Impact of port disruption on transportation network

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Abstract

Port, as a critical facilitator in international trade and logistics, plays a unique role in global supply chain activities. Maritime ports are exposed to many disruption sources such as natural disasters, labour strikes and terrorism. Disruptions in port can have a wide range of potential negative impact on its transportation networks; while sometimes also benefit other ports in close proximity. As supply chains get leaner, the magnitude of such impact is expected to grow. It is crucial to understand how transportation network is affected by port disruptions, in order to develop strategies and policies to maintain its capacity and resilience. This paper aims to present a model for intermodal transportation network that evaluates the impacts of disruptions occurring at a focal port, focusing specifically on mitigation strategies of port utilization and port alliance. Disruption frequency and duration are modeled with a Discrete Time Markov Chain distribution. Order lead times are determined by the status of focal port, congestion backlogs as well as mitigating actions of the terminal operators. Numerical studies are conducted to demonstrate the possible effects of port disruption on terminal operators, shipping companies, cargo owners, shipping routes and inland transport.

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1. Introduction

Port, as a critical facilitator in international trade and logistics, plays a unique role in global supply chain activities. The key function of seaport as a connection point of sea and inland transportation, within regions and across continents, substantiates its importance to regional economy. History has shown that seaports are susceptible to a variety of risk sources, and the resultant disruptions can have significant detrimental effects on supply chains. For example, the great Hanshin-Awaji Earthquake in 1995 caused disastrous damage to the port of Kobe, which includes direct repair costs of $5.5 billion and an estimated economic loss of $6 billion (Werner et al., 1997). The ten-day shutdown of 29 US western ports in 2002 results in a backlog of cargos and vessels for months and an average export loss of $20 million per day for the US economy (Park et al., 2008). Even though no major terrorism activities have been reported in shipping and ports, the susceptibility of such sophisticated supply chain nodes to terrorist attacks and the catastrophic potential is widely acknowledged in the literature (Pinto and Talley, 2006, Paul and Maloni, 2010).

Apart from physical damages to infrastructures, vessels and cargoes imposed by disruptive events, of particular interest is the potential operational and economic impact to supply chain entities. Disruptions in port can have a wide range of potential negative impact on its transportation networks; while sometimes also benefit other ports in close proximity. The aftermath of the 1995 earthquake saw traffic flows in the port of Kobe redirected to nearby hub ports such as Busan, Shanghai and Kaohsiung, some of which never returned even long after the cargo-handling capacity was restored (Fujita and Hamaguchi, 2012). Such impact is expected to be further magnified by the wide adoption of lean operations and just-in-time practice of modern supply chains. It is crucial to understand how transportation network is affected by port disruptions, in order to develop strategies and policies to maintain its capacity and resilience. However, little work in the supply chain risk management literature specifically focuses on the failures of transportation nodes (Berle et al., 2011). As such, the significance of our study is justified.

This paper presents a model for intermodal transportation network that evaluates the impacts of port disruptions, focusing specifically on mitigation strategies of capacity expansion and contingency rerouting. The structure of the model is a two-echelon system which involves one supplier and one customer. The goods are transported through a primary port, and possibly a back-up port. When disruption occurs, the primary port is likely to develop a backlog of containers that will not dissipate unless the port reopens, or contingency rerouting is implemented. The objective of this paper is to quantify the direct impact of port disruptions on various
stakeholders of transportation network, including ports, shipping companies, cargo owners as well as intermodal operators. The choice of mitigation strategies is then evaluated based on three important performance measures for port-oriented transportation networks, namely container backlog, inland traffic volume, and demand fulfillment ratio.

The rest of the paper is organized as follows. Section 2 presents the related literature on supply chain disruption management and port disaster analysis. Section 3 details our model configuration describes the problem setting. Section 4 then presents the results and major findings with the demonstration of numerical examples. Finally, section 5 provides our concluding remarks and areas for future research.
2. Related literature

Maritime supply chain disruptions can be caused by a variety of risk sources and can occur at any point of the maritime transportation system (Vilk and Hallikas, 2012). Using failure mode analysis, Berle et al. (2011) enumerates the set of key capacities and functions in maritime transportation systems that could render supply chains inoperable if disrupted. The consequence of such disruptions ranges from temporary delay to unrecoverable disaster. The evaluation of the network impact is widely regarded as a difficult task due to the complexity of supply chains, as well as the interplay between various stakeholders. Specifying the scope of impact of disruption, whether it is a firm, a segment of the supply chain or the entire chain, is critical for quantitative risk assessment (Lam, 2012). Most of the research on supply chain disruption management focuses on supply chain strategies and robust design of the focal firm, i.e. the supply chain ‘user’. Examples of research issues in this category include reliable logistic network design in the face of facility disruptions (Li and Ouyang, 2010, Peng et al., 2011), inventory mitigation for customer service level protection (Schmitt, 2011), and inventory management with seaport closures (Lewis et al., 2006, Lewis et al., 2012). However, supply chain disruptions are not only of major concern to supply chain firms, but also to other value-adding facilitators such as transportation networks.

The research on the disruption management for other entities along maritime supply chains is relatively limited. Several studies have been conducted to evaluate the economic impact of port disruptions due to terrorist attacks and worker strikes based on project risk analysis (Rosoff and von Winterfeldt, 2007) and input-output model (Park et al., 2008, Pant et al., 2011). These studies provide some initial insights into the extent to which maritime disruptions can have on trade and regional economics. At the operational level, Paul and Maloni (2010) develops a decision support system for maritime transportation networks that monitors ship-port allocations and ship reroutings at times of port disasters. The study provides a lower bound estimation of the actual port disruption costs by assuming optimal decisions and seamless coordination among stakeholders. Gurning and Cahoon (2011) derives a Markovian-based risk analysis methodology to evaluate the effectiveness of multiple mitigation scenarios in the context of maritime wheat supply chains. Some recent studies focus on issues related to disruption management of liner shipping operations, such as robust schedule design (Wang and Meng, 2012b) and schedule recovery (Broere et al., 2013). Most of these studies acknowledge that various entities in maritime transportation networks tend to react to disruptions in an uncoordinated manner due to discriminative risk exposure to disruptions. However, to the best of our knowledge, no relevant work has been done to specifically quantify the different disruption impact on transportation network stakeholders.
3. Model description and problem setting

We present a model of a simplified supply chain system with two echelons, namely the supplier and the customer, that are connected through a transportation network with one primary port for export, which we call port $X$. Suppose the supplier is located next to port $X$, and its production is first delivered to port $X$, then shipped to the destination port $Z$ with a weekly liner service. In the event of port disruption at the Port $X$, the supplier can use one of the neighboring ports as a back-up port for export. The choice of back-up port depends on the capacity availability and transportation cost at the time of disruption. We hereafter call this chosen back-up port $Y$. Port $X$ and Port $Y$ are connected with an inland transportation network, suppose by truck service. We consider the customer orders a single product from the supplier. Orders are shipped from the supplier to the customer through either the primary port or the back-up port, depending on the status of the primary port. Transit time on the inland routes and shipping routes is measured in discrete periods and is assumed to be deterministic. The orders will then face a stochastic port processing delay determined by the port status, as well as possible congestion backlogs. After reaching the destination port, assume that orders arrive at the customer instantaneously (i.e. customer located at the port $Z$). The details of the supply chain model are depicted in figure 1. We further model demand as deterministic based on two considerations. Firstly, the primary focus of this research is to investigate the impact of port disruptions and not the uncertainty of demand. Secondly, a typical supply chain facilitated by maritime transportation usually would place the same amount of orders on a weekly basis. As such, we model the supply chain demand for each period as deterministic in this study.

![Figure 1](image_url)  A simplified supply chain model with a seaport-oriented transportation network

Port disruptions in the model have durations of an integer amount of periods and occur independently. The state of port $X$ at any period $t$ is either open or closed. We model the port
status with a discrete-time Markov Chain $I = \{i, t \geq 0\}$ with state space $S_i = \{0, 1\}$, where $i = 0$ indicates port $X$ is open, and $i = 1$ indicates it is closed. Assume the transition probabilities are time-homogeneous and known, and define $p_{ij} = P(i_{t+1} = j \mid i_t = i)$ for all $t \geq 0$. Thus $\alpha = p_{01}$ represents the failure $p_{10}$ probability (i.e. the probability of a closed period following an open period), while $\beta = p_{10}$ represents the recovery probability (i.e. the probability of an open period following a closed period). This allows us to test a wide range of possible disruption scenarios with an expected inter-closure time of $1/\alpha$ and an expected duration of $1/\beta$. For the purpose of this research, we assume that the port $Y$ is always open. This assumption is based on the fact that, when the primary port is disrupted, there is usually a network of potential back-up ports that are highly unlikely to fail at the same time. Furthermore, it is possible to model the uncertainty of port $Y$'s status probabilistically by incorporating the uncertainty into the rerouting time and cost for the shipping company.

Assume that at period $t$, port $X$ receives $d_t$ units of product from the supplier, after the supplier receives the customer orders. In this research, a unit is defined as an aggregate quantity of product (e.g. 10 containers) such that the terminal operator, the shipping company and the intermodal operator have the capacity to process multiple units per period. Vessels from the shipping company have an inter-arrival time of $s$ periods, and clear the products queuing at port $X$ in period of arrival $q_{X}^{X}$, up to the terminal’s maximum processing capacity $u_{X}^{X}$. Thus, the processing function for port $X$ when there is no disruption at period $t$ ($i_t = 0$) is:

$$q_{X}^{X} = \begin{cases} 
(q_{t}^{X} + d_{t+1} - u_{X}^{X})^+, & \text{if } t = S_0^X + ks \\
q_{t}^{X} + d_{t+1}, & \text{if } t \neq S_0^X + ks 
\end{cases}$$

(1)

for $k \in \mathbb{Z}$, where $S_0^X$ is the time of the vessel’s first arrival at port $X$, and $(x)^+ = \max\{x, 0\}$.

During the disrupted periods of port $X$ ($i_t = 1$), the manufacturing operation at the supplier is assumed to be capacitated with a queue of finished products that does not dissipate unless freight is redirected to port $Y$. Such redirection is temporary and the shipments will go back to port $X$ once the disruption is over. We further assume that this decision of redirection is based on a reaction criterion $\gamma \in \mathbb{Z}^+$, such that redirection is only exercised when port $X$ fails to process the orders for $\gamma$ consecutive times. However, if disruptions exceed a certain amount of periods, say $\gamma^* \in \mathbb{Z}^-$ ($\gamma^* > \gamma$), then the port $X$ will lose the shipments permanently to port $Y$. 
The shipping company receives shipments from the supplier at both ports and provides sea transportation services to port $Z$, with transportation costs of $r^{xz}$ and $r^{yz}$, and transit time of $l^{xz}$ and $l^{yz}$ respectively. Suppose that the shipping company promises delivery within a certain amount of periods $L \in \mathbb{R}^+$, and its reliability is measured by the percentage of on-time delivery.

When port $X$ is disrupted and the redirection option is offered by the terminal operator, the shipping company needs to decide whether to transfer the existing queue at port $X$ to port $Y$. In this research we assume that the shipping company will always follow the option offered by the terminal operator, thus the redirection flow of cargo is decided by the terminal operator alone. Suppose the consecutive times of port $X$'s failure of delivery at period $t$ is $v_t$, and the transit time required for inland transportation is $l^{xy}$ periods, the redirection decision function for terminal operator during disrupted periods is:

\[
q^x_{t+1} = \begin{cases} 
q^x_t + d_t, & \text{if } v_t < \gamma \\
(q^x_t + d_t - u_t)^+, & \text{if } \gamma \leq v_t < \gamma', \\
q^x_t, & \text{if } v_t \geq \gamma
\end{cases}
\]

and
\[
q^y_{t+1} = \begin{cases} 
q^y_t, & \text{if } v_t < \gamma \\
(q^y_t + u_t - (q^x_t + d_t))^+, & \text{if } \gamma \leq v_t < \gamma', \\
q^y_t + d_t, & \text{if } v_t \geq \gamma'.
\end{cases}
\]

The transfer of shipments between the two ports is realized by inland transport. A transportation cost $r^{xy}$ per unit per day is borne either by the supplier or the terminal operator if the cargo handling fee is retained after disruption. As such, the expected penalty cost per unit for the shipping company and the expected inland transportation cost are influenced by the decision of the terminal operator. Lastly, the actual amount of arrival at port $Z$ for each period $t$ can be obtained as

\[
a_t = (q^x_{t+1} - q^y_{t+1}) + q^y_{t+1} - q^z_{t+1} - p_2.
\]
investment in total network capacity. The capacity investment choices are based on a number of considerations such as cost, service level, availability of resources, and long-run development of port. This research proposes three performance measures that provide evaluation of some important port investment considerations. The three performance measures are described below.

1. **Container backlog**: the percentage of expected containers backlogged each week can be a good indication of the level of congestion at the port, which affects its operating cost, efficiency and service level. The container backlog for period $t$ is calculated by dividing the unprocessed cargo at beginning of period $t+1$ by the quantity of new arrivals in period $t$. Note that since we are only dealing with one supply chain in our model, we are only interested in this quantity in the period of the supply chain’s scheduled loading operation. Hence, we set the container backlog to 0 for other periods. More specifically, we calculate it using the following equation:

$$
\begin{align*}
    r^1_t & = \begin{cases} 
        \frac{q^X_{t+1}}{d_t}, & \text{if } t = S^X_0 + ks \\
        0, & \text{if } t \neq S^X_0 + ks 
    \end{cases} 
\end{align*}
$$

2. **Inland traffic volume**: the expected inland traffic volume due to contingency rerouting indicates the level of congestion between ports, which influences the cost and schedule reliability of intermodal operators, and also affect the effectiveness of the mitigation strategy. Therefore, it is in the strategic interest of the terminal operator and port authority to keep this quantity at a level that does not disturb port city traffic. The inland traffic volume at period $t$ is

$$
\begin{align*}
    r^2_{t, \text{in}} & = \begin{cases} 
        0, & \text{if } v_t < \gamma \\
        [u_t^X - (q^X_{t-1} - d_t)]^+, & \text{if } \gamma \leq v_t < \gamma', \\
        d_t, & \text{if } v_t \geq \gamma 
    \end{cases} 
\end{align*}
$$

3. **Demand fulfillment ratio**: the expected demand fulfillment ratio per period measures the percentage of orders delivered to port $Z$ on schedule, which indicates the overall port service level and the reliability of the transportation network. Shippers and shipping companies’ choice of port is partly depending on the schedule reliability port terminals can provide. As such, the terminal operator and port authority should keep the expected demand fulfillment ratio above a reasonable level to ensure port competitiveness. The demand fulfillment ratio at period $t$ depend on the actual amount of arrival $a_t$ and the scheduled amount $e_t = d_{t-L}$, more specifically,

$$
\begin{align*}
    r^3_t & = \begin{cases} 
        \frac{\hat{a}_t}{e_t}, & \text{if } e_t > 0 \\
        0, & \text{otherwise} 
    \end{cases} 
\end{align*}
$$

where $\hat{a}_t$ is the adjusted actual amount of arrival at port $Z$, i.e. the time early or late deliveries are
adjusted to the next scheduled pick-up time for the consignee.

Besides these three performance measures, the terminal operator should also take into account the cost of investing in capacity. We use $c(u^X)$ and $c(u^Y)$ to denote the investment and operating cost per unit of capacity for port $X$ and port $Y$, representing the costs of the two mitigation strategies. Suppose the function of port $X$’s three performance measures are $g_1, g_2$ and $g_3$, respectively, we construct the cost minimization problem for port $X$ as follows:

$$\begin{align*}
\text{minimize} & \quad c(u^X) + c(u^Y), \\
\text{subject to} & \quad w_1 g_1 + w_2 g_2 + w_3 g_3 \geq \hat{g},
\end{align*}$$

where $w_1$, $w_2$ and $w_3$ are the weights assigned to the three performance measures, and $\hat{g}$ is the desired level of overall port performance.

This research does not seek to quantify the costs of mitigation strategies directly, as the cost of investment varies greatly from port to port, while the weights assigned to three measures are also subject to varied characteristics of the ports. However, we do seek to quantify the impact of $\gamma_X$ and $\gamma_Y$ on the three performance measures, as well as the trade-off pattern between themselves.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_t$</td>
<td>Hub port status at beginning of period $t$, with $i_t = 0$ indicates open status, and $i_t = 1$ indicates closed status</td>
</tr>
<tr>
<td>$d_t$</td>
<td>Demand/order in period $t$</td>
</tr>
<tr>
<td>$q^X_t$</td>
<td>Port $X$ queue length at beginning of period $t$</td>
</tr>
<tr>
<td>$q^Y_t$</td>
<td>Port $Y$ queue length at beginning of period $t$</td>
</tr>
<tr>
<td>$s$</td>
<td>Inter-arrival time of vessels</td>
</tr>
<tr>
<td>$u^X_t$</td>
<td>Maximum number of units that can be processed by port $X$ in period $t$</td>
</tr>
<tr>
<td>$u^Y_t$</td>
<td>Maximum number of units that can be processed by port $Y$ in period $t$</td>
</tr>
<tr>
<td>$S^X_t$</td>
<td>Vessel’s first arrival time at port $X$</td>
</tr>
<tr>
<td>$S^Y_t$</td>
<td>Vessel’s first arrival time at port $Y$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Decision criterion for rerouting from port $X$ to port $Y$</td>
</tr>
<tr>
<td>$\gamma^*$</td>
<td>Decision criterion for termination of port $X$’s service</td>
</tr>
<tr>
<td>$v_t$</td>
<td>Number of consecutive times port $X$ fails to deliver at beginning of period $t$</td>
</tr>
<tr>
<td>$L$</td>
<td>Maximum acceptable order lead time</td>
</tr>
<tr>
<td>$a_t$</td>
<td>Actual amount of arrival at port $Z$ for each period $t$</td>
</tr>
</tbody>
</table>

As discussed previously, we define the problem for the terminal operator to be determining a
capacity allocation \( \mathbf{u} \) that attains the best long-run average performance. In order to obtain the system performances measures we use the average reward of a fixed policy for Markov reward processes introduced in Puterman (1994).

Let \((i, \mathbf{q}, \mathbf{y})\) be the complete model state space for each time period \( t \geq 0 \), where \( \mathbf{q} = (q^x, q^r) \) and \( \mathbf{u} = (u^x, u^r) \). A decision rule at period \( t \) is a function \( \mathbf{u}_t = \delta_t (i, \mathbf{q}_t) \). A policy \( \pi \) is a sequence of decision rules, i.e. \( \pi = (\delta_1, \delta_2, \ldots) \). For a system with a fixed initial state, the average reward or gain provided by a fixed policy \( \pi \) is

\[
g^\pi (i, \mathbf{q}) = \lim_{N \to \infty} \frac{1}{N} E^\pi \left[ \sum_{t=1}^{N} r(i, \mathbf{q}_t, \mathbf{u}_t) \right] = \lim_{N \to \infty} \frac{1}{N} V^\pi_N (i, \mathbf{q}). \tag{10}
\]

The average reward equation (10) can be used to calculate the system performance measures described in the previous section. A stationary policy satisfies the condition \( d_t = d \) for all \( t \in T \). Since capacity expansion and contingency rerouting requires port investment, and will maintain their states once implemented. Thus, the mitigation strategies introduced in this paper can be considered as a stationary policy in the Markov reward process. By considering different policy options, we are able to show the impact of mitigation strategies have on the performance of port-oriented transportation network.
4. Numerical examples

For numerical examples consider a supply chain depicted figure 1, where the supplier is located close to port $X$, i.e. transportation time from supplier to port X is 0. Orders from the customer are assumed to be $d_i = 10$ units per period. To minimize storage cost, the supplier delivers its weekly production, equivalent to 70 units, to port $X$ just before the scheduled arrival time of the vessel. Port $X$ and port $Y$ are both ports-of-call along the same shipping route, which connects the two ports to port $Z$, where the customer is located. In other words, the cargos loaded onto the vessel at port $X$ and the cargos loaded at port $Y$ in the same cycle will reach port $Z$ simultaneously. Thus if port $X$ is disrupted and back-up capacity is available in port $Y$, then terminal operator can exercise contingency rerouting to transport containers to port $Y$ to meet the liner schedule. The port disruption scenarios are modeled with several sets of disruption probabilities and recovery probabilities from: $\alpha \in \{0.001, 0.003, 0.01, 0.02\}$ and $\beta \in \{0.05, 0.1, 0.2, 0.5\}$. The disruption probability set corresponds to an expected inter-occurrence time ($1/\alpha$) ranges from approximately three years to 50 days. The recovery probability set corresponds to an expected disruption duration ($1/\beta$) ranges from 20 days to 2 days. This allows us to test a wide variety of port disruption scenarios.

We examine the effect of port mitigation strategies by establishing a base case scenario, where port $X$ has a processing capacity of $u^X = 70$ units and port $Y$ has a capacity of 0, representing an extreme case of lean supply chains. As such, any disruptions occurred under the base case scenario are guaranteed to cause delays in shipments and port congestions. We seek to analyze the impact of capacity expansion and contingency rerouting on various performance measures comparing to the base case scenario. Firstly, we examine the situation where only capacity expansion is implemented for port $X$. We then examine the impact of contingency rerouting alone on three performances measures by adding processing capacity to port $Y$. Finally, we look into an integration of the two strategies, by assuming additional capacity can be allocated to either port interchangeably.

4.1 Capacity expansion

In this section we demonstrate the three performance measures for shipping and port in relation to different port $X$ processing capacity. In the following example, we specifically look into the changes in performance when the total processing capacity of port $X$ increases from 70 units to 140 units, equivalent to a variation of one week’s production of the supplier. The effects of different capacity levels is then examined and compared across varying disruption probabilities.
Figure 2 shows the expected container backlog per week of port $X$ with different total processing capacity ($r_X$). We first set $\beta=0.2$ (i.e. each disruption lasts for 5 periods on average), and investigate the benefit of additional processing capacity for varying disruption probabilities. We then set $\alpha=0.3\%$ (i.e. two consecutive disruptions have an average inter-arrival time of approximately one year), and examine the effect for varying average disruption durations. It is obvious from the graphs that larger total capacity results in lower container backlog. For $\alpha=1\%$, the expected backlogged work is reduced by more than 53% (from 44.2% backlogged to 20.5%) when the total processing capacity increases from 80 units to 90 units. However, as the capacity of port $X$ continues to increase, the mitigating capability of additional capacity deteriorates. The curves also reveal that different disruption frequency and severity have significant impacts on the performance. This implies that small but frequent disruptions, as well as infrequent catastrophic disruptions are likely to cause disturbances that result in longer backlogs and higher degree of port congestion.
In figure 3 we examine the effects of different total processing capacity on schedule reliability. Expected demand fulfillment ratio measures the weekly average percentage of orders that are delivered to the customer at port Z on time. As shown in figure 3, different disruption probabilities have a significant impact on schedule reliability. Schedule reliability is lower for ports that are experiencing frequent disruptions, as we would expect. However, additional processing capacity of port X has no apparent effect on demand fulfillment ratio. This result implies that even though excess capacity improves the port’s recovery ability, it does not improve the schedule reliability of the transportation network.
4.2 Contingency rerouting

We now assume that when port $X$ is disrupted, part of the unprocessed work is transferred to port $Y$ up to a maximum amount of port $Y$'s processing capacity. The effect of available processing capacity in port $Y$ on expected container backlog of port $X$ is depicted in figure 4. A significant impact on expected queue length is observed with an increasing amount of capacity in port $Y$. The expected backlogged work drops to zero as the capacity of port $Y$ increases to 70 units, equivalent to the supplier’s weekly production. However, the large and unstable queue length when capacity is smaller than 70 indicates that at least some excess capacity should be allocated to port $X$ to ensure minimal recovery capability.

![Figure 4](image)

Figure 4  Expected container backlog versus total processing capacity of port $Y$

Figure 5 shows that mitigation with contingency rerouting can improve demand fulfillment ratio significantly. During disrupted periods of port $X$, part of its unprocessed cargos are transferred to port $Y$ for departure and arrives at port $Z$ on time. Thus, more back-up capacity at port $Y$ means a higher percentage of on-time arrival. A significant improvement in demand fulfillment by implementing contingency rerouting is shown in the figure. Moreover, the expected demand fulfillment ratio increases proportionally to the back-up capacity at port $Y$. The ratio eventually reaches 100% as the back-up capacity at port $Y$ increases to the equivalence of a whole week’s production of the supplier. However, it is uneconomical and impractical for the terminal operator to set aside that amount of back-up capacity at another port just for contingencies. It is thus important for the terminal operator, who operates in several ports, to develop a profit-maximizing
network capacity utilization strategy that also allows the flexibility of contingency rerouting.

By having back-up capacity at port Y and implementing rerouting when disruption occurs at port X could result in a certain degree of inland traffic congestion between the two ports. As shown in figure 6, the expected inland traffic volume increases about proportionally to the back-up capacity in port Y. Moreover, such effect increases as the expected inter-closure time of port X \((1/\alpha)\) decreases. In our calculation, we measure the level of traffic congestion between two ports by aggregating the transfer of cargos for each week, which indicates the supply chain’s contribution to the traffic congestion during port closure. However, in realistic situations, this inland transfer of cargos needs to be completed before the ship’s scheduled departure time at port Y. As a result, the immediate few days following a disruption will experience heavier traffic congestion. This unevenly distributed impact is beyond the scope of the research.

![Figure 5: Expected demand fulfillment rate versus total processing capacity of port Y](image)

Figure 5  Expected demand fulfillment rate versus total processing capacity of port Y
Comparing to mitigation with port utilization, port alliance has the advantage of improving on-time delivery rate, but could potentially result in an uncontrollable backlog queue if implemented alone without sufficient capacity in port $X$. Moreover, the traffic congestion conditions on inland transport route between two ports are also among important consideration of port development. As implementing contingency rerouting requires port alliance and the inland logistic capacity proportional to port $Y$’s processing capacity, the impact of increasing inland traffic volume should also be taken into consideration.

4.3 Impact of total excess capacity on cost saving

In this previous section, we discussed that for each potential disruption scenarios, a certain combination of the two mitigations strategies can result in the optimal performance, in terms of port congestion, inland traffic and vessel schedule. The optimization of port performance requires a careful examination of the weights assigned to each performance measure, which should reflect the terminal’s competitiveness, as well as align to the port’s strategic development. In this section, we assume that the port’s primary concern is port congestion, i.e. the objective is to minimize container backlog. Now consider that the terminal operator has the fund to invest in certain amount of excess processing capacity, and can allocate the capacity to either port $X$ or port $Y$ without incurring additional cost. This section demonstrates how the trade-off between two ports’ processing capacity can affect the optimal performance level. More specifically, we seek to find the lowest achievable long-run average contained backlog by simulating the different allocation choices to determine the optimal solution. We show this result in table 1, where the expected
closure duration is fixed ($\beta = 0.2$), and the disruption probability and the total excess processing capacity are then varied. Table 1 displays the optimal choice of processing capacity allocation and the resultant expected container backlog. The table also shows the other two performance measures corresponding to the given the optimal allocations. An interesting observation is that the behavior of optimal capacity in port $X$ resembles a bell-shape curve. The optimal allocation in port $X$ increases rapidly at first, but eventually declines as more excess processing capacity is available. The results indicate that the strategic capacity allocation should first focus on improving the recovery capability of the hub port, and then allocate the resources to the back-up port for further improvement in mitigation.

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$u_r$</th>
<th>Optimal allocation</th>
<th>Container backlog</th>
<th>Demand fulfillment rate</th>
<th>Inland traffic volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1%</td>
<td>70</td>
<td>70</td>
<td>0</td>
<td>101.3793</td>
<td>0.9947</td>
</tr>
<tr>
<td></td>
<td>80</td>
<td>79</td>
<td>1</td>
<td>0.0308</td>
<td>0.9952</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>89</td>
<td>1</td>
<td>0.0149</td>
<td>0.9954</td>
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Figure 7 establishes the benefit of excess port network capacity of the on container backlog reduction. As the total processing capacity increases, there is a decreasing trend for the optimal long-run average container backlog. The results show that the first few excess processing capacity contribute the most to the backlog reduction effect. For example, when $\alpha = 1\%$, the expected work backlogged decreases from 46.9% to 19.2% when total processing capacity increases from 80 to 90 units, representing an backlog reduction of 59%. The next 10 processing capacity, however, only reduces backlog percentage by 29% to an expected 13.7% work backlogged. Interestingly, the container backlog reduction rate remains approximately unchanged from that point on, forming a kinked curve. A set of curves with similar behavior are also observed for disruption scenarios with different expected duration expected frequency is held as constant. These results show that even when cost of increasing capacity is not considered, a heavily invested mitigation effort does not guarantee benefit of the same scale. Furthermore, as the results assume optimal decision making for the terminal operator, the actual benefit of such disruption management effort can be even smaller if the terminal operator invests in either only the recovery capacity, or only the mitigation capacity.
Figure 7  Lowest container backlog versus total processing capacity
5. Conclusions and future research directions

In this paper, we present a seaport-oriented supply chain model that evaluates the key performance parameters of inter-modal transportation networks. We propose a Markov rewarding process-based methodology to solve the model, and examine the effectiveness of strategic options from port terminals’ perspective. Our results demonstrate that the impact of port disruption on transportation network can be quantified efficiently on an operational level. This study contributes to the literature by providing initial insights in disruption risk analysis for complex systems involving multiple stakeholders.

Our research highlights that port capacity expansion is essential for the disruption management of port-oriented transportation networks, especially if the ports are highly utilized. The recovery capability provided by excess processing capacity is necessary for reducing container backlogs and alleviating port congestions. However, without proactive contingency rerouting plans, the port’s service level to shipping companies as well as other supply chain entities is unlikely to improve. This study shows that the best port performance, which translates to minimal backlog, manageable inland traffic and reliable shipping schedule, can be achieved through a balance of capacity expansion and contingency rerouting. More importantly, the balance should be adjusted based on considerations involving investment, operation and transportation costs; as well as strategic alignment towards the long-run performance objectives of port and terminals.

As demonstrated in the study, other stakeholders of the transportation network such as shipping companies, cargo owners and intermodal operators are clearly impacted by the decisions of port terminals. It is thus of vital importance for all participants of maritime supply chains to be engaged in a conversation over allocation of resources towards optimal system resilience. We believe a multi-objective risk analysis model for supply chains like ours, which focuses on port-oriented intermodal cargo movement, can provide valuable quantitative evidence for such a platform. Other models such as inventory management, container routing and schedule that capture the behaviors of supply chain firms and shipping companies can also be incorporated to provide a comprehensive micro-level analysis. Such a study from key supply chain parties and government agencies is highly desirable for developing effective disruption management.

As the performance measures reported in this research are long-run expectations, the decision criteria might not capture the nature of modern businesses where short term fluctuations are often among their major concerns. It is important to realize that the disruption impact on individual supply chain firms can so overwhelming in the short term that it drastically changes the supply chain configuration. This limitation of the model indicates that for industrial practitioners, a
careful consideration that includes both the long-run performance and extreme short-run scenarios is required in choosing mitigation tactics and implementing policies.

A realistic transportation network involves several ports, shipping lanes, many inland routes and a multitude of supply chain entities. Thus future research on extending the model in a multi-echelon setting, where a network of ports is involved is still needed to fully understand the impacts of port disruptions and the potential mitigation strategies for terminal operators. Other assumptions on cargo movement in the network can also be relaxed to capture reality more closely. For example, the assumption on deterministic port processing time would not be able to reflect the uncertainty of port time in realistic situations. Wang and Meng (2012a) suggest that port time of a vessel can be formulated as random variables based on historical data of similar vessels. Complex network models of such are challenging to analyze; but generalization of model is beneficial for theory building and real-world application.
References


