NCIT

The National Center for Intermodal Transportation

A Simulation Model to Analyze the Impact of Crisis Conditions on the Performance of Port Operations

FINAL REPORT

August 2009

INVESTIGATORS:
Burak Eksioglu, Sandra D. Eksioglu, Albert Allen, Al Myles

TABLE OF CONTENTS

1 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 strategi

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-

3 METHODOLOGY

3.1 Procedures to Collect Data

As part of our data collection process we developed a survey to gather the following data. Since all research activ-

3.2.1

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.

3.2.2 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 fo

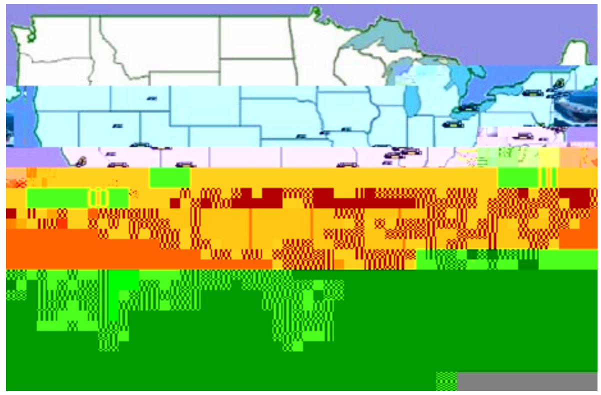

Figure 4: A snapshot of the simulation model layout

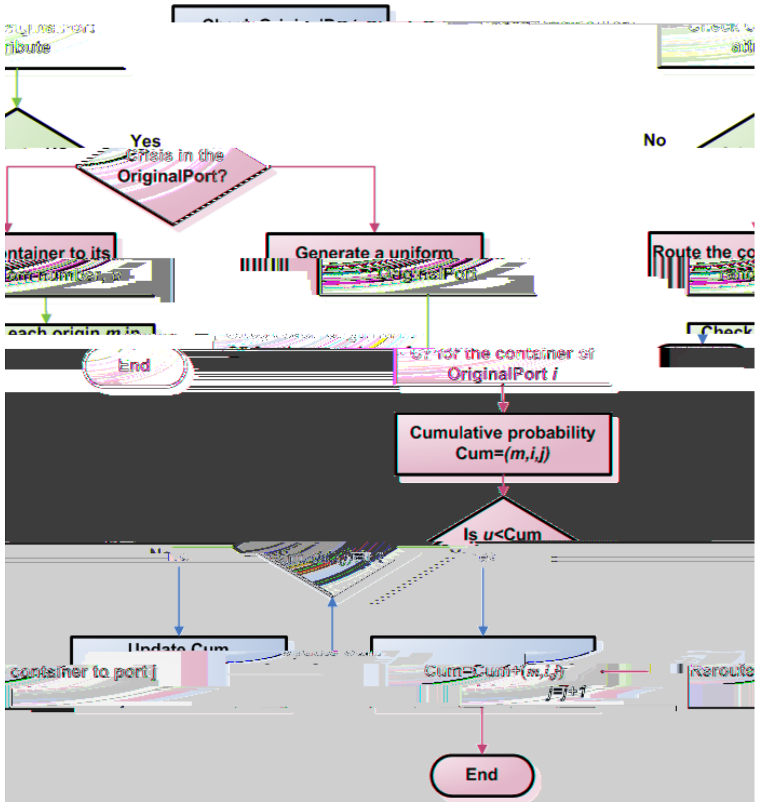

Figure 6: Flowchart for re-routing containers on Arc1

2. **Re-routing the flow of containers from the ports to their final destination (Arc2)**
   Recall, the input component C7,

4.2 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 compar

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*

APPENDIX

Interview Questions

The National Center for Intermodal Transportation

Project Title: A Simulation Model to Analyze the Impact of Crisis Conditions on the Performance of Port Operations

It would take approximately _______________ hours for a **truck** to reach a destination that is about 100 miles away from the port.

It would take approximately _____________ hours for a **train** to reach a destination that is about 100 miles away from the port.

It would take approximately _______________ hours for a **barge** to reach a destination that is about 100 miles away from the port.

4. **Crisis Conditions:**

   Under a crisis condition (e.g., a hurricane, a terrorist attack, a strike), what happens to your capacity to handle TEUs?

   If it is a minor crisis it would increase the time a TEU spends at the port by only ____%.

   If it is a major crisis we would shut down for a few days which would increase the time a TEU spends at the port by about ____%.

   If you receive more TEUs than usual how would your service time change? (When answering this question assume that you do not have enough time to significantly increase your capacity)

   If we received 2000 additional TEUs a day then the time a TEU spends at the port would increase by about ____%.

   If we received 4000 additional TEUs a day then the time a TEU spends at the port would increase by about ____%.

   If we received 6000 additional TEUs a day then the time a TEU spends at the port would increase by about ____%.

5. **Can you provide a copy of the port tariff?**