The Impact of Temporary Seaport Closures on Freight Supply Chain Costs

Brian M. Lewis
Georgia Institute of Technology
765 Ferst Drive
Atlanta, GA 30332-0205
Phone: (919) 932-7098, Fax: (404) 894-2301
Email: blewis@isye.gatech.edu

Alan L. Erera
Georgia Institute of Technology
765 Ferst Drive
Atlanta, GA 30332-0205
Phone: (404) 385-0358, Fax: (404) 894-2301
Email: alerera@isye.gatech.edu

Chelsea C. White III
Georgia Institute of Technology
765 Ferst Drive
Atlanta, GA 30332-0205
Phone: (404) 894-0235, Fax: (404) 894-2301
Email: cwhite@isye.gatech.edu

July 20, 2005
ABSTRACT

We present a decision model designed to help policy-makers understand the disruptive impact of temporary closures of a container seaport on the supply chains that it supports. Such closures may have numerous possible causes, but security-related disruptions are of particular relevance today. Importantly, temporary closures result in highly variable product delivery leadtimes, increasing inventory management costs for supply chain operators. We develop a Markov decision model for the inventory management problem faced by a firm operating an international supply chain utilizing a seaport that may unexpectedly close. Since short port closures typically lead to ships waiting to offload containers, we use a simple deterministic queuing approach to model port freight processing dynamics. The model is used to determine the likely impact of both the probability of a seaport closure and also the expected closure duration on the optimal inventory management policy and its associated long-run average cost for a firm. The results of a numerical study indicate that the expected length of a seaport closure more negatively affects a firm’s supply chain productivity than the probability of closure, for example, causing increases in the expected daily holding and penalty costs of up to 136%. Furthermore, firms that fail to plan for port closures may expect large annual cost increases. These results have important implications for the cooperation between government agencies and businesses in contingency planning and disruption management. Additionally, the computational study highlights the importance of government investments that increase the processing capabilities of highly utilized seaports.
INTRODUCTION

Due in part to manufacturing globalization and improved communication and transportation capabilities, freight supply chains now cover larger geographic areas and have more direct and indirect stakeholders. Over half of U.S. companies have increased the number countries in which they operate since the late 1980’s (1). The growing complexity of modern supply chains increases their risk of exposure to various types of major disruptions, which of course threatens the reliability of these chains. In this paper, we investigate the supply chain cost impact of a specific type of potential disruptive event: a temporary seaport closure.

Supply chain operators have long been vulnerable to minor security breaches. The primary concern for many years was cargo theft, and firms continue to rely on basic deterrent measures such as fencing, lighting, closed circuit TV, and security guards to prevent its occurrence. In the aftermath of the terrorist attacks that occurred in the United States on September 11, 2001, the notion of supply chain security quickly expanded beyond cargo theft and began receiving greater attention by both businesses and government. Businesses developed new disruption management plans, and the U.S. Bureau of Customers and Border Protection (CBP) implemented new supply chain security programs such as the Customs-Trade Partnership Against Terrorism (C-TPAT). Most importantly, however, the terrorist attacks highlighted the fact that U.S. transportation systems could and would be severely constrained, possibly to the point of closure, during such events.

In fact, border delays at the U.S.-Canadian border quickly increased from a few minutes to an extreme 12 hours after the September 11th attacks (2), and as a result Ford Motor Company was forced to intermittently idle production at five of its assembly plants due to parts shortages (3). Toyota came within hours of halting production at one plant since air shipments from Germany were delayed (4). In the event of another security disruption, seaport closures are a feasible response that would severely impact international supply chains. A 2003 report from Booz Allen Hamilton presented the results of a port security wargame in which a terrorist attack using “dirty bombs” in intermodal containers was simulated (5). The actions taken by the participating business and government leaders had significant consequences: every seaport in the U.S. was shut down for eight days, requiring 92 days to process the resulting backlog of container deliveries. The forecasted total loss to the U.S. economy was $58 billion, including the costs of spoilage, lost sales/contracts, and manufacturing slowdowns/halts. Terrorist events or threats are not the only disruptive forces that may affect seaports. For example, 29 Western U.S. seaports were closed during a 10-day lockout of stevedores in the fall of 2002. The resulting port congestion did not dissipate for months (6). Clearly, seaport closures and congestion are a major concern.

In this paper, we present a simple decision model that can help policy-makers understand the cost impact of the temporary closure of a container seaport on the supply chains that it supports. We develop a Markov decision model for optimal inventory management for a firm operating an international supply chain utilizing a seaport that may unexpectedly close temporarily, resulting in highly-variable order leadtimes. Since short port closures typically lead to ships waiting to offload containers, we use a simple deterministic queuing approach to model port freight processing dynamics. The developed model is used to assess the impacts of both the probability of a seaport closure and also the expected closure duration on the firm’s optimal inventory management policy and the associated expected cost per period. The results of a numerical study indicate that the expected length of a seaport closure more negatively affects a
firm’s supply chain productivity than the probability of closure. This has important implications for the engagement and cooperation of government agencies and businesses in contingency planning and disruption management. Additionally, the results highlight the importance of government investments that increase the processing capabilities of highly utilized seaports.

AN INVENTORY MANAGEMENT MODEL CONSIDERING PORT DISRUPTIONS

In this section, we develop an inventory management model for a firm operating a single product international supply chain that utilizes a congested seaport subject to unexpected closures. We begin by describing the problem scenario, including a simple model for freight processing at the seaport. Next, we model the decision problem using a Markov decision process, showing how the important seaport closure impacts can be captured by a random variable for the replenishment leadtime. We finally discuss how to use this model to determine optimal ordering decisions and their resultant long-run average costs.

Problem Scenario

Consider an international freight supply chain for a single product consisting of a foreign supplier and a domestic customer. The domestic customer may be a manufacturer receiving inbound parts for processing or assembly, or may represent a distribution center or a retailer receiving finished goods. At fixed time periods (e.g., each day), the customer decides how much product to order. The supplier immediately fills the order, which is then shipped by ocean carrier on an established transportation route. After a fixed transit time of $L$ periods, the order arrives at a domestic seaport for importation. Upon arrival, the seaport may be open or closed, and may or may not have a queue of backlogged freight to process; we describe the freight processing dynamics of the seaport in the next subsection. Once the order is processed through the seaport, we assume for convenience that the order arrives immediately to the customer. Suppose that each period, the domestic customer must fill uncertain demand for the product, and any unsatisfied demand is backlogged for fulfillment in subsequent periods. Let $D_t$ be a non-negative, integer-valued random variable representing customer demand in period $t$, which is identically and independently distributed with probability mass function $g$ and cumulative distribution function $G$. Let $D^{(l)}$ be the stochastic cumulative demand over $l$ periods.

In each period, assume that the timing of events at the domestic customer is as follows: first, the inventory level is reviewed, an ordering decision is made, and purchase costs are assessed; second, any outstanding orders that will arrive in the current period do so; third, demand is realized; and fourth, the inventory level is updated and holding/penalty costs are assessed. The objective of the domestic customer is to determine an ordering policy that minimizes the cost per review period (e.g., per day) over an infinite horizon. We will refer to this cost as the long-run average cost. We assume that the customer orders in discrete quantities (e.g., containers) and is charged $Sc$ per unit ordered. Holding costs are assessed at $Sh$ per unit per period for any inventory held over at the customer; pipeline inventory costs are ignored. Backlogged demand incurs a penalty cost of $Sp$ per unit backlogged per period.

Seaport Freight Processing Given Potential Closures

We now describe a model for the movement of freight through the seaport, where the port may
be open or closed for importation in each period. The port status is modeled by an exogenous, discrete-time, time-homogeneous Markov chain \( i = \{ i_t, t \geq 0 \} \) with state space \( S = \{ O, C \} \). Let \( i_t = O \) indicate that the port is open at the start of period \( t \), and \( i_t = C \) indicate that it is closed. Let \( p_{ij} = P(i_{t+1} = j | i_t = i) \) be the probability of transitioning from port status \( i \) at time \( t \) to port status \( j \) and at time \( t+1 \). The transition probability matrix is

\[
P = \begin{bmatrix}
1 - p_{OC} & p_{OC} \\
p_{CO} & 1 - p_{CO}
\end{bmatrix}.
\]

The transition probabilities \( p_{OC} \) and \( p_{CO} \) provide two different measures of the severity of seaport closures: closure likelihood and reopening likelihood. From Markov chain theory, if the port status is \( i \), then the expected number of time periods until the status transitions to \( j \neq i \) is \( 1/p_{ij} \). Therefore, the expected duration of a seaport closure is given by \( 1/p_{CO} \). Similarly, the expected time between port closures is given by \( 1/p_{OC} \).

To understand the impact that seaport closures have on the supply chains it supports, we will evaluate a range of values of \( p_{OC} \) and \( p_{CO} \) in the numerical study. On the other hand, a policy-maker may wish to estimate appropriate values of \( p_{OC} \) and \( p_{CO} \) when utilizing such a model. There are a few ways this can be done. If historical data were available, then \( p_{OC} \) and \( p_{CO} \) could be estimated directly. Since such data is generally not available and since the future may not be expected to replicate the past, alternative methods may be necessary. The values of \( p_{OC} \) and \( p_{CO} \) may be estimated indirectly using estimates for the expected inter-event times, \( 1/p_{CO} \) and \( 1/p_{OC} \). Therefore if an expert estimates that in the event of a seaport-closing disruption, the expected time until the seaport reopens is two weeks, then a reasonable estimate for \( p_{CO} \) would be 0.071 (assuming an inter-review period of one day). Another indirect estimation approach is to suppose that expert opinion has determined that the probability that the seaport will close within the next \( W \) time periods is \( p_w < 1 \). Given that the port is currently open, let \( X \) be a random variable representing the number of time periods until the port closes (for the first time), where the probability of closure each period is \( p_{OC} \). Then \( X \) is a geometrically distributed random variable such that \( P(X = n) = (1 - p_{OC})^{n-1} p_{OC} \) and \( P(X \leq n) = 1 - (1 - p_{OC})^n \). Therefore we can write \( p_w = 1 - (1 - p_{OC})^W \) and solving for \( p_{OC} \), we have

\[
p_{OC} = 1 - e^{\frac{-\ln(p_w)}{W}}.
\]

We could solve a similar equation for \( p_{CO} \).

When a port closes, it may develop a backlog of inbound freight to process. In our problem context, this freight may include not only orders that the domestic customer has placed, but also other freight being moved for other supply chain operators. We therefore assume that freight moves through the seaport according to the following simple deterministic queueing system. We first aggregate the containerized cargo that passes through the seaport into larger units of work. For example, if a seaport processes an average of 1,000 import containers per day, then we may define the unit of work to represent a collection of 500 containers or 100 containers. Units of work are processed by a workload queue at the seaport, which follows a first in, first out (FIFO) processing discipline. Let \( a(i_t) \) and \( b(i_t) \) respectively be the number of new units of work
arriving to the seaport and the maximum number of units of work that can be completed in period $t$ when the port status $i_t = i$, where

$$a(i_t) = r_0$$

and

$$b(i_t) = \begin{cases} r_i & \text{if } i_t = O \\ 0 & \text{if } i_t = C, \end{cases}$$

where we assume that $r_0$ and $r_1$ are finite, positive integer constants. Note of course that no work is processed at the seaport when it is in the closed state. Further, we assume that $r_0$ units of work arrive to the seaport regardless of its open/closed status. Clearly then, a queue of unprocessed work will develop whenever a port enters the closed state. The length of the work queue $n_t$ at the seaport at time $t$ is then a stochastic process, where $n_{t+1} = \max(0, n_t + a(i_t) - b(i_t))$. Since this work queue may persist over multiple periods when the port is reopened, this simple queuing system models the congestion effects resulting from closures. The utilization of the work queueing system at the seaport is

$$\rho = \frac{r_0}{\pi_0 r_1},$$

where $\pi_0$ is the stationary probability that the seaport is open. To ensure queue length stability, the work queueing system must satisfy the constraint that $\rho < 1$.

Orders placed by the domestic customer and units of work move through the seaport queuing system in the following manner. At time $t$, $a(i_t) = r_0$ new units of work join the work queue. The orders placed by the customer that are arriving to the seaport in the current period (those placed $L$ time periods previously) are assigned to the last of these new units of work. Orders then move through the queuing system with their assigned units of work but do not affect the units’ movements. Note that by assigning the arriving customer orders to the last arriving unit of work, we conservatively model a worst-case processing scenario. Each period, the seaport processes $\min\{n_t, b(i_t)\}$ units of work (i.e., the containers representing the units of work are moved to their next destination within or outside the seaport). Recall that $b(i_t)$ is maximum number of units of work that can be completed in a period. Therefore, if the queue length is less than $b(i_t)$, only the $n_t$ units of work in the queue are completed. Any orders that were assigned to processed units of work arrive to the domestic customer without further delay. All other outstanding orders remain in the work queue. We acknowledge that the movement of containerized cargo within and through a seaport is a very complex operation, but we believe that our queuing model provides a sufficient level of detail for the purposes of this paper.

Although this paper does not explore these extensions, modified functions $a(i_t)$ and $b(i_t)$ could capture other potential system-wide behavior that may result from a seaport closure. For example, many firms that ordinarily ship through a closed seaport may switch to alternative transportation modes or shipping lanes during the closure. Alternative shipping methods were utilized during the 2002 labor lock-out at Western U.S. seaports, when many firms used expedited air cargo as well as Canadian and Mexican seaports (and then truck and rail to the United States). To model such a case, one could set $a(C) = r'_0 < r_0$. Additionally, seaport operators or governmental agencies may decide to temporarily increase the processing capabilities of a seaport in order to reduce the backlog of work after prolonged periods of closure. This could be accomplished through extended gate hours and general hours of operation.
and in extreme cases, through the use of additional labor (e.g., the National Guard). Increasing such processing capabilities could be modeled by simply increasing the value of $r_1$.

### Markov Decision Model for Inventory Management under Uncertain Leadtimes

The stochastic models for the open/closed status of the seaport and for the queue of work remaining to be processed by the seaport at any time $t$ affect the inventory management problem faced by the domestic customer in our problem scenario by creating uncertainty in the leadtime between when an order is placed and when that order is received. Given the state of the seaport at time $t$ (e.g. the border status, $i_s$ and the work queue length, $n_t$), let $L(i_s,n_t)$ be the random variable representing the leadtime of an order placed in period $t$. A key feature of this supply chain model is that the domestic customer has complete visibility of the border status and the seaport work queue when making ordering decisions, and therefore the probability distribution of the order leadtimes is dependent on the state of the seaport system at the time of order placement. When the leadtime from the supplier to the domestic seaport is greater than one day (e.g. $L>1$), then the leadtime probability mass function is

$$P(L(i,n)=l \mid i_s = i, n_t = n) = \begin{cases} 0 & \text{if } l < L, \\ \sum_{0 \leq m \leq r_0} f(i,n)(O,m) & \text{if } l = L, \\ \sum_{0 \leq m \leq r_0} f(i,n)(C,m)p_{co} + \sum_{n_0 \leq m \leq n_0} f(i,n)(O,m)p_{oo} & \text{if } l = L+1, \\ \sum_{j \in S_j \text{ and } m \geq 0} \sum_{k \text{ and } n} p(j,m,k,i,n) p_{ko} f(i,n)(j,m) & \text{if } l > L, \end{cases}$$

where $f(i,n)$ is the joint probability mass function of the random variables representing the border status and queue length at time $t+L$ given the border status and queue length are respectively $i$ and $n$ at time $t$,

$$p_{(i,m,k,i,n)} = P(N_{j_0}(t+L, l = L-1) = \beta(m), i_{i+l-1} = k \mid i_{i+L} = j, n_{i+L} = m, i_s = i, n_t = n),$$

and $N_{j_0}(t,s)$ is a random variable representing the number of visits to state $j$ in $s$ successive transitions of a two-state Markov chain given the initial state at time $t$ is $i$. The probabilities $p_{(i,m,k,i,n)}$ can be calculated using Lemma 9 in (7), and the joint probability mass function $f(i,n)$ is calculated using explicit enumeration of border status sample paths of length $L$. The leadtime probability distribution for the special case when $L=1$ is covered in (7). We note that the shipping dynamics here prevent order crossover; that is, orders arrive in the order in which they are placed. This is a realistic assumption for most supply chain systems, and an important one in the inventory control literature.

The inventory management problem can now be formulated as a Markov decision problem (MDP) that is a specialization of the general inventory control model in (8). The reference shows that the optimal ordering policy is a stationary, state-dependent basestock policy, where the basestock (or order-up-to) levels depend on the state of an exogenous Markov process at the time of order placement. Under a stationary policy, the ordering decision rules are static through time, and under a basestock (or order-up-to level) ordering policy, when the
inventory position decreases below the order-up-to level, an order is placed to increase the system inventory level up to the order-up-to level (the inventory position is the sum of the on-hand inventory and all outstanding orders). The domestic customer may have different order-up-to levels for each combination of border status \((i)\) and work queue length \((n)\), and we denote the optimal state-dependent order-up-to levels by \(y^*(i,n)\). If the inventory position and order quantity in period \(t\) are respectively denoted by \(x_t\) and \(z(i_t, n_t)\), then

\[
\begin{cases}
  y^*(i_t, n_t) - x_t, & \text{if } x_t \leq y^*(i_t, n_t), \\
  0, & \text{otherwise}.
\end{cases}
\]

The Markov decision problem is described by the following optimality equation, where the only relevant information for decision-making is the border status \((i)\), the work queue length \((n)\), and the inventory position \((x)\):

\[
g + h(i, n, x) = \min_{y \geq x} \left\{ (y - x)c + C(i, n, y) + E[h(i, n, y - D)] \right\},
\]

where \(g\) and \(h(i,x)\) are respectively the long-run average cost and the bias, \((i_+, n_+)\) is the joint random variable for the border status and queue length in the next period, and

\[
C(i, n, y) = \sum_{l=0}^{\infty} P(L(i, n) \leq l \leq L(i_+, n_+)) E[\hat{C}(y - D^{(l+1)})],
\]

where

\[
\hat{C}(\hat{x}) = \begin{cases}
  -p\hat{x}, & \text{if } \hat{x} < 0, \\
  h\hat{x}, & \text{if } \hat{x} \geq 0.
\end{cases}
\]

Note that \(C(i,n,y)\) represents the expected holding and penalty costs incurred from the time the current order is received until just before the order placed in the next period is received. In this model, the long-run average cost is constant for all inventory levels, port statuses, and work queue lengths.

**A NUMERICAL STUDY**

We now present the results of a numerical study that investigates the effects that the closure of a seaport has on the supply chains it supports. We first describe the case study design and the solution methodology.

**Case Study Design**

Consider a supply chain where the domestic customer reviews its inventory and places daily re-supply orders in container-loads. Suppose that the deterministic leadtime from the supplier to the domestic seaport is \(L=15\) days, corresponding to typical ocean carrier service from Asia to the Western U.S. (9). With growing Asian economies (especially in China) and increased outsourcing to Asia, this transportation mode and route are increasingly important to the U.S. economy.
We assume a reasonable per container purchase cost of $c=150,000. From Theorem 1 in (7), we note that $c$ does not affect the optimal inventory policy and further that $c$ contributes to the long-run average cost per day as an additive term $cE[D]$. Therefore, we will present only results for the expected daily holding and penalty costs. Given a purchase cost of $150,000, a daily holding cost of $h=100$ per day represents a 24.33% annual holding cost rate. This rate is reasonable for most industries, and may be conservative for high-technology industries (10). Suppose that the daily penalty cost for unfilled demand is $p=1,000$, representing an annual penalty cost of 2.4 times the purchase cost. Suppose that the daily demand $D_t$ is Poisson distributed with a mean of 0.5 containers per day.

In this study, we will consider sets of seaport closure and reopening probabilities that we believe represent plausible real-world scenarios: $p_{oc} \in \{0.001, 0.003, 0.01, 0.02\}$ and $p_{co} \in \{0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$. These sets correspond to an expected inter-closure time ranging from approximately three years to 50 days, and an expected closure duration ranging from 20 days to two days. We also restrict our attention to transition probabilities that satisfy the port utilization constraint (e.g., the border utilization must be strictly less than one). Therefore we exclude from consideration the following transition probability pairs: $(p_{oc}, p_{co}) \in \{(0.01, 0.1), (0.01, 0.05), (0.02, 0.2), (0.02, 0.1), (0.02, 0.05)\}$. The remaining transition probability pairs each correspond to utilizations greater than 90%, which we believe accurately represents the situation at most major U.S. seaports.

For the seaport processing model, we let $r_0=10$ units of work per day and $r_1=11$ units of work per day. These values were again selected to provide a realistic model of potential seaport congestion. In the port security wargame described in (5), eight days of seaport closure resulted in 92 days of port congestion, and the 2002 10-day closure of Western U.S. seaports resulted in months of congestion. Given $r_0$ and $r_1$, a port closure of 10 days results in congestion that will last for at least 100 days. We will vary the value of $r_1$ to investigate the impact of port utilization on the results.

Solution Methodology

The Markov decision problem developed in the previous section is solved using the value iteration algorithm (VIA). A detailed description of the algorithm can be found in (11). To enable efficient computation, we constrain the allowable state and action spaces to be finite without substantially affecting the optimal solution.

The VIA terminates in a finite number of iterations with an $\epsilon$-optimal policy; that is, the long-run average cost at the termination of the VIA (denoted $g_\epsilon$) satisfies the following inequality: $g_\epsilon - g^* < \epsilon$, where $g^*$ is the true optimal long-run average cost. Furthermore, we approximate the true optimal long-run average cost as in Theorem 8.5.6(b) in (11) (where we denote the approximation by $g'$), and $|g'-g^*| < \epsilon/2$. For any positive $\epsilon$, the policy obtained at the termination of the VIA may be sub-optimal. However in this paper, as is common, we will refer to the policy obtained by the VIA and to the approximated optimal long-run average cost as the optimal policy and the optimal long-run average cost. We set $\epsilon=0.01$ for the numerical study, which corresponds to a maximum difference between the approximate and true optimal long-run average costs of less than one half of one cent. Again, instead of the full long-run average cost we will present only the optimal daily expected holding and penalty costs, $g'-cE[D]$. 
Numerical Study Results

Impact of the Probabilities of Seaport Closures and Re-openings

We present the optimal expected holding and penalty costs per day and selected order-up-to levels versus the border status transition probabilities in Figures 1-3. When the border is open, the optimal order-up-to levels exhibit little variation over the transition probabilities, and we therefore do not present them graphically. However, the optimal order-up-to levels do exhibit variation over the transition probabilities when the border is closed; Figures 2 and 3 depict the cases when the border is closed and there are respectively zero and 100 units of work in the seaport work queue (representing a no congestion state, and a significant congestion state respectively).

All else held constant, the optimal order-up-to levels and expected holding and penalty costs per day increase as $p_{OC}$ increases and as $p_{OC}$ decreases (representing worsening closure scenarios). In general, we see that the optimal order-up-to levels and expected holding and penalty costs per day are much more sensitive to $p_{CO}$ than to $p_{OC}$. It thus appears that, within these ranges, the expected duration of a port closure ($1/p_{CO}$) much more negatively affects a firm’s supply chain productivity as measured by cost and inventory than the probability of the port closing ($p_{OC}$). Note also that the greatest increases in the order-up-to levels and expected holding and penalty costs per day occur when $p_{CO}$ is small, corresponding to long expected closures. For example, when $p_{OC}=0.003$ and the expected closure duration increases from two to 20 days, the expected holding and penalty cost per day increases by 136%, from $548 to $1294 per day (or an annual increase in $272,243 assuming no economic discounting).

These results have important implications for the interaction between supply chain entities and government agencies. The primary focus of governmental agencies has been the prevention of disruptions (e.g., security-related incidents) that would lead to seaport closures. While prevention is critically important (for reasons beyond monetary concerns), it clear that government must engage and cooperate with transportation and supply chain firms to design effective contingency plans that reduce the duration of a potential seaport closure and quickly return the freight transportation system to a normal state of operation. Such contingency plans may include re-routing of freight to other ports of entry or in the case of extreme residual congestion, funds to enable temporary increases in processing capacity at the disrupted seaport.
FIGURE 1 Expected Holding and Penalty Costs per Day vs. Transition Probabilities ($p_{OC}$, $p_{CO}$).

FIGURE 2 Optimal Order-up-to Level ($y^*(C,0)$) vs. Transition Probabilities ($p_{OC}$, $p_{CO}$).
Impact of Supply Chain Contingency Planning

In the Markov decision model developed in this paper, we assume that the domestic customer makes optimal decisions given complete information about the port processes. Thus, the results show the best-expected performance that the domestic customer can achieve given the possibility of seaport closures. However, firms do not always utilize all available information in the development of supply chain policies and strategies, and in fact information about seaport closures is typically not included in regular supply chain planning models. Therefore, in this subsection we suppose that a firm optimizes its inventory policy without explicitly modeling seaport closures and congestion and implements the policy in a real-world environment in which these disruptions may occur. We will refer to this policy as the implemented policy. Clearly the implemented policy may be significantly sub-optimal. In this section, we investigate the expected costs of using a poor inventory management policy to provide in some sense the worst-expected performance of a supply chain firm operating in this environment.

Suppose we determine the implemented policy simply by calculating the optimal inventory policy when the probability of seaport closure is assumed to be zero, e.g. $p_{OC}=0$. We then calculate the long-run average cost of using this policy given the true closure probability for each case. To present the results, we compare the costs under the suboptimal implemented policy to the (lower) costs incurred under the optimal policy for each scenario. We interpret this cost savings as the benefit of contingency planning for port closures; another interpretation of this “savings” is the potential additional costs that could be incurred by firms operating suboptimally in systems with potential port closures. Figure 4 displays the cost savings from contingency planning versus the border status transition probabilities. We note that the implemented policy is state-invariant, such that $y^*(i,n)=12$ containers regardless of the border status and work queue length.
There are clearly scenarios for which contingency planning for port closures and congestion is critically important. Cost savings of only 1-2% correspond to annual dollar savings in the hundreds of thousands. The most impressive data point corresponds to the case when $p_{OC}=0.003$ and $p_{CO}=0.05$. The annual expected cost savings in this case is approximately $2.6$ million. These results highlight the importance of businesses engaging in contingency planning for seaport closures and congestion while developing inventory management strategies. It is further clear that supply chain firms operating under suboptimal inventory policies will face exacerbated cost impacts of seaport closures and congestion.

![FIGURE 4 Cost Savings per Day from Contingency Planning vs. Transition Probabilities ($p_{OC}$, $p_{CO}$).]

**Impact of Seaport Utilization**

Seaport utilization provides a means for measuring a port's excess processing capacity. Utilization and excess processing capacity are inversely proportional, and as the utilization increases, a seaport's ability to reduce the congestion after a disruption diminishes. Therefore closures more negatively impact highly utilized seaports. In this section, we investigate the impact of seaport utilization on the optimal expected holding and penalty costs per day and order-up-to levels.

Recall that port utilization is given by $\rho = \frac{r_0}{\pi_0 r_1}$ and is therefore affected by the processing parameters ($r_0$ and $r_1$) as well as the seaport state transition probabilities (through the stationary distribution). We fix the arrival parameter ($r_0=10$) and the probability of transitioning from open to closed ($p_{OC}=0.003$) and then vary the processing parameter ($r_1$) and the probability of transitioning from closed to open ($p_{CO}$). Table 1 displays the optimal expected holding and penalty costs per day and order-up-to levels when there is significant congestion. The table also shows the subtle differences in utilization values as the transition probabilities and arrival and
processing parameters are varied. Figure 5 displays the optimal expected holding and penalty costs per day versus port utilization when \( r_0 = 10 \) and \( r_1 = 11 \).

As the utilization increases and therefore potential congestion becomes more severe, we see that optimal expected holding and penalty costs per day and the optimal order-up-to levels increase. For a fixed arrival rate, port utilization increases because either the processing parameter \( r_1 \) decreases, \( p_{OC} \) decreases, or \( p_{OC} \) increases. We have already observed the effects of the transition probabilities on the expected holding and penalty costs per day and order-up-to levels, and we now observe the impacts of the queueing parameters. As \( r_1 \) decreases relative to a fixed value of \( r_0 \), fewer units of work can be completed in any open period, which means that queues will require a greater number periods to be reduced.

The results show that the expected holding and penalty costs per day (and order-up-to levels) increase more than linearly with seaport utilization, indicating the domestic customer’s sensitivity to increasingly severe congestion effects from port closures. When \( p_{CO} = 0.05 \) and the port utilization increases from 70.7% to 96.4%, the expected holding and penalty costs per day increase by nearly 20%. These results represent optimal decision-making, and the expected costs per day would be even greater if the domestic customer implemented a sub-optimal inventory policy. Therefore government investments that improve the processing capabilities of highly utilized seaports, especially during periods immediately after closure, are crucial to reduce the impacts on supply chain productivity by seaport closures and congestion.

<table>
<thead>
<tr>
<th>( p_{CO} )</th>
<th>( r_0 )</th>
<th>( r_1 )</th>
<th>( \rho )</th>
<th>Expected Holding and Penalty Costs per Day</th>
<th>( \gamma^*(O,100) )</th>
<th>( \gamma^*(C,100) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>1</td>
<td>24</td>
<td>0.044</td>
<td>$909</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>0.05</td>
<td>10</td>
<td>30</td>
<td>0.353</td>
<td>$981</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>0.05</td>
<td>10</td>
<td>15</td>
<td>0.707</td>
<td>$1,093</td>
<td>14</td>
<td>18</td>
</tr>
<tr>
<td>0.05</td>
<td>10</td>
<td>11</td>
<td>0.964</td>
<td>$1,294</td>
<td>19</td>
<td>33</td>
</tr>
<tr>
<td>0.1</td>
<td>1</td>
<td>24</td>
<td>0.043</td>
<td>$610</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>0.1</td>
<td>10</td>
<td>30</td>
<td>0.343</td>
<td>$632</td>
<td>12</td>
<td>13</td>
</tr>
<tr>
<td>0.1</td>
<td>10</td>
<td>15</td>
<td>0.687</td>
<td>$676</td>
<td>13</td>
<td>16</td>
</tr>
<tr>
<td>0.1</td>
<td>10</td>
<td>11</td>
<td>0.936</td>
<td>$761</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>24</td>
<td>0.042</td>
<td>$543</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>0.5</td>
<td>10</td>
<td>30</td>
<td>0.335</td>
<td>$543</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>0.5</td>
<td>10</td>
<td>15</td>
<td>0.671</td>
<td>$544</td>
<td>12</td>
<td>13</td>
</tr>
<tr>
<td>0.5</td>
<td>10</td>
<td>11</td>
<td>0.915</td>
<td>$548</td>
<td>17</td>
<td>18</td>
</tr>
</tbody>
</table>
CONCLUSIONS

In this paper, we presented a decision model useful to help policy-makers understand the cost impacts of the temporary closure of a container seaport on the supply chains that it supports. Such temporary closures may have numerous possible causes, but security-related disruptions are of particular relevance today. Although the decision model was presented in terms of seaport closures, it is applicable to international border closures in general. For example, the model can be used to analyze supply chains utilizing air cargo or supply chains in which the re-supply crosses a land border by truck or rail. Specific examples are the automotive supply chains with assembly plants in the Midwestern United States and suppliers in Canada (predominantly in the province of Ontario).

The decision model was used to determine the likely cost impacts of seaport closures, and to measure the relative importance of both the probability of a seaport closure and also the expected closure duration on the long-run average inventory cost of a supply chain firm. The results of a numerical study indicated that the expected length of a seaport closure more negatively affects a firm’s supply chain productivity than the probability of closure. For example, the expected daily holding and penalty costs increase by 136% when the expected duration of a closure increases from two days to 20 days. Furthermore, supply chains operators that fail to plan for port closures with efficient inventory management policies may expect annual cost increases up to $2.6 million. These results have important implications for the engagement and cooperation of government agencies and businesses in contingency planning and disruption management. Additionally, the computational study shows that the expected daily holding and penalty costs increase more than linearly with port utilization, highlighting the
importance of government investments that increase the processing capabilities of highly utilized seaports.

ACKNOWLEDGEMENTS

The ongoing research reported in this paper is supported by The Logistics Institute—Asia Pacific, a research partnership between the Georgia Institute of Technology and the Republic of Singapore, and the ATLANTIC Project, a research partnership between the ITS Joint Program Office of USDOT, the Canadian Transportation Ministry, and the European Commission. Brian Lewis was also supported by a Dwight D. Eisenhower Fellowship for Graduate Study in Transportation from the National Highway Institute of the U.S. Department of Transportation.

REFERENCES