Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

ANALYZING PRE-POSITIONING WITHIN A DISRUPTED BULK PETROLEUM SUPPLY CHAIN

Manuel D. Rossetti
Julianna Bright

University of Arkansas
Department of Industrial Engineering
4207 Bell Engineering Center
Fayetteville, AR 72701, USA

ABSTRACT

This paper examines the modeling of disruption events within a bulk petroleum supply chain through the use of an object-oriented simulation library. We describe how the library models disruption events and their effects on supply chain operations. This includes how to specify disruptions, mitigation strategies and metrics that can be used to assess the impact of the disruption. The modeling is illustrated via an analysis of a supply chain involving DLA Energy's bulk petroleum supply chain as impacted by a category 4 hurricane scenario. The effectiveness of pre-positioning of inventory within the supply chain is illustrated.

1 INTRODUCTION

The Defense Logistics Agency (DLA) Energy Division manages the global supply chain network for bulk petroleum products for the support of U. S. military bases. The bulk petroleum supply chain network (BPSCN) is a complex supply network that consists of external commercial suppliers, DLA fuel terminals, and end customer locations (mostly military bases). The network is supported through four major transportation modes (barge, truck, rail, and pipeline), most of which are commercial entities. The network supports eight different fuel products, which include three types of additives and five different fuel types. For the purposes of this paper, we only consider U.S. standard commercial jet fuel.

The DLA Energy supply chain network is a global inter-connected network and has many unique issues that make its efficient operation very challenging. In addition to supporting normal peace time operations, the network must plan for and be able to support both war time and contingency operations for both local and global theaters of operation. A key management issue is the uncertainty of demand because of these operations, some of which have little advance warning. In addition, there is uncertainty in supply because events may occur that disrupt the availability of fuel. We call these types of events *disruption* events. A disruption event can cause changes in both supply and demand over a period of time. An example of such an event is Hurricane Harvey, which made land fall in the Houston, Texas area in the summer of 2017. Hurricane Harvey caused serious disruptions within the Houston area that had a rippling effect within the U.S. because Houston is a key location for fuel refinery operations.

Rossetti and Bright (2018) describes the conceptual modeling required to represent bulk petroleum supply chain networks within a simulation context. In addition, they describe the basic simulation constructs of an object-oriented library that can be used to model the performance of a BPSCN over general planning horizons involving normal and contingency operations. This paper builds on the work of Rossetti and Bright (2018) to further describe the disruption scenario modeling that is supported by the simulation library as well as performance measures that are useful in understanding the behavior of a system under disruption events. In addition, the library supports the modeling of effectiveness of disruption mitigation strategies. In particular, we provide the ability to assess pre-positioning strategies within the BPSCN.

The rest of this paper is structured as follows. First, we provide background literature on supply chain simulation and disruption modeling. In Section 3, we summarize modeling of the essential elements of a BPSCN. Then, in Section 4, we describe the modeling of disruption events and pre-positioning mitigation strategies. In Section 5, we present an analysis of a scenario involving a category 3 or 4 hurricane making land fall on the east coast of the U.S. The example is used to illustrate the effect of the disruption and the effectiveness of pre-positioning inventory within the network as a mitigation strategy. In the final section, we wrap up with a summary of the findings and some goals for future research within this modeling area.

2 BACKGROUND

Because the performance analysis of supply chains is essential within industry, many commercial packages facilitate this analysis. For example, Supply Chain Guru has capabilities for simulating and optimizing supply chains and AnyLogic has specialized supply chain libraries. For background on approaches to supply chain simulation in the literature, we refer the interested reader to Oliveira et al. (2016). Oliveira et al. (2016) noted that modeling and agent based simulation "has emerged as a robust tool that can generate significant results for companies"; however, there is still a need to include enhanced real-world behavior into the simulation models. In the case of simulating bulk petroleum supply chains, Cheng and Duran (2004), Pitty et al. (2008), and Xiong et al. (2017) all illustrate the impact of using supply chain simulation for modeling the complexities involved in modeling BPSCNs; however, none include disruption modeling.

Humanitarian logistics research has predominantly featured optimization models (Rafael et al. 2013). The review by Rafael et al. found four commonly-modeled topics: routing and transportation under uncertainty in the immediate aftermath, supply chain design and supplier selection to prepare a response plan, planning the allocation and distribution of aid, and facility location/allocation (aid supplies, shelter, medical stations, etc.). Inventory location, including pre-positioning, was often incorporated in models in all four areas. Richardson et al. (2010) critiques pre-positioning models for excluding qualitative risk factors. Jahre (2017) further critiques the predominance of inventory pre-positioning as a risk mitigation strategy in her survey of published case studies. The commercial supply chain risk management literature suggests many other strategies, but they are only sporadically employed by humanitarian agencies. This critique is supported by a case study on a disaster planning in a commercial supply chain from Kamalahmadi and Parast (2017), which found that using backup suppliers or protecting regular suppliers reduced the probability of unmet demand across all scenarios more than pre-positioning inventory and had lower expected costs. Planning inventory pre-positioning is the subject of several papers in humanitarian and general commercial logistics. Ni et al. (2017) present a robust optimization (min-max) model that is more tractable than the standard two-stage stochastic models, such as that analyzed in Akkihal (2006). Walsh et al. (2002) present a case study of a commercial supply chain in which stainless steel pipes and fittings were a bottleneck component. They found that keeping inventory further up the supply chain provides more flexibility within their production facilities. Flexibility is also a mitigation strategy noted in Jahre (2017).

This paper continues a stream of research on object-oriented frameworks for simulating supply chains. As such, it represents a contribution to the conceptualization of such designs, which assists researchers and practitioners in better understanding the essential abstractions within a particular domain (e.g. supply chains). An example of this is the Java Simulation Library of Rossetti (2008). Other work in this stream includes Rossetti and Chan (2003) who built a supply chain modeling framework which contains logistics elements like facility, warehouse, product etc. and Rossetti and Thomas (2005) who built an architecture for simulating spare parts supply chain networks. Rossetti et al. (2008) and Rossetti and Chen (2012) provide the abstractions of locations, inventory holding points, stock keeping units, transportation, inventory policy, etc. that have been customized towards the bulk petroleum supply chain as described in this paper. This paper builds on this previous work by adding scenario capabilities and designing metrics to compare performance across scenarios, possibly even with different network topologies. The approach of this paper is more descriptive than prescriptive, designed for rapid iteration in a decision support system, which is a minority approach (Rafael et al. 2013). Most published models are stochastic programming models, which are computationally intensive to solve and often fairly dependent on having good data available. Complex operational constraints and dependencies in the supply chain are also more straightforward to include in a simulation model. A simulation approach incorporates uncertainty more readily and executes more rapidly, making it more feasible to use under the dynamic conditions of an emergency or disaster.

3 OVERVIEW OF BPSCN MODELING

Since the primary purpose of this paper is to illustrate disruption modeling within a BPSCN, this section provides only an overview of BPSCN simulation modeling. This is intended to provide enough context for understanding the disruption modeling and the subsequence simulation analysis. For further details on the conceptual modeling of a BPSCN, please refer to Rossetti and Bright (2018).

In essence, the supply chain consists of products (fuel types), terminals (processing and storage locations), transportation (barge, truck, rail, and pipeline), and customers (processing and storage locations). Customer locations are essentially terminals that issue fuel to end users (e.g. military aircraft) to meet end-user demand requirements. While there may be many fuel tanks at a terminal, the fuel within separate tanks is considered in aggregate. This aggregate fuel at a location is called a stock keeping unit SKU. In other words, the fuel tanks are just storage locations for the fuel at the location, similar to how a distribution center may have many storage locations for a single type of product.

Each SKU has an inventory control policy that determines when to order and how much to order from the terminal's supplying node(s) within the network. From a conceptual standpoint, the inventory policy used can be adequately represented as a (min, max) or (s, S) policy. The minimum value is called the control limit and the maximum is called the maximum authorized inventory level. When the (aggregate) fuel level at the terminal reaches the control limit, a replenishment order is placed to ensure that the inventory level goes up to the maximum authorized level. While the management of ordering within the DLA Energy supply chain is much more complex than a simple (min, max) policy, the essential elements of the replenishment processes are well-modeled by this control policy. The control limit and maximum authorized inventory levels are set based on economic (transportation costs, transportation load sizes, ordering costs, etc.) and on service considerations (including adequate safety stock protection and war reserve stocking analysis).

Each terminal has resources that facilitate the receiving and issuing of fuel, into and out of fuel storage tanks. The resources are dedicated to a specific transportation mode. For example, to handle tanker trucks the terminal must have a resource (truck racks) that permit the off-loading (pumping) of the fuel from the tanker trucks into the appropriate storage tanks. The resources have a finite capacity and can be dedicated to issuing, receiving, or to both issuing and receiving fuel. Rossetti and Bright (2018) discuss the modeling of the complex rules that permit or restrict the simultaneous operation of various resource types at a terminal due to piping constraints. For the purposes of this paper, we can consider the resources as having a finite capacity, a pumping rate, and to be assigned to the handling of various fuel types for a particular transportation mode at a particular location. The resources can be busy, idle, unavailable (unscheduled) or failed. Scheduled downtime (unavailable) and unplanned failures are the basis for modeling disruption events within the BPSCN.

Transportation within the BPSCN is handled by four major types of transportation modes (barge/ship, rail, tanker truck, and pipeline). Each mode has pre-defined load sizes. For example, one type of tanker truck has a 7800 gallon capacity. Barges have load sizes such as 714,000 gallons. Pipelines operate in pre-designated batch sizes. See Costa et al. (2014) for further details on how pipelines operate. For our purposes, a pipeline batch is essentially a unit load size for a pipeline type transportation mode. Because transportation is arranged (either by contract or spot market offerings), we do not model transportation with a finite capacity but instead only model the time that it takes to move fuel via the particular transport mode. In theory, the number of transport carriers can flex to the transport needs. In practice, the transportation requirements may in fact not be available without delay. We do not model contention for these transportation resources but rather measure the transportation requirements during the simulation. This allows for an analysis of whether or not current contracting options will be adequate in meeting the implied transportation requirements determined by normal and contingency operations. In addition, we allow transportation options to become unavailable due to disruption events.

As can be noted from this overview of modeling a BPSCN, the data requirements of such simulation modeling can be tremendous both in terms of the inputs to the model and the number and amount of data generated from the simulation. The BPSCN library described briefly in Rossetti and Bright (2018) provides the ability to input the supply chain network structure from a database and to capture all simulation output measures to a database. Unfortunately, a full discussion of the architecture and design of the BPSCN object-orient simulation library is beyond the scope of this paper. A future paper is planned that will illuminate the design of the library and its full functionality. In the next section, we describe how disruption events are included into the simulation modeling.

4 MODELING DISRUPTIONS AND METRICS

For our purposes, a disruption represents a sudden change to the system's operating processes that may cause a degradation in system performance. For example, a hurricane making land fall in an area serviced by the supply chain would be considered a disruption. Disruption events are inherently random. If they were not random, then they could be planned for in such a manner so that no degradation would be possible. By random, we assume that the exact start time and duration of the event cannot be known with certainty in advance. The disruption may or may not occur and its occurrence is governed by stochastic processes. Disruptions can be anticipated or forecasted to occur with some likelihood. For example, a hurricane is anticipated to occur at some time during the planning horizon and last for some random amount of time. Some disruptions come with a warning of increased likelihood of occurrence but others will have virtually no warning (e.g. earthquakes). We can design the system and its operating procedures to be robust with respect to disruptions. That is, if we can forecast the disruption, we can design the system or have contingency plans ready that can mitigate the degradation in system performance.

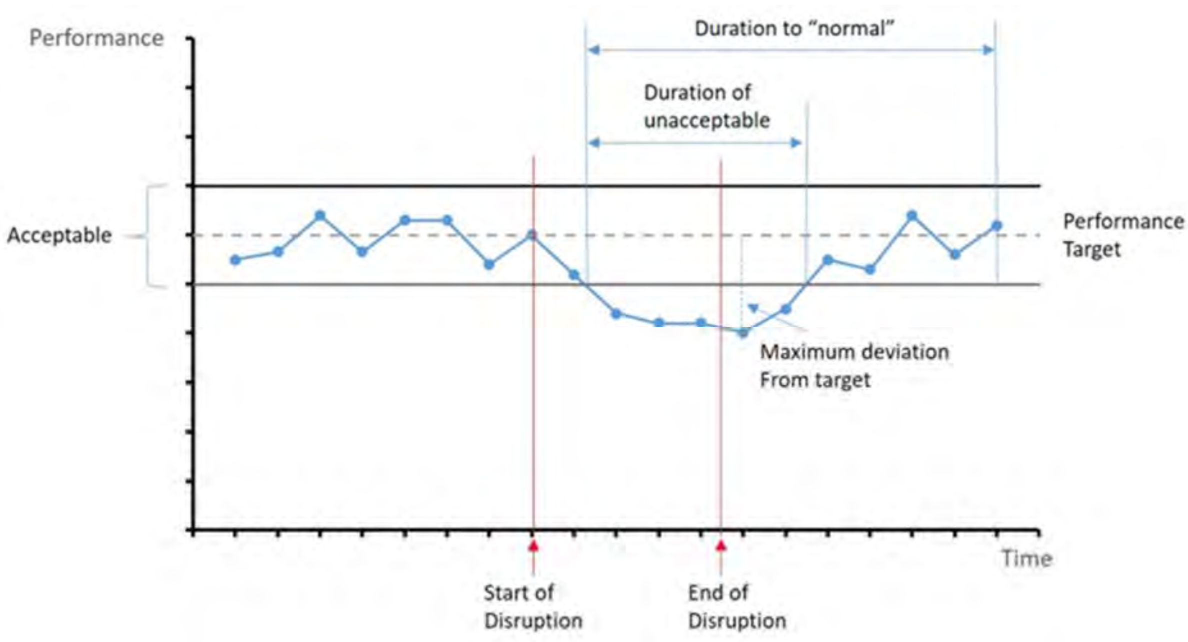

Figure 1: Degradation of performance due to disruption.

Figure 1 illustrates the notion of system performance degradation due to disruption. Prior to the disruption, the system performs within an acceptable performance band. After the start of the disruption, system performance starts to degrade, eventually reaching a low point, which may or may not be during the actual disruption event. After the disruption is ended, it is expected that the system performance will begin to return to normal and eventually reach acceptable operating performance targets. A goal of contingency planning is to reduce the time that it takes the system to return to acceptable operating performance. The ability of the system to return to an acceptable state is related to the concept of resilience. Vugrin et al. (2010) define system resilience as "Given the occurrence of a particular disruptive event (or set of events), the resilience of a system to that event (or events) is that system's ability to reduce efficiently both the magnitude and duration of deviation from targeted system performance levels." Two important components of this are the amount of deviation from targeted performance and the length of time that the system performance is degraded. A goal of the simulation modeling is to be able to estimate and understand these quantities in order to understand the effectiveness of various mitigation strategies.

Within the BPSCN object-oriented modeling framework, we model a disruption with a class called Disruption that controls when and what supply chain elements are affected. To specify a disruption the modeler must provide the following inputs:

- Predicted start time – the time that the disruption event is predicted to occur within the time horizon
- Predicted duration – the length of time that the disruption is supposed to last
- (optional) Warning time – the minimum time that a warning signal about the event can be sent out prior to the start of the disruption

A disruption may affect zero or more resources (positioned at terminals) and zero or more transportation carriers. A resource affected by a disruption can have an unplanned down time (failure) and a scheduled down time. Unplanned down times are modeled to occur at the start of the disruption and last for a possibly random duration that is specific to the particular resource that is affected. For example, a barge dock may be down for 14 days due to a storm and subsequent damage. Resources may also have planned downtimes. These are scheduled down times because of the anticipated warning associated with the event. In this case, the resource can be scheduled to be down before (prior) and after (post) disruption. For example, pipeline resources can be shut down two days prior to a storm and for two days after a storm in order to prevent serious damage or spills because of the storm. It takes time to prepare the resource to be shut down and time to bring the resource back up to full operating capacity.

Finally, a particular disruption may affect zero or more transportation options. The affected transportation option is specified by the transportation mode and the origin and destination terminals for the shipment. The transportation option for the origin-destination pair will be made unavailable for a specified (possibly) random duration time that commences at the start of the disruption. Different tuples (origin, destination, transport mode) can have different disruption down times during the disruption. When a transportation option is disrupted, any in progress shipments are delayed for the length of the disruption and any new shipments do not start their transportation until the disruption ends.

Within this framework, a time horizon may experience zero or more disruptions. This representation permits the analyst to model a planning horizon that can experience more than one disruption that affects may different terminals (their resources by mode) and their transport options. For example, an entire hurricane season can be modeled as a series of disruption events that affect terminals in the gulf coast as well as the east coast at different times with different impacts.

The BPSCN modeling framework not only captures standard supply chain metrics but also permits the collection of metrics designed to identify at risk locations. For every terminal and every resource within the network, the queuing and resource statistics are captured. This includes the number of shipments waiting to be processed by resources at each terminal (including their waiting time statistics). Each shipment is broken down into a number of work orders that are processed by receiving resources and statistics are collected on the individual work orders as they utilize the resources. Similarly for processing incoming demand requirements. The number of requirements waiting for processing, their time waiting, as well as their individual work orders as they are issued on resources are tracked. Overall, every resource reports its queuing statistics as well as the resource utilization statistics. These include the statistics on the number of units busy, idle, failed, and inactive over time. These performance measures can all be used to assess whether or not a terminal has more than or not enough resources available to adequately process shipments and demand requirements throughout the time horizon and during disruptions. Performance is also collected on the shipments as they move between locations. These include the number of and time spent for shipments moving from location I to location K. Time persistent averages are computed as well as the maximum value of the number of shipments that moved from location I to location K and the average time that a shipment spends moving from location I to location K.

Since inventory management is a key function of the supply chain, inventory performance measures are collected for every stock keeping unit within the network. This includes (first) fill rate, ready rate, proportion of time with no stock on hand, time average amount on hand, time average amount on order, time average amount on back order, time average number of back orders, average waiting time of back orders and order frequency.

As illustrated in Figure 1, disruptions degrade the performance of the supply chain over time. Because it is important to understand the impact of the disruption, specialized metrics have been designed to understand this behavior. Two types of general response variables have been designed to assist with this analysis. The first permits the definition of a *response interval*. A response interval represents an interval of time over which statistical collection can be performed. This recognizes the time dependent behavior that occurs during a simulated time horizon. For example, referencing Figure 1, there are at least four distinct intervals of time over which the performance of the system can vary. These include

1. The entire time horizon from time 0.0 to the end of the horizon, T_H
2. The pre-disruption period, from time 0.0 to the start of the disruption, T_D
3. The disruption period, from T_D to the end of the disruption, T_E
4. The post disruption period, from T_E to the end of the horizon, T_H

The BPSCN modeling framework permits statistics to be collected on *any* supply chain performance measures for *any* period of time, such as the average inventory level before, during, and after a disruption. The modeler simply defines a response schedule with the performance measures and response intervals of interest. Response schedules even allow their intervals to overlap. In addition, the schedule can be defined to repeat. For example, a schedule that collects statistics hourly can be set to repeat daily. Thus, a model with a multi-day horizon might collect hourly performance using a schedule that repeats daily.

The second general type of performance measure for disruption scenarios involves monitoring the response level. We might be interested in how well the observed response tracks the metric's target performance level (see Figure 1). Within the BPSCN, the inventory control limit is a critical performance target. In practice, the inventory control limit is not only monitored to determine when to order but more importantly to assess whether the on hand inventory level is falling substantially below the inventory control limit, indicating that the inventory control processes are degrading and the location is becoming at risk of stock outs. The metric that tracks a target level is called a *level response*. A level response defines a target level for a performance measure and collects statistics on how well the response is maintained. The following performance measures are estimated:

- Maximum and average distance above/below the target during the observation period
- Proportion of time spent above/below the target during the observation period
- Total and average time spent above/below the target during the observation period
- Probability and number crossings of the inventory level target during observation period
- Probability that the process stays above/below the target given that it was already above/below the target during the observation period

In addition to the previous metrics that focus on performance and the target level, the following metrics are defined in terms of the deviation from the target level. Let $X(t)$ be the performance at any time t and let L be the performance target level. Let $D(t) = X(t) - L$ be the performance *deviation.* Define the positive and negative deviation as follows:

$$PD(t) = \begin{cases} X(t) - L & X(t) \geq L \\ 0 & X(t) < L \end{cases} \qquad ND(t) = \begin{cases} L - X(t) & X(t) < L \\ 0 & X(t) \geq L \end{cases}$$

Then, we can define the following measures:

- $\overline{D}$, $\overline{PD}$, $\overline{ND}$, $\overline{TD}$= $\overline{PD} + \overline{ND}$ are the time average deviation, positive deviation, negative deviation and total deviation, respectively.
- $\overline{PD}/\overline{TD}$ is the proportion of the deviation due to being above the limit
- $\overline{ND}/\overline{TD}$ is the proportion of the deviation due to being below the limit
- $\overline{PD}/L\,\overline{ND}/L\,\overline{TD}/L$ are the relative sizes (as a proportion) of the positive, negative, and total deviation relative to the size of the limit.

These metrics permit an assessment of the magnitude of the deviation as well as an assessment relative to the size of the total deviation and to the size of the target level. The latter two measures do not depend on the units associated with the target performance level.

A supply chain simulation of any realistic size will collect thousands of statistical output measures for review. In the BPSCN, a well-structured database captures all outputs, to facilitate analysis of experimental scenarios. A scenario is a unique setting of the inputs, for which the analyst requires detailed outputs. For example, a scenario with and without the disruption would naturally be of interest. In addition, over 20 different database views have been prepared to facilitate the identification of locations and measures that should be of concern within a scenario and across scenarios, such as the fill rates for every SKU in every scenario. By sorting the SKU's fill rates from smallest to largest, the analyst can quickly identify which SKUs have unacceptable performance. Views for fill rate, ready rate, inventory on hand, queues, resource utilization, and level responses have all been designed. The analyst can use SQL to extract and analyze any and all metrics. Because what we really care about is how the scenarios *differ*, specialized views have been designed to identify which metrics have changed between scenarios. This is similar to the goal of multiple comparison methods, see for example, Goldsman and Nelson (1998).

To put this in context, since we are most interested in a change from the no disruption case, we developed views that permit pairwise comparison between scenarios for critical performance measures. Let θ_k be the performance of scenario, k, for some performance measure, θ. We compute the difference, relative change, and the absolute relative change for the performance measures: $D = \theta_i - \theta_k$, $RC = (\theta_i - \theta_k)/|\theta_k|$ and $|RC|$. If θ_k is the no disruption scenario and $i \neq k$ are scenarios with disruption (and possibly mitigation strategies), then, we can assess the impact of the disruption in terms of these measures.

Since our first concern is to find areas that are at risk due to the disruption, we are only concerned with performance measures that change in disruption scenarios. These comparison metrics permit a first-order screening of the scenario results, allowing us to eliminate many performance measures that are (in essence) meaningless to the assessment. For example, while a disruption event may strongly affect a particular location and its subsequent downstream customers, the locations upstream or far from the event will most likely not be affected, and thus show no difference.

The following section illustrates the analysis facilitated by the BPSCN simulation framework.

5 EXAMPLE SCENARIO ANALYSIS AND RESULTS

This section presents an analysis of a category 4-5 hurricane that impacts the Washington D.C. area. Due to confidentiality issues some of the details of the scenarios are masked or omitted. The base scenario involves the operation of 43 locations between the Houston Texas area to the mid to upper east coast of the U. S. The network configuration includes all modes of transport (truck, rail, barge, and pipeline). We assume that all locations with docks or piers can receive small (17K bbl) and medium (20K bbl) size barges, where bbl is a barrel. We also assume that suppliers are completely reliable. That is, all orders to external locations outside the network can be filled completely and arrive when scheduled. Within network ordering is generated by the operation of the (min, max) ordering policies at each location. End customer (bases) have a demand pattern that, for the sake of this analysis, can be assumed to be Poisson with an overall average rate determined from forecasted daily demand. We omit details of the current inventory settings, demand, resource specifications, transportation times, etc. due to confidentiality and space constraints. We also defer rigorous statistical analysis of the results for future papers.

The planning horizon is for 78 days, with an expected hurricane in day 31 of the horizon. The hurricane is expected to last 2 days within the affected area. It is expected that a reliable warning will be available 2 days before the event. There are two major terminals within the network that are expected to be significantly impacted. Let's call these terminals B and Y. The piers and docks at locations B and Y are expected to be unavailable for a period of 14 days after the start of the event. The pipeline headers at locations H, B, and Y are scheduled to be unavailable for 2 day prior to the event, for the 2 days of the event, and for 2 days after the event. Within the network H supplies both B and Y via pipeline. Movement of barge (small and medium size) traffic from B and Y their customers is expected to be disrupted for 2 days. For the purposes of this example B supplies terminals (D, A, J, M), which further supply their customers (e.g. J supplies W), and terminal Y directly supplies bases (L, N). For simplicity, this analysis will focus on the impact on locations B, Y, D, A, J, M, L, N, and W within the network.

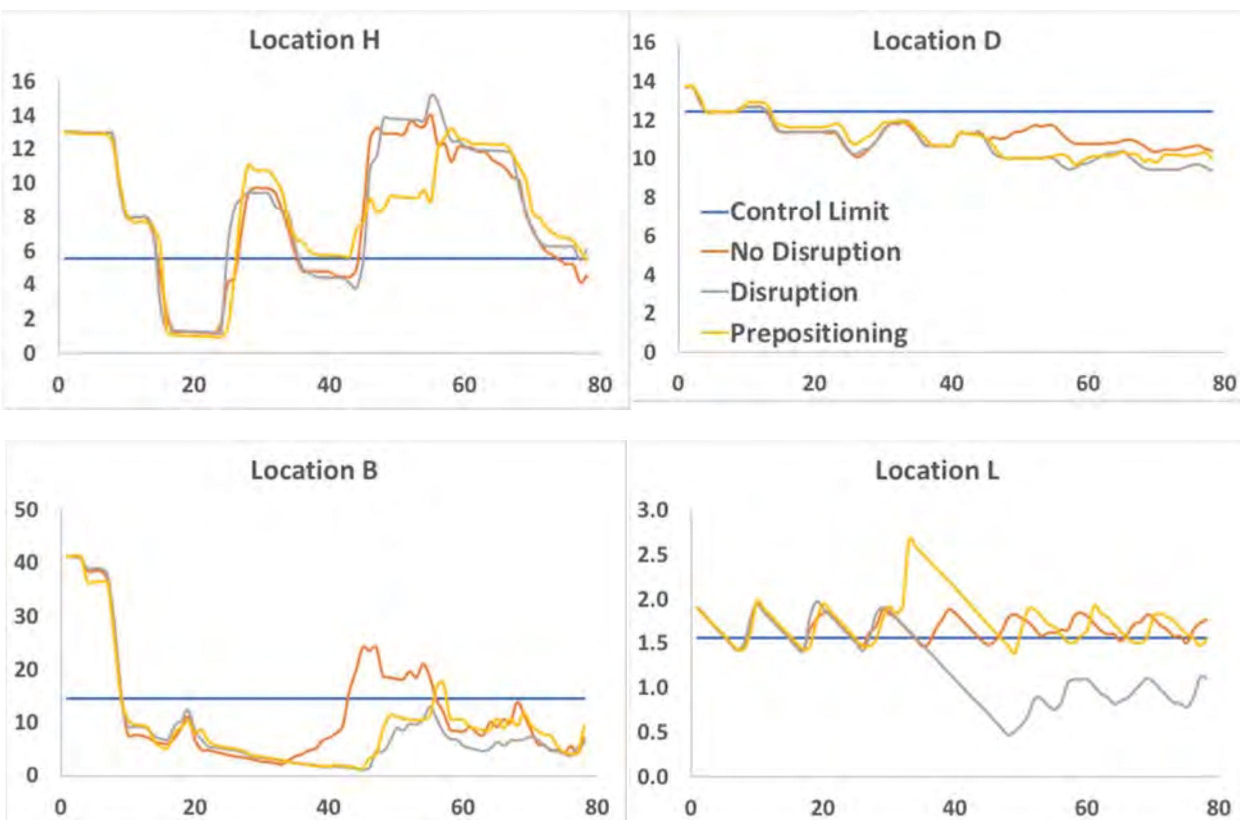

Figure 2: Inventory level (million bbls) over time with and without disruption for example locations.

Figure 2 illustrates traces of the inventory level (y-axis = gallons) over time (x-axis = days) based on 20 replications of 78 days with the disruption occurring in period 31. Location H is the main starting location for the network and supplies location B as well as other locations. Notice that there is virtually no indication of disruption effects at location H. This is to be expected because there is a large geographical distance as well as supply distance between location H and the affected locations. Location B is a key hub within the network. The behavior the inventory level for location B over time indicates that it generally has difficulty staying close to its control limit, even without a disruption. Even though the disruption occurs at time 31 and affects the docks at location B, the performance degradation for location B occurs about 6 days after the start of the disruption. The disruption clearly causes location B to not be able to meet its control limit over time. Locations D and L are customers within the network. From Figure 2, location D is barely maintaining its control limit over time, with the disruption having a delayed effect starting around day 45. Location L is the most seriously affected location within the network. Clearly, location L is almost immediately affected by the disruption and the location is not able to get back to its control limit during the planning horizon. However, none of the locations stock out during the entire planning horizon.

To demonstrate how the model can be used to understand the effect of mitigation strategies, we pre-position inventory at location L one day prior to the disruption. That is, given the two day warning, we cause an extra shipment of fuel sized to utilize all of location L's storage capacity to arrive 1 day before the event (day 30) in the simulation. The maximum authorized limit, the order-up-to level in a (min, max) policy, is typically set below a location's tank storage capacity, called the maximum fill level. This is a one-time planned shipment for this location due to the information shown in Figure 2.

Table 1: Performance at location L for various metrics across scenarios for n = 20 replications.

	No Disruption		**Disruption**		**Pre-Positioning**	
Metric	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
On Hand (bbls)	1639576.23	9449.34	1229475.69	69588.72	1724847.22	26372.08
Amount Back Ordered (bbls)	0.00	0.00	0.00	0.00	0.00	0.00
Amount On Order (bbls)	297751.17	7333.88	707707.77	71023.06	257898.68	34258.98
#Replenishments Received	7.80	0.41	6.95	0.22	6.25	0.44
Dock Receiving Utilization	0.17	0.01	0.17	0.01	0.16	0.01
Avg. Time Below CL	3.80	0.16	13.57	1.96	3.71	0.20
Max. Dist. Below CL	384525.05	27714.87	1324029.45	133835.61	380146.45	40295.76
Max. Time Below CL	4.25	0.12	43.03	6.32	4.33	0.32
P(below to below)	0.87	0.01	0.97	0.01	0.88	0.01
Fraction of time below CL	0.39	0.01	0.71	0.06	0.33	0.02
Relative deviation from CL	0.05	0.01	-0.21	0.04	0.10	0.02
Receiving time spent in queue	0.63	0.03	0.63	0.03	0.60	0.05
Receiving number in queue	0.13	0.01	0.12	0.01	0.12	0.01
Pre: Amount on order			280742.62	13681.17	283012.74	21215.99
During: Amount on order			710348.24	110236.23	35093.83	156944.36
Post: Amount on order			1075655.67	82567.10	239305.17	76624.05

Table 1 presents selected metrics for location L in order to illustrate the types of measures that are captured and to provide insights into their interpretation. As previously mentioned, many of the standard inventory measures are captured. Table 1 shows that at location L the average on hand inventory is impacted because of the disruption, decreasing to 1,229,475 from 1,639,576 bbls. We also see that pre-positioning has a positive impact on the inventory level. As noted from Figure 2, the location did not experience a stock out. Thus, the amount back ordered is zero across the three scenarios; however, the amount on order does increase during the disruption. Table 1 suggests that queueing and utilization statistics are not impacted by the disruption. In other words, location L is likely to have enough resource capacity in the face of a disruption. The newly created metrics that track the adherence to the control limit show interesting results. For example, the percentage of time spent below the control limit (CL) goes from 39% for the no disruption case to 71% when disruption occurs. The pre-positioning strategy allows this metric to be improved over the no disruption scenario. It is interesting to note that the metric that tracks the probability that if the inventory on hand is already below the limit for it to stay below goes up significantly when there is a disruption (from 87% to 97%). Thus, under normal conditions (no disruption) location L is likely to stay below its control limit and under the stress of a disruption, it is virtually certain to do so. This indicates that location L should be considered for resilience initiatives. Finally, as previously mentioned the framework allows for collection of statistics over specific periods of time. The last three rows of Table 1 illustrate what happens to the amount on order pre-disruption, during disruption, and post disruption for the scenarios containing disruption and pre-positioning.

Table 2: Pairwise comparison analysis for inventory on hand (bbls) for n = 20 replications.

				No Disruption				
Location	**Scenario**	$\bar{x}$	s	$\bar{x}$	s	$\bar{D}$	RC	$\|RC\|$
W	Disruption	7116.10	2877.20	8772.68	2186.37	-1656.59	-0.19	0.19
W	Pre-Position	8330.50	2204.36	8772.68	2186.37	-442.19	-0.05	0.05
B	Disruption	896013.25	199544.14	1180080.12	209843.55	-284066.87	-0.24	0.24
B	Pre-Position	975590.29	177157.28	1180080.12	209843.55	-204489.83	-0.17	0.17
L	Disruption	1229475.69	69588.72	1639576.23	9449.34	-410100.54	-0.25	0.25
L	Pre-Position	1724847.22	26372.08	1639576.23	9449.34	85270.99	0.05	0.05
A	Disruption	1320100.52	201003.05	1467035.34	288844.25	-146934.82	-0.10	0.10
A	Pre-Position	1431288.68	289846.12	1467035.34	288844.25	-35746.66	-0.02	0.02
J	Disruption	4325665.94	306457.50	4599228.25	460779.55	-273562.31	-0.06	0.06
J	Pre-Position	4426247.00	308573.14	4599228.25	460779.55	-172981.26	-0.04	0.04

Table 2 presents a pair-wise difference analysis of the inventory on hand performance of interesting locations. The table contains locations where the absolute relative change when compared with the no disruption case was higher than 5% when considering the disruption versus the no disruption case. That is the results are for, $D = \theta_i - \theta_k$, $RC = (\theta_i - \theta_k)/|\theta_k|$ and $|RC|$ when $\theta_k$is the no disruption scenario. For example, we see in the first row of Table 2 referring to location W, that the average inventory level at W is decreased by 19% due to the disruption and that prepositioning supplies at L indirectly impacts a customer that is not in the direct chain of L. Furthermore considering location L in Table 2, we see that the disruption has the highest impact (relative change of -25%) on location L's inventory.

The impact of the planned pre-positioning of inventory on these two locations can be investigated. Notice that the supply chain for location W, is (H-B-J-W) and the supply chain for location L is (H-J-L). Thus, locations W and L only have location H in common for their replenishment chains. According to row 3 of Table 2, the chain, H-B-J-W, is being positively impacted because of inventory being injected at location L, in chain H-Y-L. We see that pre-positioning reduces the impact on inventory at location W from -19% to -5% relative change. Thus, the demand pull from L, through Y on to H is lessened by supplying location L by an alternative supply chain and allows the chain H-B-J-W to better serve W during the disruption. We see similar side-effects for locations B, A, and J within Table 2.

Obviously, pre-positioning inventory at location L shows a dramatic effect (Table 2). Not only is the impact of disruption mitigated by the pre-positioning, it actually causes a surplus of inventory over the no disruption scenario. Thus, we probably could have reduced the size of the pre-positioning shipment for location L. This brings up very interesting optimization problems in trying to find locations and amounts for pre-positioning that maximize the benefit to the entire network. The fact that the complex linkages of the supply chain cause possibly widespread (non-localized effects) make this a challenging problem. Simulation is necessary to properly model this complexity.

6 SUMMARY AND FUTURE WORK

An object-oriented simulation modeling framework has been developed to simulate the operation of bulk petroleum supply chain networks (BPSCN). Scenarios in the BPSNC framework may contain disruption events as well as different network configurations or demand data. The framework includes metrics facilitate scenario comparison, such as assessing the impact of disruptions on the supply chain's performance. Because of the complex and inter-connectedness of supply chains, disruptions in supply, demand, or capacity can have far reaching and significant impacts. The BPSCN simulation framework enables logistics capabilities analysis (LCA) in order to understand the inventory and capacity of the network down to the resource level. In addition, its specialized statistics and database structure facilitates contingency and war gaming analysis and the assessment of mitigation strategies.

The BPSCN simulation framework is designed to adapt readily to modeling other types of products. Future work could examine any conceptual and modeling differences required for the adaptation. Even in the example presented in this paper the number of metrics produced by the simulation can be overwhelming. Current metrics primarily focus on the SKU (product/location) level. In order to better facilitate strategic decisions, metrics need to be formulated at aggregated levels to permit quicker determination of impacts at higher levels, such as network, region, or product. For example, a disruption event typically directly impacts a set of locations. Furthermore, metrics are needed to capture the *propagation* of effects and *delayed* impacts. Since the supply chain supports end-customers, e.g. military aircraft, future work could examine the effect on end-customers (e.g. wait times, weapon system availability, etc.).

Finally, once the performance of the BPSCN has been measured with and without disruptions, the analyst is faced with developing mitigation strategies. The simple pre-positioning strategy illustrated in this paper motivates many optimization questions, such as when, where, and how much to pre-position. Future work could examine the use of the BPSCN simulation framework within a simulation optimization context. Within such a context, it will be important to formulate the optimization problem in such a way that captures the many competing objectives and discrete choices.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 0732686 and the support of the Defense Logistics Agency. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation or the Defense Logistics Agency.

REFERENCES

Akkihal, A. R. 2006. *Inventory Pre-positioning for Humanitarian Operations*. Master's thesis, Massachusetts Institute of Technology, Engineering Systems Division. Cambridge: Massachusetts Institute of Technology.

Goldsman, D. and B. L. Nelson. 1998. "Comparing Systems via Simulation". In *Handbook of Simulation*, edited by J. Banks. doi:10.1002/9780470172445.ch8, New York, United States. John Wiley & Sons.

Jahre, M. 2017. "Humanitarian Supply Chain Strategies: A Review of How Actors Mitigate Supply Chain Risks". *Journal of Humanitarian Logistics and Supply Chain Management* 7(2):82–101.

Kamalahmadi, M. and M. M. Parast. 2017. "An Assessment of Supply Chain Disruption Mitigation Strategies". *International Journal of Production Economics* 184:210–230.

Ni, W., J. Shu, and M. Song. 2017. "Location and Emergency Inventory Pre-Positioning for Disaster Response Operations: Min-Max Robust Model and a Case Study of Yushu Earthquake". *International Journal of Production and Operations Management* 27(1):160–183.

Oliveira, J. B., R. S. Lima, and J. A. B. Montevechi. 2016. "Perspectives and Relationships in Supply Chain Simulation: A Systematic Literature Review". *Simulation Modelling Practice and Theory* 62:166–191.

Pitty, S., W. Li, A. Adhitya, R. Srinivasan, and I. A. Karimi. 2008. "Decision Support for Integrated Refinery Supply Chains". *Computers & Chemical Engineering* 32:2767–2786.

Rafael, D., B. Joshua, T. Ange-Lionel, G. Bridget, N. ManWo, L. Francesco, and N. Letizia. 2013. Humanitarian/Emergency Logistics Models: A State of the Art Overview. In Proceedings of the 2013 Summer Computer Simulation Conference (SCSC '13). Society for Modeling & Simulation International, Vista, CA, Article 24.

Richardson D., S. de Leeuw, I. F. A. Vis. 2010. "Conceptualising Inventory Prepositioning in the Humanitarian Sector". In *Collaborative Networks for a Sustainable World*. PRO-VE 2010, edited by L. M. Camarinha-Matos, X. Boucher, and H. Afsarmanesh. IFIP Advances in Information and Communication Technology, vol. 336. Berlin, Heidelberg: Springer.

Rossetti, M. D. 2008. "JSL: An Open-Source Object-Oriented Framework for Discrete-Event Simulation in Java". *International Journal of Simulation and Process Modeling* 4(1):69–87.

Rossetti, M. D., and H. T. Chan. 2003. "A Prototype Object-Oriented Supply Chain Simulation Framework". In *Proceedings of the 2003 Winter Simulation Conference*, edited by S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, 1612–1620. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rossetti, M. D. and S. Thomas. 2006. "Object-Oriented Multi-Indenture Multi-Echelon Spare Parts Supply Chain Simulation Model". *International Journal for Modeling and Simulation*. 26(4):359–369.

Rossetti, M. D. and Y. Chen. 2012. "A Cloud Computing Architecture For Supply Chain Network Simulation". In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 3225–3236. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rossetti, M. D., M. Miman, and V. Varghese. 2008. "An Object-Oriented Framework for Simulating Supply Systems". *Journal of Simulation* 2:103–116.

Rossetti, M. D. and J. Bright. 2018. "Bulk-Petroleum Supply Chain Modeling". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 3060–3071. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Vugrin, E. D., D. E. Warren, M. A. Ehlen. 2011. "Framework for Infrastructure and Economic Systems: Quantitative and Qualitative Resilience Analysis of Petrochemical Supply Chains to Hurricane". *Process Safety Mgmt.* 30(3):280–290.

Walsh, K., J. C. Hershauer, T. A. Walsh, I. Tommelein, and A. Sawhney. 2002. "Lead Time Reduction Via Pre-Positioning of Inventory in an Industrial Construction Supply Chain". In *Proceedings of the 2002 Winter Simulation Conference*, edited by E. Yucesan, A. A.Chen, J. J. Snowdon, and J. M. Charnes, 1737–1744. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Xiong, B., B. Li, R. Fan, Q. Zhou, and W. Li. 2017. "Modeling and Simulation for Effectiveness Evaluation of Dynamic Discrete Military Supply Chain Networks". *Complexity* on-line access, http://doi.org/10.1155/2017/6052037

AUTHOR BIOGRAPHIES

MANUEL D. ROSSETTI is a Professor in the Industrial Engineering Department at the University of Arkansas. He received his Ph.D. in Industrial and Systems Engineering from The Ohio State University. His research and teaching interests involve simulation modeling, logistics optimization, and inventory analysis applied to manufacturing, distribution, and health-care systems. He serves as an Associate Editor for the International Journal of Modeling and Simulation and is active in IIE, INFORMS, and ASEE. He served as co-editor for the WSC 2004 and 2009 conference, the Publicity Chair for the WSC 2013 Conference, and was the 2015 WSC Program Chair. Dr. Rossetti is the author of Simulation Modeling and Arena by Wiley, now in its 2nd edition. He can be contacted at rossetti@uark.edu and https://sites.uark.edu/rossetti/.

JULIANA BRIGHT is a Ph.D. student at the University of Arkansas. She received her M.S. in Industrial Engineering from Oklahoma State University. Her research interests include failure in network models and the effects of model uncertainty in inventory management. She has learned several programming languages, including Python, Java, VBA, and R. Her team won the IIE Undergraduate Technical Paper Competition in 2010 for their work on improving distribution from a local manufacturer to its dealers. She was also an ABF Doctoral Academy Fellow from 2011-2015. She can be contacted at brightj@uark.edu.