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A SIMULATION MODEL OF PORT OPERATIONS DURING CRISIS CONDITIONS

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ABSTRACT

We consider the supply chain for containerized items that arrive at a port in the U.S. whose final destination is also in the U.S. Ports are important entities in global supply chains. As such, when a port cannot operate because of a crisis, such as a natural or man-made disaster, it is critical that freight flow is not disrupted. We develop a simulation model that can be used to make effective re-routing decisions so that the time for freight to reach its final destination is not significantly increased in a crisis. The simulation model will evaluate and report the performance of the supply chain under different re-routing strategies. The output can be analyzed to find the best re-routing strategy that minimizes congestion and delays during crisis conditions. The model can also be used by various decision makers such as port managers, ocean carriers, or transportation companies for strategic decision making.

1 INTRODUCTION

A wide variety of industries rely on efficient port operations to receive the raw materials for their businesses as well as to ship their products to their customers. Natural catastrophes (e.g. earthquakes, hurricanes) and man-made disasters (e.g. terrorist attacks, fires) negatively impact these industries due to delays in the flow of materials through the affected port in a supply chain. Impacts of crisis conditions, such as congestions and increase in lead times, should be assessed to mitigate their negative effects on the performance of supply chains. The fact that most of the supply chains are now tightly connected networks all around the world, intensifies the global impacts of threats from natural disasters, terrorist attacks, wars, worker strikes, etc. However, recent studies show that the majority of supply chains are incapable of dealing with crisis conditions, and have low level of disaster preparedness (Lee 2004, Hale and Moberg 2005). Supply chain risk management is still an issue which is in infancy (Juttner 2005) as most of the U.S. companies ignore the importance of drawing up emergency plans for crisis conditions (Lee 2004). Accordingly, the gap between theory and practice in disaster planning for supply chains is highlighted by Tang (2006).

In this study, we describe a simulation model that can be used to effectively control freight transportation in order to minimize supply chain disruptions during crisis conditions. The simulation model can be used to evaluate the performance of supply chains that include ports as part of the chain. In our supply chain setting, freight going to a crisis stricken port is rerouted to other ports. The objective is to minimize congestion and the increase in lead times during crisis conditions. The main performance measure is the lead time, which is defined as the total time the freight spends in the system from its origin to its final destination.

To demonstrate the use of the model we simulated and evaluated the performance of several ports in the U.S. based on the following cases: (i) under normal conditions without any disruptions and (ii) under crisis conditions where one or more ports are affected by a disaster. The simulation model also enables the decision maker to perform what-if analyses by specifying different re-routing scenarios. Although one would expect a significant increase in lead time when there is a crisis at a port, it is not clear if there are significant differences among various re-routing strategies. Statistical analyses are conducted in order to evaluate whether or not there are significant differences in the lead time under normal and crisis conditions, and also among various re-routing strategies. The difference in lead time under several scenarios is estimated in Section 3.

The simulation model is flexible and user-friendly, and is developed using *ProModel*. The model is intended for use by ocean carriers, logistic companies, port operators, and federal emergency management agencies. Using the model requires no prior knowledge of simulation techniques. Since the model reads the input data from an *Excel* sheet, it is also very easy to change the data and run new scenarios with different supply chain dynamics.

1.1 Supply Chain Management during Crisis Conditions

The continuous flow of goods, information and money between different entities (such as retailers, wholesalers, distributors, etc.) of a supply chain results in interaction. These interactions create mutual interdependencies between entities, making supply chains highly vulnerable to crisis conditions. Hence, entities of a supply chain are not only susceptible to disruptions to their own operations but also to disruptions at upstream and downstream levels (Sheffi 2001). In other words, a crisis at one of the supply chain entities, such as a port, could significantly affect the operations of other entities in the supply chain even if they are not directly affected by the crisis itself. For instance, 29 West Coast ports in the U.S. were disrupted for two weeks in 2002, and this resulted in a 1.1% decrease in nominal gross domestic profit in Hong Kong, Malaysia and Singapore (Barnes et al. 2005). Therefore, the ability to quickly adjust operations in response to sudden changes, referred to as agility, is very important. According to Lee (2004), efficient supply chains are not only time- and cost-effective, but also agile. Agility of supply chain operations is a necessity to compensate for the vulnerable structure of the system resulting from interdependencies. Therefore, if back-up plans and "what-if" analyses are performed prior to a disaster, the responsiveness of the supply chains during crisis conditions increases. However, it may not be practical to consider all possible scenarios, therefore, simulation tools such as the one proposed here will help supply chains become more agile and be ready for disruptions in advance.

Disaster preparedness and quick adjustments to sudden changes are critical issues since crisis conditions are typically unpredictable. The simulation tool we have developed prepares the supply chains for disruptions at U.S. ports, thereby enhancing the flexibility, agility and adaptability of supply chains during crisis conditions.

1.2 Port Operations

Ports are major intermodal facilities where multiple modes of transportation (rail, barge, trucks) meet. Crisis conditions in and around ports will significantly impact port operations leading to undesired effects such as delays in the flow of materials through the port.

The U.S. is the world's largest importer and exporter, and the nation's 361 seaports are the gateways for more than 80% of the foreign trade (McCown 2005). In addition, all freight moving in, out, and within the U.S. amounts to more than 15 billion tons annually, valued at over $9 trillion. Of the $9 trillion about $2 trillion is due to international trade. It is estimated that the overall freight volumes will grow by more than 60% by 2020. "*In the same time interval, every major U.S. port is projected to at least double the volume of cargo it is expected to handle*" as argued by the report of National Chamber Foundation of the U.S. Chamber of Commerce (2003).

Although ports are critical transfer nodes in a supply chain, they usually are vulnerable to crisis conditions. For instance, Biederman (2007) mentions a report by the U. S. Government Accountability Office (GAO) that investigated 17 ports in the U.S. According to this report, 12 out of these 17 ports were subjected to at least one hurricane or earthquake since 1998, and 8 of them experienced problems in overcoming crisis conditions.

Computer simulation is not a new methodology used in maritime transportation networks to monitor and improve the performance of port operations and the corresponding supply chains. We provide a few examples of simulation studies of maritime transportation and logistics: Rensburg and He (2005) developed a simulation tool, SimSea, to simulate transport of containers by container vessels. Valentine and Silva (2005) proposed an alternative approach in the simulation of large-scale maritime infrastructure systems and implemented the proposed approach in the port of Tanger. Sasso (2008) integrated Geographic Information Systems (GIS) with *Arena* simulation software in order to simulate the transit of ocean-going vessels through the Panama Canal. Additionally, a port modeling simulation with optimization capability of operational and economic performance measures was developed by Dahal et al. (2003). Chang et al. (2005) simulated and evaluated the overall performance of bunkering services at port of Kaohsiung. Cortes et al. (2004) simulated the freight traffic at Sevilla inland port. A wide variety of simulation studies in maritime transportation and logistics systems are available in the literature. However, most of the studies analyze a given system at a micro level under normal conditions. In other words, most of the simulation studies focus on a specific entity within a supply chain, and ignore crisis conditions. In our study, we develop a simulation model for macro-level analyses. We consider the impact of crisis conditions on the whole system by including upstream and downstream entities of the ports. A future extension of this work would be to generalize the approach so that it could be applied to the existing port simulation models listed above. To do so, further modeling and data collection would be required. For example, the severity of a crisis could be estimated using the increase in lead time as a function of the increase in the number of containers a port receives.

2 METHODOLOGY

2.1 Procedures to Collect Data

As part of our data collection process we developed a survey to gather the following data. Since all research activities that involve surveying human subjects require Institutional Review Board (IRB) approval to ensure compliance with federal regulations and ethical standards, we submitted our survey instrument to the IRB. After obtaining IRB approval, we contacted and visited several inland and coastal ports on the Gulf of Mexico in order to collect data for the simulation model. The data consists of the following:

- The arrival process: Based on expert opinion and conversations with port managers, the arrivals of ships to a port are assumed to follow a Poisson process. The numbers of containers on each ship is assumed to be uniformly distributed between a low and a high value that the user defines.
- Source of containers: In the scenario we present as an example, it is assumed that containers are coming from three sources: Asia, Europe, and South America. The arrival process of containers is defined for each source-port pair.
- Port activities: These consist of setup operations such as docking, positioning of a ship, etc. and unloading/loading containers. The setup time per ship and the unloading/loading time per container are assumed to follow triangular distributions. The low, high, and most likely values are entered by the user. Also, each port has a certain capacity that determines how many cranes can unload or load at any given time.
- Waiting time: This is the time a container spends at a port waiting for a truck or a train to pick it up for delivery.
- Destination: The exact destination of a container can be easily tracked, but for our purposes the distance that the container travels once it leaves the port is more important. Therefore, four destinations are defined in our sample problem: (i) destinations that are within 100 miles, (ii) destinations that are between 100 and 300 miles, (iii) destinations that are between 300 and 600 miles, and (iv) destinations that are beyond 600 miles.
- Mode of transportation: A container can potentially leave a port by truck, train, or barge. In our case we ignore barges. Data were collected on the percentage of containers using each mode of transportation.
- Transportation capacity: The number of outbound trucks and trains that are available for each port is an important factor in determining how well a port can react to a crisis condition. For example, following Hurricane Katrina some ports had difficulty hiring truck drivers because they were able to make more money hauling debris.

In addition, we asked port managers whether they have a contingency plan in a time of crisis. We were informed about the details of the plans such as re-routing strategies or alternative plans that are preferred by the ports during crisis conditions. We also investigated the publicly available online data on the web site of the American Association of Port Authorities <www.aapa-ports.org>. The online data gave us a general insight about the operations of the ports that we were not able to contact and visit.

2.2 Simulation Model

The software package consists of two components: a MS *Excel* spreadsheet and a simulation model developed in *ProModel*. The data we collected are stored in a spreadsheet, thus providing the user with easy access to the input data that drives the model. The spreadsheet includes seven main components denoted by C as follows:

C1. Mean inter-arrival time of containers for each source-port pair
C2. Time it takes to complete operations (i.e. docking, positioning, overall setup of the ship, etc.) at each port
C3. Distribution of the number of containers per ship at a port
C4. Time it takes for loading/unloading a container at each port
C5. Final destinations of the containers after they leave the port
    (a) Percentage of containers whose final destination is within 100 miles
    (b) Percentage of containers whose final destination is between 100 and 300 miles
    (c) Percentage of containers whose final destination is between 300 and 600 miles
    (d) Percentage of containers whose final destination is beyond 600 miles
C6. Ports that are subject to crisis conditions
C7. Re-routing scenarios of the affected ports

Let *N, M,* and *K* denote the number of ports evaluated by the simulation model, the number of origins, and the number of final destinations, respectively. All of the input components are represented as matrices in the input spreadsheet, but they are stored as arrays in the simulation model. The first six components (C1 through C6) are represented as single matrices in the spreadsheet. C1 is a *N* by *M* array, C2 is *N* by *3*, C3 is *N* by *2*, C4 is *N* by *3*, C5 is *N* by *K*, and C6 is *N* by *1*. In general, let *(i,j)* denote the entry in i^{th} row and j^{th} column of an array. In C1, (*n,m*) is the mean inter-arrival time of the ships from their origin *m* to port *n.* In C2, entries (*n,1*), (*n,2*) and (*n,3*) are the parameters of the triangular distribution which represent low, most likely, and high values of the time required for port operations at port *n,* respectively. In C3, (*n,1*) and (*n,2*) are the parameters of the uniform distribution which denote the mean, and the half range of the number of containers per ship arriving to port *n*, respectively. In C4, entries (*n,1*), (*n,2*) and (*n,3*) are the parameters of the triangular distribution which represent the low, most likely, and high values of time required for unloading/loading a container at port *n,* respectively. In C5, (*n,k*) is the percentage of containers that go from port *n* to the final destination *k*. C6 is a binary array: the entry in the n^{th} row is 1 when there is a crisis condition at port *n*; and 0, otherwise. C7, the rerouting scenario array, consists of *M* matrices of size *N* by *N.* Let (*m,i,j*) denote the entry in the i^{th} row and j^{th} column of the m^{th} array in C7. So, (*m,i,j*) represents the percentage of ships that are coming from source *m* and originally scheduled to arrive at port *i*, but that are re-routed to the port *j* because of a crisis at port *i*. The sum of entries in each row of an array in C7 must be equal to 1. Figure1 provides an example of a re-routing scenario array.

m_1 — *New port destionation* (columns); *Original destination* (rows)

	n_1	n_2	n_3	n_4	n_5	n_6	n_7
n_1	1	0	0	0	0	0	0
n_2	0.25	0	0.75	0	0	0	0
n_3	0	0	1	0	0	0	0
n_4	0	0	0	0	0	0	0
n_5	0	0	0	0	0	0	0
n_6	0	0	0	0	0	0	0
n_7	0	0	0	0	0	0	0

Figure 1: Example of re-routing scenario array

Figure 1 shows port destinations of ships that are coming from source m_1 (*m=1*). In Figure 1, entry (*1,2,1*) = 0.25 means that 25% of ships that are coming from source m_1 and originally scheduled to arrive at port *2* (n_2), are re-routed to the port *1* (n_1) because of a crisis at port n_2. Similarly, 75% of the ships that are originally scheduled to arrive at port n_2, are re-routed to port n_3. Note that (*1,3,3*) is one, which indicates that 100% of the ships originally scheduled to arrive at port n_3 are routed to n_3.

After the user defines these required data components, the simulation model is run in order to evaluate the performance of the supply chain. The resulting performance measures are reported by the simulation model in accordance with the specified re-routing scenario. In this study, the performance measure of interest is the total time that a container spends in the system under different scenarios (i.e. no crisis conditions, crisis conditions with different re-routing scenarios including the option of minimal re-routing). Under a crisis condition, the user continues simulating and comparing the performance of the different re-routing strategies until a stopping criteria. The stopping criteria can be either to simulate a fixed number of re-routing scenarios or to stop when a satisfying performance measure defined by the customer is reached. This mechanism allows the user to perform 'what if' analyses in order to search for the best re-routing scenario during crisis conditions.

2.2.1 System Description

The supply chain simulated in this study consists of the following three layers denoted by L. Containers move from L1 to L3.

L1. Origin *m* from where containers arrive at the ports (*m*=1,2,…,*M*)
L2. Port *n* where containers are routed to (*n*=1,2,…,*N*)
L3. Final destination *k* of the containers (*k*=1,2,…,*K*)

When ships arrive at a port, they first join a queue (Q1) in order to gain access to the port. While in Q1 activities such as docking, positioning, and other setup operations will take place. The ship which has waited for the longest time period leaves Q1 and enters the port. Once a ship enters the port, containers are unloaded off the ship and/or loaded on the ship. Following the unloading/loading operations containers that are unloaded join queue (Q2) where they wait for a resource (train or truck) that will transport them to their final destinations. When containers reach their final destination, they exit the system. Figure 2 illustrates this flow.

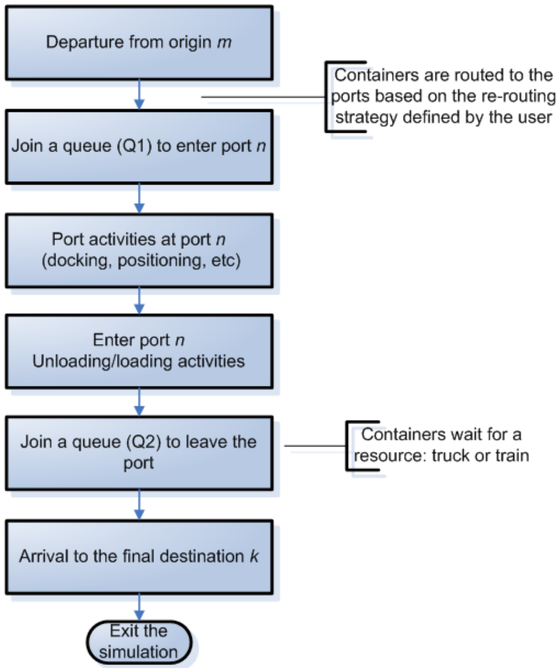

Figure 2: Entity flow diagram of the containers in the supply chain

The system is simulated based on the following modeling assumptions:

1. Seven U.S. ports are considered; one port from each of the following states: California, Texas, Louisiana, Mississippi, Florida, New Jersey, and Massachusetts. These were selected because, according to the American Association of Port Authorities statistics (2007), ports in these states are among the busiest in the U.S. This information is obtained from 2007 U.S. port cargo tonnage rankings and North America port container traffic statistics published by the American Association of Port Authorities `<www.aapa-ports.org>`. However, other ports can easily be added to the model.
2. When containers arrive at a port, they may be required to wait before departing for their final destination. Since we aim to provide a general measure of the supply chain's performance under different re-routing scenarios, we assume that containers go to one of four destinations, grouped as (i) within 100 miles, (ii) between 100 and 300 miles, (iii) between 300 and 600 miles, and (iv) beyond 600 miles.
3. It is assumed that ships/containers are coming to ports from three sources: Pacific Ocean (from Asia), Atlantic Ocean (from Europe), and Gulf of Mexico (from South America). In the simulation model, ships coming from the same origin can be routed to different ports. The re-routing of the ships during crisis conditions is performed based on the percentages contained in C7 of the system's input sheet .
4. When containers leave a port, they are transported by either train or truck. It is assumed that, if a container is going to a destination within 300 miles, it is transported by a truck; otherwise, it is transported by a train. It is also assumed that one truck carries two containers and one train carries twenty containers. For example, from the port in California, containers are transported to the Southwest part of the U.S. by trucks, to the Midwest by trains, and to the Northeast by trains. When a container is at a port in Texas, Louisiana, Mississippi, or Florida, transportation to the Southwestern and Northeastern parts of the U.S. is performed by train, and transportation to the Midwest is done by trucks. For ports in New Jersey and Massachusetts, containers are delivered to the Northeastern part of the U.S. by trucks, to the Midwestern and Southwestern parts of the U.S. by trains.

2.2.2 Main Elements of the Simulation Model

Figure 3 illustrates the general framework of our simulation study and Figure 4 provides a snapshot of the simulation model layout.

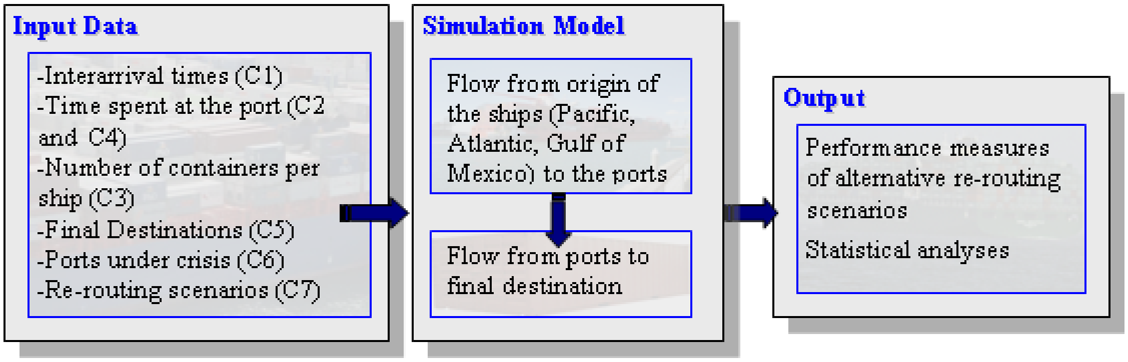

Figure 3: Framework of the simulation

In *ProModel* terms, the model contains the following constructs:

- **Entities:** There is only one entity type, container, in the simulation model.
- **Locations (static resources):** Seven ports, two queues for each port, three origins, and four final destinations are considered in the simulation. A total of 28 locations are used in the simulation model.
- **Arrivals:** Since ship arrivals to a port follow a Poisson process, the inter-arrival times are exponentially distributed. Mean inter-arrival times of containers for each port are defined in the spreadsheet (component C1 of the input). As stated above, C1 is N by M matrix, where N=7 and M=3 in our supply chain setting.
- **Attribute:** Container's intended port of entry.
- **Arrays:** C1 is a 7 by 3 array containing the inter-arrival times of the containers from their origin to the ports, C2 is a 7 by 3 array of port operations time (docking, positioning of a ship, etc.) at each port, C3 is a 7 by 2 array containing the parameters of the uniform distribution which denote the mean, and the half range of the number of containers per ship arriving at each port, C4 is a 7 by 3 array of unloading/loading time at each port, C5 is a 7 by 4 array of the percentage of the containers going from a port to the four possible final destinations, and C7 is composed of three 7 by 7 arrays which represent the re-routing scenarios.

Figure 4: A snapshot of the simulation model layout

2.2.3 Simulation of Crisis Conditions

When one or several ports are subject to a crisis, re-routing scenarios are considered for the containers of the affected ports. This re-routing mechanism influences the flow of containers from their origin to the ports, and from the ports to their final destinations. Figure 5 illustrates the general flow of the containers between different layers of the supply chain. Re-routing changes the ways that containers move on Arc1, and on Arc2. As explained below, the simulation model considers two different algorithms for the re-routings on Arc1 and Arc2.

Figure 5: Re-routing affect the flow of containers at Arc1 and Arc2

1. **Re-routing the flow of containers from their origins to the ports (Arc1):** As soon as an arrival of a container is generated by the simulation model, an attribute called *OriginalPort* is assigned to each container. This attribute indicates the port destination of the container. Even if the containers of the affected port are re-routed to another port, information about the original port of the re-routed containers are not lost. If there is no crisis condition in the original port, then the container is sent to that port. Otherwise, the re-routing scenario defined by the user in input array C7 is applied by the simulation model, and the containers of the affected port are re-routed based on that re-routing scenario. This process is illustrated in Figure 6.

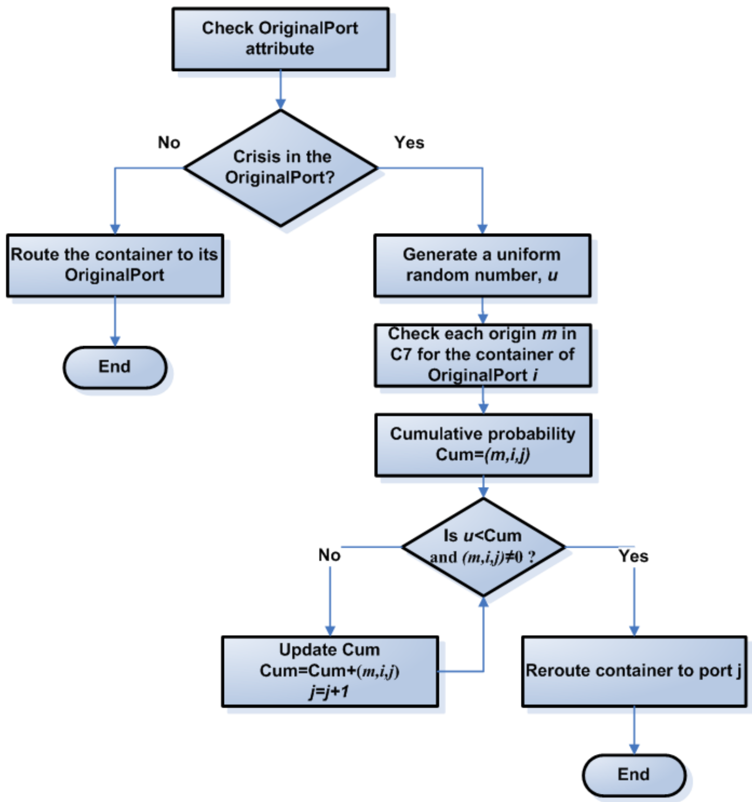

Figure 6: Flowchart for re-routing containers on Arc1

2. **Re-routing the flow of containers from the ports to their final destination (Arc2):** Recall, the input component C7, (m,i,j) defines a re-routing scenario for the containers of the affected port i. Similarly, in input array C5 the user defines the final destination for the containers of each port. During a crisis condition, even if the containers of the affected port i are re-routed to an alternative port j, the containers of the port i are sent to their final destination by considering the final destination definitions of port i while they are at port j. The flow of the containers on Arc2 is illustrated in Figure 7. Additionally, if a container leaves the port on a train then it waits in Q2 until twenty containers are accumulated, otherwise two containers are transported by a truck.

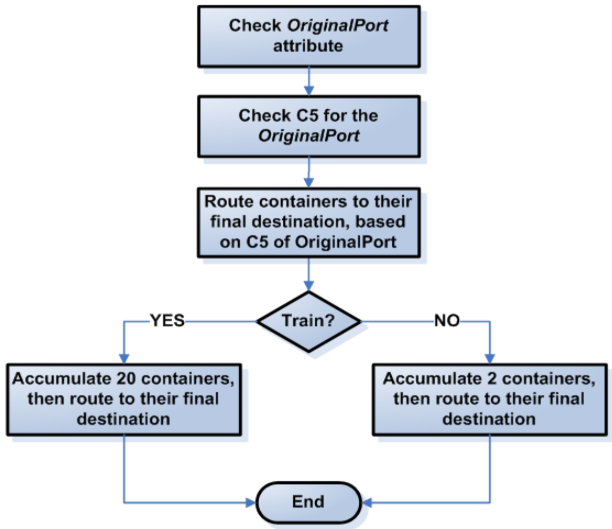

Figure 7: Flowchart for re-routing containers on Arc2

3 TEST AND MEASUREMENT

3.1 Performance Measure

The total time that a container spends in the system is considered as the main measure of our supply chain's performance. This represents the time interval between the arrival of a container to the system from its origin, until it exits the simulation by reaching its final destination. That is, the performance measure is the lead time of the containers. In this study, the lead time under different re-routing scenarios is analyzed and statistically compared in order to evaluate the performance of the supply chain. Lead time of the containers is affected by the following four components:

1. **Maritime transportation time:** time required to transport containers from their origin to the ports. In case of a crisis, the maritime transportation time of containers may increase due to re-routing.
2. **Setup and operational time:** time spent for docking, positioning, unloading/loading, and other port activities. During a crisis the setup and operational times will typically increase not only at the port directly affected by the crisis but also at other ports.
3. **Inland transportation time:** time interval between the departure of the containers from a port and their arrival at the final destination. Inland transportation time depends on two parameters: the mode of transportation due to its speed (train or truck) and the distance traveled.
4. **Waiting time:** total time a container spends at Q1 (queue to enter the port), and Q2 (queue where they are stored to be picked up by a train or truck). When the freight of an affected port is re-routed, congestion at the alternative port can be engendered due to capacity limitations. For example, limited capacity of the storage area (Q2) may block the port operations, and consequently increase the waiting time at Q1. The capacity constraints of a port are the maximum number of ships that can be unloaded/loaded at a given time and the capacity of the storage area Q2. The waiting time in Q2 is primarily affected by the availability of trucks and trains that transport containers to their final destinations. For example, following hurricane Katrina port managers reported having difficulty finding truckers to carry their cargo. This was due to the fact that truckers were able to receive better pay hauling debris rather than transporting containers. In the scenarios we simulate, it is assumed that the number of available trains and trucks is unlimited.

3.2 Statistical Analyses: An Example

The results and statistical analyses provided in this section demonstrate how the simulation model can be used by various decision makers such as port managers, ocean carriers, transportation companies, or customers (i.e. industrial firms). The use of the model is not only limited to re-routing decisions in crisis conditions, but it can also be used by container carriers to determine which ports they should utilize and how much capacity they should allocate to each port.

In our example problem a port in Texas (TX) is subject to a crisis condition. The following five scenarios are simulated to measure the performance of the system:

1. Scenario 0 (Normal or Base Scenario): In this case we assume that all ports are operating under normal conditions without any crisis.
2. Scenario 1: 25% of the ships coming from the Pacific Ocean that were originally destined to Texas (TX) are re-routed to California (CA) and the remaining 75% are re-routed to Louisiana (LA). Additionally, 75% of the ships coming from the Gulf of Mexico that were originally destined to TX are re-routed to CA and the remaining 25% to LA. Since the traffic at the CA and LA ports are higher due to re-routing, the processing of containers at these ports take longer.
3. Scenario 2: 75% of the ships coming from the Pacific Ocean that were originally destined to TX are re-routed to CA and the remaining 25% to LA. Additionally, 25% of the ships coming from the Gulf of Mexico that were originally destined to TX are re-routed to CA and the remaining 75% to LA. Since the traffic at the CA and LA ports are higher due to re-routing, the processing of containers at these ports take longer.
4. Scenario 3: 25% of the ships coming from all sources that were originally destined to TX are re-routed to CA, another 25% to LA, and the remaining 50% still go to TX. However, the time required for port operations at Texas increases due to the impacts of the crisis.
5. Scenario 4: 50% of the ships coming from all sources that were originally destined to TX are re-routed to CA and the remaining 50% to LA.

Data used in the above scenarios are based on information gathered from port officials with whom we visited. Thus, the input data is realistic. Each scenario is replicated 30 times and each replication is simulated for 195 hours of which 150 hours corresponds to the warm-up period. When simulating different scenarios common random numbers are used. The warm up period is chosen to be 150 hours after simulating the normal case for 300 hours and analyzing the performance of the system. At the end of 300 hours of simulation, we plotted the average time a container spends in the system, and observed that the system reached steady state after about 150 hours of simulation. As we will show later, we performed statistical analyses on the average time a container spends in the system. Each scenario is replicated 30times so that the distribution of each of the means is approximately normally distributed.

The results of the simulation study are summarized in Table 1, which shows the mean percentage increase in the corresponding performance measure with respect to the "Normal Scenario." For example, the average number of containers in Q1 in California under scenario 1 increased by 64.9% compared to the normal scenario. As expected, the average length of Q1 in California and Louisiana increased under all four scenarios. Note that the length of Q1 in Texas became zero under scenarios 1, 2, and 4 because all ships destined for Texas are re-routed to other ports under these three scenarios. However, under scenario 3, only 50% of the ships are re-routed; thus, the average size of Q1 decreases by 53.3% rather than 100%. As can be seen from Table 1, the size of Q2 did not change as much as Q1. This is due to the assumption related to the number of trucks and trains. In simulating the five scenarios it was assumed that the number of trucks and trains available to transport containers is very large. Therefore, containers in Q2 are quickly picked up by a truck or a train.

Table 1: Mean percentage change in average queue length and lead time

	Scenario 1	*Scenario 2*	*Scenario 3*	*Scenario 4*
Average queue length (Q1 in CA)	64.9	80.4	45.6	83.2
Average queue length (Q1 in LA)	100.0	172.3	69.1	130.8
Average queue length (Q1 in TX)	-100.0	-100.0	-53.3	-100.0
Average queue length (Q2 in CA)	2.5	3.5	1.8	2.1
Average queue length (Q2 in LA)	1.5	4.9	-0.6	1.2
Average queue length (Q2 in TX)	-100.0	-100.0	-3.4	-100.0
Average time in system (lead time)	1.2	-0.2	0.2	0.4

Table 1 also shows the percent change in the average time a container spends in the system. For example, under scenario 1 each container spent an average of 9500 minutes (see Table 2) in the system whereas the lead time was about 9390 minutes under the normal scenario corresponding to an increase of 1.2%. The increase under scenarios 3 and 4 compared to the normal case were 0.2% and 0.4%, respectively. Under scenario 2, however, containers actually spent less time on the average in the system compared to the normal scenario. In the following paragraphs an explanation for this decrease in lead time is provided.

To determine the significance of these changes statistical tests were performed. The average time a container spends in the system under each scenario (based on 30 replications) were collected. Pair-wise comparisons of the means were performed for each possible pair out of five scenarios, leading to a total of 10 tests. As can be seen from Table 2, the sample variances were quite different for different scenarios. Therefore, we assume that the population variances are unequal. Based on this assumption, Welch's t-test was the most appropriate statistical test to use. Before performing the t-tests, goodness of fit tests for normality were executed to evaluate if the assumptions of the t-test are valid for the output data. Kolmogorov-Smirnov and Anderson-Darling tests were performed on the observations collected from each scenario for this purpose. As the p-values in Table 3 indicate, the distribution of the observations are not significantly different from the normal distribution.

Table 2: Pair-wise comparisons of the lead time

	Normal	*Scenario1*	*Normal*	*Scenario2*	*Normal*	*Scenario 3*	*Normal*	*Scenario 4*
Mean	9390.47	9500.38	9390.47	9370.33	9390.47	9408.12	9390.47	9424.87
Variance	3048.50	6107.90	3048.50	2090.97	3048.50	3570.21	3048.50	3415.94
Hypothesized Mean Difference	0		0		0		0	
df	52		56		58		58	
t Critical two-tail	2.007		2.003		2.002		2.002	
t Stat	-6.291		1.539		-1.188		-2.343	
P(T<=t) two-tail	0.000		0.129		0.240		0.023	

	Scenario1	*Scenario2*	*Scenario1*	*Scenario 3*	*Scenario1*	*Scenario 4*
Mean	9500.38	9370.33	9500.38	9408.12	9500.38	9424.87
Variance	6107.90	2090.97	6107.90	3570.21	6107.90	3415.94
Hypothesized Mean Difference	0		0		0	
df	47		54		54	
t Critical two-tail	2.012		2.005		2.005	
t Stat	7.867		5.137		4.238	
P(T<=t) two-tail	0.000		0.000		0.000	

	Scenario2	*Scenario 3*	*Scenario2*	*Scenario 4*	*Scenario 3*	*Scenario 4*
Mean	9370.33	9408.12	9370.33	9424.87	9408.12	9424.87
Variance	2090.97	3570.21	2090.97	3415.94	3570.21	3415.94
Hypothesized Mean Difference	0		0		0	
df	54		55		58	
t Critical two-tail	2.005		2.004		2.002	
t Stat	-2.751		-4.026		-1.098	
P(T<=t) two-tail	0.008		0.000		0.277	

Table 2 provides the results of the t-tests. All tests were performed at the 5% significance level. As can be seen from the p-values in Table 2 there is no significant difference in the average time a container spends in the system under the normal scenario versus scenarios 2 and 3. This indicates that the 1.2% increase in average lead time under scenario 1 compared to the normal scenario, although small, is statistically significant. Similarly, the 0.4% increase in lead time under scenario 4 compared to the normal scenario is also significant. These results are encouraging because the increase in lead time, although statistically significant, has not drastically increased in our example. Clearly, this will depend on the severity of the disaster and the model assumptions, but it is interesting to see that through effective re-routing the increase in lead time can be kept small. As a matter of fact, the lead time under scenario 2 was actually slightly smaller compared to the normal scenario. This might indicate that the port in Texas was already too busy even before the crisis, and by re-routing the ships we were able to reduce the average time a container spends in the system. While the t-test indicates that this difference in lead time is insignificant, it provides a good illustration of how the simulation model can be used for strategic decision making purposes by transportation companies, ocean carriers, and industrial firms. It can also be seen from Table 2 that the time a container spends in the system is statistically different for all pair wise comparisons of scenarios 1, 2, 3, and 4 except for one pair (i.e., scenario 3 vs. scenario 4).

Table 3: Output analyses: test for normality

	Kolmogorov Smirnov	**Anderson Darling**
Scenario 1	0.820	0.824
Scenario 2	0.887	0.968
Scenario 3	0.973	0.988
Scenario 4	0.570	0.672
Scenario 5	0.992	0.994

4 CONCLUSION AND FUTURE RESEARCH

Ports are critical transfer nodes of a supply chain because they are vulnerable to crisis conditions. The simulation tool developed in this study enables decision makers to prepare for possible crises at U.S. ports by providing a capability to analyze ways to adjust to sudden changes. The simulation model captures and presents the general behavior of complex supply chain interactions, both under normal conditions and under different user-defined re-routing scenarios. This study demonstrates how simulation can be used to mitigate the impact of crisis conditions on the performance of supply chains. The simulation tool can be used to estimate the performance of the U.S. supply chains at a macro level, and to prepare supply chains for disruptions through "what if" analyses. This macro view can also improve the effectiveness of strategic decisions made by ocean container carriers, logistics companies, federal emergency management agencies, and port operators.

Future enhancements to this simulation tool could include the integration of optimization methodologies . Instead of what-if analyses, simulation optimization and heuristic optimization could be employed to find the "best" re-routing strategy that minimizes the increase in lead time and congestion during crisis conditions. Additionally, the severity of the crisis can be quantified. For example, a function can be developed that estimates change in setup and operational times with respect to the change in the number of containers a port receives. However, further modeling and data collection would be required to expand this study.

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REFERENCES

American Association of Port Authorities. 2007. U.S. Ports Cargo Tonnage Rankings. Available via <http://www.aapa-ports.org/Industry/content.cfm?ItemNumber=900&navItemNumber=551> [accessed March 16, 2009].

American Association of Port Authorities. 2007. North American Port-Container Traffic. Available via <http://www.aapa-ports.org/Industry/content.cfm?ItemNumber=900&navItemNumber=551> [accessed March 16, 2009].

Barnes, P., and R. Oloruntoba. 2005. Assurance of security in maritime supply chains: Conceptual issues of vulnerability and crisis management. *Journal of International Management* 11:19–540.

Biederman, D. 2007. Risky Business. *Traffic World* May7:18-23.

Chang, Y., and C. Chen. 2006. Knowledge-based simulation of bunkering services in the port of Kaohsiung. *Civil Engineering and Environmental Systems* 23: 21–34.

Cortes, P., J. Munuzuri, J. N. Ibanez, and J. Guadix. 2007. Simulation of freight traffic in the Seville inland port. *Simulation Modeling Practice and Theory* 15:256–271.

Dahal, K., S. Galloway, G. Burt, and J. Mcdonald. 2003. A Port System Simulation Facility with an Optimization Capability. *International Journal of Computational Intelligence and Applications* 3:395-410.

Hale, T., and C. R. Moberg. 2005. Improving supply chain disaster preparedness: A decision process for secure site location. *International Journal of Physical Distribution & Logistics Management* 35:195-208.

Juttner, U. 2005. Supply chain risk management. *The International Journal of Logistics Management* 16:120-141.
Lee, H., L. 2004. The Triple-A Supply Chain. Harvard Business Review
McCown, B.A. 2005. Intermodal Transportation Challenges of the 21st Century. *Forth Worth*.
National Chamber Foundation of the U.S. Chamber of Commerce. 2003. Trade and Transportation: A Study of North American Port and Intermodal Systems.
Rensburg, J. J. Van, Y. He, and A. J. Kleywegt. 2005. A Computer Simulation Model of Container Movement by Sea. In *Proceedings of the 2005 Winter Simulation Conference,* ed. M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 1559-1566.
Sasso,D., and W. E. Biles. 2008. An Object-Oriented programming approach for a GIS data-driven simulation model of traffic on an inland waterway. In *Proceedings of the 2008 Winter Simulation Conference,* ed. S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, J. W. Fowler.
Sheffi, Y. 2001. Supply Chain Management under the Threat of International Terrorism. *International Journal of Logistics Management* 12:1-11.
Statistics on U.S. transportation Systems. Available via <http://www.thesafetylibrary.com> [accessed March 16, 2009].
Tang, C. 2006. Perspectives in supply chain risk management. *International Journal of Production Economics* 103:451-488.
Valentin, E. C., S. Steijaert, and R. A. Bijlsma. 2005. Approach for Modeling of Large Maritime Infrastructure Systems. In *Proceedings of the 2005 Winter Simulation Conference,* ed. M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 1577-1585.

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