scheduling for several specific areas in a refinery such as fuel oil, crude oil, Liquefied Petroleum Gas (LPG) and asphalt. Pinto and Moro [44] focused on production planning in a refinery. Similarly, another study conducted by Ponnambalam et al. [45] solved a multi-period planning model in the oil refinery industry. Jia and Ierapetritou [46] proposed an MILP for customer order scheduling and gasoline blending. Other studies related to the midstream activities can be found in [47-50].

Most of the studies of the downstream oil supply chain have dealt with designing the network and determining the material flow [22]. The mathematical programs apply to distribution of products, optimization of transporting products from the refinery to the market, and sometimes considering storage and blending [32]. Sear [51] was the first study to address supply chain management and logistics in the downstream supply chain. The author developed a linear programming model that involved crude oil purchasing, transportation to the depots and customers by considering different costs at each stage.

Downstream PSC network design models include Al-Qahtani and Elkamel [52] who studied a mixed-integer program model to minimize cost in the strategic planning of a multi refinery network and to develop a methodology for integrating production and capacity expansion using different feedstock. In their numerical example consisting of three refineries, they showed that integrated planning of refineries in an area is economically attractive compared to decentralized management. Ross [53] developed a profit maximizing supply network model in the downstream oil supply chain by focusing on performance planning through resource allocation. The approach was tested on a realistic sized problem and managerial implications were provided. Kim et al. [54] formulated a model that combined a network design model and a production planning model for multi-site refineries. They showed that using a model which integrates strategic and tactical decisions can be more profitable compared to using separate models at refineries. More recently, Fernandes et al.[5] proposed a profit maximizing MILP model for strategic planning of downstream petroleum supply chain. The model solves the design of uni-entity and multi-entity networks and considers depot locations, transport modes, and resource capacities and network affectations. However, it excludes inventories, imports, and exports. The model was further tested for the Portuguese PSC and compared profits for uni-entity and multi-entity networks under individualistic operations. The authors later extended their work with a dynamic MILP which presented a collaborative design and tactical planning with multistage inventories while maximizing profit. The main results demonstrated improved profits compared to when the individualistic operation was considered. [26]

Operational and tactical planning of downstream PSC is presented in several studies. Escudero et al. [55] developed a two stage model for supply and distribution scheduling of a multi operator multi product petroleum supply chain by considering demand, supply cost and selling prices. Rejowski and Pinto [56] focused on discrete MILP models to address the problem of oil products distribution from one refinery to several distribution centers via pipeline. Neiro and Pinto [57] proposed a mixed-integer linear program as a general modeling framework for petroleum supply chain which included operational planning of refineries, storage, and transportation of petroleum products. They presented a case study consisting of four refineries, two pipeline networks and five storage terminals for product distribution. Ronen [58] addressed two scheduling formulations for a problem of distributing petroleum products by considering refineries that produce light/white products such as gasoline, kerosene, diesel oil, etc., and refineries that produce heavy/black products such as base stock for lubes, and residual oil. In the same context, Relvas [59] proposed the scheduling of a multi-product pipeline from a single origin (refinery) to a single destination (tank farm) through a mixed integer linear model and a heuristic was applied and validated using a real-world scenario. Mir Hassani [60] developed a capacitated linear programming model for operational planning of the transportation network between refineries and depots to satisfy demand, while minimizing total inventory and transportation costs. More recently, Guajardo et al. [61] used linear programming to formulate decoupled and integrated planning models for a supply chain of specialty oil products by considering production, transportation, sales and distribution decisions. The results indicated that the integrated model outperforms the decoupled approach mainly because the total costs for the oil company decreased in that model and the total contribution of the company and the seller increased. However, the seller may get worse premiums in the integrated approach. Therefore, the authors suggested contribution sharing rules in order to achieve better outcomes for the whole company as well as the seller. Stebel [62] presented an optimization model for planning and scheduling activities in pipeline networks for petroleum products. More on the transportation side, Magatão et al. [63] developed an MILP for scheduling commodity flows (gasoline, diesel, kerosene, alcohol, etc.) on pipeline systems. Boschetto et al. [64] developed a two-level MILP for planning and sequencing pumping activities in a pipeline network. The authors proposed the solution in a sequential fashion that was applied to a real-world pipeline network with 30 multi product pipelines associated with 14 node areas. Herran et al. [65] developed a discrete mathematical approach to solve the operational planning of a multi pipeline system for petroleum products. More recently, Fiorencio et al. [32] proposed an MILP model for the downstream petroleum supply chain with the use of a decision support system that allows the evaluation of different investment alternatives in logistics networks. They evaluated the features of the proposed system with two case studies.

Selecting an appropriate mode of transportation is a significant element of distribution network design as reported in Jayamaran and Vaidyanathan [66]. Therefore, supply chain network design with multimode transportation has become the focus of research attention in recent years. Sadjady and Davoudpour [67] studied a two-echelon supply chain network design problem in a single period, multi-commodity context. Their MIP model included location and capacity of the facilities and determined the choice of transportation modes. A Lagrangian relaxation was developed and the results indicated that the solution is effective and efficient for small and large-sized problems. Olivares-Benitez et al. [68] studied a bi-objective MIP in a two-echelon single-product system. The supply chain design problem incorporated the selection of transportation channels that produced a cost-time tradeoff. The proposed metaheuristic algorithm delivered efficient alternatives for the decision maker in scenarios with changing parameters of demand or costs. According to Li and Xiaopeng [69] only a few recent studies have tried to integrate inventory management and transportation mode choices into logistics network design. That being said, the authors proposed a logistics network design framework that integrates location selection and operational strategies of expedited transportation decisions involving nonlinearity. They developed several mathematical models to determine optimal solutions to the number of suppliers and locations, assignments of suppliers to terminals, the expedited shipment percentages and inventory levels. Sarkar and Majumder [70] studied a two echelon facility location model and added product types and transportation modes as dimensions to the model and developed a separate objective function in each step. They investigated the variations between each of the objective functions and showed that the increment or reduction of costs depends on the type of dimension used. A comprehensive review on freight transportation and supply chain optimization is presented in Bravo and Vidal [71]. Similarly, a full review of recent literature in multimodal transportation considering all levels of decision making can be found in [72].

According to the recent literature, some authors focused on integrated approaches to address the problems of enterprise-wide optimization in the petroleum industry [3]. As such, Koo et al. [49] and Robertson et al. [50] have studied the midstream in an integrated manner. The former studied the application of a special type of dynamic simulator to provide decision support for optimal refinery supply chain design and operation optimization of design decisions regarding capacity investments and optimization of policies’ parameters. The latter focused on developing a non-linear programming model for refinery production, scheduling and unit operation optimization, where each problem has a different decision making layer and independent objective function. In another study, Al-Othman et al. [73] proposed a multi period stochastic planning model that captures oil production, processing and distribution under uncertain market conditions. Al-Qahtani and Elkamel [52] proposed an MILP model for simultaneous analysis of the process network and integration of production capacity expansions in a multiple refinery complex. Their analysis showed that integrated planning of refineries outperforms decentralized management in terms of cost reduction.

2.2. Uncertainty in the Petroleum Supply Chain

In the last decade, supply chain disruption has gained considerable attention. Challenges to the supply chains such as outsourcing, globalization, Just in Time (JIT) and lean concepts have brought more sources of risk to the supply chains and their effects can ripple through the chain quickly [74]. Disruptions are unavoidable, but if they are handled appropriately, their adverse effects can be minimized. Most of the current research has focused on two major perspectives in developing mitigation strategies for supply chain disruptions. The first approach deals with high level strategic decisions in the form of a comprehensive framework, and the second approach provides detailed tactical strategies including inventory control, flexible supply chain configurations, and procurement contract strategies [75].

Facility disruptions are among the most crucial issues in supply chain disruption literature, mainly because decisions related to them are costly, difficult to reverse and their impact spans a long time horizon [76]. As a result, a large number of proposed approaches focusing on decision making under uncertainty have been applied to facility location problems. The common goal in these stochastic optimization models is to optimize the expected value of the objective function. The first studies that minimized the expected cost in facility location problems under scenario based approaches were offered by Sheppard [77] and Mirchandani et al.[78]. The stochastic P-median problem was addressed by Weaver and Church [79] and further Mirchandani et al. [78] relaxed the single constraint of P facilities to be opened and therefore, developed an Uncapacitated Fixed-charge Location Problem (UFLP). Louveaux [80] presented Stochastic Capacitated P-median Problem (CPMP) and Capacitated Fixed Charge Location Problem (CFLP) in which production costs, selling prices and demands were random. Ravi and Sinha [81] proposed a two stage stochastic model and an approximation algorithm for UFLP where the facility decisions occur at either the first or second stage. Snyder et al. [82] and Snyder and Daskin [76] introduced disruptions with reliability models extending the traditional uncapacitated facility location and P-median problems with random disruptions. Shen et al. [83] and Snyder et al [82] relaxed Snyder and Daskin [76]'s assumption (i.e. all facilities have the same disruption probability) and developed scenario based approaches to enumerate all or a sample of disruption scenarios to formulate the problem as a stochastic programming model. Berman et al. [84], Shen et al. [83], Cui et al. [85], Aboolian et al. [86], and Lim et al. [87] considered site-dependent disruption probabilities and used nonlinear terms to calculate the probability that a customer is served by the rth closest facility when the original facility fails. To simplify the problem, Lim et al. [87] assumed that each customer is assigned to one unreliable facility which may be disrupted, and then to a reliable facility that may not fail. In this regard, there are several studies which focused on facility fortification in order to protect the supply chain against random disruptions [88]. Furthermore, two stage stochastic supply chain network design models were proposed by Santoso et al., Vila et al., Azaron et al., and Klibi et al. [89-92]. Daskin et al. [93] and Snyder et al. [94] also developed stochastic versions of location-inventory models in facility location and proposed different algorithms to solve the problems. For an extensive review on supply chain disruption and OR models the reader is directed to Snyder et al. [16], and Klibi et al. [92].

Most of the prior research on supply chain risk management and disruption does not take into account the characteristics of different types of supply chains or industry specifics [19]. In addition, studies of optimization problems under uncertainty in the oil industry primarily focus on random demands, price fluctuations and costs rather than on disruptions. In fact, very few considered risk management [95]. Cigolini and Rossi [21] identified operational risks in three stages of the oil supply chain and then proposed a risk management approach that includes risk analysis, risk assessment and risk control. Doukas et al. [96] overviewed the security risks of the oil and gas supply chain. Further, Fernandes et al. [20] developed a risk management hierarchical framework that was used to construct a decision tree to develop quantitative analysis such as a mathematical model to optimize the risk management process. In another study Carneiro et al. [95, 97] incorporated risk management in a two stage stochastic model with fixed recourse and three sources of uncertainty within a refinery. In order to deal with the uncertainties, a conditional value at risk (CVaR) approach was adopted to maximize the expected net present value of the supply chain. Khor [98] formulated four petroleum refinery planning models to hedge against uncertainty associated with demand, yield and price.

Leiras et al. [97] reviewed the studies focused on uncertainty in the oil industry based on supply chain segment, planning level and problem type. The majority of the reviewed studies focused on the midstream segment and dealt with uncertainty in demand. Other studies include Dempster et al. [99] which a proposed deterministic and stochastic multistage supply, transformation and distribution scheduling problem, i.e. the Depot and Refinery Optimization Problem (DROP), for strategic and tactical level planning of logistics operations in the oil industry assuming uncertainty in product demands and spot supply costs. The multistage stochastic formulation demonstrated a more realistic treatment of uncertainty with a more favorable Expected Value of Perfect Information (EVPI) values. Lababidi et al. [48] proposed an optimization model for a petrochemical company under uncertain operating and economic conditions. Al Othman [73] studied an integrated supply chain of the petroleum industry and developed a two stage stochastic model for multiple time periods capable of generating production forecasts that are resilient to uncertainties in market demand and prices. Ribas et al. [100] and Oliveira et al. [31] focused on uncertainty over the investment decisions in petroleum supply chains from the strategic decision making level which is usually ignored in the literature. In this regard, MirHassani and Noori [101] studied a multi-period two stage stochastic planning model for capacity expansion of a petroleum distribution network under uncertain demand. Their results indicated that the stochastic optimization model produces guaranteed profitability comparable to the deterministic case and foresees the effects of changes in demand conditions so that corrective actions would be less costly. In the upstream section, Li et al. [102] proposed a methodology including impact analysis of extreme events and optimization under scenarios of emergency when importing crude oil from a foreign country. A multi-objective programming model was formulated and optimal decisions were simulated under different scenarios. Another study by Adhitya et al. [103] considered disruptions such as crude oil arrival delay in the refinery supply chain and proposed different heuristics for rescheduling of refinery operations in order to improve the computational performance and to make minimal changes to the operations compared to total rescheduling.

The uncertainties affecting supply chains and various major disruptions have motivated many researchers to identify supply chain mitigation strategies that are efficient, yet resilient to disruptions. However, effectiveness of risk mitigation strategies is contingent on the internal and external environments and that there is no one-size-fits-all strategy. Most of the current research has focused on two major perspectives in developing mitigation strategies for supply chain disruptions. The first approach deals with high-level strategic decisions. This approach identifies and categorizes supply chain risks and recommends a wide range of mitigation strategies. The second approach focuses on providing detailed tactical strategies. This category includes flexible supply chain, product flow, inventory control, and procurement strategies [75]. Implementing these mitigation strategies will result in resilient supply chains which help firms to reduce costs and to sustain their operations during and after a major disruption [104]. For a more comprehensive review about evaluating and proposing efficient supply chain risk mitigation strategies in the presence of a variety of risk categories, risk sources, and supply chain configuration, the reader is referred to Talluri et al. [105].

Supply chain resiliency is another interesting area of research in the supply chain disruption which has gained a lot of attention. Resiliency is the ability to return to a stable state after a disruption [106] and therefore, supply chain resiliency can be defined as the ability of a supply network to bounce back from disruptions [107]. There is an abundant amount of theoretical literature about supply chain resiliency, e.g. Tang [104] ; however, Christopher [108] was one of the first authors who gave a fundamental introduction to supply chain resiliency, risks and principals of creating a resilient supply chain. Seferlis et al. [109] and Pettit et al. [110] developed conceptual frameworks about supply chain resilience. Briano et al. [111] conducted a literature review about supply chain vulnerability and resiliency. The basics of vulnerability analysis and risk sources in the supply chain were discussed. Similarly, Bhamra et al. [106] provided a review of resilience literature and its application at the organizational level and suggested more empirical research with real world case studies need to be done at supply chain and organizational levels.

The quantitative approaches for assessing supply chain resiliency are also addressed by several papers. Falasca et. al [112] proposed a simulation based framework and discussed the impacts of disruptions on supply chain performance, and time to recovery. Another simulation based study was conducted by Smith and Vidal [113] in order to measure the resilience of the commercial supply network structures when affected by disruption. The main results showed that increasing the relationship resources may result in a more resilient network structure. Yet in another study Vugrin et al. [114] developed a resilience costs measurement methodology for a chemical supply chain during a hurricane. Simulation scenarios were conducted and the performance measure was calculated in terms of costs. Lastly, Klibi and Martel [107] studied several stochastic model approaches to design a resilient supply chain for the location-transportation and location-allocation problems under uncertainty. Using a scenario based supply network design approach the authors proposed two design models using stochastic programming and three design models to improve supply network resilience.

2.3. Geographic Information System (GIS) Applications in the Petroleum Industry

GIS is a powerful technology for which the potential applications and benefits are yet to be understood. It enables users to capture, analyze and manage spatially referenced data. Since its first conceptualization in the 1950's and 1960's, GIS has evolved tremendously in its application and capabilities [2]. It was first used to manage simple mapping operations and analyze spatial data. However, today's applications of GIS go beyond geography and can be used in environmental science, business, resource planning, asset mapping, land use planning, engineering and transportation [6].

Moreover, GIS is becoming a frequently used tool in disaster, risk and emergency management for better information management, mitigation, response and recover from disasters. Flood modeling, wildfire mapping, vulnerability analysis, congestion analysis, transportation modeling and fire response route optimization are among the applications of GIS [6].

Petroleum companies have used GIS to make decisions about where to drill a well, route a pipeline and build a refinery. GIS provides the petroleum industry solutions throughout the whole oil supply chain. In other words, all the major oil companies use GIS technology to manage their location-based information from wells and pipelines to facilities and retail outlets.

In recent years, an extensive body of literature focused on models and solutions that can be used as decision support tools for strategic and tactical decision making analysis in the service industry [27]. Different approaches using GIS with other quantitative methods to develop a complete decision making system have been developed by authors (Panichelli and Gnansounou, [115]; Graham et al., [116]; Muttiah et al., [117]). GIS is used in the location selection process by using spatial and statistical methods to analyze attribute and geographic information followed by applying optimization methods to different types of supply chains [27]. In this context, Petroleum companies are using GIS to make decisions about their location-based information from wells and pipelines to facilities and retail outlets.

An et al. [22] studied a comprehensive review of the literature in biofuel and petroleum supply chain. The authors indicated that IT driven models, in particular GIS, are the new trend in planning and management within specific types of supply chains. Some of the works in the area of critical infrastructure in petroleum supply chain have been studied by [6]. Briggs et al. [1] also reported GIS applications in analyzing data in the case of an oil spill, the distribution of the affected area, location and quantity of the oil spilled. Shah [118] emphasized applications of GIS on process industry supply chains and the importance of GIS to visualize the output of large scale distribution network design models. In this context, Camm [119] was probably the first study that applied GIS in an integer programming network optimization in order to streamline manufacturing and distribution operations, and to achieve a huge annual cost savings. Other applications of GIS as a source of information to enhance the communication between partners are noted in Min and Zhou [120] and Gardner and Cooper [121] who discussed the importance of supply chain mapping and visualization with the help of GIS. There is an abundant amount of studies which utilized GIS to make decisions and/or develop mathematical models in biofuel based supply chains (e.g. Frombo et al., [28]; Haddad and Anderson, [29]; Noon et al., [30]; Voivontas et al., [122]). However, GIS application is still in its infancy when it comes to supply chain optimization. As a result, incorporating GIS techniques in these areas of research offers a better understanding of supply chain optimization.

2.4. Summary

Based on the commonly identified issues and relevant logistics aspects from the reviewed models in the literature, preliminary work on PSC modeling has not focused on multi-echelon, multi-product and multi-mode models when designing the supply chain. Within the literature, we found two review papers that focused on strategic, tactical and operational planning models in the petroleum supply chain. Fernandes et al. [20] reviewed the supply chain management literature with insights for the petroleum supply chain and An et al. [22] reviewed the literature on the petroleum and bio-fuel industries. A considerable amount of research has been done on the upstream and midstream sections of the oil industry with the focus on refinery planning, scheduling, and crude oil production. However, reviewing more recent literature shows an increasing interest in modeling the petroleum supply chain distribution as an integrated network in a more cost efficient way involving strategic and tactical planning. In other words, there is a lack of studies in the petroleum supply chain literature that have focused on the optimization of logistics operations given the relationship between refining and distribution operations in the supply chain. Additionally, considering the importance of GIS and its increasing applications in the process industries and facility location decisions, developing models that utilize this tool to design the supply chain becomes inevitable.

Moreover, studies that focused on uncertainties in the petroleum supply chain did not consider facility disruptions and their effects on the PSC decisions or performance measures. Uncertainties such as unstable prices, fluctuations in oil production, and unpredictable product demand are among the most popular research subjects in the petroleum industry literature. On the other hand, there is a rich body of literature on supply chain disruption in general, however, these studies did not separate their models nor develop mitigation strategies based on different types of disruptive events. According to [16], multi- echelon supply chains are also not fully studied under the risk of disruptions. As it is also revealed in the literature review, the effects of disruptions on petroleum supply chains have not been investigated thoroughly. To the best of our knowledge, very little or no work has been done to develop a multi echelon model under the risk of disruption in the PSC. This research is expected to fill the gap in quantitative analysis of disruption risks in the PSC.

3. MODEL DEVELOPMENT

In this chapter, we provide a detailed description of optimization models for the downstream petroleum supply chain. Section 3.1 focuses on developing deterministic models (single mode and multimode) models and section 3.2 focuses on stochastic models. The objective is to develop multi-echelon, multi-product and multi-mode network design, and to compare the impact of using multimodal transportation on supply chain configuration and performance measures to the single-mode supply chain design model. The single-mode model is a particular case of the proposed multimode model, where there is only one mode of transportation (pipeline) used. The multimode MILP model minimizes the total cost of the supply chain by utilizing multiple modes of transportation to distribute petroleum products from refineries to distribution centers and to the demand nodes. Transportation networks and DC locations are created in GIS in order to obtain accurate costs for analyzing the proposed model.

This chapter also reviews two multi-echelon, multi-product models that we developed for downstream PSC in the presence of facility disruptions. The first model is a Stochastic Mixed Integer Linear Programming (SMILP) formulation to design the supply chain network by considering random disruptions on refineries. The model optimizes the location of distribution centers and allocation of products with multi-product, multi-echelon multimode transportation as a reactive mitigation strategy. The second model is a Stochastic Linear Programming (SLP) model which considers weather-related disruptions (hurricanes) on refineries and incorporates both proactive and reactive mitigation strategies to minimize the total cost of product distribution.

3.1. Single-mode and Multimode Supply Chain Design Models

In the proposed multimode MILP model, we assume that there is a set I of refineries i with capacities Si, a set J of candidate sites to locate distribution center j with capacity Vj, and a set K of demand nodes k available to be served. The transportation mode $r \in R$ moves product p from the refinery to the DC and from DC to the demand node. The complete notation for the deterministic models is summarized in Table 2.

Table 2. Notations and Parameters Used in the deterministic models.

Indices	Description
i	Index of refineries; $i \in I$
j	Index of possible distribution center locations; $j \in J$
k	Index of customers (demand nodes); $k \in K$
r	Index of transportation modes; $r \in R$; 1= pipeline, 2 = barge, 3 = rail, 4 = truck
p	Index of products (gasoline, diesel, jet fuel); $p \in P$
Parameters	
D_{kp}	Annual demand for product p at demand node k
f_j	Fixed cost of opening the distribution center at location j
C_{ijpr}	Transportation cost per unit of product p from refinery i to distribution center j via transportation mode r
T_{jkpr}	Transportation cost per unit of product p from distribution center j to demand point k via transportation mode r
S_i	Capacity of refinery i (Tons of products per year)
α_p	Refinery capacity utilization per product p; $\alpha_p = 1$
β_j	Cost per unit of capacity at Distribution Center j
M	A large number (10^9)
N_r	Percentage of total products carried by mode r
Decision variables	
X_j	1, if a distribution center is opened at j; 0, otherwise
Y_{ijpr}	Amount of product p shipped from refinery i to distribution center j with mode r
Z_{jkpr}	Amount of product p shipped from distribution center j to demand point k with mode r
V_j	Capacity of distribution center j (Tons per year)

The multimode supply chain design model includes the location of distribution centers and their capacities, four modes of transport, and material flow from refineries all the way to the demand nodes. The flexibility to choose from multiple modes of transportation to move products, adds a decision to the model that is the transportation mode available to ship products. Therefore, the following decisions need to be optimized in the multimode model: 1) site selection from |J| potential distribution center locations 2) the capacity of each distribution center 3) the amount of each product to ship from refinery *i* to distribution center *j* with mode *r* in the primary transportation 4) the amount of each product to ship from distribution center *j* to demand node *k* with mode *r* in the secondary transportation. The mathematical formulation of the multimode model is presented below.

$$\min \quad \sum_{j\in J} f_j X_j + V_j \beta_j + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{r\in R} C_{ijpr} Y_{ijpr} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P}\sum_{r\in R} T_{jkpr} Z_{jkpr} \qquad (1)$$

$$s.t.$$

$$\sum_{j\in J}\sum_{r\in R} Z_{jkpr} = D_{kp} \qquad \forall p\in P, \forall k\in K \qquad (2)$$

$$V_j \le M X_j \qquad \forall j\in J \qquad (3)$$

$$\sum_{p\in P}\sum_{k\in K}\sum_{r\in R} Z_{jkpr} \le V_j \qquad \forall j\in J \qquad (4)$$

$$\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} \alpha_p Y_{ijpr} \le S_i \qquad \forall i\in I \qquad (5)$$

$$\sum_{i\in I}\sum_{r\in R} Y_{ijpr} - \sum_{k\in K}\sum_{r\in R} Z_{jkpr} = 0 \qquad \forall p\in P, \forall j\in J \qquad (6)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{p\in P} Y_{ijpr} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P} Z_{jkpr} = \sum_{k\in K}\sum_{p\in P} 2N_r D_{kp} \qquad \forall r\in R \qquad (7)$$

$$X_j \in \{0,1\} \qquad \forall j\in J \qquad (8)$$

$$Y_{ijpr} \ge 0 \qquad \forall i\in I, \forall j\in J, \forall p\in P, \forall r\in R \qquad (9)$$

$$Z_{jkpr} \ge 0 \qquad \forall j\in J, \forall k\in K, \forall p\in P, \forall r\in R \qquad (10)$$

The objective function (1) minimizes the total cost of opening distribution centers and shipment of three types of products (gasoline, diesel and jet fuel) from refineries to the final customers. The first term represents the fixed cost of locating distribution centers and the second term indicates the capacity cost of the opened distribution centers. The first and second terms represent the total fixed and variable costs of opening distribution centers. The third term states the cost of transporting products from refineries to DCs. Finally, the fourth term incorporates the cost of transporting products from DCs to demand nodes.

Constraint (2) ensures that demand for each petroleum product is satisfied by receipts from distribution centers. Constraint (3) limits the capacity of each distribution center that is opened, meaning that capacity cannot be assigned without a distribution center being opened. Constraint (4) ensures that the flow out of each distribution center is less than the capacity of the distribution center, while constraint (5) limits the amount of flow out of each refinery to the capacity of the refinery. Constraint (6) is the flow conservation constraint: the flow into the DC equals the flow out. Constraint (7) ensures that each mode carries the assigned percentage of products from refineries to DCs and to demand nodes in order to satisfy the demand. Note that the flow on individual links is not restricted, however, the percentage of petroleum products carried by each mode for the entire trip (overall mode capacity) is different and derived from [123]. Constraint (8) invokes integrality requirements. Finally, constraints (9) and (10) are non-negativity constraints.

The single-mode model is a particular case of the above model, where pipelines are used as the only mode of transportation, $r=1$. In other words, the multimode model is considered as an improvement to generalize the pipeline model. The pipeline model follows the approach that was developed in [124].

The pipeline model includes the location of the distribution centers and material flow from refineries to the DCs and from DCs to demand nodes. Therefore, the following decisions need to be optimized: 1) site selection for $|J|$ potential distribution center locations 2) the capacity of each distribution center 3) the amount of fuel products to ship from refinery *i* to distribution center *j* in the primary transportation 4) the amount of each fuel product piped from distribution center *j* to demand node *k* in the secondary transportation.

The mathematical formulation for the problem is as follows:

$$\min \quad \sum_{j\in J} f_j X_j + V_j \beta_j + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} C_{ijp1} Y_{ijp1} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P} T_{ijp1} Z_{jkp1} \tag{11}$$

$s.t.$

$$\sum_{j\in J} Z_{jkp1} = D_{kp} \qquad \forall p \in P, \forall k \in K \tag{12}$$

$$V_j \le M X_j \qquad \forall j \in J \tag{13}$$

$$\sum_{p\in P}\sum_{k\in K} Z_{jkp1} \le V_j \qquad \forall j \in J \tag{14}$$

$$\sum_{p\in P}\sum_{j\in J} \alpha_p Y_{ijp1} \le S_i \qquad \forall i \in I \tag{15}$$

$$\sum_{i\in I} Y_{ijp1} - \sum_{k\in K} Z_{jkp1} = 0 \qquad \forall p \in P, \forall j \in J \tag{16}$$

$$X_j \in \{0,1\} \qquad \forall j \in J \tag{17}$$

$$Y_{ijp1} \ge 0 \qquad \forall i \in I, \forall j \in J, \forall p \in P \tag{18}$$

$$Z_{jkp1} \ge 0 \qquad \forall j \in J, \forall k \in K, \forall p \in P \tag{19}$$

The objective function (11) minimizes the total cost of opening distribution centers, and shipment of three types of products (gasoline, diesel and jet fuel) from refineries to the demand nodes. The first term represents the fixed cost of locating distribution centers, and the second term indicates the capacity cost of the opened distribution centers. The first and second terms represent the total fixed and variable costs of opening distribution centers. The third term states the cost of transporting products from refineries to DCs; and finally, the fourth term incorporates the cost of transporting products from DCs to demand nodes.

Constraint (12) ensures that demand for each fuel product is satisfied by receipts from distribution centers. Constraint (13) limits the capacity of each distribution center that is opened, meaning that capacity cannot be assigned without a distribution center being opened. Constraint

(14) ensures that the flow out of each distribution center is less than the capacity of the distribution center, while constraint (15) limits the amount of flow out of each refinery to the capacity of that refinery. Constraint (16) is the flow conservation constraint: the flow into the DC equals the flow out. Constraint (17) invokes integrality requirements. Finally, constraints (18) and (19) are non-negativity constraints.

3.2. Supply Chain Design Model in the Presence of Random Disruptions

In reality, facilities are susceptible to disruptions and may not be fully functional all of the time. In the case of PSC, when a random disruption such as a fire or unscheduled maintenance occurs at a refinery, it interrupts the refining operations and therefore the capacity will be lost to some extent or completely. Unlike most of the prior research which assumed that the disrupted facility loses all of its capacity, we calculated the lost capacity depending on the severity of disruption in each scenario. In other words, in any scenario where disruption occurs, refineries may still run at a fraction of the normal capacity. We assume that disruption probabilities are uniformly distributed and occur independently.

In the downstream PSC optimization problem, decisions such as DC locations are strategic decisions that need to be taken before the uncertainty in refinery capacity unfolds. Note that in our study, we assume that refinery locations are fixed and known. On the other hand, transporting refined products from refineries to DCs and from there to demand nodes occurs after realization of the uncertainty (i.e. refinery disruption). As such, the structure of the problem lends itself to be modeled as a two stage stochastic optimization problem where the first-stage decisions are taken before the uncertainty is realized. Second-stage decisions are taken once the uncertainty has materialized. The second stage decision in the aforementioned model includes using multiple modes of transportation to ship products from refineries to the DCs and to demand nodes. This operational decision can be considered as a reactive mitigation strategy.

The goal of this study is to determine the optimal configuration of the downstream PSC along with the tactical decisions that minimize the total cost of the supply chain under uncertainty. In the proposed stochastic model, we assume that there is a set Ω of disruption scenarios ω, a set I of refineries i with random capacities $S_i(\omega)$, and a set J of candidate sites to locate distribution center j with capacity V_j, and a set K of demand nodes k available to be served. The transportation mode $r \in R$ moves product p from the refinery to DC and from DC to demand nodes in the primary and secondary transportation, respectively. The complete notation for the stochastic models is summarized in Table 3.

Table 3. Notations and Parameters Used in the Stochastic Models.

Indices	Description
i	Index of refineries; $i \in I$
j	Index of possible distribution center locations; $j \in J$
k	Index of customers (demand nodes); $k \in K$
r	Index of transportation modes; $r \in R$;1= pipeline, 2 = barge, 3 = rail, 4 = truck
p	Index of products (gasoline, diesel, jet fuel); $p \in P$
ω	Index of stochastic scenarios; $\omega \in \Omega$
Deterministic parameters	
D_{kp}	Annual demand for product p at demand node k
f_j	Fixed cost of opening the distribution center at location j
C_{ijpr}	Transportation cost per unit of product p from refinery i to distribution center j via transportation mode r
T_{jkpr}	Transportation cost per unit of product p from distribution center j to demand point k via transportation mode r
α_p	Refinery capacity utilization per product p; $\alpha_p = 1$
β_j	Cost per unit of capacity at Distribution Center j
M	A large number
N_r	Percentage of total products carried by mode r

Table 3. Notations and Parameters Used in the Stochastic Models (Continued).

h_p	Holding cost per unit of reserved material at distribution center j
g_{ijr}	Cost of contracting a third party logistics provider to reserve products on each route from refinery i to distribution center j with mode r
U_{ijr}	Upper-bound limit on the shipment of total products from refinery i to DC j via transportation mode r
O_{jkr}	Upper-bound limit on the shipment of total products from DC j to demand node k via transportation mode r
Stochastic parameters	
$S_i(\omega)$	Capacity of refinery i (Tons of products per year)
First stage decision variables	
X_j	1, if a distribution center is opened at j; 0, otherwise
V_j	Capacity of distribution center j (Tons per year)
IN_{jp}	Amount of inventory of product p held at distribution center j
b_{ijr}	Amount of products contracted to be reserved on reliable third party logistics provider to be shipped from refinery i to distribution center j with mode r
Second stage decision variables	
$Y_{ijpr}(\omega)$	Amount of product p shipped from refinery i to distribution center j with mode r during scenario ω
$Z_{jkpr}(\omega)$	Amount of product p shipped from distribution center j to demand point k with mode r during scenario ω
$l_{ijpr}(\omega)$	Amount of reserved product p shipped from refinery i to distribution center j with mode r

The decisions to be optimized are: 1) site selection from $|J|$ potential distribution center locations 2) the capacity of each distribution center 3) the amount of each product to ship from refinery i to distribution center j with mode r in primary transportation during scenario ω 4) the amount of each product from distribution center j to demand node k with mode r in secondary transportation during scenario ω. The proposed model determines the optimal configuration of the downstream PSC along with the associated operational decisions that maximizes its economic performance under each scenario ω with a random probability of occurrence. A stochastic mixed integer linear programming (SMILP) model is proposed to minimize the expected total cost of downstream PSC by determining the optimal level of aforementioned decision variables. The mathematical formulation of the model is presented below.

$$\min \sum_{j\in J} f_j X_j + V_j \beta_j + E_\omega \left[\sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R} C_{ijpr} Y_{ijpr}(\omega) + \sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{r\in R} T_{jkpr} Z_{jkpr}(\omega) \right] \qquad (20)$$

$s.t.$

$$\sum_{j\in J}\sum_{r\in R} Z_{jkpr}(\omega) = D_{kp} \qquad \forall p\in P, \forall k\in K, \forall \omega\in\Omega \qquad (21)$$

$$V_j \le MX_j \qquad \forall j\in J \qquad (22)$$

$$\sum_{p\in P}\sum_{k\in K}\sum_{r\in R} Z_{jkpr}(\omega) \le V_j \qquad \forall j\in J, \forall \omega\in\Omega \qquad (23)$$

$$\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} \alpha_p Y_{ijpr}(\omega) \le S_i(\omega) \qquad \forall i\in I, \forall \omega\in\Omega \qquad (24)$$

$$\sum_{i\in I}\sum_{r\in R} Y_{ijpr}(\omega) - \sum_{k\in K}\sum_{r\in R} Z_{jkpr}(\omega) = 0 \qquad \forall j\in J, \forall p\in P, \forall \omega\in\Omega \qquad (25)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{p\in P} Y_{ijpr}(\omega) + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P} Z_{jkpr}(\omega) = \sum_{k\in K}\sum_{p\in P} 2N_r D_{kp} \qquad \forall r\in R, \forall \omega\in\Omega \qquad (26)$$

$$X_j \in \{0,1\} \qquad \forall j\in J \qquad (27)$$

$$Y_{ijpr}(\omega) \ge 0 \qquad \forall i\in I, \forall j\in J, \forall p\in P, \forall r\in R, \forall \omega\in\Omega \qquad (28)$$

$$Z_{jkpr}(\omega) \ge 0 \qquad \forall j\in J, \forall k\in K, \forall p\in P, \forall r\in R, \forall \omega\in\Omega \qquad (29)$$

The objective function (20) minimizes the total cost of first stage decisions opening distribution centers, and second stage decisions, shipment of three types of products (gasoline, diesel and jet fuel) from refineries to the final customers in each scenario. The first term represents the fixed cost of locating distribution centers and the second term indicates the capacity cost of the opened distribution centers. The first and second terms represent the total fixed and variable costs of opening distribution centers. The third term states the cost of transporting products from refineries to DCs in scenario ω with mode r. Finally, the fourth term incorporates the cost of transporting products from DCs to demand nodes in scenario ω with mode r.

Constraint (21) ensures that demand for each petroleum product is satisfied by receipts from distribution centers. Constraint (22) limits the capacity of each distribution center that is opened, meaning that capacity cannot be assigned without a distribution center being opened. Constraint (23) ensures that the flow out of each distribution center is less than the capacity of the distribution center, while constraint (24) limits the amount of flow out of each refinery to the capacity of the refinery. Constraint (25) is the flow conservation constraint: the flow into the DC equals the flow out. Constraint (26) ensures that each mode carries the assigned percentage of products from refineries to DCs and to demand nodes in order to satisfy the demand. Note that the flow on individual links is not restricted; however, the percentage of petroleum products carried by each mode for the entire trip (overall mode capacity) is different and derived from [123]. Constraint (27) invokes integrality requirements. Finally, constraints (28) and (29) are non-negativity constraints.

3.3. Supply Chain Model in the Presence of Anticipated (Weather-related) Disruptions

Weather related disruptive events are a special case of random disruptions, because they can be anticipated in advance. Storms, tornados and hurricanes are examples of anticipated disruptions. The scope of this research is limited to developing mathematical models in the presence of hurricane disruptions.

A major hurricane or storm rarely happens, but they can be disastrous. The recovery from such disasters depends heavily upon the supply chain ability to respond quickly to demand by transporting petroleum products to the demand nodes with optimal routes and modes in order to minimize the total supply chain cost in the presence of disruptions.

In the following paragraphs, we introduce the downstream PSC model in the presence of an anticipated (weather-related) disruption. Similar to the previous model, we investigate the effects of disruption on the refineries. The structure of the problem to be modeled is a two stage stochastic linear program where the first stage decisions include determining the location and capacity of the DCs along with two proactive mitigation strategies: holding extra inventory at a subset of DCs and reserving an extra capacity of products on 100% reliable transportation modes for the shipment of products in the event of a disruption. This extra capacity would allow shipments from non-disrupted refineries to the DCs in order to satisfy the demand. The second stage decisions which incorporate the reactive mitigation strategies are used once the disruption hits. Similar to the previous model, we proposed multiple modes of transportation to be used to deliver products to DCs and demand nodes in the primary and secondary transportation respectively.

In order to find the optimal configuration of the PSC and to minimize the total cost under disruption, the following decisions need to be optimized: 1) the amount of each product to ship from refinery i to distribution center j with mode r in primary transportation during scenario ω 2) the amount of each product from distribution center j to demand node k with mode r in secondary transportation during scenario ω 3) the amount of each product to hold at distribution center j as extra inventory 4) the amount of each product to be reserved on the perfectly reliable transportation modes to be shipped from refinery i to distribution center j with mode r5) the amount of reserved products shipped from refinery i to distribution center j with mode r in primary transportation during scenario ω.

The mathematical formulation of the stochastic program is presented below.

$$\min \sum_{j\in J}\sum_{p\in P} h_p IN_{jp} + \sum_{i\in I}\sum_{j\in J}\sum_{r\in R} g_{ijr} b_{ijr} \tag{30}$$

$$+ E_\omega\left[\sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R} C_{ijpr}(Y_{ijpr}(\omega)+l_{ijpr}(\omega)) + \sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\sum_{r\in R} T_{jkpr} Z_{jkpr}(\omega)\right]$$

$s.t.$

$$\sum_{j\in J}\sum_{r\in R} Z_{jkpr}(\omega) = D_{kp} \qquad \forall p\in P, \forall k\in K, \forall \omega\in\Omega \tag{31}$$

$$\sum_{p\in P}\sum_{k\in K}\sum_{r\in R} Z_{jkpr}(\omega) \le V_j \qquad \forall j\in J, \forall \omega\in\Omega \tag{32}$$

$$\sum_{p\in P}\sum_{j\in J}\sum_{r\in R} \alpha_p (Y_{ijpr}(\omega)+l_{ijpr}(\omega)) \le S_i(\omega) \qquad \forall i\in I, \forall \omega\in\Omega \tag{33}$$

$$\sum_{i\in I}\sum_{r\in R} Y_{ijpr}(\omega) + l_{ijpr}(\omega) + IN_j - \sum_{k\in K}\sum_{r\in R} Z_{jkpr}(\omega) = 0 \qquad \forall j\in J, \forall p\in P, \forall \omega\in\Omega \tag{34}$$

$$\sum_{p\in P} Y_{ijpr}(\omega) \le U_{ijr} \qquad \forall j\in J, \forall k\in K, \forall r\in R\ne 4, \forall \omega\in\Omega \tag{35}$$

$$\sum_{p\in P} Y_{jkpr}(\omega) \le O_{jkr} \qquad \forall j\in J, \forall k\in K, \forall r\in R\ne 4, \forall \omega\in\Omega \tag{36}$$

$$\sum_{p\in P} l_{ijpr} \le b_{ijr} \qquad \forall i\in I, \forall j\in J, \forall r\in R\ne 4 \tag{37}$$

$$\sum_{p\in P} IN_{jp} \le V_j \qquad \forall j\in J \tag{38}$$

The objective function (30) minimizes the total cost of first stage decisions, namely holding extra inventory and reserving extra capacity of products on the reliable transportation modes. Second stage decisions include shipment of three types of products (gasoline, diesel and jet fuel) and the reserved products from refineries to the final customers in each scenario. The first term states the cost of holding extra inventory at the DCs, while the second term represents the cost of reserving an extra capacity of products on transportation modes to be moved by the reliable logistics provider. The third term represents transporting products, including reserved ones, from refineries to DCs in scenario ω with mode r. Finally, the fourth term incorporates the cost of transporting products from DCs to demand nodes in scenario ω with mode r.

Constraint (31) ensures that demand for each petroleum product is satisfied by receipts from distribution centers. Constraint (32) ensures that the flow out of each distribution center is less than the capacity of the distribution center, while constraint (33) limits the amount of total flow of products out of each refinery to the capacity of the refinery. Constraint (34) is the flow conservation constraint: the total flow into the DC equals the total flow out. Constraint (35) is the upper-bound limit on the shipment of products from each refinery to each DC via each transportation mode. Constraint (36) restricts the shipment of products from each DC to each demand node via each transportation mode. Constraint (37) states that the amount of reserved products shipped must be less than the reserved capacity on the reliable transportation modes. Finally, constraint (38) limits the amount of extra capacity to hold in DCs to the capacity of that DC.

3.4. Summary

The problem as defined in chapter 1 involves strategic and tactical planning for the downstream petroleum supply chain in order to capture the multi-echelon and multi-product network design and flow volumes in the network. Strategic decisions include determining the locations and capacities of the distribution centers, and tactical planning decisions include shipment cost from refineries to DCs and to demand nodes. To achieve that, we proposed deterministic MILP models in order to minimize the total cost of the supply chain, which corresponds to the aggregation of costs of location and shipment along the supply chain. Our goal is to illustrate the importance of using multimode transportation when designing the supply chain. Furthermore, since in reality facilities are susceptible to disruptions, we proposed two stage stochastic models with recourse for each disruption category and developed appropriate mitigation strategies with regards to the type of disruption (random or anticipated). The model structures discussed in this chapter provide a comprehensive mathematical framework for this research. Chapters 4 and 5 incorporate the case study and the results obtained from the case study in order to validate the developed models.

4. CASE STUDY AND PARAMETER SET UP

To assess the efficiency of the proposed models, we consider a realistic case study of the downstream U.S. petroleum supply chain in two regions of the United States. The study area is limited to the Gulf Coast and East Coast regions. These two regions are defined as a part of the Petroleum Administration for Defense Districts (PADDs) [12]. The Gulf Coast region (PADD 3) is the primary supplier for the East Coast region (PADD 1) which has a limited refining capacity, and a high population density [14]. In addition, the Gulf Coast is regularly exposed to hurricanes. For instance, hurricanes Katrina and Rita, which were the two most catastrophic hurricanes in U.S. history, made landfalls in the Gulf Coast region and caused 91% of the offshore crude oil production and 83% of daily gasoline production to be lost in 2005 [25]. According to Yeletasi [6], 113 offshore oil platforms were destroyed during Hurricanes Katrina and Rita and 52 were extensively damaged. Therefore, at one time, around one third of the U.S. refining capacity was shut down and it took several months to be restored [24]. The recovery from such disasters depends heavily upon the ability of the supply chain to respond quickly to the product demand, to transport products to the market and to resume operations at the production sites.

While we considered imports in the case study, exports are not included. The reason is that according to Energy Information Administration (EIA) data [125], the amount of exports for gasoline, diesel and jet fuel from the East Coast to other countries is negligible compared to the demand for products in the East Coast region. In addition, the interregional trades between the East Coast and other regions is negligible [15]. In general, pipelines are the primary transport mode for crude oil and petroleum products, followed by water carriers. Rail and trucks, however, transport a small fraction of the final disposition of petroleum products. The overall capacity of each mode is restricted to the percentage of products carried by each mode, N_r (see section 2.1).

However, this parameter does not restrict transfer volumes on individual links in the primary and secondary transportation. Since no capacity constraints are imposed on the links between two nodes, we simply have to consider the quantities to be shipped and to add the transfer flows to determine the pattern of commodity movements in the network.

In this study, stochastic scenarios are ruled by randomizing the refinery capacity, $S_i(\omega)$. We validate the developed models with a case study for random disruptions, such as a fire or unplanned refinery downtime, and a case study for hurricanes occurring on the refineries in two states of the Gulf Coast area or PADD 3: Texas and Louisiana. The reason is that these two states have accounted for 90% of the refining capacity in the Gulf Coast area (Figure 6). Based on data from the U.S. petroleum supply chain, as of 2013, there are 51 operating refineries in the Gulf Coast area and 11 operating refineries in the East Coast region which produce fuel products. Only these refineries are considered in the analysis. Refineries' physical locations were extracted from Google Earth interface and imported into GIS. Imports were also considered from a physical supply location (such as a refinery) in the East Coast which has access to the transportation networks. The annual capacity of the refineries were obtained via the EIA website [126]. In addition, we assume that each unit of capacity that a single refinery allocates to make each unit of a product is the same for all products and is equal to 1 ($\alpha_p=1$) [127].

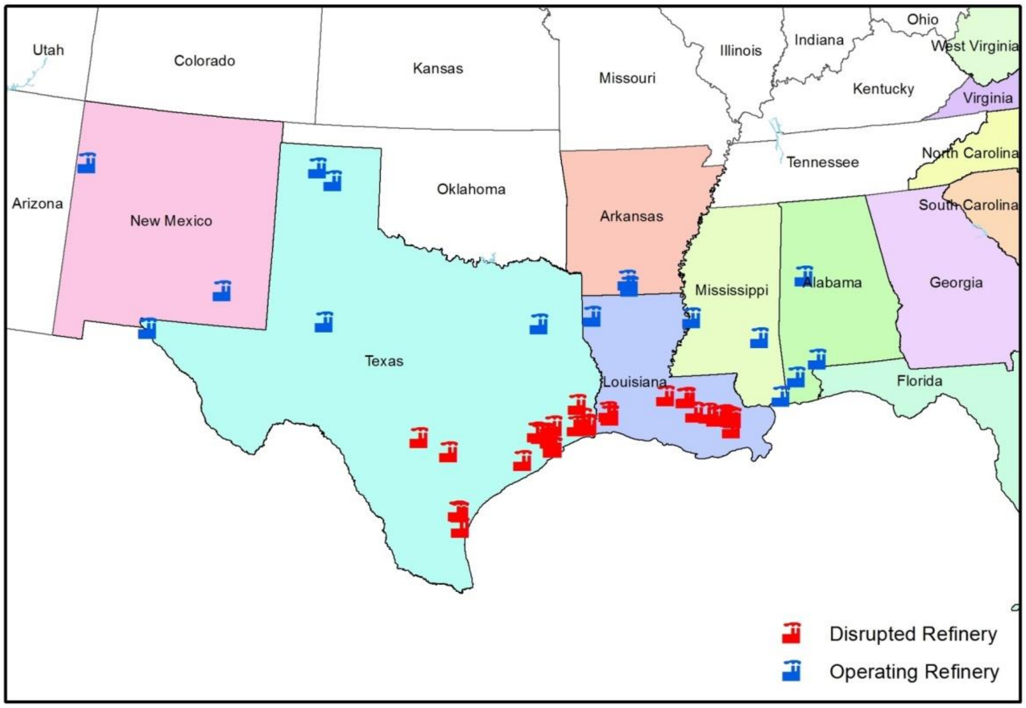


Figure 6. Disrupted Refineries in Gulf Coast (PADD 3) Region.

Potential distribution center locations were set in the areas near customers in the East coast region. They were chosen from 57 potential state counties in which the population is greater than or equal to 300,000 that have access to the demand nodes via transportation networks. Potential DC locations are created in GIS with a symbol representing the DCs on the map. The median house price in each county was taken to be equal to the fixed cost of locating a distribution center [85], and the cost per unit of annual capacity, β_j was derived from [124].

Finally, 180 demand nodes were chosen from state counties in the East Coast with a population of 150,000 or more and 60 airports which have 150,000 or more passengers annually. Similar to the DCs, demand nodes were created in GIS with a unique symbol. The annual deterministic demand is obtained from the annual demand data [128], which contains consumption values in transportation, commercial and industrial usage. We assumed that demand is completely satisfied and no shortage is allowed. For gasoline and diesel fuel, we obtained the demand values for each node by calculating the proportion of the total demand to the total population in that state and distributing it to each node with regard to the population of that particular county: $\left({total\ state\ demand}/{total\ state\ population} \right) \times population\ of\ the\ demand\ node$

For jet fuel, we took the same approach; however, instead of using population data, enplanement weight and landed weight (cargo weight) values were used. We took the standard weight for a person onboard according to Federal Aviation Administration (FAA) [129] to calculate the enplanement weight and the final demand. The population data are derived from the Census bureau online resources. The enplanement and landed weight data were also derived from FAA [130]. Figure 7 represents the refineries, DCs, and demand nodes in the colored study area within the GIS environment.

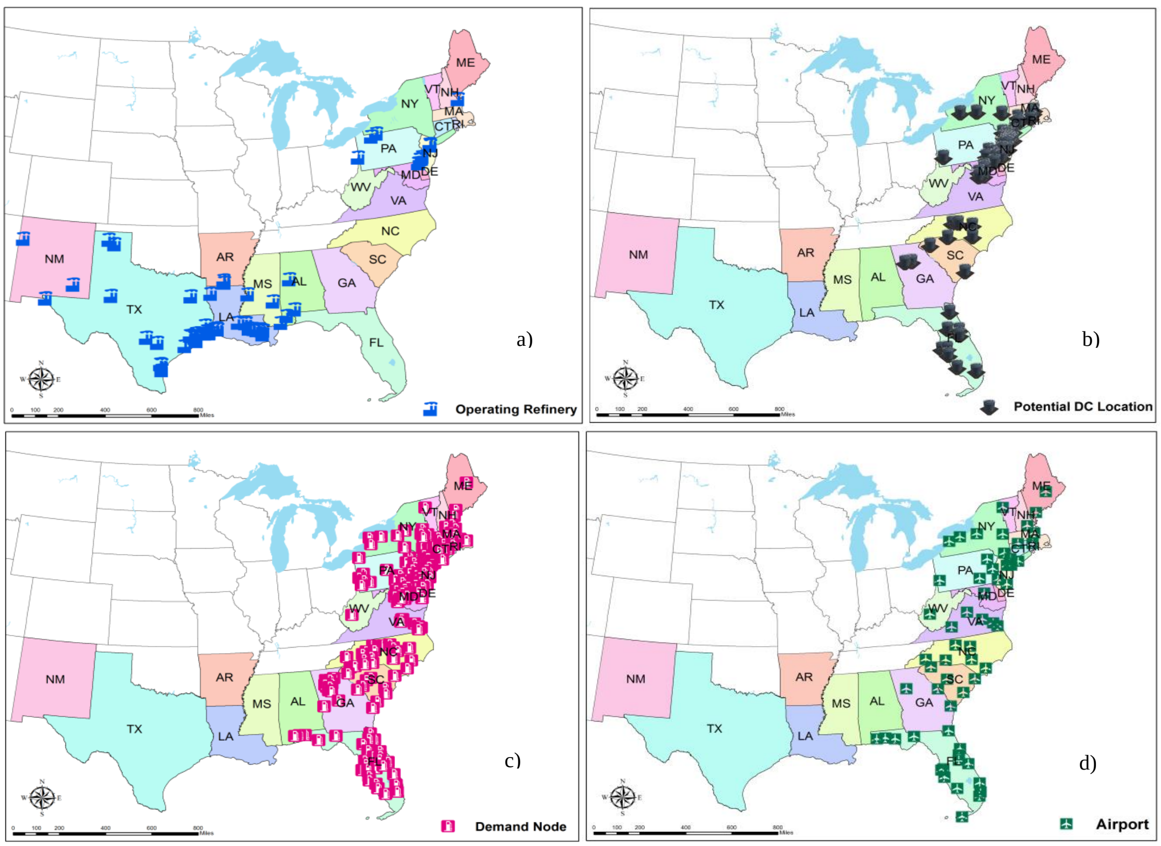


Figure 7. a) Refineries b) Potential DC Locations c) Demand Nodes d) Airports in the Study Area.

The MILP models determine the optimal level of key logistics decision variables that minimize the total cost of the petroleum supply chain: a) location of DCs from the potential locations in the East Coast region, b) transfer volumes from refineries in the Gulf Coast and East Coast to the DCs and to the demand nodes in the East Coast region, and c) the transportation modes which are used to move products from one point to another. The stochastic models will determine the optimal level of key logistics decision variables that minimizes the expected total cost of the PSC. In addition, the performance of the stochastic model will be compared with the deterministic models in the presence of random disruptions to validate the effectiveness of the proposed stochastic model. We illustrate the advantages of incorporating both proactive and reactive mitigation strategies into our models and emphasize that it is necessary to differentiate these strategies depending on the type of disruption.

4.1. Transportation costs

As mentioned earlier, we considered four modes of transportation in this study: pipeline, barge, rail and truck. It was assumed that pipelines connect each refinery to each DC and each DC to each demand node, with the exception of DCs in Florida. In other words, Florida DCs are not connected to the pipelines originating from the Gulf Coast [131], and therefore, when pipeline is the only mode of transportation, demand in Florida must be satisfied from DCs outside of Florida.

According to [132] transportation cost vary with the distance over which the freight must be transferred, which is reasonable because the amount of fuel used depends on distance and the amount of labor is a function of distance. Therefore, the longer the distance the products will be transported, the lower the unit distance transportation cost will be. Our study assumes that the transportation cost is a linear function of cost paid per unit distance. Assuming that third-party carriers are used, the transportation cost for shipping one ton of product *p* by pipeline is .49 cents per ton-mile [133], by barge is 1 cent per ton-mile [134], by rail 7 cents per ton-mile, and by truck 18 cents per ton-mile [134]. Costs were adjusted by the inflation rate to 2013 Dollars.

In order to obtain the cost of transportation for each unit of products from refineries to distribution centers and demand nodes, we first developed the transportation network for each mode in GIS to obtain the real distance between each pair of nodes. The National Highway Planning Network (NHPN) dataset was used to visualize truck routes, the Waterway Network dataset was used for barge, and the Railway Network was used to build the rail transportation network in GIS. Transportation networks were provided by the Bureau of Transportation Statistics National Transportation Atlas Database [135]. For the pipeline network we assumed that a straight line connects each refinery to each DC and each DC to each demand node. Pipelines may be used to transport jet fuel to the airports as well. Although we did not limit the transportation mode selection at any point along the supply chain, there are certain limitations for each transportation network, since not all transportation networks are available for all nodes. For example, barges can only serve a subset of nodes which have access to the waterway network. However, trucks or rail can serve almost all of the nodes, because their networks reach almost every node. Pipelines can serve any node along the supply chain as well. In addition, for the distribution centers that are opened in the same location as their demand nodes, we assume a 1 mile distance between the pair where pipeline and/or truck are being used. Barge or rail, however, may not be used for this type of location. Figure 8 depicts an example of waterway and truck networks between refineries, DCs and demand nodes.

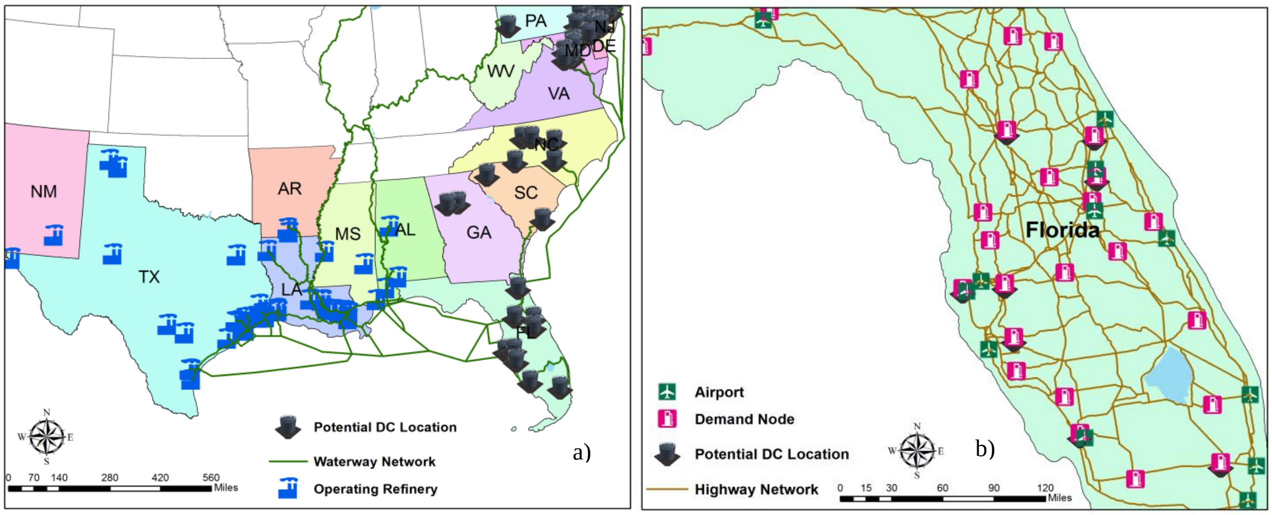


Figure 8. a) Waterway Network and b) Highway Network Used in the Analysis.

After setting data points and transportation networks for supply chain entities on the GIS map, we used the approach proposed by Kang et al. [136] to calculate the travel distance from each refinery to each DC location and to each demand node along the shortest-distance path in GIS. The shortest path algorithm is applied by the "Network Analyst" extension in ArcGIS 10.1. This solver calculates the shortest distance between each origin and destination specified in the model and presents the output as a matrix. The transportation cost for each mode on each link is determined by the aforementioned procedure in order to be used in the optimization model.

4.2. Modeling Random Disruptions in Downstream PSC

In the proposed stochastic mixed integer linear programming (SMILP) model, refineries are susceptible to random disruptions. The main computational burden is imposed by the number of refineries. In order to make the problem computationally tractable, we limited the number of scenarios to 15. To determine the random capacities for disrupted refineries a similar approach as Azad et al. [17] is adopted. We generated 15 scenarios in which the disruption probability at refinery *i (qi)* is uniformly distributed over [0.025, 0.15] and occurs independently. Accordingly, we consider that the percentage of total capacity of a disrupted refinery follows a uniform distribution of $U[0.2, 0.6]$. We introduced a Bernoulli random variable θ_i in each scenario which takes a value of 1 if disruption occurs at refinery i (*i.e.* $\theta_i \leq qi$), and 0 otherwise. Thus, the random capacity at each refinery is then determined by the following equation:

$$S_i(\omega) = S_i(1 - \theta_i \times U[0.2, 0.6]) \tag{39}$$

4.3. Modeling Anticipated Disruptions (Hurricanes) in Downstream PSC

Weather related disruptive events such as hurricanes are examples of anticipated disruptions. In the oil industry, with the prediction of an incoming hurricane, if evacuation is required, infrastructure shutdown will begin 72 hours prior to the landfall of the hurricane [23]. This preparation time gives the supply chain the possibility to take some proactive actions in order to further reduce the damaging effects of a hurricane. Therefore, it would be appropriate to consider both proactive and reactive mitigation strategies when modeling the supply chain under this particular type of disruption.

The Gulf of Mexico, unlike any other oil producing regions in the U.S., is regularly exposed to hurricanes. As mentioned in the previous section, we only focus on hurricanes affecting refineries in Texas and Louisiana and develop a stochastic model that minimizes the total supply chain cost in the presence of disruption by considering appropriate mitigation strategies. Since hurricanes make landfall in certain months of the year, the hurricane model is based on a monthly time horizon.

In order to obtain random capacities for refineries, different hurricanes occurred in the region and their categories are derived from NOAA's hurricane research division [137]. Unlike random disruptions, hurricane disruptions occur with a discrete probability. The total number of hurricanes and their probabilities are shown in Table 4.

Table 4. Hurricane Categories, Counts and Probabilities (1851-2012).

Hurricane Category	1	2	3	4	5
Count	42	23	24	11	2
Probability	0.41	0.23	0.24	0.11	0.02

To determine the random capacities for refineries in each scenario, we adopted the approach presented in [138]. The simulated production outage for each storm category was assumed to be normally distributed with a mean and standard deviation as shown in Table 5. The mean and standard deviation numbers illustrate how weather-related disruptions impacts increased dramatically with the severity of the storm. In addition, the large standard deviation values imply that extreme events, such as hurricane Katrina, are relatively rare.

Table 5. Loss in Production of Normal Monthly Production by Type of Hurricane [138].

Hurricane Severity	Mean	Std Dev
Moderate Hurricane (Category 1 and 2)	0.079	0.095
Intense Hurricane (Category 3, 4, 5)	0.344	0.41

To derive random capacities for the refineries in each hurricane category, we used a doubly truncated normal distribution described in [139]. Since random capacities are constrained to be greater than zero and less than 100%, we must truncate the normal distribution in order to derive the expected value of lost capacity for each refinery. For this purpose, we used the mean and standard deviation values shown in Table 5, in order to determine the points of truncation in each category in order to derive the adjusted mean values of the truncated normal distribution in terms of the original population parameters. Finally, the expected value of lost capacity for each category is derived by calculating the area under the probability density function of the doubly-truncated normal distribution.

To illustrate, let the points of truncation be K_L and K_R for the left and right side of the normal distribution respectively. Then, for each category, we derive the values as depicted in Table 6 according the approach taken in [139].

Table 6. Point of Truncation in each Hurricane Category.

Point of Truncation	Category 1	Category 2	Category 3	Category 4	Category 5
K_R	0.13	1	0.53	0.89	1
K_L	0	0.13	0	0.53	0.89

Consequently, we determined the mean values of the truncated normal distribution in terms of the original population parameters (i.e. Table 5) for each category according to the following equation:

$$E(x) = \mu + \sigma\left[\frac{1}{F(K_R) - F(K_L)}(f(K_L) - f(K_R)\right] \tag{40}$$

Where $F(K_R)$ and $F(K_L)$ are the cumulative probability, while $f(K_L)$ and $f(K_R)$ are the probability density functions of the normal distribution. In the end, the expected value of lost capacity, $E(x_l)$ in each category is derived by calculating the area under the probability density function of the doubly-truncated normal distribution given by:

$$E(x_l) = \frac{1}{F(K_R) - F(K_L)} \int_{K_L}^{K_R} \frac{x}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)} dx \tag{41}$$

Finally, the random capacity for each disrupted refinery in each category (scenario), *S(ω)*, is determined by subtracting lost capacities from the actual capacity for each refinery (Appendix C).

Proactive mitigation strategies which are considered in the hurricane model are taken prior to realization of disruption. They include holding extra inventory at a subset of DCs, and reserving extra capacity on perfectly reliable transportation modes in order to ship transfer volumes when needed. The holding costs for the three types of fuel are calculated based on the holding cost ($/bbl) for a year given in [140] and then converted to monthly time units per ton of each product. Gasoline costs 79.3 cents per ton, diesel fuel costs 87.1 cents per ton, and jet fuel costs 65.3 cents per ton to hold. The cost of contracting a third party logistics provider to reserve products on each route from refinery i to distribution center j with mode r, g_{ijr}, is also assumed to be equal to 10% of the cost of shipping products on each route based on the distance traveled. Pipelines are excluded from capacity reservation, since they normally run very close to their capacity. For other modes, no specific upper-bound was considered when reserving extra capacity to ensure that the model finds key links that can be used upon disruptions.

5. SOLUTION PROCEDURE AND RESULTS

This chapter describes solution procedure and numerical results for the case study for both deterministic and stochastic models. We compare the pipeline model with multimode model in order to demonstrate the importance of using multiple transportation modes in designing the supply chain. Furthermore, we present results from the stochastic models and compare them against deterministic models to validate the performance benefits of the proposed stochastic models. Finally, we discuss separating the models based on the type of disruption, and why it is necessary to consider different mitigation strategies for each type of disruption. Both deterministic MILP models are coded in GAMS (General Algebraic Modeling System) and executed by XpressMp solver to global optimality using the parallel computing platform of NEOS (Network Enabled Optimization Solution) server [141] hosted at www.neos-server.org/neos. The stochastic models are also coded in GAMS and executed by XpressMp solver with the optimality gap set at <1% for the random disruption model and global optimality conditions for the hurricane model.

5.1. Computational Results for the Deterministic Models

The pipeline model has 1,068 constraints, 51,870 continuous variables and 57 discrete variables. The multimode model, however, has 1,072 constraints, 207,309 continuous variables and, 57 discrete variables. The results from the pipeline model show that the optimal number of distribution centers opened is 13, while the multimode model selected 20 optimal distribution centers to open. Figure 9 presents the optimal locations and capacities of the distribution centers where pipeline is the only mode of transportation. DC symbols are presented with proportional symbols to the optimal capacities allocated for a more realistic visualization.

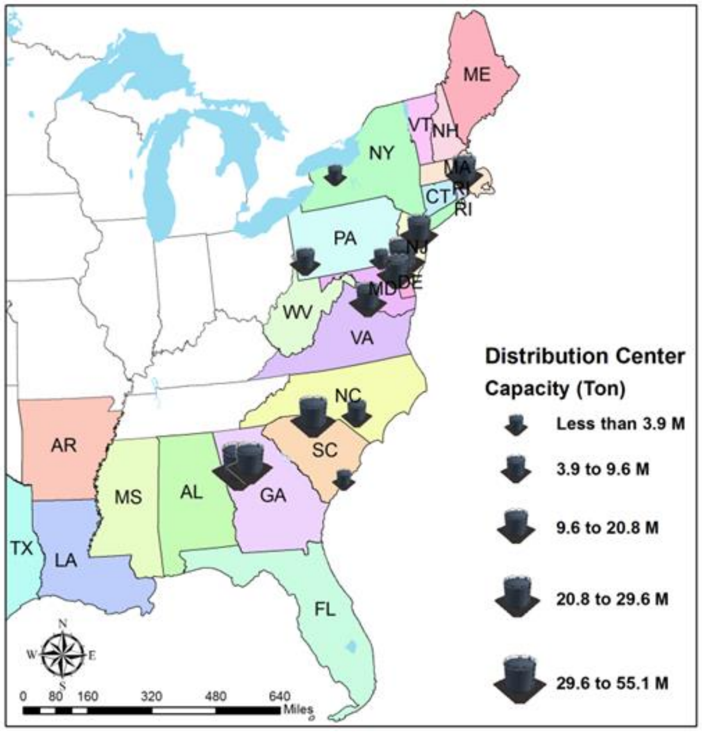


Figure 9. Optimal Distribution Center Locations and Annual Capacities in Pipeline Model.

As expected, no distribution center was opened in the State of Florida, since Florida DCs are not connected to the pipeline network originating from the Gulf Coast [131] and therefore, demand in that state is going to be satisfied from the closest DCs opened outside of Florida. Distribution centers receive transfer volumes from refineries via pipeline and ship them to demand nodes to satisfy the total demand. However, not all DCs transfer the same mix of products to the demand nodes. In particular, since the demand for each product is different, all DCs receive and ship gasoline and diesel; however, only 12 DCs receive and ship jet fuel to the airports. In other words, only one DC is opened to transfer gasoline and diesel. The current supply chain structure of the pipeline model has an annual minimum total cost of $775 Million, which uses the selected refineries, DCs, imports, and demand nodes. The total shipment cost for transfer volumes consists of almost 90% of the total cost of the supply chain; therefore, transportation cost is a critical parameter in the cost efficiency of the downstream petroleum supply chain. This observation is particularly important when designing the supply chain from the multimode perspective. If the supply chain is designed with a single (primary) mode, while alternate modes are selected at the tactical level, the resulting supply chain configuration may not be efficient in terms of costs. In other words, single mode strategic planning is not efficient with multimode scheduling. In the following section, we validate the aforementioned observation and present the results of the multimode model. We compare the important performance measures of both supply chain models by considering strategic planning with single and multimode selection.

5.1.1. Comparison of the Pipeline Model vs. the Multimode Model

The results of the multimode model suggest 20 distribution centers be opened which are shown in Figure 10. Similar to the pipeline model, the combination of products received by the opened DCs is not consistent across them in the multimode model. All DCs receive and ship gasoline and diesel; however, jet fuel is received and shipped from only 17 DCs.

The number of opened DCs, their locations, and their capacities are different in the multimode model compared to the pipeline model (see Figure 9 and Figure 10). The reason is that the multimode model chooses optimal DC locations with regard to the accessibility to the transportation networks and the availability of transportation modes. Such decision does not exist in the pipeline model. As an example, Figure 5 shows that the multimode model opens a distribution center in Florida, while Figure 4 shows that the pipeline model does not open any DCs in that state. This discrepancy is because DCs in Florida can only receive petroleum products from the Gulf Coast via barge and therefore, in the pipeline model DCs in that state cannot receive products directly from the Gulf Coast area. Consequently, the demand must be satisfied from the DCs located outside of the state. As a result, the transportation mode selection decision alters the number, location and capacity of the distribution centers in the multimode model. Transfer volumes in the multimode model are carried by pipeline, barge and rail from refineries to DCs in the primary transportation and all four modes are used by the model in the secondary transportation to carry transfer volumes from DCs to demand points.

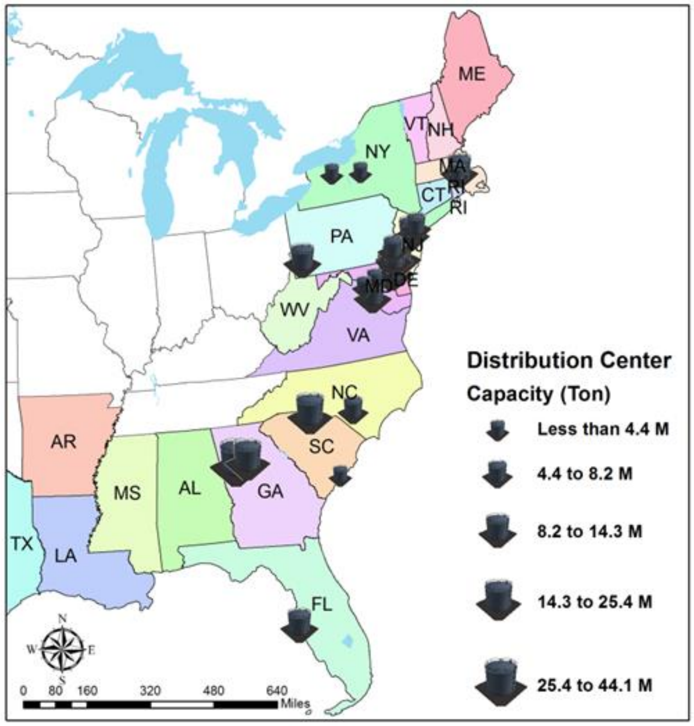


Figure 10. Optimal Distribution Center Locations and Annual Capacities in Multimode Model.

In the primary transportation, as expected, pipeline was the main mode of transport which carries the highest portion of all three products from refineries to distribution centers. Barge transports the second highest volume, and rail carries a small portion of products within the East Coast region to the distribution centers. In the secondary transportation, pipelines access most of the locations and airports, followed by barge, and finally trucks which are chosen for the short haul distances. Figure 11 depicts the transfer volumes moved by the transportation modes in the primary and secondary transportation.

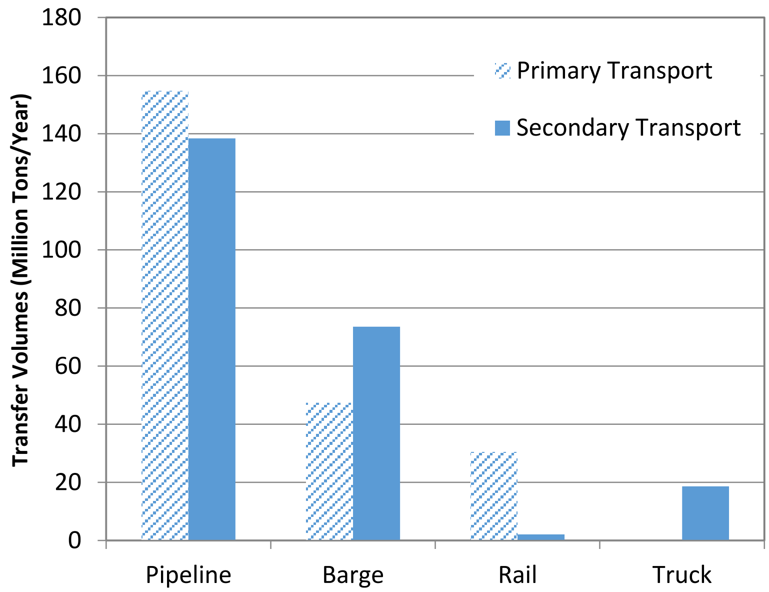


Figure 11. Transfer Volumes in the Primary and Secondary Transportation

The strategic planning of the supply chain allows each DC to utilize multiple chosen modes to deliver to demand nodes, meaning that distribution centers may receive products via one mode (e.g. pipeline/barge) and send the products with another mode or a combination of modes (e.g. truck, rail, and pipeline). This is an important feature of our multimode model which has not been addressed in previous studies. For simplicity, the handling cost to load and/or unload products from one mode to another is considered to be constant across all the DCs. In addition, there is no mode preference for a specific product as mode selection only depends on the accessibility of the node and its distance to the transportation network. Gasoline is the most carried product followed by diesel and jet fuel due to the difference in demand for each product.

In order to investigate the efficiency of using the multimode model as opposed to the single mode model, and to explore the benefits of using multimode transportation to the strategic planning, we fixed the distribution center locations derived from the pipeline model into the multimode model and forced the model to choose the distribution centers selected by the pipeline model followed by transportation mode assignment, while maintaining the same constraints in the model. The results from this experiment identified that the resulting pipeline-based DC selection is not efficient for multimode transportation assignment as both total cost and secondary transportation cost increased for the supply chain (Table 7). This is mainly due to the strategic design of the pipeline-based distribution centers which prevents the multimode model from selecting transportation modes in each echelon in a cost effective manner. In other words, the locations of the pipeline-based distribution centers may not be optimally accessible by the transportation modes other than pipeline and, therefore, it results in excess total costs in the multimode model as is shown in Table 7. Although it appears that the total supply chain cost increased by only 2%, the profit can be significantly affected, since the petroleum supply chain has a relatively low net refined product profit margin ($.5 to $1 per bbl for a simple refinery's output) [142]. On the other hand, since the pipeline model ships to fewer DCs in the primary transportation, there is no surprise that the primary transportation cost is lower. However, this does not guarantee a lower overall transport cost as can be seen in the table. The multimode model, on the other hand, yields a more realistic and efficient supply chain design that selects appropriate modes, for example barge, in the primary transportation as well as the secondary transportation. The results would be lower overall shipment costs and lower total supply chain cost. That being said, our multimode model optimizes the location of the DCs by considering the allocation of transfer volumes to the selected transportation modes in order to satisfy the demand and minimize the total supply chain cost. Therefore, it is necessary to incorporate multimodal transportation decisions in the strategic design of the supply chain to prevent additional costs and to improve supply chain efficiency.

Table 7. Cost Comparison (in $Millions) of Multimode Model with Pipeline-based Planning and the Multimode Model.

	Multimode Model	Multimode Model with Pipeline-based Planning
Primary Transportation Cost (Refinery to DC)	544.4	525.8
Secondary Transportation cost (DC to Demand)	179.8	218.2
Total PSC Cost	810.9	829

In order to better represent the importance of considering multimodal transportation in strategic planning, further statistical analysis was conducted on the capacity of the opened distribution centers in both models. As such, statistical measures such as mean, standard deviation, and median of DC capacities are reported in Table 8.

Table 8. Statistics Measures for DC Capacity in Pipeline-based Planning and Multimode Models.

	Multimode Model	Multimode Model with Pipeline-based Planning
Mean	11,631,171	17,894,110
Median	9,553,869	15,642,857
Standard Deviation	10,430,425	14,445,158

As can be seen in Table 8, the DC capacities derived with pipeline-based planning model have much larger standard deviation, mean and median compared to those with the multimode based planning model. This observation indicates that the pipeline-based planning model has more variability in DC capacity allocation and favors impractical extremes in DC capacities. As a result, the supply chain network design model will not be optimal and distribution centers might become more vulnerable to random events, such as disruptions.

5.2. Solution Procedure and Computational Results for the Stochastic Models

This section focuses on the proposed solution procedures and the results derived from the stochastic models. Mitigation strategies and their benefits are elaborated and, further a comparison between the stochastic and deterministic models is conducted in order to gain a deeper understanding of their performance.

5.2.1. Random Disruption Model

The stochastic mixed integer linear programming (SMILP) model which proposes an optimal supply chain design in the presence of random disruptions is required to select: 1) DC locations from $|J|$ potential locations 2) the capacity of each distribution center 3) the amount of each products to ship from refinery i to distribution center j with mode r in primary transportation during scenario ω and, 4) the amount of each product shipped from distribution center j to demand node k with mode r in secondary transportation during scenario ω.

The main computational burden in modeling the random disruption is imposed by the number of random variables (capacity of the refineries). The number of possible outcomes grows exponentially as the number of random variables increases; therefore, we limited the number of scenarios to 15 in order to make the problem computationally tractable. Since there are 63 random variables and 15 outcomes for each, the total number of scenarios is 63^{15} in the random disruption model. In the hurricane model, the number of outcomes is 5, therefore 63^{5} scenarios are generated. Consequently, solving the SMILP model with random disruptions is practically impossible due to the fact that 1) the underlying distribution of the uncertain parameters is continuous and 2) the number of possible realizations is extremely large [143]. As a result, in order to solve the SMILP model, we adopted the Sample Average Approximation (SAA) approach explained in [144] to estimate the first stage decision variables of the master problem, and then solve the sub-problem as a simple stochastic linear programming (SLP) model. To do so, first, we generated 30 samples of unique stochastic values for the random variable (refinery capacity) with each sample containing 15 scenarios, and solved the model with each sample to derive the binary variable X_j. Similar to the deterministic models, the SMILP model is coded in GAMS and executed by XpressMP solver (with the optimality tolerance gap set at <1%) using the parallel computing platform of NEOS. The 15 scenarios in the random disruption model are used to convert the SMILP model into the DEM (Deterministic Equivalent Model) which contains 1,051,543 constraints, 3,108,895 continuous variables and 57 binary variables. The results from solving the model showed that 40 DCs are opened in 14 of the samples, 41 DCs are opened in 13 samples, and in the remaining 3 samples, 39 DCs are opened (Table 9). Note that the DCs which are opened in *x* runs are exactly the same in terms of capacity and location across all runs. For example, all 40 DCs which are opened in 14 runs have the same locations and capacities. Based on the derived results it was determined that the number of DCs to open should be 40. The expected total supply chain cost is estimated as $837.8 Million by taking the average objective function value over the 14 samples.

Table 9. Sample Average Approximation Approach for Solving First Stage Decision Variables in SMILP Model.

Sample	Number of DCs Opened	Objective Function Value
1	41	850,136,493.85
2	40	843,124,286.93
3	40	844,194,794.29
4	41	851,114,947.85
5	41	832,051,856.54
6	41	836,532,589.32
7	40	843,096,723.80
8	40	835,241,770.12
9	41	837,165,001.30
10	40	834,333,556.36
11	40	836,810,259.27
12	40	835,815,210.80
13	41	855,153,805.28
14	41	845,593,600.61
15	40	835,232,378.90
16	41	839,595,796.11
17	41	830,806,141.06
18	40	835,027,282.60
19	41	853,504,245.19
20	39	828,097,434.09
21	40	844,248,125.47
22	40	837,181,002.98
23	40	834,324,872.85
24	41	836,767,456.26
25	39	838,763,055.93
26	40	833,422,688.55
27	41	853,072,034.60
28	40	837,206,704.60
29	41	847,455,056.76
30	39	826,930,112.56

In a similar approach, we derived the capacity of each opened DC by taking the average of capacity values over all scenarios throughout 14 samples. Locations of the opened DCs along with their capacities are shown in Figure 12. The Distribution centers are presented with proportional symbols to optimal capacities allocated for a more realistic visualization.

After deriving first stage variables, we fixed the DC locations and capacities in the model and re-solved the random model as a Stochastic Linear Program (SLP) in order to derive the upper bounds for the hurricane model from the transfer volumes in primary and secondary transportation explained in the next section.

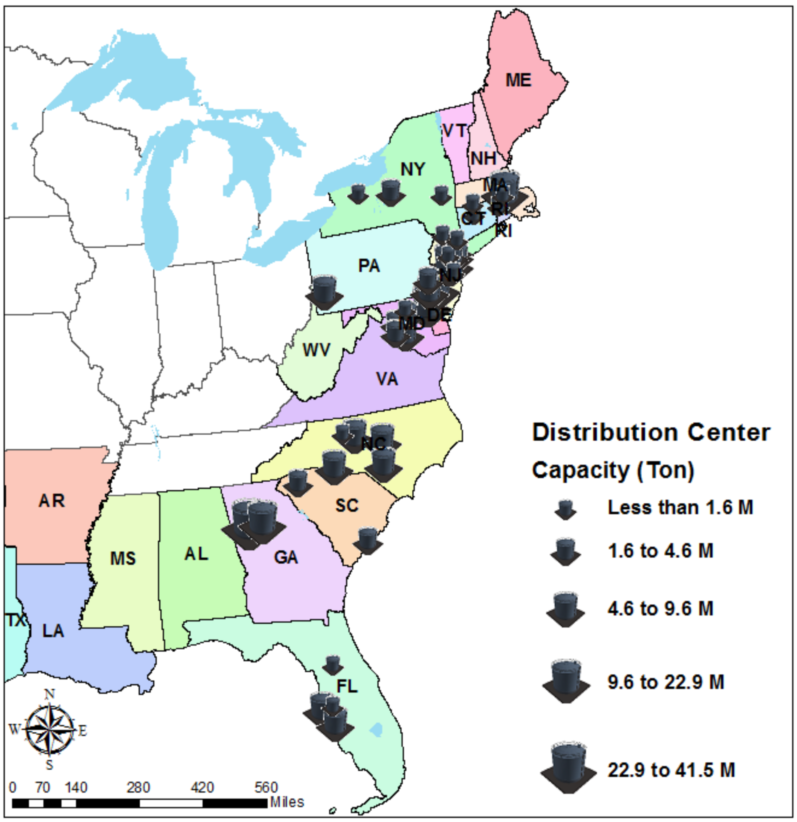


Figure 12. Optimal Distribution Center Locations and Annual Capacities in SMILP Model for Random Disruptions.

Transfer volumes in the stochastic model are carried by all modes in both primary and secondary transportation. Figure 13 depicts the average of transfer volumes in all scenarios for the primary and secondary transport. Unlike the multimode model which uses trucks only in the secondary transport, in the random model, trucks are used in both primary and secondary transport to ship products to DCs and demand nodes when disruption happens. In addition, rail is used to move more products in the secondary transport compared to the multimode model. As expected, pipelines carry the most volume, followed by barge, which is used almost equally in the primary and secondary transport.

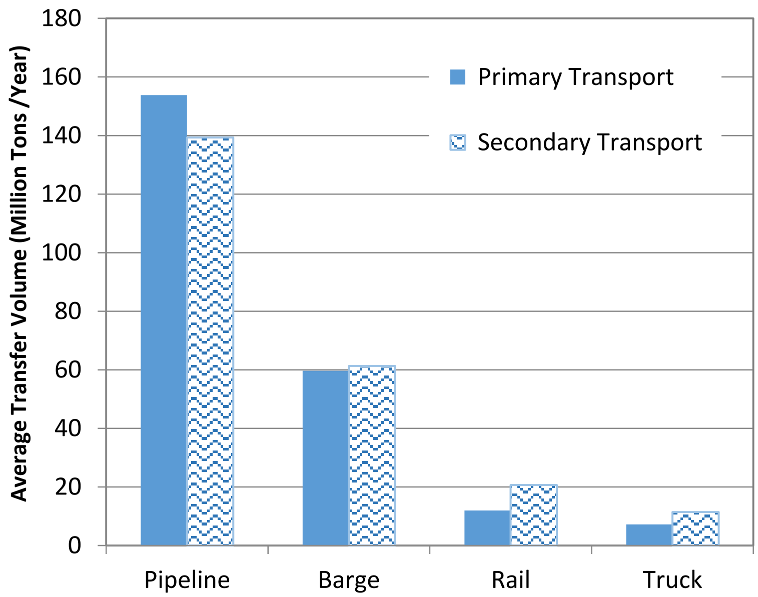


Figure 13. Average Transfer Volumes in the Primary and Secondary Transport (Stochastic Random Model).

5.2.2. Hurricane Model

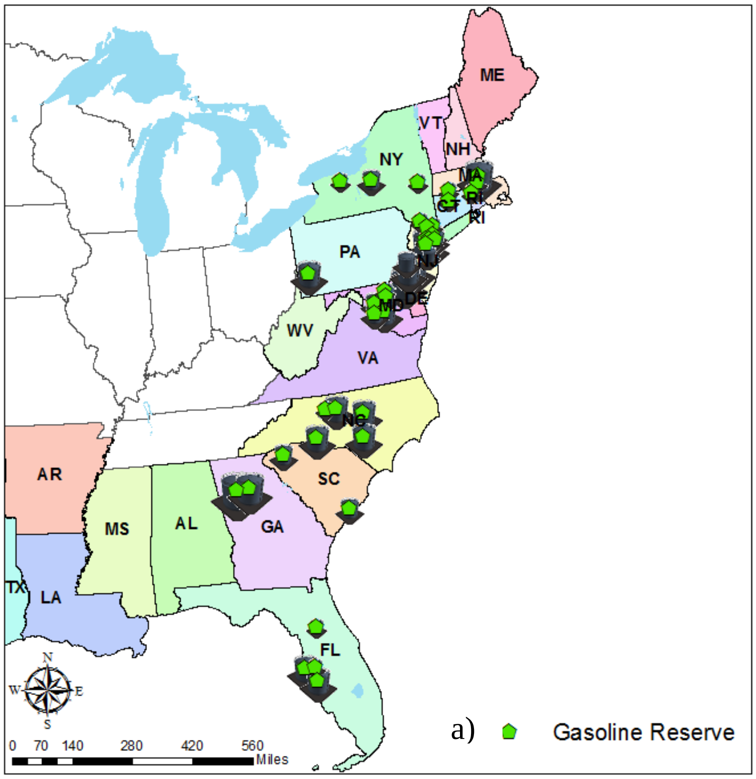
Solving the first stage of the SMILP problem provided us with the number, location and the capacities of the DCs (first stage decision variables) for the entire supply chain. These values remained unchanged in the hurricane model, since they are strategic decisions. On the other hand, we proposed proactive mitigation strategies in the first stage along with reactive mitigation strategies in the second stage to minimize the expected total supply chain cost under risk of hurricanes. In addition, we restricted the volume of products moved by barge, rail and pipeline on each link in the hurricane model (constraints 35 and 36). After solving the SLP random model, transfer volumes in the primary and secondary transportation are derived and increased by 10% to be used in the hurricane model as the upper-bounds. For truck, we relaxed the upper-bound on the flows in order to benefit from the flexibility offered by this mode. The hurricane model is coded in GAMS and executed by XpressMP solver to global optimality using the parallel computing platform of NEOS. The 5 scenarios in the hurricane model are used to convert the SLP model into the DEM (Deterministic Equivalent Model) which contains 1,459,621 constraints and 1,266,256 continuous variables. The expected monthly total minimum cost of the supply chain is determined to be $30.2 Million.

In addition to the expected total cost, results of the hurricane model determined the decision variables used in proactive and reactive mitigation strategies along with the transfer volumes in the primary and secondary transportation in each hurricane scenario. As mentioned in the previous chapter, two proactive mitigation strategies are considered in the first stage: the amount of reserved capacity to ship from refinery i to DC j with the reliable logistics provider (b_{ijr}) and the extra inventory of each product held at distribution centers (IN_{jp}). Deriving b_{ijr} provides us with the key routes (links), total amount, and modes of transportation to reserve capacity (Table 10). A total of 9 main routes are chosen for the modes to reserve extra capacity on. As can be inferred from Table 10, only a subset of refineries from PADD 1 (East Coast) are chosen to supply reserved products to the selected DCs via rail and barge (see Appendix A and B for the list of refineries and distribution centers). In addition, the import terminal (additional one refinery that we assumed in PADD 1) was also chosen by the model to reserve capacity on barge in one of the routes as shown in the table. Rail is only used in one route, while barge is used in most of the selected key routes between refineries and DCs. The amount of reserved volume then will be shipped for each product via barge or rail in each hurricane scenario within the second stage (l_{ijpr}).

Table 10. Reserved Capacity of Products to be Shipped from refinery *i* to DC *j* via Selected Transport Modes

Refinery to DC Route	Mode of Transport	Total Reserved Volume (Ton/Month)
55 → 26	Barge	386,876.8
55 → 29	Barge	181,040.9
55 → 30	Barge	72,490.1
58 → 21	Rail	966,548.2
59 → 30	Barge	712,442.6
59 → 32	Barge	48,317.7
60 → 29	Barge	1,001,732
62 → 23	Barge	86,904.7
63 → 32	Barge	679,022.5

The other proactive mitigation strategy that was considered in the first stage represents the extra inventory of products held at a subset of distribution centers (IN_{jp}). The buffer inventory is held strategically in order to be shipped via transportation modes in the second stage when a hurricane makes land fall. Figure 14 depicts the opened DCs and the subset of DCs which were chosen by the model to hold the extra inventory.



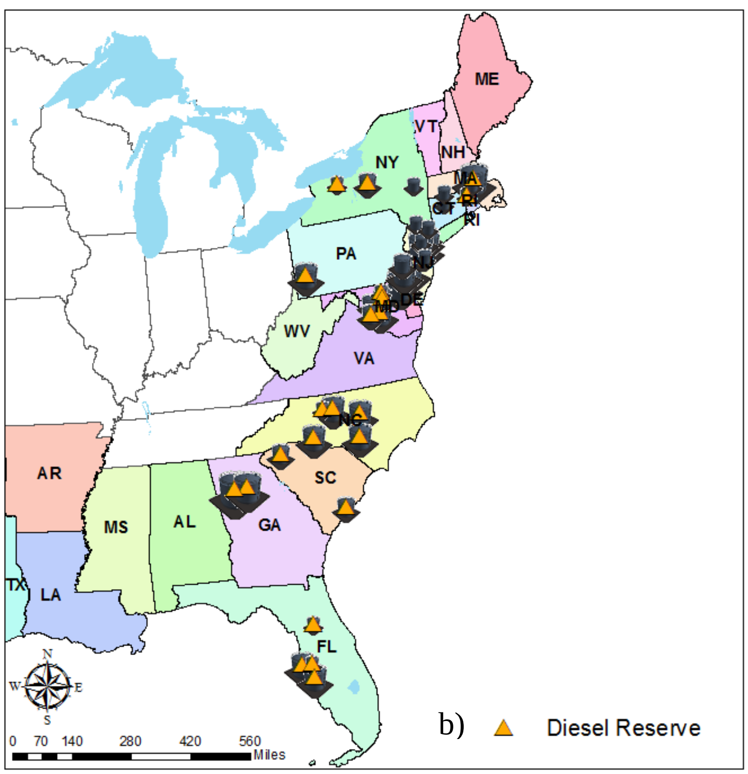


Figure 14. a) Gasoline b) Diesel and c) Jet fuel Reserve in Hurricane Model.

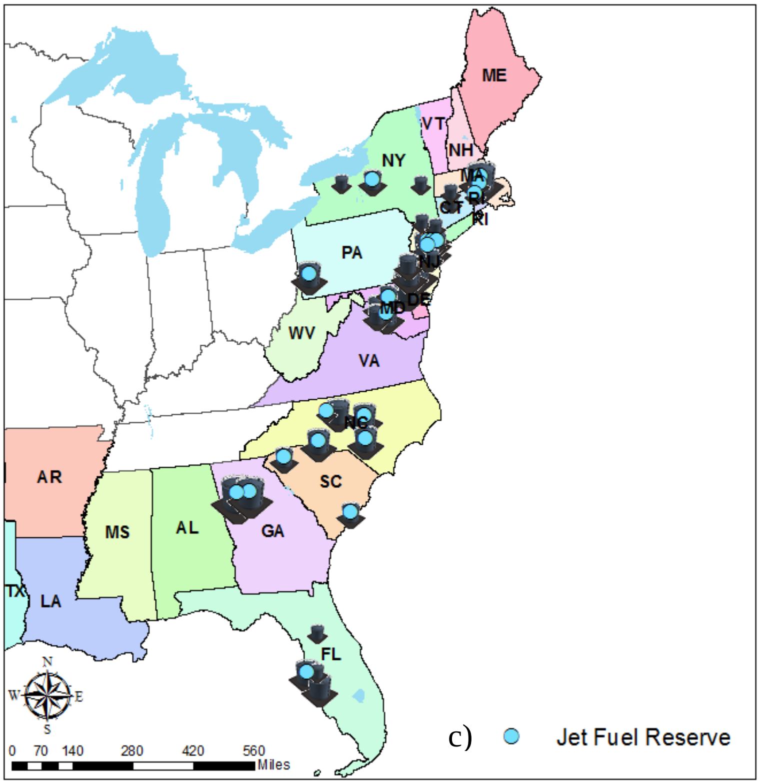


Figure 14. a) Gasoline b) Diesel and c) Jet fuel Reserve in Hurricane Model (continued).

Figure 14 demonstrates that most of the DCs hold extra inventory for gasoline, while diesel and jet fuel are held in fewer DCs. This is expected, since the demand for gasoline is more than the other two products and, therefore, more reserve is needed to prevent shortage of demand. Table 11 also reveals that the majority of extra inventory held at the DCs, around two third, is related to gasoline storage. Reserved products are moved to the demand nodes via secondary transportation when the disruption is realized.

Table 11. Number of DCs to Hold Extra Inventory and Total Reserved Volume of Petroleum Products

	Total Reserved Volume (Ton/Month)	Number of Reserve Locations (DCs)	Percentage of Total Reserved Volume
Gasoline	10,380,625.9	35	73%
Diesel	2,123,101.2	22	15%
Jet Fuel	1,660,670.9	20	12%

Decision variables related to reactive mitigation strategies taken in the second stage include using multiple transport modes to move transfer volumes, extra inventory and reserved products on modes in the primary and secondary transportation. Results from the transfer volumes in the second stage illustrate that the model redirects the supply to non-disrupted refineries, and includes imports in the East Coast region. Another observation from the results demonstrates that in both primary and secondary transportation pipelines, barge and trucks were used to move products and DC reserves. On the other hand, rail is only used when transferring contracted products to reserve on the modes. Figure 15 depicts the amount of each product transferred via selected modes (barge and rail) within all 5 categories of hurricanes.

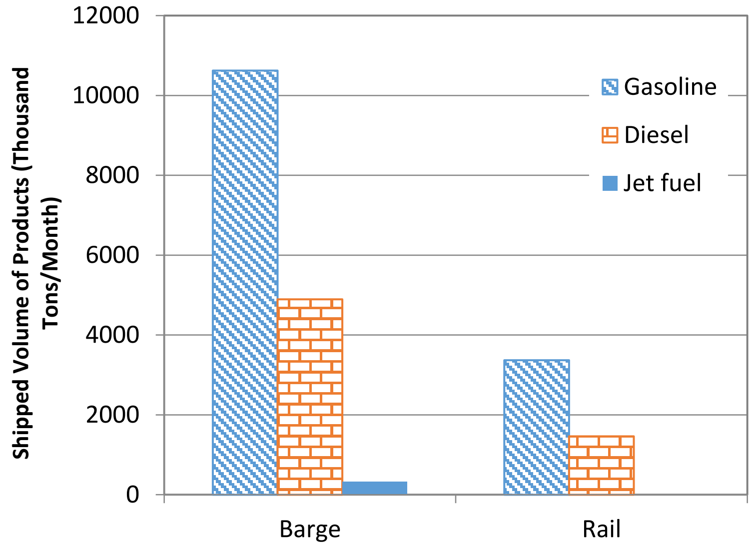


Figure 15. Total Volume of Contracted Products Shipped via Barge and Rail during All Hurricane Scenarios in Primary Transportation.

It is implied from Figure 15 that the majority of shipped volume is gasoline (68%) followed by diesel (31%). The smallest shipped volume (less than 2%) is Jet fuel which is only moved via barge. The rest of the demand for jet fuel is satisfied via transfer flows in the primary and secondary transportation. The shipped volumes are sourced by the total amounts reserved on each selected mode and each key route as shown in Table 10.

5.3. Comparison of Hurricane Model vs. Deterministic Multimode Model

In order to validate the cost-efficiency and performance of the hurricane model, we compared the deterministic multimode model and hurricane model in terms of shipment costs and expected total supply chain costs. The difference between the expected costs of the stochastic model vs. the deterministic model under uncertainties is used to compare the results. As mentioned in the previous section, for the hurricane model, the optimal values of the DC capacities and locations have been determined by the random model. For the deterministic multimode planning model, we substituted the DC capacities and locations of the hurricane model with the first stage variables derived from multimode model to compare the shipment cost and expected total costs. Both models are linear and solved to global optimality. Table 12 summarizes the expected costs of the hurricane model vs. the deterministic multimode planning model in the presence of disruptions.

Table 12. Comparison of Hurricane Model vs. Deterministic Multimode planning Model in the Presence of Disruptions.

	Hurricane Model	Multimode Planning Model
Expected Shipment Cost ($ Million)	30.2	37.8
Expected Total Cost ($ Million)	37.9	45
Number of DCs	40	20

It is inferred from the above table that the hurricane model has 25% (=100*(37.8-30.2)/30.2) less expected shipment costs than that of the deterministic multimode model. Moreover, the deterministic multimode planning model incurs 19% additional costs for total supply chain compared to hurricane model. The aforementioned results are driven by the number and location of DCs in the hurricane model, which are from 40 DCs planned by the random model. As a result, it is necessary to consider planning for disruptions when designing the supply chain.

5.4. Importance of Differentiating Mitigation Strategies for the Random and Hurricane Model

As explained in the previous sections, we proposed different mitigation strategies for each stochastic problem based on the type of the disruption. Since a hurricane disruption is anticipated in advance, we proposed proactive mitigation strategies which occur before realization of disruption. However, for the random disruptions, there is no preparation period, and therefore, only reactive mitigation strategies are proposed. As a result, if we fail to differentiate the mitigation strategies for these two models, when an anticipated disruption occurs the supply chain may face serious shortages or very high costs. We verified this assumption by removing any proactive mitigation strategies from the hurricane model and solved the problem with only reactive strategies as in the random model. The problem resulted in infeasibility and supply could not match demand in the monthly time horizon that we considered for the hurricane model.

5.5. Summary

In this chapter, we presented the solution approach and numerical results of the deterministic and stochastic models. In addition, comparisons were made between deterministic models and deterministic models vs. stochastic models. The objective was to present the benefit of using multimode transportation in strategic planning and to examine the cost-efficiency and performance of the stochastic models vs. deterministic multimode model. The results for the first set of comparisons validated that incorporating multimodal transportation decisions in strategic planning of the supply chain prevents excess costs and improves supply chain efficiency. Results of the stochastic models and their unique mitigation strategies were also elaborated and analyzed. A comparison between the hurricane model with stochastic planning and the deterministic multimode model under the risk of hurricane disruptions was also conducted. The results verified that the hurricane model with stochastic planning outperforms the multimode model in the presence of disruptions. Therefore, it is necessary to consider disruptions when strategically designing the supply chain. As a final note, failing to separate the mitigation strategies for different disruption categories would result in the infeasibility of the model and therefore, it is crucial to propose appropriate mitigation strategies for each type of disruption as discussed throughout this research.

6. SENSITIVITY ANALYSIS

This chapter presents sensitivity analysis regarding a number of key model parameter changes and impacts on the supply chain. The purpose is to examine how our model depends on its important input factors in order to assist with the strategic and tactical decision-making process within the petroleum industry supply chain. In addition, in order to solve the large scale problem, using historical data analysis, current literature and assumptions were inevitable. Consequently, results may become aggregate and therefore, conducting sensitivity analysis is beneficial to calibrate the model with the changes occurring in all aspects of supply chain design. The results of the sensitivity analysis can help managers in the petroleum industry make better decisions related to infrastructure expansion or reduction in an area as well as the economic impacts on logistics operations and the supply chain.

6.1. Impact of Cost per Unit of Capacity (β_j) on Petroleum Supply Chain Design and Total Cost

In order to solve the proposed model, we have assumed βj to be a percentage of the average gasoline, diesel and jet fuel price in the East Coast region considering the total demand for each of the products. In the base case, we assumed that βj would be 10% of the weighted average sales price per gallon for each product. For sensitivity analysis, we varied the percentage between 10% and 40% to investigate the effects of βj on the supply chain decision variables. Figure 16 represents the results of the sensitivity analysis on the total cost of the supply chain.

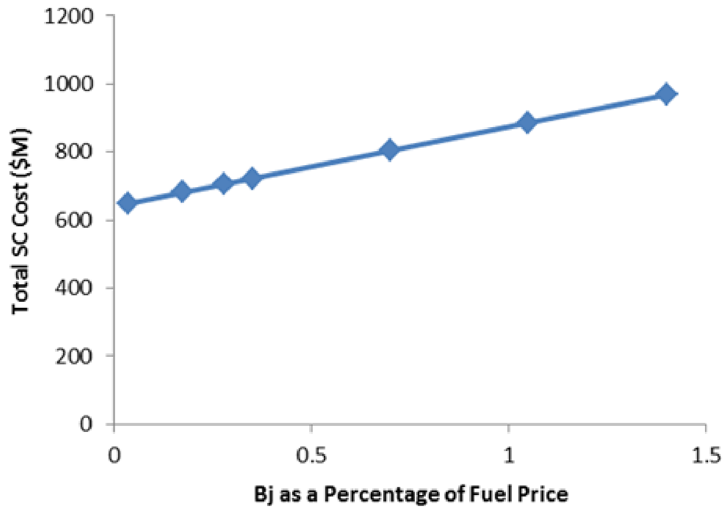


Figure 16. Impact of Cost per Unit of Capacity (*βj*) on Total Cost

It can be inferred from Figure 16 that, as we expected, when *βj* increases, the total supply chain cost increases linearly. In other words, the cost per unit of capacity directly affects the total cost of the supply chain. However, the opened distribution centers remained the same, despite the changes in *βj*, which implies that the optimal location of the distribution centers is insensitive to the cost of its capacity. Only a few DC capacities changed, and these changes were less than one percent of the capacity values prescribed by the base model. Therefore, results are consistent across all values of *βj* and any change in the value of this parameter has little effect on the supply chain configuration.

6.2. Impact of Refinery Capacity Utilization per Product (α_p) on Petroleum Supply Chain Design and Shipment Costs

The units of capacity that each refinery allocates to produce each unit of product p, refinery capacity utilization (α_p) [127] is assumed to be the same for all products and equal to 1. For sensitivity analysis, the value of this parameter was varied between 1 and 1.5 for each of the three products in order to examine the effects on supply chain shipment costs.

The results of the sensitivity analysis show that when α_p for gasoline changes to 1.5 (α_1=1.5), the number of distribution centers opened remains at 20; however, when α_p for diesel changes to 1.5 (α_2=1.5), the opened distribution centers increases by one to 21 (one excess DC is opened in Delaware County, DE). In the case of jet fuel when α_3=1.5, opened distribution centers remained at 20. These results imply that the optimal locations of the distribution centers are not quite sensitive to the changes in the parameter α_p, since the DC locations have not changed dramatically between the base model and each sensitivity case. Although the number of opened DCs has not changed drastically from the base model (20), the capacity values of opened DCs varied considerably in each case. When α_1=1.5, the capacity of the DCs changed 24% on average and when α_2=1.5, the capacity values changed 10% on average. In the case where α_3=1.5, capacities changed 1% on average. Therefore, while the locations of the DCs did not change dramatically by changing α_p, the capacities of the opened DCs were heavily dependent on this parameter, especially in the case of gasoline and diesel fuel. Therefore, having an accurate estimate of this parameter can be beneficial to determine the distribution center capacities.

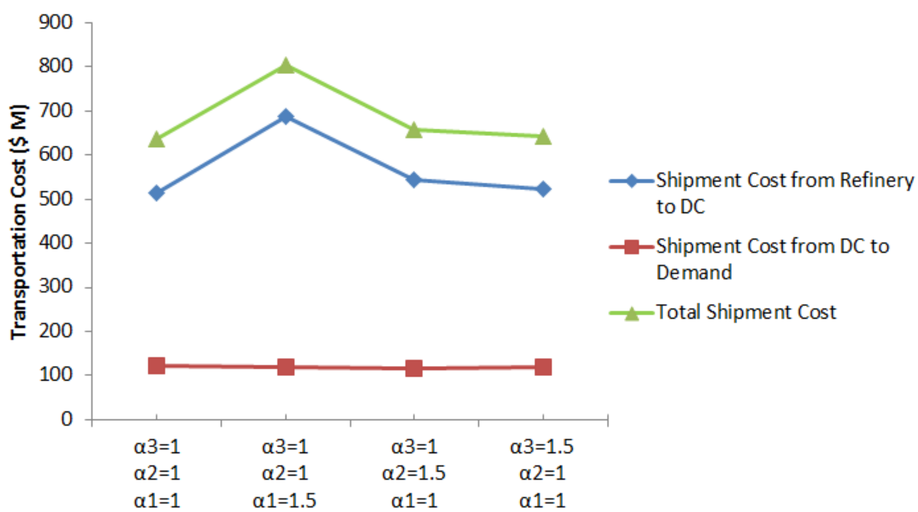


Figure 17. Impact of Refinery Capacity per Unit of Product on SC Shipment Costs

Another observation from the sensitivity analysis is shown in Figure 17. The figure indicates that the overall shipment cost is significantly impacted when the refinery capacity for gasoline increases from 1 to 1.5. However, the impact of increasing the refinery capacity for diesel and jet fuel is less dramatic. Another important observation is that increasing the refinery capacity for any of the products does not have a significant impact on the shipment cost from DCs to demand nodes. As can be seen in Figure 17, the shipment cost between DCs and demand nodes stays relatively flat for all values of α_p, while any increase in αp impacts the shipment cost from refineries to DCs. This implies that changing the value of α_p for any of the products results in a change in the volume of products shipped from the refineries to the DCs and, therefore, the shipment cost will be affected. On the other hand, the shipment cost from DCs to demand nodes remains unchanged from the base model when α_p changes, showing that these two parameters are not related.

6.3. Impact of Decreasing Gasoline Demand on PSC Strategic Planning

In the case study we obtained the demand values for the petroleum products from EIA online resources [128]. However, product demands may change over time and impact the future supply chain decisions. Therefore, to assess how the multimode supply chain design model scales with respect to changes in future demand, we have performed a sensitivity analysis on total consumption values of the three petroleum products in our study for the period of 2013 to 2040 [145]. The forecast values indicated that gasoline demand will decrease by 27%, while diesel and jet fuel demands will increase by 18% and 10% respectively (Figure 18). Such changes in demands may impact the supply chain decisions significantly. Therefore, we investigate the effects of changes in this parameter on supply chain decisions in further details.

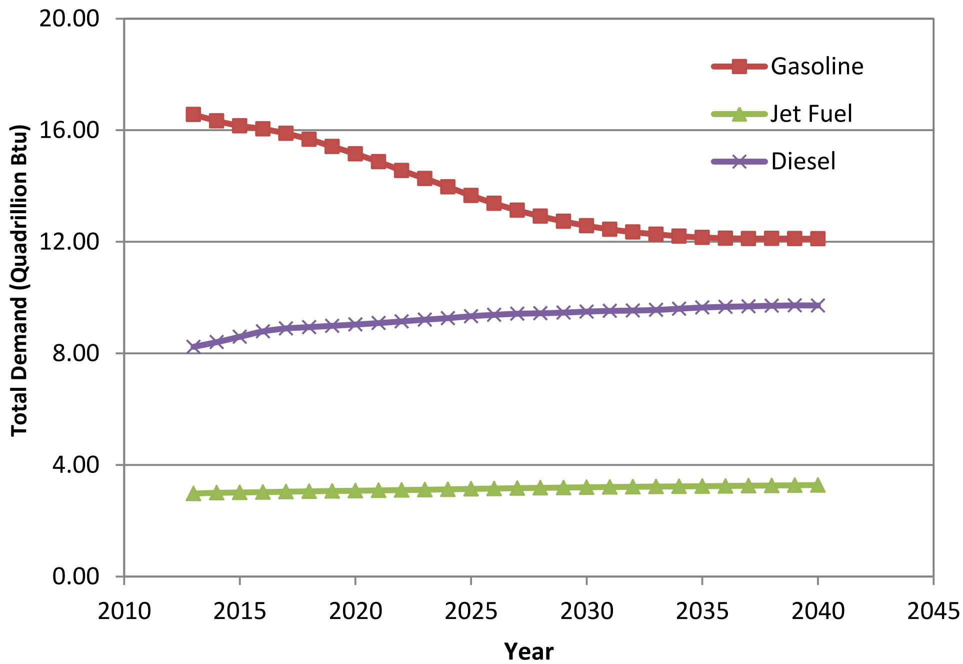


Figure 18. Total Demand Forecast for Petroleum Products during 2013-2040 [145]

Three scenarios were developed with regard to the changes in demand values where (a) the supply chain model completely re-optimizes the location of DCs, their capacities and allocation of the products, (b) the supply chain only optimizes the allocation of products, while distribution center locations and capacities remain fixed from the base multimode model and (c) DC locations remain fixed from the base model, however the capacities are optimized according to the changes in demand, and products are allocated to the DCs and demand nodes. The scenarios are optimized to global optimality and compared to each other and to the base model to evaluate the impact of changes in product demands on the supply chain design and decision variables. The results of the scenario analysis are presented in Table 13.

Table 13. Impact of Future Product Demands on Supply Chain Decisions

	Base model	Scenario (a)	Scenario (b)	Scenario (c)
Total SC cost ($Million)	810.9	608	619.2	608.6
Number of opened DCs	20	17	20	20
Total annual capacity for the opened DCs (Million Ton)	232.6	199.2	232.6	199.2
Primary Transportation Cost ($Million)	544.4	376.5	380	378.5
Secondary Transportation Cost ($Million)	179.8	157.6	154.4	155

Table 13 indicates that the total supply chain cost is reduced in all three scenarios, mainly because the demand for gasoline, which is the most consumed product, has decreased. This shows that gasoline demand has the most significant impact on supply chain performance measures and therefore, any change in the demand should be carefully monitored. Scenario (a) has the least total supply chain cost, since the supply chain design is re-optimized with regard to the changes in demand values. Re-optimization of the supply chain leads to different capacities for the distribution centers and in some cases closure or opening new DCs. According to the model results, four of the previously opened DCs in New York, Massachusetts and Maryland are closed in scenario (a); instead, one new DC is opened in Providence County, RI. Therefore, yet again, the multimode model choses the DC locations with regard to the accessibility of the DCs to the transportation networks and availability of the transportation modes to satisfy the demand with lowest cost.

In scenario (b) and (c), the supply chain is not re-optimized completely as mentioned above. Therefore, demand must be satisfied considering the same supply chain design as the base multimode model. As can be seen from Table 4, Scenario (c) performs very well in terms of costs despite the changes in demand, since the capacities of the located DCs are optimized with regard to the changes in demand. Scenario (b), however, has larger total cost compared to the other scenarios, since DC capacities and locations stayed the same as the base model despite the change in demand. As a result, unlike scenario (c) where the DC capacity utilization is at 100%, in scenario (b) only a very few DCs are utilized completely. Instead, most of the DCs are utilized around 80% (Figure 19) and, because the histogram is skewed left, there exists a distribution center which is not used at all. This distribution center is likely to be closed over the forecasted time period in scenarios (a) and (c).

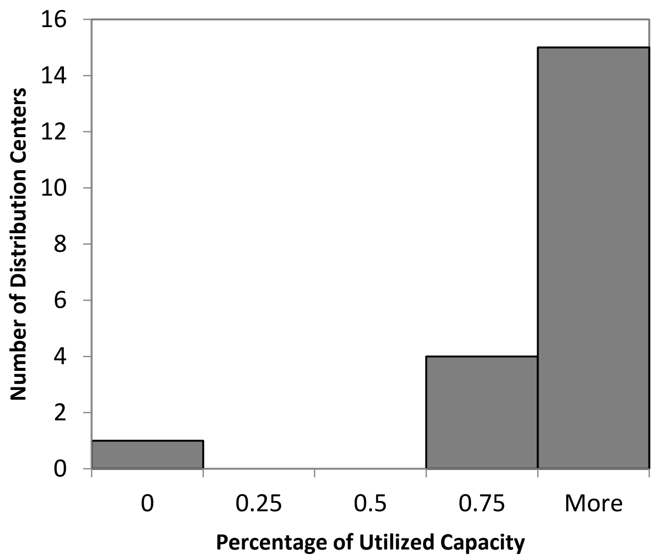


Figure 19. Histogram of DC Capacity Utilization for Scenario (b)

It is also worth mentioning that despite the change in the number of opened DCs and the reduction or expansion of the capacities in scenario (a), the re-optimized supply chain does not have a noticeably different configuration than that of other scenarios, meaning that the re-optimized supply chain won't have much scattered distribution centers compared to the base model, scenario (b) and scenario (c). This observation implies that the current supply chain configuration performs well and it is robust to the changes in future demand, therefore, by optimizing DC capacities according to the demand, we can obtain nearly similar results as the re-optimized supply chain model without opening any new DCs. Moreover, as expected, the primary and secondary transportation costs decreased in all three scenarios compared to the base model with more savings reported in the primary transportation.

Overall, the scenario analysis results imply that the decrease in gasoline demand has an impact on the supply chain decisions and design. If the supply chain is not re-optimized at all as in scenario (b), over the forecasted period, as gasoline demand declines, we will expect DC closure due to low capacity utilization. However, because even a low-utilized distribution center has fixed and variable costs, the total cost of the supply chain will increase compared to when the supply chain design is re-optimized. On the other hand, if the supply chain design remains intact and only the DC capacities are optimized according to the changes in demand, the total cost can be decreased, even very close to the optimal solution. This also shows that the multimode supply chain configuration tends to perform robustly by considering changes in key parameters in the future. Finally, optimizing the supply chain leads to the lowest costs and the most suitable configuration to deal with the changes in demand. Therefore, a trade off should be made in order to minimize the overall impact of demand on supply chain design and costs by considering the supply chain constraints for capacity expansion or reduction as well as re-optimization.

6.4. Impact of Contracted Reserved Products (b_{ijr}) on Total Costs and Logistics variables in the Hurricane Model

The amount of reserved products to be shipped from refinery *i* to DC *j* by the reliable logistics provider (b_{ijr}) is considered as one of the proactive mitigation strategies in the first stage of the hurricane model. In the base hurricane model we did not consider any upperbounds on the amount that can be reserved on the modes, therefore, we conducted a sensitivity analysis to study the impact of restraining the capacity that can be reserved on the transportation modes.

Parameter μ_i is defined such that it represents the maximum ratio (percentage) of products that can be supplied from refinery *i* and reserved on mode *r*. The average capacity for each refinery *i* throughout all scenarios is determined and used to derive the maximum amount of products supplied from refinery *i* to place an upper-bound on b_{ijr}. Therefore, the following constraint was added to the model: $\sum_{j \in J} b_{ijr} \leq \mu_i \bar{S}_i \quad \forall i, r$. Next, the hurricane model was solved multiple times by considering μ_i =0.02, 0.05, 0.1, 0.15, 0.2.

Figure 20 presents the impact of changing the maximum allowable ratio of products, μ_i, on the total amount of products that can be contracted to reserve on transportation modes. As is shown in Figure 20, as μ_i increases, the same modes (barge and rail) are chosen to reserve products. As the percentage change in μ_i increases, the total reserved products on each mode increases linearly while the amount reserved on barge increases at a greater rate.

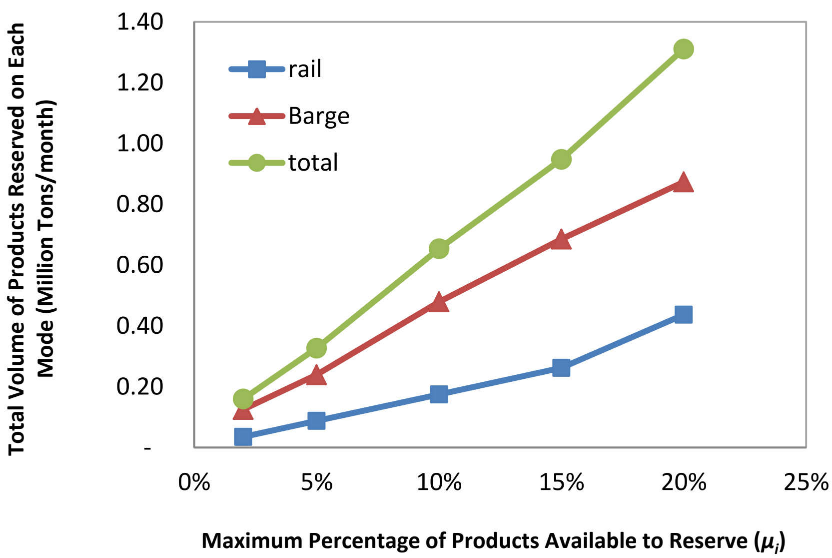


Figure 20. Impact of Change in Percentage of Available Products on Total Volume Reserved on Each Mode

Another result from the sensitivity analysis reveals that as the percentage of products that can be reserved on modes increases, the number of DCs holding extra inventory of each products decreases except for jet fuel. Table 14 shows that jet fuel is insensitive to the changes in reserved products on transportation modes, while gasoline and diesel reserves decrease as more capacity becomes available on the modes to reserve products. As a result of decrease in the number of DCs to hold extra inventory, the total reserved volume of products also decreased linearly.

Table 14. Impact of Change in Maximum Percentage of Products Available to Reserve (μ_i) on Number of DCs Holding Extra Inventory

	Petroleum Products		
μ_i	Gasoline	Diesel	Jet fuel
0.02	39	25	23
0.05	38	25	23
0.1	37	23	23
0.15	37	23	23
0.2	37	21	23

Finally, the impact of changes in (μ_i) on the total supply chain cost is represented in Figure 21. It is shown in Figure 21 that increasing the percentage of available products reserved on modes has a reverse impact on total costs: the total cost of the supply chain decreases linearly by the increase in the total amount allowed to be reserved on the transportation modes. In other words, it would be cheaper to reserve capacity on the modes than holding extra inventory in DCs and shipping it to the demand nodes. Therefore, considering the limitation of transportation mode capacities and their availability, a trade off should be made in choosing a combination of the aforementioned proactive strategies in order to minimize the total PSC cost.

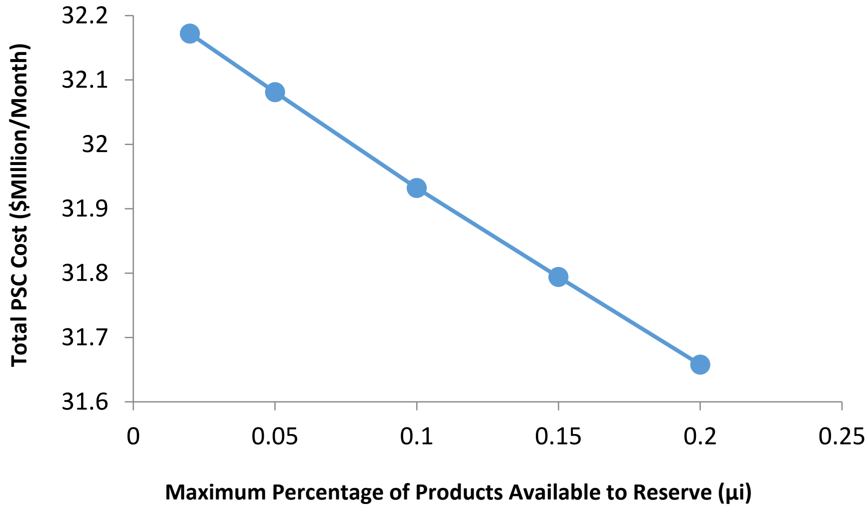


Figure 21. The Impact of Change in Maximum Percentage of Products Available to Reserve on the Expected total PSC.

In summary, the sensitivity analysis results imply that the proactive mitigation strategies which are considered before realization of disruption can play an important role on supply chain performance measures such as total cost, shipment cost, and inventory holding costs. Therefore, it is necessary to conduct a cost benefit analysis on the available resources and their limitations in order to make more robust decisions especially when modeling the supply chain under the risk of disruptions.

7. CONCLUSIONS AND FUTURE RESEARCH

The petroleum industry includes the global process of exploration, production, refining, and marketing of oil and petroleum products. Oil accounts for a large percentage of the world's energy consumption and is vital to many industries. Due to the importance of the PSC and the myriad challenges and uncertainties facing the oil industry, optimization of the PSC with a strong focus on cost reduction has increased over the past decade. Therefore, this research provides deterministic and stochastic multi-echelon, multi-product and multimode models that allow for strategic and tactical planning of the petroleum supply chain. Products considered in this study are gasoline, diesel and jet fuel. The deterministic MILP multimode model determines the distribution center locations and their capacities, routes, transportation modes, transportation costs, and transfer volume of products. The goal of the MILP is to minimize the costs related to the location and allocation of the petroleum products considered in the study thereby minimizing the total annualized downstream petroleum supply chain cost. On the other hand, the deterministic MILP single-mode (pipeline) model considers only one mode of transport in strategic and tactical decision making to minimize the total annualized downstream PSC costs. An important feature of our multimode model is that it incorporates multimodal transportation planning in the strategic design of the supply chain to enhance the efficiency and improve the supply chain performance measures. We validated the cost efficiency of the multimode model by conducting a thorough comparison between the multimode model and the pipeline-only model. The results illustrated that single mode strategic planning would not be optimal with multimode scheduling. Therefore, the multimode model demonstrated a more cost-efficient structure by optimizing the location of the distribution centers along with selecting the appropriate transportation mode or modes at any point in the supply chain to satisfy the total demand.

In addition to deterministic models, we developed a two stage SMILP model in the presence of random disruptions on refineries, and a two stage SLP model with recourse in the presence of anticipated (weather-related) disruptions. We specifically focused on hurricanes in the Gulf of Mexico region for the weather-related disruptions on refineries. Each model is designed with appropriate mitigation strategies suitable for the type of disruption in order to minimize the expected total supply chain cost. Two types of mitigation strategies were proposed when developing stochastic models: proactive mitigation strategies, which occur before the realization of uncertainty and reactive mitigation strategies, which occur after the realization of uncertainty. In the random model, since there is no prior information or preparation period, only reactive mitigation strategies are used in the second stage to cope with the uncertainty of the disruption. Multimodal transportation is used as the reactive mitigation strategy. In the hurricane model, however, since there is a preparation period, both proactive and reactive mitigation strategies are proposed. Proactive mitigation strategies include contracting a reliable third party logistics provider to reserve extra capacity of products on transportation modes and holding extra inventory at a subset of DCs for each product. Multimodal transportation is again used in the hurricane model as the reactive mitigation strategy.

The goal of the SMILP random model is to optimize the expected total supply chain costs by optimizing locations and capacities of the DCs in strategic planning and allocating the transfer volumes to DCs and demand nodes using multiple transportation modes in the second stage within an annual time horizon. The strategic decisions determined in the random model remained unchanged in the hurricane model, which is based on a monthly time horizon. Therefore, the hurricane model minimizes the cost of first stage variables (i.e. holding extra inventory of products and contracting a reliable third party logistics provider) and the expected shipment costs of the products in the second stage via multimodal transportation. Further, a comparison between the deterministic multimode model and the stochastic hurricane model was conducted in order to determine the value of stochastic solution and to compare the performance of both models under uncertainty. The results from this experiment depicted that shipment costs and total cost of the multimode model increase significantly in the presence of uncertainty compared to that of the hurricane model. Therefore, the hurricane model outperforms the deterministic model under uncertainty. Lastly, we emphasized the importance of separating the mitigation strategies for the stochastic models by examining the feasibility of the hurricane model without proactive mitigation strategies. The model did not present any feasible results without the proper proactive mitigation strategies.

Moreover, this study includes a realistic case study of the downstream petroleum supply chain in two regions of the United States: PADD 3 and PADD 1. The case study was selected to demonstrate the primary model features (detailed decisions about location, transportation modes, road networks, and transfer volumes) and to conduct spatial analysis to assist the decision making process. In addition, GIS was applied to the transportation networks using distance as an impedance factor and shortest path algorithms to consider detailed and realistic decisions on transportation planning.

The results of the case study for deterministic models indicated that the optimal supply chain design is different when planning for single mode and multimodal transportation. In other words, it is crucial to consider multimodal transportation when locating the facilities at the strategic level. Failing to do so will result in additional costs and a sub-optimal supply chain configuration as presented in the study. For stochastic models, the same case study set up is used; however, since the refinery capacities are randomized, they are determined via separate approaches for each type of disruption. In the case of random disruptions, we adopt the Sample Average Approximation (SAA) heuristic approach from prior literature to derive random capacities for the disrupted refineries. In the case of a hurricane, we limited the disrupted refineries to the off-shore refineries in Texas and Louisiana only, and derived random capacities with regards to hurricane categories and shut-in production simulated data from Energy Information Administration resources. Results of the case study for stochastic models determined the optimal strategic design of the supply chain in the presence of random disruptions which remained unchanged in the hurricane model. Instead, results of the hurricane model unveiled key decision variable values used to quantify mitigation strategies taken in the first and second stage of the hurricane model.

Sensitivity analysis was also conducted on several key parameters and variables in deterministic and stochastic models, which recommends several insights to PSC managers and the key stakeholders. The first set of sensitivity analysis was performed on the cost per unit of capacity which is a parameter to consider within the strategic decisions. The results of this experiment showed that the locations of potential distribution centers are insensitive to the annual variation of cost per unit of capacity. Therefore, the exact value of this parameter does not play a significant role in the optimality of the supply chain design, as was shown in the study. The second set of sensitivity analysis was done on the refinery capacity utilization per product. It revealed that the cost of shipping petroleum products from refineries is influenced by the capacities that refineries allocate to produce each specific type of product. However, the shipment cost from distribution centers to demand nodes is insensitive to the changes in the capacity each refinery allocates to produce petroleum products.

A scenario analysis was also conducted on the impact of future product demands, specifically declining gasoline demand, on the supply chain decisions. It is shown that the current supply chain design performs fairly well compared to the re-optimized supply chain in terms of DC locations, transportation costs and total cost. However, the current DC capacity utilization may not be at 100%, if the capacities are not re-optimized according to the demand. As a result, a few of the distribution centers are expected to close over the forecasted period.

Lastly, a sensitivity analysis was conducted on the impact of contracted reserved products on the total cost and logistics variables of the hurricane model. We studied cases where the reserved capacity is restricted to an allowable maximum amount of products that can be supplied from a subset of refineries. The results demonstrated that as the ratio of supplied products increases, total reserved products on each mode (barge and rail) increase linearly. Another result illustrated that the number of DCs holding extra inventory of gasoline and diesel decreases, while jet fuel is revealed to be insensitive to the changes in the maximum allowable amount of supplied products. Lastly, the results showed that the total SC cost decreased linearly, which indicates it would be cheaper to reserve capacity on the modes than holding extra inventory in DCs and shipping it to the demand nodes. Therefore, considering the limitation of transportation mode capacities and their availability, a trade off should be made in choosing a combination of the aforementioned proactive strategies in order to minimize the total PSC cost.

This study provided sound fundamentals for strategic planning in the PSC and supply chain risk management against catastrophic disruptions. However, it is clear that much additional work needs to be done. We address further study directions on a more comprehensive perspective in the following paragraphs.

First, the models provided in this study focused on a static time horizon, which is annual. Although this time period was suitable for our strategic analysis, incorporating multi-period time horizons in the model will serve as a valuable foundation for analyzing tactical decisions, especially in the presence of disruptions. In this regard, adding transport fleet scheduling to the multi-period time horizon context along with the transportation mode selection in our study will serve as a valuable foundation for future research.

In addition, in our study, we assumed that demand is deterministic and always satisfied. In order to gain more realistic results from the models, it would be critical to consider extending the stochastic models with product demand and market price uncertainties. There exist a considerable number of studies on the PSC which focus on price, yield, and demand uncertainties (e.g. Khor et al. [98] , Leiras et al. [97], and Al-Othman et al. [73]). However, these papers did not consider disruptions. Therefore, it would be very useful to have both represented in one unified model to create a comprehensive study of the PSC under uncertainty.

Finally, our proposed models only optimized the strategic (location) and tactical (shipment) costs for the products in deterministic and stochastic contexts. Future work can optimize the PSC by considering multiple criteria such as sustainable measures and environmental performance. For example, incorporating greenhouse gas emissions from select transportation modes can be added to the objective as an environmental measure in order to develop bi/multi-objective optimization models for the downstream PSC.

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APPENDIX A. LIST OF REFINERIES

Refinery ID	Refinery Name	State
1	Equistar Chemicals LP	TX
2	Shell Deer Park Refining	TX
3	Total Petrochemicals USA Inc.	TX
4	Pasadena Refining System, Inc.	TX
5	Exxon Mobil Refinery	TX
6	Navajo Refining Co LP	NM
7	Total Petrochemicals & Refining USA, Inc.	TX
8	Hunt Refining Co: Refinery	AL
9	Coutret & Associates Inc.	LA
10	Valero Houston Refinery	TX
11	Motiva Enterprises LLC	TX
12	Western Refining	TX
13	Provenance Consulting LLC-Borger	TX
14	Calcasieu Refining	LA
15	Conocophillips Alliance Refinery	LA
16	Exxon Mobil	LA
17	Murphy Oil Corporation	AR
18	ConocoPhillips	TX
19	Marathon Grayville Refinery	LA
20	Delek Refining Ltd	TX
21	Valero Bill Greehey Refinery	TX
22	Alon	TX
23	shell chemical LP	AL
24	Goodway refining LLC	AL
25	cross oil refining and marketing Inc.	AR
26	Chalmette refining LLC	LA
27	Motiva enterprises-convent	LA
28	Motiva-Norco	LA
29	Pelican refining company	LA
30	Alon refining Krotz springs Inc.	LA
31	Citgo petroleum corporation	LA
32	placid refining Co.	LA
33	Shell oil products US	LA
34	Valero energy corporation	LA

Refinery ID	Refinery Name	State
35	Valero refining New Orleans	LA
36	Chevron USA Inc.	MS
37	Ergon refining Inc.	MS
38	Hunt southland refining Co.	MS
39	Western refining southwest	NM
40	BP products	TX
41	Citgo refining	TX
42	Flint hills resources	TX
43	Houston refining	TX
44	Lazarus energy LLC	TX
45	Marathon petroleum	TX
46	Philips 66 company	TX
47	Premcor refining	TX
48	South Hampton resources	TX
49	Valero energy Corp- sunray- three rivers	TX
50	Valero refining-Texas city	TX
51	Western refining company	TX
52	Sunoco Marcus Hook Refinery	PA
53	Irving Oil	NH
54	American Refining Group Inc.	PA
55	Paulsboro Refining Co	NJ
56	Delaware city refining co LLC	DE
57	Hess corporation	NJ
58	Philips 66 company	NJ
59	Monroe energy	PA
60	Philadelphia energy solutions	PA
61	United refining co	PA
62	Ergon west Virginia	WV
63	Delaware oil terminal	DE

APPENDIX B. LIST OF DISTRIBUTION CENTERS

Distribution Center ID	Name	State
1	Albany	New York
2	Suffolk	Massachusetts
3	Hampden	Massachusetts
4	Norfolk	Massachusetts
5	Hartford	Connecticut
6	Providence	Rhode Island
7	Fairfield	Connecticut
8	Orange	New York
9	Westchester	New York
10	Rockland	New York
11	Passaic	New Jersey
12	Bergen	New Jersey
13	Bronx	New York
14	Nassau	New York
15	Essex	Massachusetts
16	New York	New York
17	Hudson	New Jersey
18	Queens	New York
19	Somerset	New Jersey
20	Kings	New York
21	Union	New Jersey
22	Berks	Pennsylvania
23	Allegheny	Pennsylvania
24	Richmond	New York
25	Monmouth	New Jersey
26	Montgomery	Pennsylvania
27	Mercer	New Jersey
28	Lancaster	Pennsylvania
29	Philadelphia	Pennsylvania
30	Delaware	Pennsylvania
31	Camden	New Jersey
32	New Castle	Delaware
33	Baltimore	Maryland
34	Baltimore City	Maryland

Distribution Center ID	Name	State
35	Montgomery	Pennsylvania
36	Prince George's	Maryland
37	Fairfax	Virginia
38	Forsyth	North Carolina
39	Guilford	North Carolina
40	Wake	North Carolina
41	Mecklenburg	North Carolina
42	Cumberland	North Carolina
43	Greenville	South Carolina
44	Gwinnett	Georgia
45	Cobb	Georgia
46	Charleston	South Carolina
47	Duval	Florida
48	Marion	Florida
49	Volusia	Florida
50	Seminole	Florida
51	Pinellas	Florida
52	Hillsborough	New Hampshire
53	Manatee	Florida
54	Lee	Florida
55	Broward	Florida
56	Monroe	New York
57	Onondaga	New York

APPENDIX C. STOCHASTIC CAPACITY OF REFINERIES DURING HURRICANE SCENARIOS

Mean Value of Lost Capacity (Ton/Month)						Random Capacities (Ton/Month)				
Refinery ID	0.068	0.19	0.28	0.69	0.94	Category 1	Category 2	Category 3	Category 4	Category 5
1	0	0	0	0	0	0	0	0	0	0
2	76513	215301	310549	772810	1056075	1045993	907205	811956	349696	66430
3	39075	109955	158598	394676	539341	534192	463313	414669	178591	33926
4	23398	65841	94969	236333	322959	319875	277433	248305	106941	20315
5	80607	226823	327168	814168	1112593	1101971	955756	855410	368410	69986
6	360438	360438	360438	360438	360438	360438	360438	360438	360438	360438
7	39075	109955	158598	394676	539341	534192	463313	414669	178591	33926
8	123579	123579	123579	123579	123579	123579	123579	123579	123579	123579
9	195666	195666	195666	195666	195666	195666	195666	195666	195666	195666
10	20591	57940	83573	207973	284204	281490	244141	218508	94108	17877
11	66685	187647	270662	673550	920432	911645	790683	707668	304781	57898
12	418794	418794	418794	418794	418794	418794	418794	418794	418794	418794
13	501180	501180	501180	501180	501180	501180	501180	501180	501180	501180
14	18251	51356	74076	184340	251908	249503	216397	193678	83414	15846
15	114979	323543	466678	1161341	1587019	1571868	1363304	1220169	525506	99829
16	1724951	1724951	1724951	1724951	1724951	1724951	1724951	1724951	1724951	1724951
17	284917	284917	284917	284917	284917	284917	284917	284917	284917	284917
18	57794	162628	234574	583743	797708	790092	685259	613313	264143	50178
19	122139	343691	495739	1233659	1685844	1669750	1448199	1296151	558230	106045
20	205964	205964	205964	205964	205964	205964	205964	205964	205964	205964
21	46797	131682	189938	472666	645917	639751	554865	496609	213881	40630
22	229993	229993	229993	229993	229993	229993	229993	229993	229993	229993
23	274619	274619	274619	274619	274619	274619	274619	274619	274619	274619
24	14074	14074	14074	14074	14074	14074	14074	14074	14074	14074
25	25746	25746	25746	25746	25746	25746	25746	25746	25746	25746
26	45042	126744	182815	454941	621695	615760	534058	477987	205861	39107
27	54986	154727	223177	555383	758953	751707	651967	583516	251310	47741

Mean Value of Lost Capacity (Ton/Month)						Random Capacities (Ton/Month)				
Refinery ID	0.068	0.19	0.28	0.69	0.94	Category 1	Category 2	Category 3	Category 4	Category 5
28	54635	153739	221753	551838	754109	746909	647805	579792	249706	47436
29	0	0	0	0	0	0	0	0	0	0
30	18719	52673	75975	189067	258367	255900	221946	198644	85552	16252
31	100098	281668	406278	1011033	1381617	1368427	1186857	1062248	457492	86908
32	13337	37529	54132	134710	184086	182329	158137	141534	60956	11580
33	10529	29629	42736	106350	145331	143944	124845	111737	48123	9142
34	29248	82301	118711	295417	403698	399844	346791	310381	133676	25394
35	47967	134974	194687	484483	662065	655745	568737	509025	219228	41646
36	1132804	1132804	1132804	1132804	1132804	1132804	1132804	1132804	1132804	1132804
37	78953	78953	78953	78953	78953	78953	78953	78953	78953	78953
38	37760	37760	37760	37760	37760	37760	37760	37760	37760	37760
39	74147	74147	74147	74147	74147	74147	74147	74147	74147	74147
40	107678	302998	437044	1087596	1486243	1472054	1276734	1142688	492136	93489
41	38139	107321	154800	385223	526423	521397	452215	404737	174313	33114
42	67644	190345	274553	683232	933664	924750	802050	717842	309162	58730
43	60512	170276	245605	611195	835223	827249	717485	642156	276566	52538
44	2684	7553	10894	27110	37047	36693	31824	28483	12267	2330
45	18719	52673	75975	189067	258367	255900	221946	198644	85552	16252
46	57794	162628	234574	583743	797708	790092	685259	613313	264143	50178
47	67855	190939	275410	685366	936580	927639	804555	720084	310128	58914
48	0	0	0	0	0	0	0	0	0	0
49	854752	854752	854752	854752	854752	854752	854752	854752	854752	854752
50	52646	148143	213680	531750	726657	719720	624224	558686	240616	45709
51	418794	418794	418794	418794	418794	418794	418794	418794	418794	418794