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STAKEHOLDER-CENTRIC ANALYSES OF SIMULATED SHIPPING PORT DISRUPTIONS

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ABSTRACT

The Maritime Transportation System is crucial to the global economy, accounting for more than 80% of global merchandise trade in volume and 67% of its value in 2017. Within the US economy alone, this system accounted for roughly a quarter of GDP in 2018. This paper defines an approach to measure the degree to which individual stakeholders, when disrupted, affect the commodity flows of other stakeholders and the entire port. Using a simulation model based on heterogeneous datasets gathered from fieldwork with Port Everglades in FL, we look at the effect of varying the timing and location of disruptions, as well as response actions, on the flow of imported commodities. Insights based upon our model inform how and when stakeholders can impact one another's operations and should thereby provide a data-driven, strategic approach to inform the security plans of individual companies and shipping ports as a whole.

1 INTRODUCTION

The *Maritime Transportation System (MTS)* is critical to the global economy, accounting for more than 80% of global merchandise trade in volume and 67% of its value in 2017 (Hoffman and Sirimanne 2017). Within the US economy, the MTS accounted for roughly a quarter of the United States' GDP in 2018 (Martin Associates 2019). Disruptions, whether natural or manmade, affect the flow of commodities upon which modern commerce depends. Individual stakeholders—whether terminal operators, drayage companies, or landlord ports—may be affected differently depending upon the timing and location of such disruptions, as well as mitigations for or responses to such disruptions. This paper employs queueing network simulation to quantify the impact of disruptions to stakeholders within the MTS.

The movement of commodities within a shipping port requires coordination among several organizations. Stakeholders include *Ocean Carriers (OC)* to move goods and passengers to/from the port, *Terminal Operators (TO)* in order to transit cargo between land and water, *Drayage Companies (DC)* in order to transport freight by truck, and local law enforcement as well as *Customs and Border Protection (CBP)* to screen containers and protect against terrorism, narcotics, and human trafficking. Furthermore, the *US Coast Guard (USCG)* works to ensure the safety of all involved and protect commerce by developing *Area Maritime Security Committees (AMSC)*.

Disruptions to the MTS can have cascading affects that affect the ability of a port to function. In order to prepare for potential disruptions, stakeholders within *Area Maritime Security Committees (AMSC)* must work together to develop *Area Maritime Security Plans (AMSP)*. AMSP must consider a variety of hazards including natural disasters (e.g. hurricanes, storm surge), technical threats (e.g. power outage), manmade disruptions (e.g. terrorism, active shooter), and threats related to a dependence on automation (e.g. cyber attacks). For example, a consequence of the NotPetya 'ransomware' affecting Maersk, was trucks collecting, "bumper to bumper, farther than [one] could see" (Greenberg 2018). Today just-in-time supply chains rely upon dependencies between stakeholders to drive efficiency; as a result, risk assessment *must* consider a multi-stakeholder perspective.

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Therefore, our paper's primary contribution is to use simulation to understand how disruptions impact commodity flows through shipping ports, both to individual stakeholders as well as to the port as a whole. Section 2 surveys the academic literature for approaches to model supply chain disruptions in general as well as in the context of the MTS. Section 3 defines the simulation model as well as a formalism from graph theory to analyze stakeholder-specific impacts. The process used to verify, calibrate, and validate our model is discussed in Section 4. Section 5 presents results from analyses to understand the degree to which individual stakeholders can affect commodity flows through the port. Finally, Section 6 concludes.

2 RELATED WORK

The primary contribution of this research paper is a model to *measure the impact of shipping port disruptions to multiple stakeholders* within the MTS. Specifically, this paper describes a simulation-based approach—based on actual vessel schedules and bills of lading—coupled with a graph-theoretic approach, to understand the degree to which a disruption of one stakeholder's operations affects other stakeholders individually and collectively. To the best of our knowledge, understanding impact in terms of measures of performance as they apply to specific stakeholder areas of responsibility is a novel contribution and as such, an improvement over the state of the art.

Extensive research has been done by the simulation community to understand the impact of supply chain disruptions. Schmitt and Singh (2009) used discrete event simulation to model the flow of material through a supply chain network and combined this with a Monte Carlo approach to determine whether a risk occurs and for how long. Finke et al. (2010) simulated the flow of products and disruptions within an aerospace company's supply chain. While many of these studies use qualitative analysis to compare baseline and disrupted measures of performance, Melnyk et al. (2014) proposed to use outlier detection from time-series analysis to quantify transient responses to a disruption. Our research is similar at a high level in that it uses a graph-theoretic construct, a hierarchy tree (Buchsbaum and Westbrook 2000), to analyze the impact of a disruption. Work done by Macdonald et al. (2018) has looked at using structured experimental design to build a theory of supply chain resilience that links a disruption to its impact on the supply chain. Structured experimental design has also been emphasized in research done by Sanchez et al. (2015) and our results section reflects this approach.

Much research has also been conducted on *port-related* disruptions and their impact. Although there is a vast, decades-long, tradition of simulating shipping port operations in general (Dragović, Tzannatos, and Park 2017), we focus on modeling disruptions within the MTS. Modeling disruptions and mitigation/response actions as decreases or increases in capacity was studied by Netto et al. (2015) as well as Hosseini and Barker (2016). Disruptions resulting from cyber-physical dependencies also have been explored within the literature (Beyeler et al. 2004; Beaumont 2017).

Regional and national impacts of shipping port disruptions have also been extensively studied within the simulation and economic literature. Studies include models to support freight re-routing (Martagan et al. 2009), and regional commodity flows (Maloni and Paul 2013; Almaz 2012). In addition to simulation, optimization techniques to model disaster impacts to shipping ports have also been employed (Novati et al. 2015; Vugrin et al. 2014). Within the economic literature, there are several studies that have defined approaches to measure the impact of port disruptions to regional, national, and international supply chains (Pant et al. 2011; Jung et al. 2009; Rose et al. 2018). These economic models, however do not consider the degree of influence individual stakeholders have on commodity flows (and thereby business interruption losses) on others.

3 MODEL DEFINITION

Our simulation model was developed to capture the flow of imported commodities through a shipping port to their destinations. Given a graph-based representation of a transportation network, the approach instantiates a queueing network simulation to capture the movement of entities (e.g. vessels and *Twenty-foot*

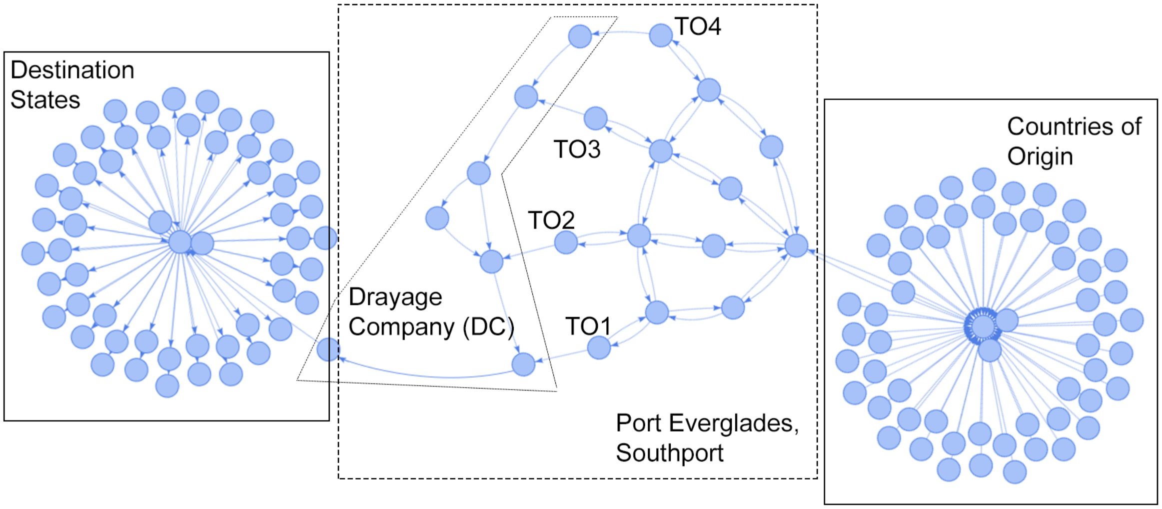


Figure 1: A transportation network based on container operations in Port Everglades, FL.

Equivalent Units (TEUs)) through the port. Stakeholder areas of responsibility are defined as subgraphs within the transportation network; stakeholders are responsible for the movement of entities within these subgraph regions.

The model constructed is based on extensive fieldwork at Port Everglades, FL which included meetings with operators, law enforcement, customs, security managers, and the US Coast Guard. This paper focuses on disruptions to container operations lasting a few days as this was of most interest to our collaborators. This model could be used for longer-term disruptions as well if desired.

Inputs to the shipping port model consist of (1) a graph-based representation of a transportation network, (2) vessel and commodity flows through the port for a given period of time, and (3) disruption, mitigation, or response events.

3.1 Transportation Network

The intent of our study is to quantify the impact of disruptions to the MTS within a shipping port. Therefore, we represent the transportation network as a directed graph whose nodes encode different locations and edges encode roads (or seaways) between those locations. The transportation network encodes the topology of the intermodal transportation system within a port and as such both seaways for vessels as well as roadways for trucks are represented. In the future, other modes of transportation, such as rail, may be included. Figure 1 illustrates an example transportation network along with stakeholder subgraphs.

Definition 1 A *transportation network* is a multidigraph $G_{Trans} = (V, A, s, t, l_V, l_A, f_C, f_T)$ in which the following holds:

- V is a set of locations
- A is a set of roadways
- $s(t) : A \longrightarrow V$ assigns each edge a source (target) node
- $l_v(l_A) : V \longrightarrow \Sigma_V(\Sigma_A)$ assigns a type from an ontology to each vertex (edge).
- $f_C(f_T) : V \cup A \longrightarrow \mathbb{N}$ assigns each location and roadway a capacity (service/travel time).

3.2 Vessel and Commodity Flows

In addition, the model also requires a schedule of entities (e.g. vessels, TEU) based on (but not limited to) vessel schedules and bills of lading.

Definition 2 A *set of commodities* K has elements of the form $k = (o,e,d,l,B)$ where the following holds:

- $o,d \in V[G_{Trans}]$ are the source and destination locations for the TEU.
- $e,l \in [0,T]$ are the earliest available and latest arrival times of the TEU.
- B is the type of commodity transported in the TEU.

The transportation network (G_{Trans}) is used to instantiate a queueing network simulation. Each element within the queueing network for land-side (sea-side) operations has a capacity (c), the number of TEU (vessels) that can be simultaneously served, a service/travel time (t), an r.v. based on a Gaussian distribution, a queue length, and queueing discipline (e.g. FIFO). The geocoding of locations informs the travel time t. Where possible, travel times were computed using Google Maps, while within and outside of the port, travel times are based on a geodesic distance assuming a travel time of either 15 or 65 mph depending upon whether the TEU travels via forklift or highway truck.

Events modeled within the queueing network include the arrival and departure of vessels or TEU. Calibration of routes taken by entities through the transportation network is discussed in more detail in Section 4.

3.3 Disruption, Mitigation, and Response Events

Using the above framework, it is possible to model the effect of disruptions to the MTS, mitigations to limit the impact of future disruptions, and responses to recover from a disruption that has occurred. These events may be scheduled within the simulation in addition to the entity arrival and departure events mentioned above. Although we provide the definition of a disruption, mitigation and response events take a similar form.

Definition 3 A *disruption* is an event of the form $d = (t_s^d, t_e^d, B^d, f_C, f_T)$ in which the following holds:

- $[t_s^d, t_e^d]$ define a closed time interval in which the disruption occurs.
- B^d is the type of disruption.
- $f_C(f_T) : V[G_{Trans}] \cup A[G_{Trans}] \longrightarrow \mathbb{N}$ are updated capacities (service/travel times).

This approach is applicable to model the effect of a variety of cyber-physical disruptions. Adjusting capacities and travel/service times is useful to look at changes in *availability* of cyber-physical resources. For example, both the effect of an oil spill on a road as well as the failure of a *Gate Operating System (GOS)* may be modeled as a decrease in the rate of flow of traffic in the MTS—either due to a decrease in capacity and/or an increase in service time for some time interval. Similarly, mitigation and response may be modeled as an increase in resource capacitiy or decrease in service/travel time before or after a disruption event. Such an approach is not suitable to model all types of disruptions, however. For example, a data integrity attack—such as that experienced in the 2011-2013 Port of Antwerp hack, does not result in a reduced rate of traffic flow (Bateman 2013).

3.4 Measures of Performance

The intent of our simulation model is to provide insight into the impact of a disruption on commodity flows of individual stakeholders and the shipping port as a whole. In addition, we want to look at the effect of the timing and location of mitigation or response actions to lessen a disruption's impact. The degree to which our simulation can provide such insights depends upon the measures of performance used.

There are many different ways to quantify a port's overall ability to move cargo. For example, the *Bureau of Transportation Statistics (BTS)*, in their Port Performance Freight Statistics Program Annual Report to Congress, uses measures of port throughput and capacity. In order to understand how the location and duration of a disruption affects the ability of stakeholders to provide their services (and thereby generate revenue), we need to consider measures of stakeholder performance. In this manner, we can *measure resilience as the ability for a stakeholder to continue to provide a business-critical function given a disruption* (Alderson et al. 2015).

Our stakeholder-centric analyses of measures of performance define a *hierarchy tree* ($T_{Stakeholders}$) over the transportation network (G_{Trans}). We construct the tree so that subtrees correspond to subnetworks within which stakeholder are responsible for TEU movements. Using this approach, we are able to aggregate measures of performance within a given stakeholder subgraph by specifying a *view* on the transportation network. More information on hierarchy trees may be found in (Buchsbaum and Westbrook 2000).

Definition 4 A rooted tree T is a *hierarchy tree* of G if $L(T) = V(G)$ where $L(T)$ denotes the set of leaves of T. For clarity, in the remainder of this discussion, we refer to elements of $V(G)$ as *vertices* of G and to elements of $V(T)$ as *nodes* of T.

Definition 5 A subset U of $V(T)$ is a *view* of G if the set $\{leaves(v) | v \in U\}$ partitions $V(G)$.

In order to understand the impact of a disruption (or mitigation/response) on individual stakeholders and the port as a whole, we look at the number of TEU in the subgraphs specified by a view on the transportation network over some time interval. This measure of performance gives insight into the locations of TEU among different stakeholders in the shipping port and reflects the volume of TEU moved by different port stakeholders. By filtering on the type of commodities within the TEU, we can also consider the economic impact of a disruption on the movement of specific goods as shown in Figure 2.

4 MODEL VERIFICATION, CALIBRATION, AND VALIDATION

This section describes verification, calibration, and validation of our network simulation for Port Everglades, FL. Although a full *Verification, Validation, and Accreditation (VV&A)* process (e.g. the US *Department of Defense (DoD)*'s VV&A methodology) is beyond the scope of our research, it is important to make explicit the degree to which these steps have been taken within our research.

4.1 Verification

During several meetings with Port Everglades, we reviewed the transportation network topology, stakeholder subgraph regions, vessel schedules, and commodity flows generated by our model. The current simulation of the shipping port transportation network was built using the SimPy process-based discrete-event simulation framework (Matloff 2008). The data used to generate the simulation scenario were obtained directly from Port Everglades. Moreover, the code by which the data was transformed into an input scenario for the simulation was written in Python. This code, along with the simulation code itself, uses a unit testing framework to test for errors in implementation. One simulation run of the entire month-long scenario takes 4 minutes to complete on a MacBook Pro with 2.2 GHz Intel i7 processor and 16 GB memory. Longer run-times are possible depending upon the level of logging.

4.2 Calibration

Our intent is to understand the overall behavior of container operations at PEV and to develop robust policies based upon this behavior, not to perfectly calibrate the system (Sanchez et al. 2015). Table 1 lists several of the data sources used to calibrate components of the simulation model. Since vessel arrivals to the port within the simulation are scheduled directly from PEV's Vessel Calls dataset, we focused our calibration efforts on the movement of imported, loaded TEU from a berth, through the port, to a destination state.

Table 1: A table of data sources used to define, calibrate, and validate the simulation model used in this paper.

Stakeholder Data Sources				
Organization	Data Source	Version	Entities	Scale
FDOT	Traffic Sensors	March-July 2017	Class 1-9 Vehicles on port roads	Daily
PIERS (IHS Inc.)	Commodity Group Origin-Destination Pairs	FY2017, FY2018	Loaded TEU Import, Export	Monthly
PIERS	Vessel Commodities	FY2017, FY2018	Commodity TEU Import and Export by Vessel	Daily
PEV	Vessel Calls	FY2017	Vessel	Hourly
PEV	Financial Report	FY2017, FY2018	Loaded TEU Import, Export	Monthly

4.2.1 Demand Matrix Estimation

Within the microscopic simulation literature, some consider estimating the number of trips between an *Origin-Destination (O-D)* pair during a time period the first (and potentially only necessary) step to model calibration (Chu et al. 2003). We estimate the O-D pairs from the PEV Vessel Calls FY2017 and *Port Import/Export Reporting Service (PIERS)* FY2017 datasets.

Vessels The PEV Vessel Calls dataset provides the time (hour) and location (berth) at which a vessel arrives at and departs from the port. Within the time period of interest, vessels arrive just outside of the seaway and proceed to the berth. As such, the O-D matrix for vessels over a given time period is completely determined by the vessel calls dataset.

TEU Once having docked at a berth, the simulation needs to be able to unload TEU of different types of commodities from the vessel. In order to estimate the O-D demand matrix for TEU of different commodity types, we used the PIERS Vessel Commodities FY2017 dataset. The PIERS Vessel Commodities dataset contains approximately 70 commodity groups (e.g. Glass/Ceramic, Apparel, Fruits and Vegetables). For each commodity group, there is a monthly count of TEU imported from a source country to a destination US State via Port Everglades. These counts provide frequencies by which we created an empirical distribution of source/destination pairs for every commodity group. At times, the destination field may simply indicate the location of the company that imported the TEU, however, stakeholders at Port Everglades confirmed this was a good approximation to understand regional dependencies on commodities.

4.2.2 Route Choice Calibration

The choice of route by which commodities move from origin to destination is also important in order to understand the impact of disruptions to particular roads as well as traffic volumes throughout the port. Such calibration is important to understand both how long TEU spend in different system components, and traffic volumes on key roads in South Port. Chu et al. (2003) considers this important enough that for medium-size networks, this is the second step of model calibration for microscopic simulations.

Figure 2 shows that at a high level, imported TEU move from a berth to loading dock, through a TO's container yard, to a shared road and out to a destination state via highway. There are variations within this high-level flow once a TEU is offloaded to a loading dock. For example, the container yard through which a TEU is routed (and thereby its dwell time) is determined by the shipping line of the vessel that transported the container. In addition, a container may be selected for inspection, requiring it to be re-routed to an inspection facility. These constraints inform the selection of a path that a TEU must take through the port to its eventual destination node.

Although several different algorithms are being explored for path selection through a port, the simulation currently implements a shortest path algorithm whose edge weights are based on edge capacities at a given time and travel time costs. As the simulation progresses, a container's route through the system may be adjusted according to the utilization of roads, resulting in backtracking. Beyond their destination, container routes are further constrained based on whether it is selected for inspection. Data sources used to calibrate route choices include feedback from stakeholders and PEV Vessel Calls.

4.3 Validation

Validation is necessary to determine the degree to which the simulation provides an accurate representation of South Port operations at Port Everglades, FL. In order to validate the movement of entities through the system, we can compare simulation results to several datasets in Table 1.

Vessels The timing, location, and number of vessels arriving within the port is given by the PEV Vessel Calls dataset. Across multiple runs, we see some stochastic behavior in terms of when vessels arrive at berth. Nonetheless, we could qualitatively see some alignment between the time series for simulated vessel arrivals and the vessel calls data. Due to space constraints, we do not show the simulated versus actual number of vessel calls in May 2017.

TEU The timing, location, and number of containers arriving to South Port is given by the PEV Vessel Calls dataset and the PIERS Vessel Commodities dataset. As such, the model only simulates imported, loaded TEU. The PIERS Vessel Commodities dataset provides us with a distribution of commodity types to expect within the target month. The PEV Financial Report provides us with loaded container volumes. Another dataset, such as those from *Electronic Data Interchange (EDI)* may prove more consistent and such data would also allow us to validate route choice through the port. We note that although more validation needs to be done in order to support actual decision making, the results of the next section illustrate the viability of our approach to understand the impact of a disruption on stakeholders individually and collectively.

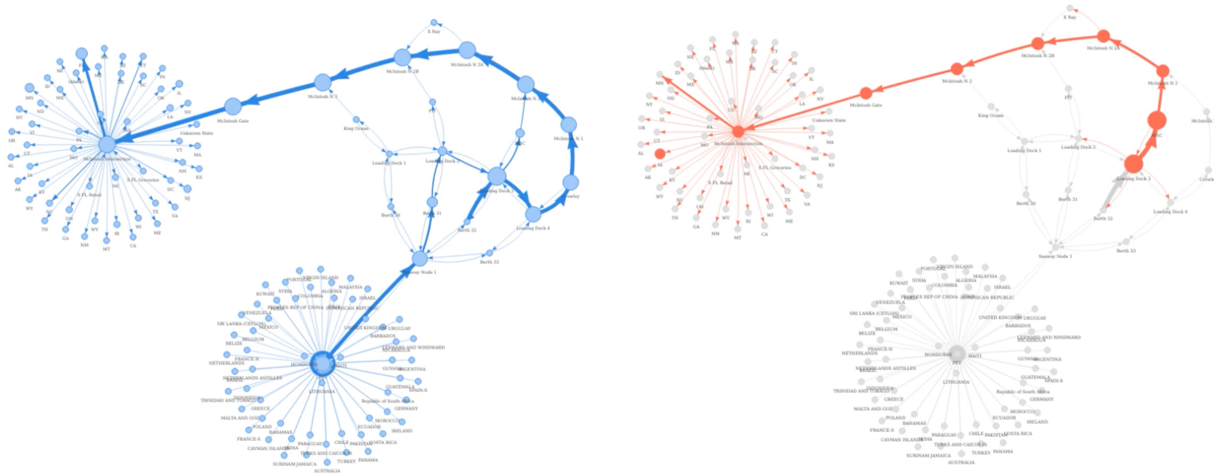
5 RESULTS AND DISCUSSION

This section presents results from simulating container operations at Port Everglades during May 2017. The stakeholders considered in this use case include four *Maritime Terminal Operators (TO)* and a *Drayage Company (DC)*. There are two primary goals of our study. First, we want to understand the impact of varying the time and location of a disruption on the entire shipping port. As such we measure how a stakeholder-controlled region of the MTS can directly or indirectly affect port operations. Second, given a disruption, we want to understand the impact on individual stakeholders as well as the effect of the timing of response actions on reducing disruption impact.

We consider an experimental scenario in which the location and duration of a disruption that decreases capacity at an interection are varied. This could be due to traffic congestion at an intersection following a ransomware attack at a Terminal Operator (TO) or due to enforcing an increased screening procedure for trucks. We measure impact using the performance measure of number of TEU in a stakeholder region although other measures, such per-TEU time spent in system, could also be employed.

5.1 Number of Simulation Runs

In order to conduct this study, we needed to consider the number of independent simulation runs that were required to obtain a good measure of centrality for our measures of performance. In general, although the resultant measures of performance are rarely, if ever normally distributed, we would be justified in using an approach based on the t-test assuming that the distribution is symmetric enough (Law 1983; Truong et al.). Nonetheless, after looking at the distributions on measures of performance on a test case, we employed a two-sided, Wilcoxon One-Sample Rank-Sum test to compute number of runs (D'Abrera and Lehmann 2006). We found that the median value for time TEU spent in the system was shifted by around



(a) Imported TEU, All Commodities. (b) Imported TEU, Soybeans.

Figure 2: Depending on the time and location, disruptions may affect specific commodity types whose flows differ from overall commodity flows at a given time.

1.32 minutes with one run, and 0.12 minutes for five runs. The 95% confidence interval had a total length of roughly 11 minutes for 1 run, and 6 minutes for 5 runs.

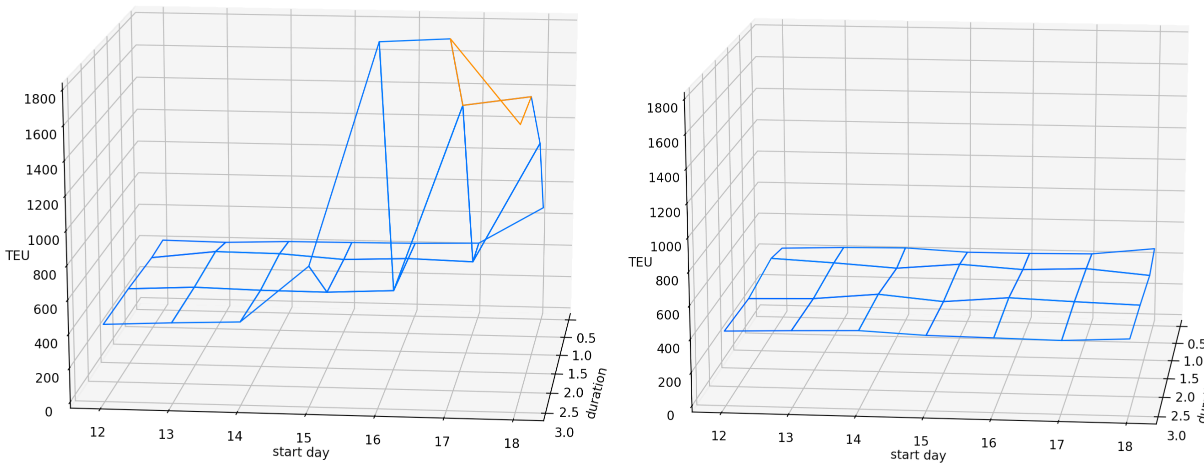
5.2 Experiment 1: Stakeholder Influence on Port-Wide Operations

Our first experiment sought to understand how a disruption to an individual stakeholder can influence port-wide operations. Given the traffic congestion at intersections that resulted from the NotPetya incident (Greenberg 2018), we chose to disrupt intersections that connect a terminal operator (TO) to a shared roadway leaving the port. Figure 3 shows two of the response surfaces obtained by varying the start time and duration of a disruption at all TO intersections. More information about *Response Surface Methodology (RSM)* may be found in Hood and Welch (1993). We consider a response surface in which the start time of a disruption varies from Friday to Thursday of the following week, and the disruption duration ranges from half a day to 3 days. Based on the discussion above, we compute each response surface point using 1 run as this is adequate precision for initial exploration and to understand overall system behavior.

The results indicate that a disruption to Operator 1's intersection (I3) has the ability to most influence the overall port operation. This is consistent with what we might expect as this intersection is a single point of exit for all traffic. However, our analysis shows that the timing of the disruption relative to when commodities flow through the port, is important to understand impact as well. For example, the impact of a disruption on May 12 or 13, even if lasting for several days, is significantly less than that of a disruption that starts the following week but only lasts half a day. This reflects the arrival times of vessels to Southport within the simulation.

5.3 Experiment 2: Stakeholder Influence on Individual Stakeholders

The second experiment considers the degree to which a stakeholder's commodity flows affect other individual stakeholders. The results shown in this experiment (and the third) are derived from an earlier version of the PEV network and flows than those used in the first experiment. In this earlier version, only 3 TO's were represented. Nevertheless, the results presented, mapped into the names shown in Figure 1, are consistent with the conclusions drawn above: a disruption to Terminal Operator 1 that causes congestion at Intersection 3 has more impact than a similar disruption to Terminal Operator 4.

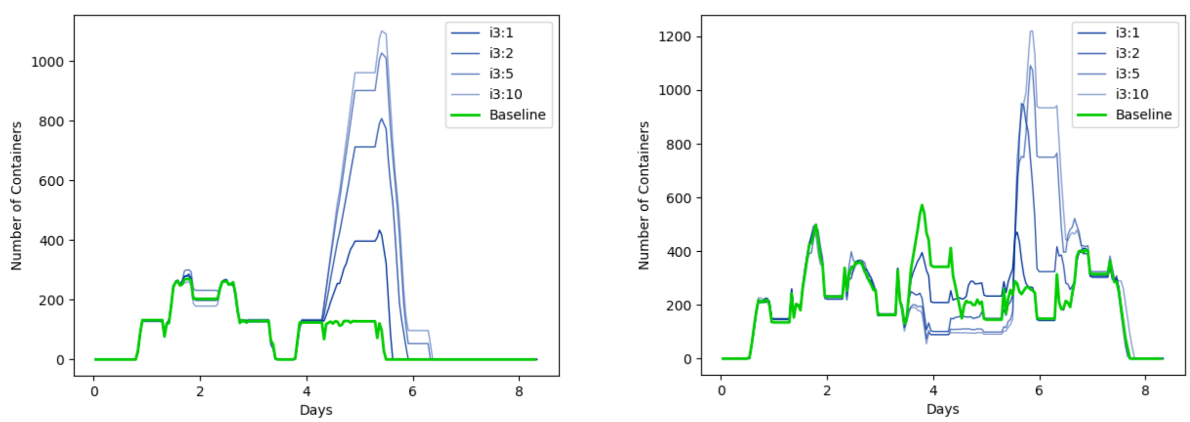


(a) Disrupting Intersection for Operator 1 (I3)

(b) Disrupting Intersection for Operator 4 (I1)

Figure 3: The impact of a varying the location, timing and duration of a disruption on the number of TEU within Port Everglades.

Figure 4 illustrates the impact of a reduced traffic rate at different intersections on individual port stakeholders. Reduced trafic rate at each intersection lasts for 2 days. Figure 4a illustrates that Operator 4's container count, late in Day 5 increases from around 100 TEU in Day 5 to 400-1100 as service times increase. Operator 4 was impacted most severly regardless of the intersection chosen to be disrupted.



(a) Operator 4

(b) Drayage Company

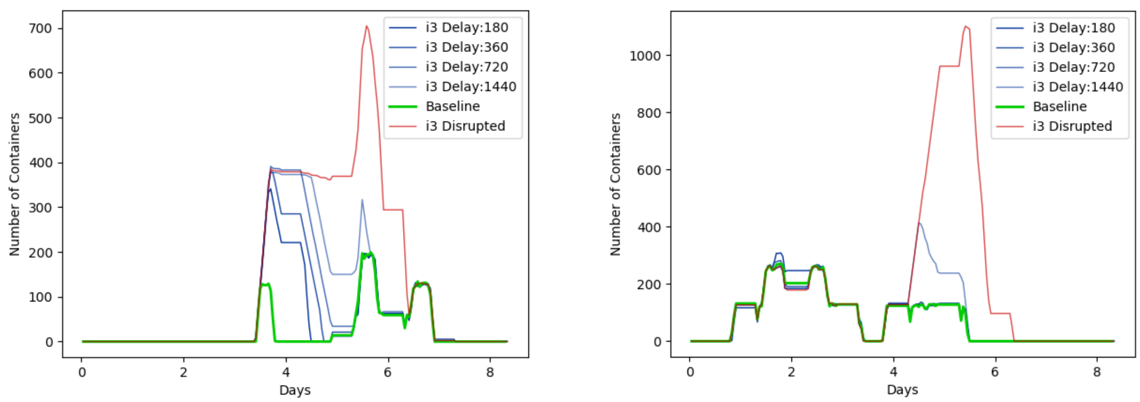
Figure 4: The impact of a disruption to Intersection 3 on the number of TEU within each stakeholder region. Green (blue) curves show number of TEU under baseline (disrupted service time) conditions.

Figure 4b shows that after the disruption midday on Day 2, the number of TEU in the Drayage Company's stakeholder region drops below baseline. This is because containers aren't moving out of the container yards. This result indicates a potential loss of revenue for truck drivers due to opportunity cost as well as secondary congestion caused by moving backlogged containers out of the port.

5.4 Experiment 3: Impact of Time to Recover on Commodity Flows

Shipping port stakeholders need to understand the effect of different response strategies. One important consideration is the impact of different recovery timeframes on commodity flows. Figure 5 illustrates results from restoring operations to a baseline service time (30s per TEU) over the course of 3 hours, 6 hours, half a day, and a day following a disruption at Intersection 3. The red line shows the impact of a disruption without any response.

Our results show that the fastest response may not be the best choice for an security manager if a slightly slower response is *close enough* to restoring baseline operational levels. Figure 5b shows that for Operator 4, as long as service is restored in half a day, overall operations won't be drastically affected. This is in contrast with Operator 1 in which no matter how quickly services are restored, the number of TEU deviates from the baseline in Figure 5a.



(a) Operator 1 (b) Operator 4

Figure 5: The effect of varying the time to recover following a disruption at Intersection 3.

6 CONCLUSION

Shipping ports are a backbone of our civilization and global commerce depends upon their proper operation. As a competitive shipping industry drives higher efficiencies to support a just-in-time supply chain, disruptions to these ports have the potential to impact communities who depend upon commerce enabled by ports. In order to prepare for disruptions ranging from ransomware attacks to increasing extreme weather events, stakeholders need to understand how disruptions of varying durations and at different locations affect themselves individually and as a whole. Moreover, as stakeholders' businesses become increasingly dependent on social and infrastructure-based interdependencies (e.g. cyber, electrical power), risk assessment approaches need to take into account the degree to which stakeholder systems can be affected by an *environment* which includes other stakeholder systems. Therefore, we have developed an approach that combines simulation with a graph-theoretic approach to measure the impact of disruptions to stakeholders individually or collectively. The intent of such work is to provide stakeholders with a data-driven, risk assessment tool with which they can develop strategic security plans and invest in resources to secure our Maritime Transportation System in an evolving natural, technological, and adversarial environment.

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