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# NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

**IMPROVING THE RESILIENCE OF COAL TRANSPORT  
IN THE PORT OF PITTSBURGH —  
AN EXAMPLE OF DEFENDER-ATTACKER-DEFENDER  
OPTIMIZATION-BASED DECISION SUPPORT**

by

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November 2012

**Approved for public release; distribution is unlimited**

Prepared for: United States Coast Guard Atlantic Area Operations Analysis Division

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## **ABSTRACT**

This technical report summarizes research that has produced an optimization-based decision support system for assessing the resilience of the Marine Transport System conveying coal in the Port of Pittsburgh area. We describe waterside data with the throughput and storage capacities of locks, pools, and transfer points; landside data with road and rail capacities; a set of coal contracts (i.e., grade of coal, source, destination, quantity, and delivery date); and some policy costs for using these alternate conveyances, and perhaps suffering some shortage. An “operator’s model” is presented that uses this data to emulate the best cost-minimizing policy to operate this Marine Transport System. This operator’s model is then manipulated to emulate loss of key components and evaluate the best possible system response, where it may be necessary to transfer from the least-expensive, waterborne barge conveyance to rail and/or road transport, and it may be necessary to allocate shortages among system customers. Systematic evaluations lead to a “resilience curve” for the system. Generalizing, simultaneous loss of sets of components can be modeled, as can the effects of defending certain components, rendering them invulnerable to attack. The final product, a Defender-Attacker-Defender optimization system, can advise the best use of a given defensive budget, where an attacker will observe these defensive preparations and alter his plans accordingly, and the operator, observing losses due to attacks, responds as best able to operate the surviving infrastructure. This system can be applied without change to any other Marine Transport System conveying any set of commodities as flows through a transport network, although considerable effort may be required to develop the appropriate input data and then run the model to perform the analysis.



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# TABLE OF CONTENTS

<b>I. INTRODUCTION.....</b>	<b>1</b>
<b>A. RISK-BASED PRIORITIZATION.....</b>	<b>3</b>
1. Assessing Port Security Risk.....	5
2. Concerns About the Use of Probabilities to Assess Terrorism Risk .....	6
<b>B. OPERATIONAL RESILIENCE .....</b>	<b>7</b>
<b>C. PREVIOUS WORK ON PORT RESILIENCE AT THE NAVAL POSTGRADUATE SCHOOL .....</b>	<b>12</b>
<b>D. OBJECTIVES OF THIS STUDY .....</b>	<b>14</b>
<b>II. COAL TRANSPORT IN THE PORT OF PITTSBURGH .....</b>	<b>17</b>
<b>III. APPLYING DEFENDER-ATTACKER-DEFENDER MODELS TO THE INLAND WATERWAY SYSTEM .....</b>	<b>27</b>
<b>A. BUILDING THE OPERATOR’S MODEL.....</b>	<b>28</b>
<b>B. ASSUMED INPUT DATA .....</b>	<b>31</b>
1. Terminals .....	31
2. River Network .....	31
3. Rail Network.....	32
4. Road Network.....	32
5. Contracts.....	32
6. Penalty Costs .....	33
<b>C. ANALYSIS OF THE MONONGAHELA RIVER .....</b>	<b>34</b>
<b>D. ANALYSIS NOT (YET) PERFORMED .....</b>	<b>40</b>
1. Multiperiod Analysis .....	41
2. Including More Detailed Rail and Road Systems .....	42
3. Expanding the Scope to the Rest of the Three Rivers .....	42
<b>E. PERFORMING THIS ANALYSIS FOR OTHER RIVER PORTS .....</b>	<b>42</b>
<b>F. DISCUSSION .....</b>	<b>44</b>
<b>IV. SUMMARY AND CONCLUSIONS .....</b>	<b>47</b>
<b>APPENDIX A. COAL SHIPMENT DATA .....</b>	<b>49</b>
<b>APPENDIX B. MATHEMATICAL FORMULATION .....</b>	<b>55</b>
<b>A. THE OPERATOR’S MODEL.....</b>	<b>55</b>
<b>B. THE ATTACKER’S MODEL.....</b>	<b>59</b>
<b>LIST OF REFERENCES .....</b>	<b>61</b>
<b>INITIAL DISTRIBUTION LIST .....</b>	<b>65</b>

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## LIST OF FIGURES

Figure 1.	Excerpt from the Consequence Equivalency Matrix (USCG 2012f).....	4
Figure 2.	The Inland Waterway System. The Port of Pittsburgh, located in the upper right of the figure, is at the start of this river system. Source: PPC (2012b).14	
Figure 3.	Dams and pools on the Monongahela River. Source: USACE (2012). .....	18
Figure 4.	The Port of Pittsburgh consists of the Ohio, Monongahela, and Allegheny Rivers. This picture illustrates the location of various locks and dams (L/D) in our study area, listed in the table to the right. Along the Ohio River our study area is bounded by the Hannibal L/D, on the Allegheny River by the Allegheny L/D 5, on the Monongahela River by Morgantown L/D. Source: USACE 2012. ....	19
Figure 5.	We identify 18 relevant pools in this Three-River transport system. ....	20
Figure 6.	We identify 44 terminals that can serve as either the origin or destination for coal shipment in this river transport system. ....	21
Figure 7.	Coal flows through the Pittsburgh study area by four-week “month” during 2009. Seasonal fluctuations are mostly consistent across pools, with the first eight weeks of the CY showing the largest overall flows.....	25
Figure 8.	Coal flow through each pool in the Pittsburgh area. Pools 0 through 60 constitute the Ohio River. Pools 70 through 100 constitute the Allegheny River. Pools 110 through 170 constitute the Monongahela River. In gray scale, the months proceed from the bottom up for each bar. ....	25
Figure 9.	Comparison of cargo capacity of rail car, truck, and barge. Source: PPC (2012c). ....	27
Figure 10.	The most economical way to move coal is by barge. Source: USACE 2012. ....	28
Figure 11.	The operator’s model takes input data on terminals, networks for each mode of transport, contracts, and costs. Its output identifies the shipping, transfers, and storage that result in the lowest possible cost, possibly including shortages at some destinations. ....	30
Figure 12.	Baseline operating costs (left-most, green) and the cost of the best 15 single attacks to the Monongahela River. Dams are attacked first, restricting navigation through pools. Locks are then attacked, restricting the ability to transit between pools.....	36
Figure 13.	The resilience curve for coal transport on the Monongahela River in the absence of defenses. With only one or two coordinated attacks, the total operating cost of the system dramatically increases. The addition of a third, fourth, or fifth attack on water assets does little to further increase the operating cost. ....	38
Figure 14.	Resilience curves for coal transport in the presence of different defensive efforts. Perfect defense of dams lowers the curve (from circles to squares). Defense of dams and locks causes an attacker to consider landside assets. If an attacker can isolate a terminal by interdicting all three transfers (to river, road, and rail), then the operating cost becomes arbitrarily high (triangles). If we assume that coal can always be transported by road and that locks and	

dams can be perfectly protected, then the worst case disruption is more modest, even in the presence of multiple losses (diamonds). ..... 39

## LIST OF TABLES

Table 1.	Total flows (in thousands of tons of coal) by terminal origin and destination during CY 2009. Due to space limitations, we show only rows and columns that have nonzero entries. ....	22
Table 2.	Total amount of coal (in thousands of tons) shipped or received at each terminal of the Port of Pittsburgh in 2009. ....	23
Table 3.	Rank ordering of locks in terms of CY 2009 coal that was “locked through” in the upstream, downstream, and combined directions. ....	24
Table 4.	Most impactful simultaneous attacks: 0 through 5. For two simultaneous attacks, 213,250 tons of coal is transported via river and 153,742 tons of coal is transported via rail. The cost to operate the system becomes \$598,421. ....	37
Table 5.	Total flow of coal (in tons) that go on, off, and through a specific pool, by week, in Calendar Year 2009. ....	54

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## LIST OF ACRONYMS AND ABBREVIATIONS

AD	Attacker-Defender
CEM	Consequence Equivalency Matrix
CI/KR	Critical Infrastructure/Key Resources
CPLEX	Optimization software package
CY	Calendar year
DAD	Defender-Attacker-Defender
DHS	Department of Homeland Security
DOD	Department of Defense
DOT	Department of Transportation
GAMS	Generalized Algebraic Modeling System
GDP	Gross Domestic Product
HSC	Homeland Security Council
IBM	International Business Machines
ICW	Intracoastal Waterway
L/D	Lock and Dam
MSRAM	Maritime Security Risk Analysis Model
MTS	Marine Transportation System
NIPP	National Infrastructure Protection Plan
NMSRA	National Maritime Strategic Risk Assessment
NPS	Naval Postgraduate School
NRC	National Research Council
NYPD	New York Police Department
ORAM	Operational Risk Assessment Model
PPC	Port of Pittsburgh Commission
PRA	Probabilistic Risk Analysis
PWCS	Ports, Waterways, and Coastal Security
RIN	Risk Index Number
ROI	Return On Investment
TEU	Twenty Foot Equivalent Unit shipping container



TVC	Threat, Vulnerability, and Consequence
USACE	United States Army Corps of Engineers
USCG	United States Coast Guard
USMC	United States Marine Corps
USDOT	U.S. Department of Transportation
VADM	Vice Admiral

## EXECUTIVE SUMMARY

This technical report summarizes research that has produced an optimization-based decision support system for assessing the resilience of the Marine Transport System conveying coal in the Port of Pittsburgh area. This is the latest in a long sequence of such contributions by the authors to other infrastructure systems, including water, oil and gas pipelines, highway networks, electric grids, telecommunications networks, social networks, etc.; a total of nearly 150 such applications to date.

The centerpiece of this work is an “operator’s model” that emulates how this Marine Transport System can best be operated given the condition of each of its components. We describe waterside barge components, with the throughput and storage capacities of locks, pools, and transfer points, and landside road and rail capacities; a set of coal contracts (i.e., grade of coal, source, destination, quantity, and delivery date); and some policy costs for using these alternate conveyances and perhaps suffering some shortage.

The operator’s model uses this data to emulate the feasible interactions of all components that satisfy physical limitations, while incurring minimal total system costs. Once we are convinced the operator’s model faithfully represents how the Marine Transport System can be used, it is easy to conduct “what-if” analysis that inflicts hypothetical damage on components and then observes the best possible response to operate the surviving components.

Next, an “attacker model” is posed that represents how a hypothetical, intelligent adversary would apply limited resources to optimally choose components to attack, knowing that the operator will respond as best possible. The attacker chooses the best worst-case attacks he can afford, and our operator responds by resorting to alternate means of conveyance, likely at increased cost. We can use the attacker model to evaluate the “return on investment” that an attacker receives from increased attack effort.

We argue that the attacker and operator models provide a natural means to trace out the “resilience curve” of this regional part of the Marine Transport System.

Finally, we add a third level to advise where to make investments to harden, defend, or otherwise render components more resistant to, or invulnerable to attack. The final product, a “defender-attacker-defender” optimization system, can advise the best use of a given defensive budget, where an attacker will observe these defensive preparations and alter his plans accordingly, and the operator, observing losses due to attacks, responds as best able to operate the surviving infrastructure.

This system can be used to plan over an extended time horizon and account for estimated reconstitution times of damaged components, which may vary from days for road and rail, to weeks or months for bridges, locks, and, especially, dams. For example, this defender-attacker-defender decision support model can advise how to preposition assets and products in anticipation of a scheduled interruption of component availability, say for maintenance or new construction.

The U.S. Coast Guard already tends systems that collect information about infrastructure components of the Marine Transport System. These are ideal to use in support of the defender-attacker-defender decision support system we describe. Much of the required data is already collected. What is missing, and essential, is the interaction between components—how they behave as a system.

These defender-attacker-defender decision support models do not require probabilistic risk assessment of any attacker intent, nor do we require any probabilistic assessment of vulnerability to attack. Following standard military planning doctrine, we plan based on attacker capabilities, not intent. We note that the only situation where military planners might assess attacker intent is when the time horizon is very short and intelligence is very strong. This is a rare situation that we cannot rely on for continued, routine planning to defend our infrastructure. Further, even if we do assess these probabilities of intent and vulnerability, they are obviously not independent, as is customarily assumed (i.e., an attacker would surely change his probability in response to any change in vulnerability). We avoid these complications, and the requirement that such probabilities be stated for some fixed time epoch.

This system can be applied without change to any other Marine Transport System conveying any set of commodities that can realistically be represented by flows through a

transportation network, although considerable effort may be required to develop the appropriate input data and then run the model to perform the analysis.

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This report extends the research in Engel (2011) and Onuska (2012); excerpts from these theses also appear in this report.

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## **I. INTRODUCTION**

The Marine Transportation System (MTS) of the United States consists of “waterways, ports, and intermodal landside connections that allow various modes of transportation to move people and goods to, from, and on the water” (U.S. Department of Transportation [USDOT], 2012). As noted in United States Coast Guard (USCG) Publication 3-0 (2012b, p. 9):

“The United States claims sovereignty over 3.4 million nautical square miles of maritime territory, which comprises the MTS. The MTS includes 95,000 miles of coastline and 361 ports, from the largest mega-ports to the smallest fishing harbors and marinas. The MTS also includes the system of interconnected inland rivers and the Intracoastal Waterway (ICW), which consists of 12,000 miles of navigable waters connecting inland metropolitan areas, industrial complexes, and the agricultural heartland of the country. The MTS includes the Great Lakes, along 6,700 miles of U.S. coastline and 1,500 miles of international maritime border with Canada, that connect the industrial north and northern population centers of the Midwest through the St. Lawrence Seaway System to the Atlantic Ocean.”

U.S. interests additionally extend much farther to islands such as Hawaii, Puerto Rico, and Guam. (For background on the size and scope of the MTS, see also Chapter 3 of Rodrigue et al., 2009, or Transportation Research Board, 2012.)

The MTS is vital to the economic welfare of the United States. Consider the following statistics (quoted directly from U.S. Department of Transportation, 2012):

- Waterborne cargo and associated activities contribute more than \$649 billion annually to the U.S. GDP, sustaining more than 13 million jobs.
- MTS activities contribute over \$212 billion in annual federal, state, and local taxes.
- Over 45 million TEUs (twenty-foot equivalent container units) and 1.5 billion tons of foreign traffic were handled in 2006, with a value of nearly \$1.3 trillion dollars.
- Approximately 99% of the volume of overseas trade (62% by value) enters or leaves the U.S. by ship.

A prolonged disruption to MTS operations has the potential to cause significant economic consequences.



The USCG has responsibility for protecting the MTS through its Ports, Waterways, and Coastal Security (PWCS) mission.

“The PWCS mission entails the protection of the U.S. Maritime Domain and the U.S. Marine Transportation System (MTS) and those who live, work or recreate near them; the prevention and disruption of terrorist attacks, sabotage, espionage, or subversive acts; and response to and recovery from those that do occur. Conducting PWCS deters terrorists from using or exploiting the MTS as a means for attacks on U.S. territory, population centers, vessels, critical infrastructure, and key resources. PWCS includes the employment of awareness activities; counterterrorism, antiterrorism, preparedness and response operations; and the establishment and oversight of a maritime security regime. PWCS also includes the national defense role of protecting military outload operations” (USCG 2012c).

PWCS is only one of 11 missions assigned to the USCG (see Engel 2011 for a complete list and discussion). The Department of Homeland Security (DHS), however, has stated that the highest priority for the USCG is preventing terrorism and enhancing security (USCG 2012h).

The USCG faces several challenges in executing its PWCS mission.

- *There are many potential sources of disruption to the MTS.* These include both *nondeliberate hazards* (e.g., weather events, natural disasters, accidents, and failures) and *deliberate threats* (e.g., terrorism, sabotage, vandalism, and crime).
- *The Coast Guard has a geographically vast and complex operational area.* The Coast Guard operates in the maritime domain. The physical characteristics of the sea present varying, dynamic and dangerous weather, seas states and water conditions. The maritime industry continues to evolve as the world remains fully dependent on global maritime trade in an advancing technology and information age. Varied and overlapping international and sovereign legal and policy regimes governing the maritime domain pose practical operational challenges (USCG 2012b).
- *The Coast Guard has limited resources.* In 2011, the Coast Guard consisted of approximately 43,000 active duty members (USCG 2012g) and had an operating budget of \$10.5 billion (USCG 2012a Posture Statement). That same year, the New York City Police Department (NYPD) had approximately 34,000 uniformed officers (NYPD 2011).

As a result, the Coast Guard needs to make judicious use of its resources in order to succeed in the PWCS mission and its other mission areas. As noted by Commandant

Admiral Robert J. Papp, Jr., (USCG 2011a), a key question is how to prioritize activities and the use of limited resources across this diverse set of activities.

## **A. RISK-BASED PRIORITIZATION**

Risks to the MTS threaten lives, economic stability, and national security. As defined in the DHS Risk Lexicon (DHS 2010, p. 27), risk is “potential for an unwanted outcome resulting from an incident, event, or occurrence, as determined by its likelihood and the associated consequences.”

Risk is a key organizing principle in Coast Guard strategies, programs, and activities. All Coast Guard risk models are linked, with primary governance of risk-related efforts being managed by the Coast Guard’s Enterprise Strategy, Management, and Doctrine Oversight Directorate (CG-095). Coast Guard risk assessments, and the tools that guide those assessments, span the tactical, operational, and strategic levels of the Coast Guard.

This section briefly describes these tools and how they are used.

At the strategic level, the National Maritime Strategic Risk Assessment (NMSRA) is an all-mission risk assessment that informs budget and planning guidance. The NMSRA is a biennial, broad, horizontal assessment across the Coast Guard’s enduring roles of safety, security, and stewardship, and is inclusive of all Coast Guard mission programs. The assessment produces three main products: a residual risk profile, a USCG risk reduction profile, and key observations (USCG 2012f). The residual risk profile estimates the expected societal loss that remains after the USCG has performed all of its prevention and response activities. The USCG measures societal loss in the context of each specific mission. For example, in the case of the USCG’s Search and Rescue mission, societal loss is measured in lives lost in maritime distress. The USCG risk reduction profile estimates the amount of risk that is avoided due to the USCG’s response activities. Finally, the NMSRA offers key observations including risk drivers and risk management opportunities.

The NMSRA is built around the Consequence Equivalency Matrix (CEM), which maps different levels of consequence from different types of impacts onto a common value scale. In the CEM, rows correspond to different risk-related, impact categories

such as “Death & Injury” and “Direct Economic Loss” (see Figure 1), and columns correspond to consequence levels ranging from 0 to 9 that represent the severity of damage for each impact category (USCG 2012f).

	Category 0	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	Category 9
Impact Types	0	1.729	5.188	6.3	22.05	47.25	343	3,462	34,647	346,497
Death and Injury	No deaths; Injuries that are not life-threatening	No deaths; 1 life-threatening injury	No deaths (for non-PWCS incidents: 1-5 life-threatening injuries)	1 death and others with life-threatening injuries	2 to 5 deaths and others with life-threatening injuries	6 to 9 deaths and others with life-threatening injuries	10 to 99 deaths and others with life-threatening injuries	100 to 999 deaths and others with life-threatening injuries	1000 to 9,999 deaths and others with life-threatening injuries	10,000 to 99,999 deaths and others with life-threatening injuries
	Category 0	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	
	0	0.155	1.65	16.5	165	1,650	16,500	165,000	1,650,000	
Direct Economic Loss (Including Property Damage)	<\$10,000 in damage/loss	\$10,000 to \$299,999 in damage/loss	\$300,000 to \$2.9 million in damage/loss	\$3 million to \$29 million in damage/loss	\$30 million to \$299 million in damage/loss	\$300 million to \$3 billion in damage/loss	\$3 billion to \$29 billion in damage/loss	\$30 billion to \$299 billion in damage/loss	≥\$300 billion in damage/loss	

Figure 1. Excerpt from the Consequence Equivalency Matrix (USCG 2012f).

The underlying idea of the CEM is that having a common value scale facilitates the comparison of risks from different types of impacts. For example, the following three impacts map to the same column in the CEM: (1) economic damage between \$3 million and \$29 million, (2) life-threatening injuries for 1-5 people, and (3) interruption of port commerce for one week.

The USCG measures risk in terms of a basic unit known as a Risk Index Number (RIN) that “represents or provides equivalent pain thresholds for an expected annualized loss of \$1 million dollars” (USCG 2012e, p. 3). RINs are used as a common risk currency among all Coast Guard missions with measurable consequences. The intent is to compare, for example, the risks of drug trafficking to those of terrorism, and then to direct resources to these efforts accordingly.

The Operational Risk Assessment Model (ORAM) translates the high-level, strategic risk assessment in the NMSRA to the operational level (USCG LANT-7 2012d). The view of risk in ORAM is essentially the same as in the NMSRA, but it accommodates more frequent reassessments to examine how individual resource contributions are mitigating risk. Using RINs as a common metric, ORAM assesses risk individually for the Coast Guard’s missions and also subdivides each mission into geographic regions. ORAM supports the service’s decision making not only for short-fused, operational planning (e.g., the Deepwater Horizon oil spill response event in 2011), but also in support of operational force apportionment planning.

Planning at the tactical level in the USCG uses color-coded risk score cards, called Green-Amber-Red, to assess benefits and risks before executing a specific mission. For example, Green-Amber-Red assessment is used every day at USCG small boat stations to determine risk in day-to-day activities. The objectives of this type of operational risk management are to recognize the inherent risks during sortie execution and to assess the trade-offs associated with mitigating, transferring, or accepting those risks.

Thus, RINs are used for long-term planning while Green-Amber-Red assessments are used for daily mission planning.

### **1. Assessing Port Security Risk**

The Marine Transportation Security Act of 2002 mandates that vessels and ports conduct vulnerability assessments as part of local area maritime security plans (Maritime Transportation Security Act 2002). The USCG Captain of the Port is the Federal Maritime Security Coordinator charged with coordination of the local Area Maritime Security Committee, who develops and implements those plans.

In 2006, DHS established the National Infrastructure Protection Plan (NIPP) to protect the United States Critical Infrastructure and Key Resources (CI/KR).

“The overarching goal of the NIPP is to build a safer, more secure, and more resilient America by preventing, deterring, neutralizing, or mitigating the effects of deliberate efforts by terrorists to destroy, incapacitate, or exploit elements of our nation's CI/KR and to strengthen national preparedness, timely response, and rapid recovery of CI/KR in the event of an attack, natural disaster, or other emergency” (DHS 2009, p. 1).

The NIPP provides guidance for all Department of Homeland Security (DHS) entities to analyze terrorism risk using assessments of Threat (T), Vulnerability (V), and Consequence (C). In a so-called “TVC model,” a threat is typically characterized in terms of the probability that a specific target will be attacked (DHS 2009). To account for uncertainties, this threat can be represented as a single-point estimate of probability (i.e., that an attack occurs) or with a probability distribution (Willis 2007). Vulnerability is assessed as “the likelihood that an attack is successful, given that it is attempted” (DHS

2009, p. 33). “Consequence is the magnitude and type of damage resulting from successful terrorist attacks” (Willis 2007, p. 599). The overall risk in a TVC model represents an expected loss, typically measured in lives lost or dollars in damage. Greater expected losses equate to higher risk values.

With the NIPP as guidance, the Coast Guard developed the Maritime Security Risk Analysis Model (MSRAM) to serve as a terrorism risk management tool. The intent of MSRAM is to give Coast Guard analysts across the country the ability to perform detailed risk analysis for potential terrorist targets in their areas of responsibility. The results of these analyses support a variety of risk management decisions at the strategic, operational, and tactical levels. MSRAM assesses risk-based scenarios that consist of a combination of target and attack mode, in terms of threat, vulnerability, and consequence. Threat is defined as the intent, capability, and presence of terrorists to deliver the attack on the class of target in location throughout the U.S. domain. Vulnerability is the probability of a successful attack based on the following factors: (1) innate difficulty of the attack, (2) ability of the owner-operator, other law enforcement and the USCG to intervene either collectively or independently, and (3) the ability of the target to withstand the attack. Consequence is the negative impact of a successful attack on the United States in terms of: deaths and/or injuries, environmental impacts, impacts to national security, symbolic impacts, and economic impact to the national GDP.

The relative risk for the associated scenario(s) is expressed as the Risk Index Number or (RIN) which can be further categorized into five levels: very low, low, medium, high, and very high. MSRAM is embedded with a set of terrorism scenarios spanning the USCG’s PWCS mission, and it has the functionality to compare results of a risk assessment and rank scenarios.

## **2. Concerns About the Use of Probabilities to Assess Terrorism Risk**

An important feature in TVC models of risk, as implemented in MSRAM, is that they assess the likelihood of both non-deliberate hazards and deliberate threats using static probabilities. Understandably, there is a longstanding desire on the part of analysts and policy makers to assess the risk from “all hazards” in a single model. As

documented by Cox (2008) and the National Research Council (NRC 2008, 2010), however, there are problems with using TVC methods to do this.

First, there is not enough historical data to assess the probability of a future terrorist attack, and it is questionable, in this context, whether past events are representative of future ones. Relying on subjective assessment from subject matter experts to assess probabilities has inherent biases and simply cannot be validated against ground truth (see Brown and Cox 2011 and references therein). Second, deliberate attacks from an adversary are distinctly different from non-deliberate events, such as accidents, failures, or natural disasters, and should be handled separately. We represent acts of nature as random events, based on seasonal or climatic conditions, because historical data is readily available for characterizing these probabilities, and we can use science to validate these parameters. We also collect data on technological failures and can perform laboratory “stress tests” to assess when and how system components fail; we characterize them using probabilistic measures such as hazard rates or mean time between failures. Even human errors or mishaps can be characterized by probabilities.

Once an intelligent adversary enters the scenario, however, the rules change (see Engel 2011 for a detailed discussion). This adversary conducts thoughtful planning and observation of CI/KR, then makes a deliberate decision about whether, when, and how to attack. The assumption that an adversary behaves randomly according to known probabilities cannot be validated and is simply not prudent.

## **B. OPERATIONAL RESILIENCE**

There is an alternative to the risk-based assessment and prioritization currently promoted by DHS and used by USCG. In its National Strategy for Homeland Security (Homeland Security Council [HSC] 2007), the U.S. government recognizes that a traditional security focus on prevention will not be enough to keep systems like the MTS operational.

“We will not be able to deter all terrorist threats, and it is impossible to deter or prevent natural catastrophes. We can, however, mitigate the Nation’s vulnerability to acts of terrorism, other man-made threats, and natural disasters by ensuring the structural and operational resilience of our critical infrastructure and key resources . . . . We must now focus on the resilience of the system as a

whole—an approach that centers on investments that make the system better able to absorb the impact of an event without losing the capacity to function” (HSC 2007, pp. 27–28).

The term “operational resilience” is of key importance here. Infrastructure systems like the MTS are more than just an inventory list of assets. The importance of an individual waterway, port, or intermodal landside connection comes from its contribution to the overall function of the system; in the case of the MTS, we can measure this function in terms of things like the ability to move cargo from point of origin to destination. This interoperability is one of the reasons that the connection between coastal ports, Western Rivers, and littoral environments is important.

Thus, we define operational resilience as the continued function of a system in the presence of disruptions (see Alderson et al., 2012, for background and discussion). In the context of the PWCS mission, the objective of operational resilience is to deny consequences to the adversary; this leads to deterrence.

There is now a large literature on the application of *system interdiction models* to assess the impact of disruptions to the operation of infrastructure systems, some focusing explicitly on the MTS. Brown et al. (2005, 2006) provide an introduction and review of the main concepts, which we briefly review here.

System interdiction models use game theory to investigate the interactions of two opponents. The first opponent, or *player*, is trying to ensure the operation of some system; we call this player the “operator” or the “defender.” The second player is trying to *interdict* (syn. *attack*) that operation; we call this player the “attacker.” In a system interdiction model, player behavior is sequential (i.e., players take turns) and the behavior of each player is modeled as an explicit decision, not a random event. For this reason, system interdiction models are closely associated with Stackelberg games (von Stackelberg 1952).

Development of a system interdiction model requires that (1) we focus on a specific system of interest and (2) we restrict attention to an unambiguous and mutually agreed on measure of performance. Our modeling and analysis proceed in three basic steps.

First, we build a model that reflects the normal (e.g., Marine Security Level 1) operation of the system. We take a systems perspective: the overall system is comprised of individual *components* that work collectively to provide its *function*. We identify a notional operator (also called the defender) who makes decisions about the activities in the system, and we measure system performance relative to some clearly stated objective. In practice, the operator can be an individual, a group of individuals, or a set of prescribed operating rules—the key point is that the operator reconciles, in an intelligent manner, what we would like the system to do with what it can actually do. The operator uses available components as best he can to maximize the agreed on measure of performance. We use this *operator’s model* as the basis for a variety of “what-if” analyses.

The operator’s model is flexible enough to assess system performance following *any* loss of component functionality, for any number of damaged or destroyed components. As such, the operator’s model mimics real-life system performance as best as can be done, and shows how the system operator would respond to maximize his measure of performance in the face of any disruption. There are a number of infrastructure systems that use such models today, such as our electric generation and distribution grid, which independent system operators manage minute-by-minute with industry-standard models. Other infrastructures, such as transport, distribution, and storage systems, operate on such basic physical principles, and we can easily model them.

The damage to or loss of an individual component, or a set of them, affects what the operator can do, and it therefore has the potential to affect the performance of the system. We refer to the change in optimal system performance that results from the worst-case loss of system components as the *consequence* associated with that loss. Assessing the consequence associated with the damage to or loss of a component means simply rerunning the operator’s model with the damaged components, and without the destroyed ones. If any damaged component was used previously, then the operator may need to choose a different set of activities to best exploit the capabilities of his surviving infrastructure. If that component was critical to system operation, then the resulting system performance will be degraded, even after the operator has wisely adjusted system



activities. Thus, the operator's model allows us to investigate in a systematic way how the degradation or loss of one or more components affects the performance of the *entire* system.

An important feature of many systems, particularly infrastructure systems, is that the loss of a component in one location can affect the operation of the system in an entirely different location; the geographic disparity often makes this non-intuitive and therefore hard to identify in advance. Another important feature is that the consequence associated with the loss of multiple components in combination can be (much) greater than the sum of the consequences associated with the losses of these same individual components. For example, imagine a railroad transportation system that uses two bridges in parallel to span a river. It could be that the impact to moving trains across the river is impacted only slightly by the loss of either bridge (because the other serves as a backup), but the loss of both bridges is catastrophic. Thus, it is important to assess the consequences from not only the loss of individual components, but also from combinations (sets) of components. The potential number of scenarios to consider therefore depends on the total number of system components and their possible combinations, which can be very large, even for a system of modest size.

In principle, it is possible to assess resilience by exhaustively enumerating the loss of every possible combination of components. If it is not practical to consider all possible combinations (e.g., because this would take too long), then one must decide where to focus. Probabilistic Risk Analysis (PRA) techniques, including TVC models, focus on the “most likely” independent losses of individual system components, as specified by static probabilities. As discussed, the justification for doing this depends entirely on the validity of the assessed individual probabilities, and on the independence of these probabilities between attack, damage, and components; such independence assumptions are dangerous in the case of an intelligent adversary.

An alternate technique that avoids the pitfall of having to assess the probability of each scenario is to consider the “worst-case” combinations of system components. Our notion of worst case derives from a hypothetical intelligent adversary, who we call the *attacker*, who targets combinations of components to harm the overall function of the

system in the worst possible way. We assume that the attacker knows everything about the system and its operation, but that he has limited capability to attack and damage or destroy components. We can measure the capability of the attacker in several ways, such as the number of components that he can simultaneously attack or the total budget of resources (e.g., individuals, money) available for the attack. Our attacker is not intended to be a realistic representation of any particular adversary (e.g., an Al Qaeda cell), but a notional construct that allows us to identify worst-case disruptions.

We also assume that the attack(s) will be simultaneous, and that immediately afterward our nation will be on elevated alert, with enhanced defenses.

Thus, the second step in our overall analysis is to solve an optimization problem, called an *attacker-defender (AD)* model, which yields the worst-case disruption as a function of attacker capability. By solving the AD model for different levels of attacker capability, we characterize the operational resilience of the system.

Our ultimate objective is to improve the operational resilience of the system. We do this by making defensive investments in component hardening, redundancy, capacity expansion, or the construction of new infrastructure. Given that we have a limited budget for such investments, the key question is where to make investments so they have the greatest effect. For any proposed improvement to the system, we can run the AD model to assess the extent to which it mitigates the worst-case disruption. Given a list of defensive investment options and a specific budget, we form yet another optimization problem, called a *defender-attacker-defender (DAD)* model, whose solution identifies the combination of affordable investments that improves our operational resilience the most. This is the third, and final, step in our analysis.

The 2010 NRC review of DHS approaches to risk analysis advocates the use of this technique with the following conclusion and recommendation.

“Conclusion: These network disruption and systems resilience models (which supplant and move away from current limitations of TVC analyses for CI/KR) are ideal for longer-term investment decisions and capabilities planning to enhance infrastructure systems’ resiliency, beyond just site-based protection. Such models have been used in other private sector and military applications to assist decision-makers in improving continuity of operations.

Recommendation: DHS should continue to enhance CI/KR data collection efforts and processes and should rapidly begin developing and using emerging state-of-the art network and systems disruption resiliency models to understand and characterize vulnerability and consequences of infrastructure disruptions” (NRC 2010, p. 69).

Our report follows this NRC guidance in developing a model to assess the operational resilience of the MTS.

### **C. PREVIOUS WORK ON PORT RESILIENCE AT THE NAVAL POSTGRADUATE SCHOOL**

There have been several studies conducted at the Naval Postgraduate School (NPS) on port operations using the AD perspective.

Pidgeon (2008) develops a simulation model to estimate the costs associated with disruptions at major ports on the West Coast of the United States. His operator’s model considers the advantageous choice by each incoming cargo ship of a U.S. port, given that some U.S. port facilities may have been closed by a maritime security event. He then includes the movement of individual containers from each ship to land-based transport. He considers various scenarios, ranging from striking union workers to earthquakes in California, that could cause delays in the handling of containerized cargo, and he identifies infrastructure components that are potential bottlenecks and would impede the U.S. maritime shipping capacity. He also identifies where commercial and government investment in additional seaport infrastructure would alleviate West Coast port congestion and improve the operational resilience of West Coast shipping.

Bencomo (2009) extends this work to analyze the impact of various disruptions on the multi-modal transportation system for containerized cargo into and out of North America from both the East Coast and West Coast. He considers a single integrated operator who ships by road, rail, and water to balance supplies and demands at minimum cost. He develops an AD model, in which the attacker deliberately targets components to raise the shipper costs maximally. He also considers the potential impact of labor strikes and natural disasters. He suggests that future areas of study investigate more accurate representations of transport systems.

De la Cruz (2011) evaluates the ability of the MTS to import various goods into Hawaii via refrigerated and non-refrigerated containers. Using AD modeling, he identifies system components (e.g., specific piers, cranes, and terminals) that are vital to maintain uninterrupted flow of containerized shipments. His work assesses the operational resilience of the Hawaiian MTS in the presence of worst-case disruptions measured in terms of delivery shortages. In addition, he analyzes the ability of the U.S. Naval Base at Pearl Harbor to serve as an alternate port for Honolulu Harbor. By identifying key components of the system and analyzing the system's resiliency to attacks, he identifies the greatest areas of need for improved equipment and increased capacity.

Ileto (2011) uses an AD model to assess the resilience of the fuel supply chain of the Hawaiian Islands. Crude oil is shipped from the mainland to two refineries on Oahu, where it is refined into automobile gasoline and fuel for electricity generation and aviation. These finished products are transported by pipeline and truck on Oahu, and they are also transported by barge from Oahu to the neighboring islands. Ileto identifies worst-case attacks and assesses their consequences. He also uses the model to quantify the benefit of proposed defensive investments.

All of these studies focus on the operation of "blue water" ports. The Inland Waterways System of the United States, however, is a system of more than 25,000 miles of navigable waters in the eastern United States (Figure 2). As of mid-2011, there had not been comparable analysis of inland port operations.



Figure 2. The Inland Waterway System. The Port of Pittsburgh, located in the upper right of the figure, is at the start of this river system. Source: PPC (2012b).

#### D. OBJECTIVES OF THIS STUDY

Following a visit in September 2011 by Alderson and Engel to the USCG Atlantic Area Operations Analysis Division (LANT-7) and a briefing of VADM Robert Parker, Commander, Coast Guard Atlantic Area, we were charged with developing a model of the Port of Pittsburgh as a proof-of-concept in using DAD analysis to assess the resilience of inland maritime operations in the presence of deliberate and non-deliberate disruptions.

Pittsburgh is currently the second-largest inland port and the 20th largest overall port in the United States (Port of Pittsburgh Commission 2012a). It is uniquely located at the convergence of the Ohio, the Allegheny, and the Monongahela Rivers, known collectively as the Three Rivers. These rivers connect to three of the four largest coal-mining states in the United States: Kentucky, West Virginia, and Pennsylvania. There is \$9 billion of commerce flowing through the Port of Pittsburgh annually, and coal comprises 76% of this total, making it by far the most influential commodity in this area (PPC 2012b). This coal is critical for electricity generation and steel production.

The Coast Guard interest in this project goes beyond protection of marine assets. “USCG missions and actions foster economic prosperity and national security by ensuring that the marine transportation system supplying food, energy, raw materials, consumer goods and technology is safe, secure, and reliable” (USCG 2011a, p. 6). Therefore, the USCG needs to understand the resilience of the system that moves coal through the Port of Pittsburgh along the Three Rivers.

This study addresses the following questions:

- How can we measure and assess the resilience of coal transport in the Port of Pittsburgh?
- What, if anything, can the USCG do to improve this resilience, and how much will it help?
- What would be required to extend this analysis to other parts of the Inland Waterway System?
- What are the prospects for using operational resilience as a unifying concept for evaluating PWCS mission objectives and initiatives for the entire MTS?

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## II. COAL TRANSPORT IN THE PORT OF PITTSBURGH

We begin with a descriptive model for marine transport in the Port of Pittsburgh. This requires that we understand the basic function and operations of this system, so as to be able to assess the consequences of disruption to that function. River transportation is a primary means of moving large quantities of bulk commodities, and our focus is on the bulk shipment of coal.

River transport depends on terminals, locks, and dams. *Dams* maintain the water level, so large vessels can transit without running aground. The body of water between two dams is known as a *pool*. Dams create a tiered sequence of pools as one moves downstream through the river system. Figure 3 illustrates the sequences of pools on the Monongahela River upstream from and including Pittsburgh. *Locks* enable vessels to transition from one pool to the next by raising or lowering the water level in an enclosed chamber that connects the pools. Passing through a lock, known as “locking-through,” can take 30 minutes to several hours, depending on the queued backlog, number of barges, and the number of parallel locks available for use.

*Terminals* provide the means to move bulk commodities onto and off of the river, and can also provide temporary storage of a bulk commodity.

The United States Army Corps of Engineers (USACE) has responsibility for the continued operation of the Inland Waterway System. In total, the USACE operates and maintains 12,000 miles of commercial inland navigation channels, including dredging riverbeds and repairing the 600 dams under its responsibility (USACE 2012). The average age of the 192 inland waterway locks is 50 years (Gillis 2009). For example, the Monongahela River has two of the oldest locks maintained by the USACE, built in 1905 and 1907, yet in Calendar Year (CY) 2009, together they locked through 10,602 vessels carrying 26 million tons of cargo (USACE 2012).



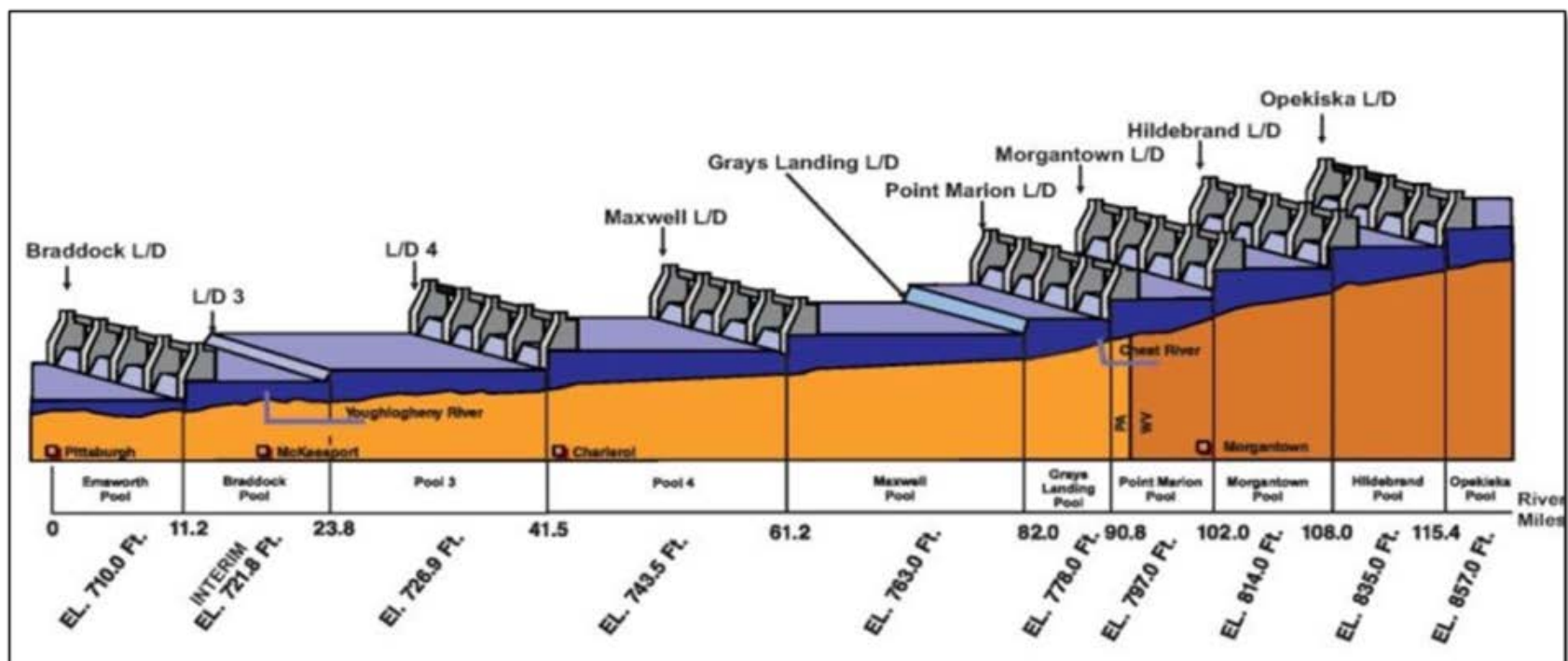


Figure 3. Dams and pools on the Monongahela River. Source: USACE (2012).

Scheduled maintenance on locks and dams can create shipping delays of weeks to months, even when it is announced to the public far in advance. Unscheduled loss of a lock or dam that results in an uncontrolled release of water can be even more disruptive and even have cascading effects, potentially damaging downstream infrastructure.

The study area for our analysis radiates out from the Pittsburgh pool (i.e., between Emsworth Lock & Dam on the Ohio River, Braddock Lock & Dam on the Monongahela River, and Allegheny Lock & Dam 2 on the Allegheny River); see Figure 4. It stretches up to the Allegheny Lock & Dam 5 on the Allegheny River, up to the Morgantown Lock & Dam on the Monongahela River, and down to the Hannibal Lock & Dam on the Ohio River.

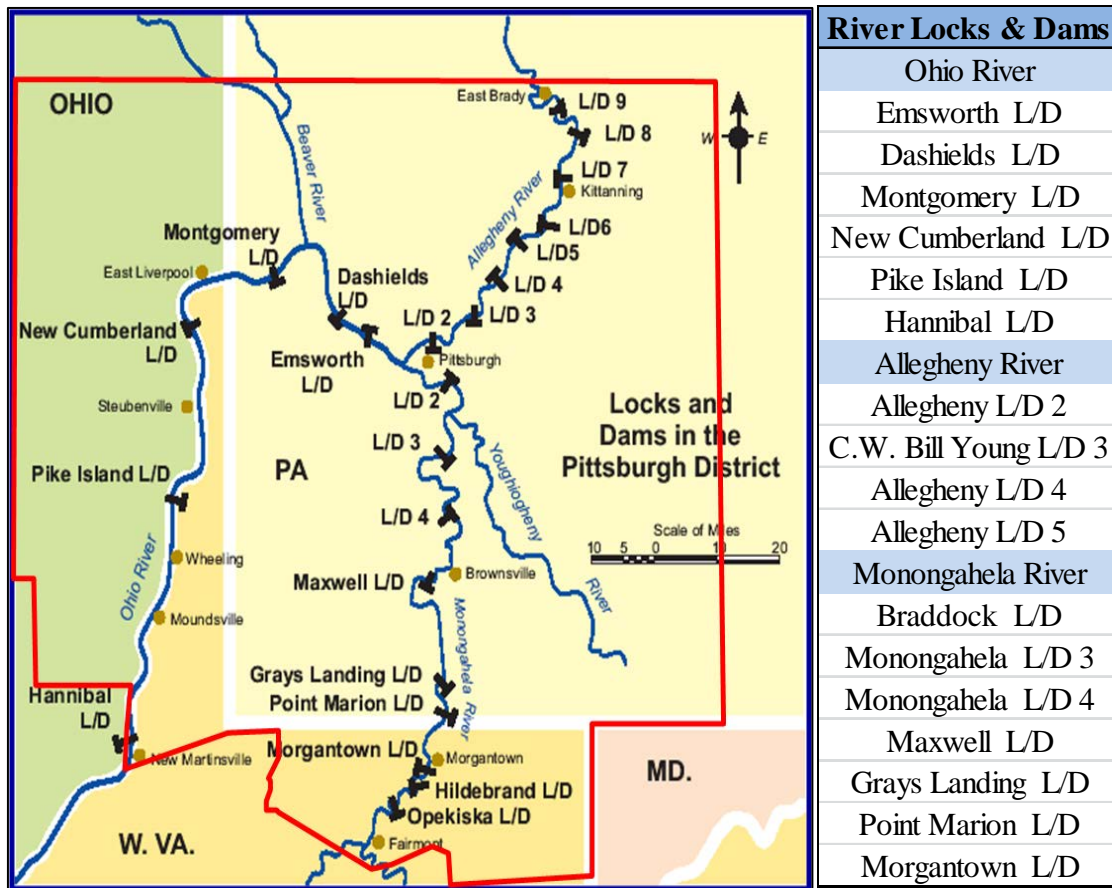


Figure 4. The Port of Pittsburgh consists of the Ohio, Monongahela, and Allegheny Rivers. This picture illustrates the location of various locks and dams (L/D) in our study area, listed in the table to the right. Along the Ohio River our study area is bounded by the Hannibal L/D, on the Allegheny River by the Allegheny L/D 5, on the Monongahela River by Morgantown L/D. Source: USACE 2012.

Collectively, there are 18 different pools in the study area; see Figure 5. We label these in increasing order, starting downstream and moving upstream.

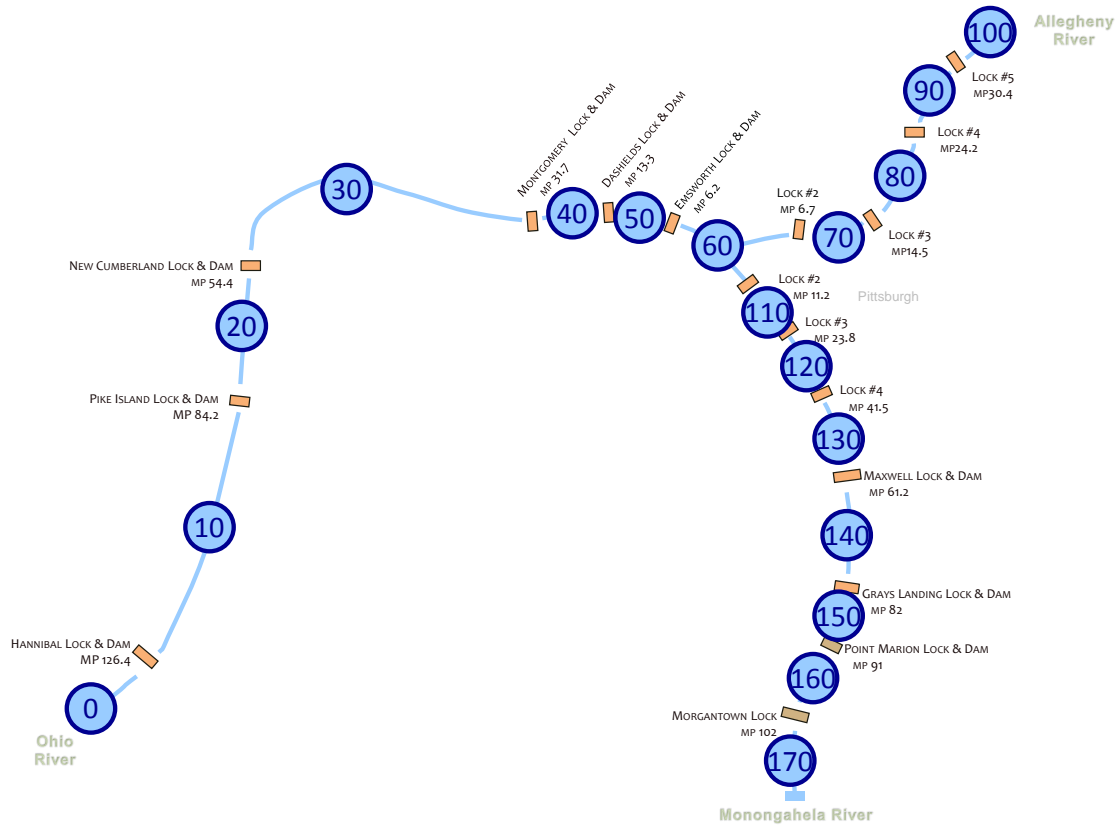


Figure 5. We identify 18 relevant pools in this Three-River transport system.

We have identified a total of 44 river terminals that have the ability to support coal movement. In contrast to locks and dams, terminals tend to be privately owned and operated. Because data regarding the transport of coal at these facilities is considered proprietary and a potential source of competitive advantage for the stakeholders, we refer to each terminal using a generic, but unique, identification number; see Figure 6. These numbers are also sequential, increasing in value in the upstream direction, and with values that correspond to the pool to which they belong. For example, Terminals 11-17 are part of Pool 10, Terminals 21-24 are part of Pool 20, and so on. We have invented a single artificial terminal, named the “Ohio Superterminal” (i.e., Terminal 0) to represent all terminals downstream from the Hannibal Lock and Dam on the Ohio River and therefore outside the study area.

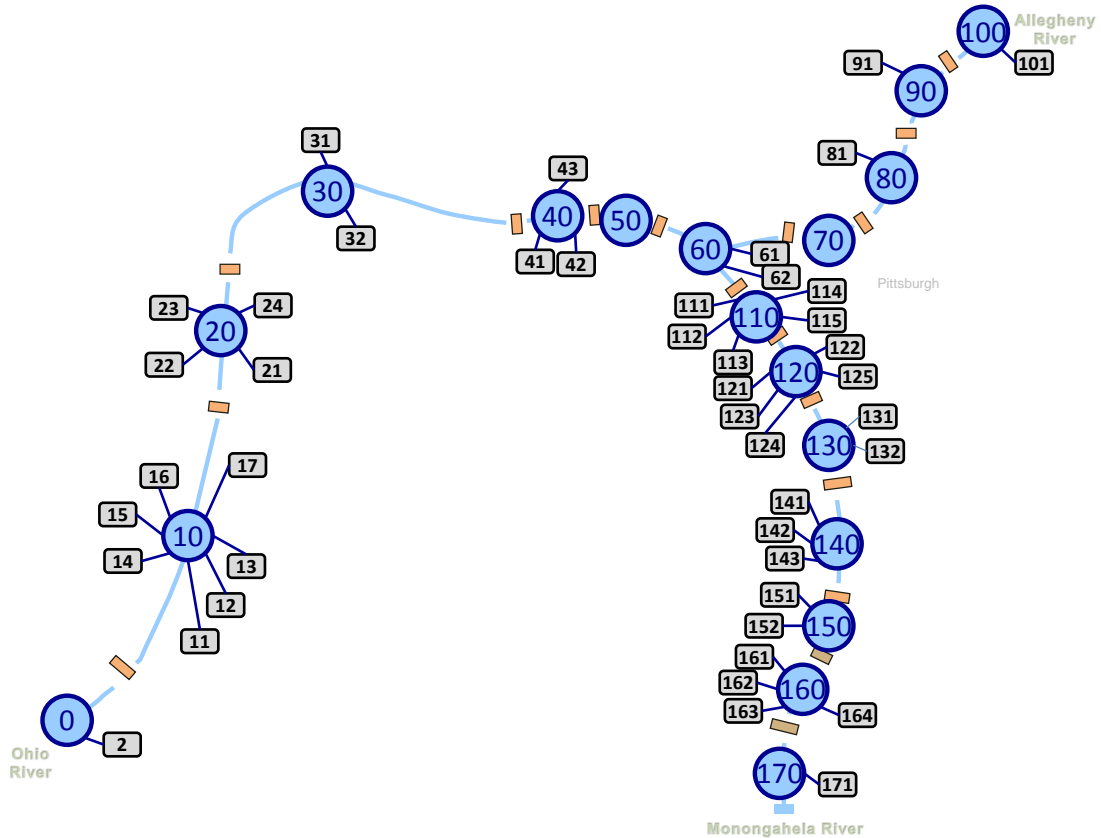


Figure 6. We identify 44 terminals that can serve as either the origin or destination for coal shipment in this river transport system.

We obtained data on marine shipments for CY 2009 from the Army Corp of Engineers Planning Center of Expertise for Inland Navigation as well as the U.S. Energy Information Administration. After filtering out records that did not pertain to the transport of coal, there were more than 2,600 individual recorded shipments, each with a specific origin (beginning point) and destination (ending point). In cases where the origin or destination was downstream on the Ohio River and outside the study area, we simply used the Ohio Superterminal instead. Table 1 summarizes the total flow of coal (in tons) by origin and destination during CY 2009.

		DESTINATION																						TOTAL
		0	11	13	16	31	32	41	42	61	62	81	101	111	113	115	121	123	125	131	141	161	171	
ORIGIN	0									425.9	77.3	44.2	1.8	66.7	2694.1	5.2		60.5	744.5	29.1	131.8	75.6		4356.7
	22										326.5							25.5					6.1	358.1
	42											154.8						7.8			965.0	539.9	36.7	1704.1
	43											9.5				14.1					38.3			61.9
	101	35.5																						35.5
	112	1.6																						1.6
	114	19.6																						19.6
	115	90.7															10.5							101.2
	122	8.8																2.9						11.8
	124	54.1										60.7												114.8
	131					1.4				3.3								101.7			77.7			184.1
	132	920.2	10.0	216.9			10.0				331.7	809.9				14.7	38.6	0.6			618.5	487.5		3458.6
	142	3631.5			39.9	468.4	85.2	237.4						406.6				71.5		327.2	1361.3			6628.8
	151										9.3										143.9			153.2
	152										1.0							36.5			72.6	32.6		142.8
	162	26.5							1.1		4.1							61.4			671.8	664.3		1429.1
	163																				1.0	180.9		181.9
	171																	8.1						8.1
TOTAL		4788.4	10.0	216.9	39.9	469.8	95.2	237.4	1.1	429.2	749.9	1079.1	1.8	473.3	2694.1	34.0	49.1	376.5	744.5	356.3	4081.8	1980.8	42.8	18951.8

Table 1. Total flows (in thousands of tons of coal) by terminal origin and destination during CY 2009. Due to space limitations, we show only rows and columns that have nonzero entries.

The origin-destination matrix in Table 1 is sparse—only a relatively small number of terminals serve as the source or destination for coal shipments, and shipments to or from a terminal tend to have a small number of other terminals to whom they ship or from whom they receive. The row sums and column sums of Table 1 reveal the total amount of coal shipped or received by terminal, which we summarize by rank order in Table 2.

SHIPPED BY ORIGIN					RECEIVED BY DESTINATION			
RANK	TERMINAL	TONS	% OF TOTAL		RANK	TERMINAL	TONS	% OF TOTAL
1	142	6628.8	34.97%		1	0	4788.4	25.27%
2	0	4356.7	22.99%		2	141	4081.8	21.54%
3	132	3458.6	18.25%		3	113	2694.1	14.22%
4	42	1704.1	8.99%		4	161	1980.8	10.45%
5	162	1429.1	7.54%		5	81	1079.1	5.69%
6	22	358.1	1.89%		6	62	749.9	3.96%
7	131	184.1	0.97%		7	125	744.5	3.93%
8	163	181.9	0.96%		8	111	473.3	2.50%
9	151	153.2	0.81%		9	31	469.8	2.48%
10	152	142.8	0.75%		10	61	429.2	2.26%
11	124	114.8	0.61%		11	123	376.5	1.99%
12	115	101.2	0.53%		12	131	356.3	1.88%
13	43	61.9	0.33%		13	41	237.4	1.25%
14	101	35.5	0.19%		14	13	216.9	1.14%
15	114	19.6	0.10%		15	32	95.2	0.50%
16	122	11.8	0.06%		16	121	49.1	0.26%
17	171	8.1	0.04%		17	171	42.8	0.23%
18	112	1.6	0.01%		18	16	39.9	0.21%
SUM		18951.8	100.00%		19	115	34.0	0.18%
					20	11	10.0	0.05%
					21	101	1.8	0.01%
					22	42	1.1	0.01%
					SUM		18951.8	100.00%

Table 2. Total amount of coal (in thousands of tons) shipped or received at each terminal of the Port of Pittsburgh in 2009.

The majority of coal moves through only a very small number of terminals: the top five shipping terminals account for more than 92% of all coal shipped by volume, and the top five receiving terminals account for more than 77% of all coal received.

We also use the data in Table 1 to determine the total amount of coal that moves through each of the pools, and therefore each of the locks. Because there is only one way to move coal along the river, we know that, for example, a shipment of coal that originates at a terminal in Pool 10 and is delivered to a terminal in Pool 30 must also pass

through Pool 20. Our sequential numbering scheme allows us to quickly compute the total flow of coal moving through each pool in both the upstream and downstream directions. These appear in Table 3.

UPSTREAM TRANSIT			DOWNSTREAM TRANSIT			COMBINED TRANSIT		
RANK	LOCK	KILOTONS	RANK	LOCK	KILOTONS	RANK	LOCK	KILOTONS
T1	LOCK 40-50	6,480.8	1	LOCK 130-120	7,546.3	1	LOCK 60-50	12,652.3
T1	LOCK 50-60	6,480.8	2	LOCK 120-110	7,351.6	2	LOCK 110-60	12,482.9
3	LOCK 60- 110	5,440.8	3	LOCK 110-60	7,042.1	3	LOCK 50-40	12,302.9
T4	LOCK20- 30	4,714.8	4	LOCK 60-50	6,171.5	4	LOCK 40-30	10,299.5
T4	LOCK30- 40	4,714.8	5	LOCK 50-40	5,822.1	5	LOCK 120-110	10,022.7
T6	LOCK 0-10	4,356.7	6	LOCK 40-30	5,584.7	6	LOCK 30-20	9,734.5
T6	LOCK 10-20	4,356.7	7	LOCK 140-130	5,414.4	7	LOCK 20-10	9,376.4
8	LOCK 130-140	2,977.0	T8	LOCK 20-10	5,019.7	8	LOCK 130-120	9,368.7
9	LOCK 110-120	2,671.1	T8	LOCK 30-20	5,019.7	9	LOCK 10-0	9,145.1
10	LOCK 120-130	1,822.4	10	LOCK 10-0	4,788.4	10	LOCK 140-130	8,391.5
11	LOCK 150-160	1,178.4	11	LOCK 150-140	1,037.3	11	LOCK 150-140	2,183.1
12	LOCK 140-150	1,145.8	12	LOCK 160-150	774.0	12	LOCK 160-150	1,952.4
T13	LOCK 60-70	210.3	T13	LOCK 100-90	35.5	T13	LOCK 70-60	245.8
T13	LOCK 70-80	210.3	T13	LOCK 70-60	35.5	T13	LOCK 80-70	245.8
15	LOCK160- 170	42.8	T13	LOCK 80-70	35.5	15	LOCK 170-160	50.9
16	LOCK 80-90	1.8	T13	LOCK 90-80	35.5	T16	LOCK 100-90	37.3
17	LOCK 90-100	1.8	17	LOCK 170-160	8.1	T16	LOCK 90-80	37.3

Table 3. Rank ordering of locks in terms of CY 2009 coal that was “locked through” in the upstream, downstream, and combined directions.

Not surprisingly, the most-heavily used locks are those surrounding Pittsburgh in Pool 60—Emsworth Lock & Dam on the Ohio River and Monongahela Lock #2 on the Monongahela River—that locked through the most coal overall in 2009, with nearby locks playing a significant role in both the upstream and downstream directions.

Our coal shipment data include individual transport dates, which allow us to look for seasonal patterns in these coal shipments. Appendix A presents the total week-by-week movement of coal through each of the pools during 2009. Figures 7 and 8 summarize this data on a month-by-month basis.

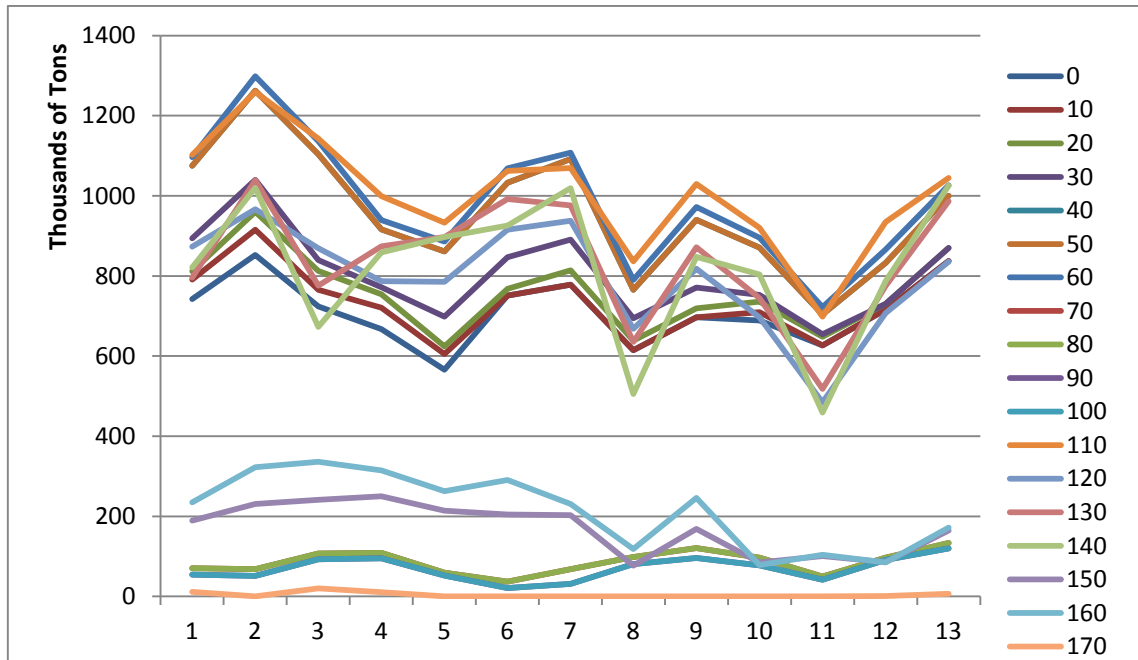


Figure 7. Coal flows through the Pittsburgh study area by four-week “month” during 2009. Seasonal fluctuations are mostly consistent across pools, with the first eight weeks of the CY showing the largest overall flows.

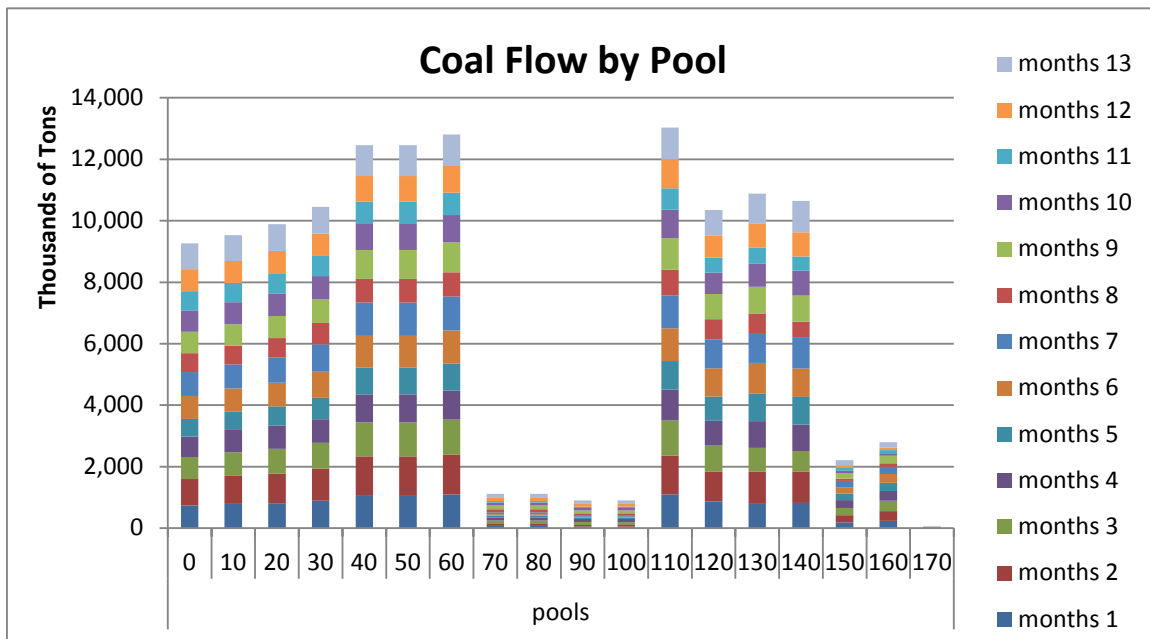


Figure 8. Coal flow through each pool in the Pittsburgh area. Pools 0 through 60 constitute the Ohio River. Pools 70 through 100 constitute the Allegheny River. Pools 110 through 170 constitute the Monongahela River. In gray scale, the months proceed from the bottom up for each bar.



In summary, data about coal movement on the Ohio, Allegheny, and Monongahela Rivers provides a sense of transport operations under normal conditions. We observe that the majority of coal movement on the Ohio River originates from outside the study area and moves upstream toward Pittsburgh, while on the Monongahela River the majority of flow originates at mines on the river itself and then moves downstream toward Pittsburgh. We can identify the pools, locks, and terminals that carried the most volume of coal on a weekly, monthly, or annual basis.

These historical flows also allow for a rudimentary “what-if” analysis: if a pool, lock, or terminal is damaged for a period of time, we can estimate the impact based on the amount of flow that used those components during a similar epoch. Doing this, however, implicitly assumes that coal shipments do not adjust in their routing or volume in the face of damaged infrastructure. In practice, we recognize that coal transport companies proactively manage their shipments to mitigate any such disruptions. Capturing this perspective, however, requires a deeper style of analysis and additional modeling detail, which we address next with our optimization-based models.

### III. APPLYING DEFENDER-ATTACKER-DEFENDER MODELS TO THE INLAND WATERWAY SYSTEM

The starting point in applying DAD modeling is the development of an appropriate operator's model for marine transport in the Port of Pittsburgh. Although there are multiple modes of transport for coal in this region, the enormous capacity of the river system and its low operating costs make it the primary means of bulk commodity shipment through the Port of Pittsburgh. The Port of Pittsburgh Commission reports that "inland waterway transportation is generally the least-costly transportation mode. Average cost ranges between \$0.005 and \$0.01 per ton-mile of cargo moved. This compares to nearly \$0.05 for rail and \$0.10 for truck" (PPC 2012b). Figure 9 shows cargo capacity of different modes of transport; clearly barges can carry much more cargo.

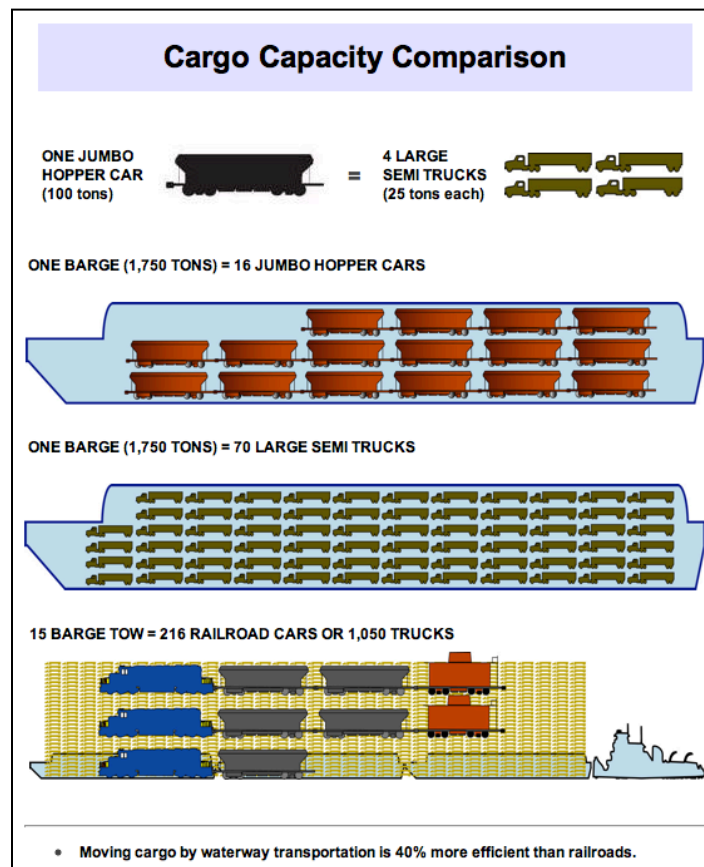


Figure 9. Comparison of cargo capacity of rail car, truck, and barge.  
Source: PPC (2012c).

In practice, the most cost-effective means for moving coal on the river is via multiple barges pushed by a single towboat. Figure 10 displays a “12-barge tow.”



Figure 10. The most economical way to move coal is by barge.  
Source: USACE 2012.

The interruption of coal delivery along these primary river-shipment routes would have significant implications. In the short term, rail transport might not be able to pick up the slack because of limited capacity and availability of rail cars. Additionally, transporting large volumes of coal via truck could place an extreme burden on the road network, causing immediate bottlenecks in and around the Pittsburgh metropolitan area. In the long term, the large demand volumes for coal could make it cost prohibitive to supply adequate quantities by means other than river.

Many coal consumers maintain some level of reserves on hand to mitigate fluctuations in delivery or consumption rates and for emergency situations. These reserves are finite, however, and steel manufacturers in the Pittsburgh region cannot run out of coal or they risk huge financial losses and catastrophic facility “cold shutdowns.”

Thus, the key tensions driving the movement of coal are transport costs and severe operating penalties for running out of coal at an energy provider or a steel mill.

#### **A. BUILDING THE OPERATOR’S MODEL**

Our modeling of river operations has evolved with several research efforts.

Engel (2011) builds a network flow model of coal transport (see Ahuja et al., 1993, pp. 1–20, for relevant background information). Each individual arc represents

either river or rail transport, with a per-ton transport cost. The transport cost on river arcs is lower than on rail arcs. Each demand location has a per-ton penalty cost for a coal shortage. The network is a simplified view of the Point of Pittsburgh where the Three Rivers meet, and rail arcs represent abstract movement directly from source to destination. The demand for traffic is derived from our 2009 USACE data, but aggregated to consider net supplies or demands. That is, if a particular terminal was both an origin and a destination for coal over the year, only the net difference is input to this model. The time horizon for this model is a single week, and there are no provisions for inventory. The solution to this operator's model is the set of coal movements that satisfy demand at minimum cost, while observing capacity constraints and other restrictions on allowable flow.

Engel (2011) additionally presents an AD model based on *cost-based interdiction*. Interdiction is commonly defined as “activities conducted to divert, disrupt, delay, intercept, board, detain, or destroy, as appropriate, vessels, vehicles, aircraft, people, and cargo” (Department of Defense, 2011, p. I-1). For the rest of this report, we use *interdiction* (or *attack*) to mean the interruption of commodity movement through our system. In cost-based interdiction, we assign a per-unit penalty cost to each arc; if this arc is attacked, then this arc incurs both the normal per-unit transport cost and the per-unit penalty cost (see Brown et al. 2005, Alderson et al. 2011, or Dixon 2011 for background information). Using notional cost data, Engel's analysis provides proof-of-concept about the potential insights from the application of this technique to river operations.

Onuska (2012) develops a multicommodity, multimodal network flow model of coal transport in this region, focusing (solely for economy of exposition) on the Monogahela River. He presents a detailed network of nodes and arcs representing coal transport on river, rail, and roads, and with explicit transfer operations to move coal from one mode to another. Each mode of transport has finite capacities with its own costs. Onuska uses USACE transport data from 2009 to generate synthetic “contracts” (i.e., source, destination, quantity, date) for network demand, based on historical shipments. This model allows for multiple time periods and accounts for inventory to be

carried from one time period to the next. His operator’s model routes flows in order to satisfy contracted supplies and demands at minimum transportation cost.

In this report, we extend the analysis using the model first presented in Onuska (2012), which we summarize here, but repeat in its entirety in Appendix B for completeness. This model mimics the real-world behavior of coal transport in the Port of Pittsburgh and allows for systematic investigation of “what if” disruption scenarios (see Figure 11). For example, to assess the impact of a terminal closure, one updates the input data to the operator’s model to reduce (possibly to zero) the capacity of the terminal of interest. The *consequence* of this scenario is then measured in terms of the resulting changes in flows, shortages, and costs. If the operating costs do not change as a result of the terminal closure, then the system has the ability to adjust its flows without any adverse effect, and we conclude that the terminal in question is not critical (i.e., not critical individually). Alternatively, we might say that the system was “operationally resilient” to the loss of that terminal.

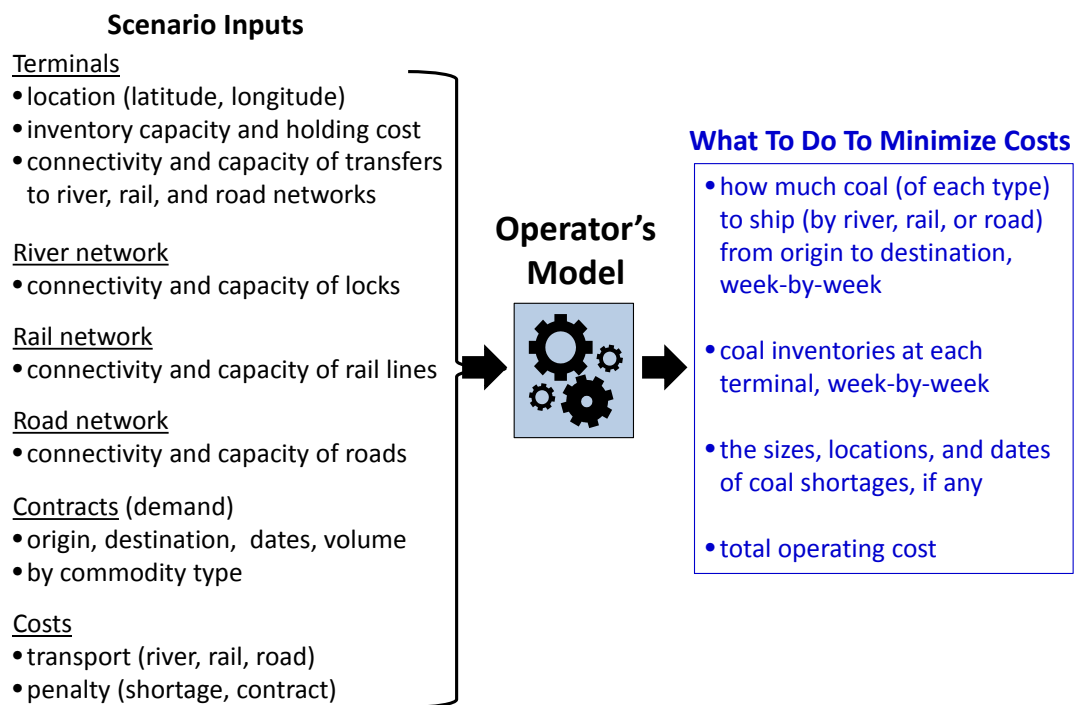


Figure 11. The operator’s model takes input data on terminals, networks for each mode of transport, contracts, and costs. Its output identifies the shipping, transfers, and storage that result in the lowest possible cost, possibly including shortages at some destinations.

Given an appropriately validated operator's model and a specified attacker capability, the AD model finds the worst-case scenario, defined as the one that yields highest operating cost, even after the operator has rebalanced flows as best as possible, after suffering loss of capacity or components. In this case, we typically specify attacker capability in terms a maximum number of attacks or a more general budget (e.g., number of personnel).

## **B. ASSUMED INPUT DATA**

In this analysis, we assume the following input data.

### **1. Terminals**

Terminals are locations that serve as origin, destination, and/or transshipment points for coal and can also serve as storage locations. Terminals are typically limited in their capacity to transfer commodities on or off a specific mode of shipment. Each terminal is unique and its transfer capacity depends on the availability of different coal handling equipment (e.g., conveyors, electric whirler cranes, hoists, or clamshell buckets). Additionally, some terminals are not accessible by every mode of transportation. For instance, some terminals do not have rail lines or have limited road access.

We assume the average cost for loading coal onto barges, rail cars, or trucks is \$0.15 per ton. Because offloading is more labor intensive and costs are higher, we assume the cost of this is \$0.30 per ton.

We assume that any terminal node can carry inventory. In practice, however, power plants typically carry a certain amount of inventory (on average, a 45-day supply) in order to compensate for interruptions in supply such as miner's strikes and/or holidays, adverse weather, or transportation problems (Phillips 2008). Coal is inventoried in closed silos and open storage.

### **2. River Network**

For the purposes of our analysis, we assume that an individual river segment has unlimited capacity. Each lock, however, has an assumed throughput capacity of 30.24

million tons per week. We assume that the costs of transporting commodities by river are less than other modes of travel, and we use an assumed cost per ton-mile of \$0.008.

### **3. Rail Network**

The railroad network around the Port of Pittsburgh is extensive, with considerable path diversity that allows for rerouting in the presence of an interdiction. For this reason, we do not explicitly model rail capacity, except at bridges that serve as natural bottlenecks. Like locks on a river, bridges can create bottlenecks for rail traffic, because only a finite number of trains can traverse the bridge during a given time epoch. We assume each bridge has throughput capacity of 28.5 million tons per week.

In practice, there might be additional capacity limitations due to other bottlenecks and limited availability of rail cars or engines. Although we could model these additional features explicitly, in this analysis we have not.

We assume that the average cost to move coal by rail car is \$0.05 per ton-mile (PPC 2012b).

### **4. Road Network**

The road network around the Port of Pittsburgh is even more extensive than the rail network, and for this reason we do not explicitly model road segments and their capacity, except at bridges that create bottlenecks and limit total throughput. There are a total of 75 road bridges that cross the Ohio, Monongahela, and Allegheny Rivers. We assume each road bridge can handle 1.75 million tons of coal per week.

Transporting coal by trucks on roads is the most expensive option, which we assume is \$0.10 per ton-mile (PPC 2012b).

### **5. Contracts**

Actual coal shipments reflect contracts between producers (mines) and consumers (utilities and steel producers). Our working definition is that a *contract* is an agreed on shipment of a specific commodity amount from an origin (producer) to a destination (consumer) at a specific time. In this analysis, we consider two types of coal, creatively

labeled as COAL\_A and COAL\_B, which, respectively, represent bituminous coal (used for energy) and lignite coal (used for steel production).

In practice, we have no knowledge of future contracted shipments (only the shippers do), so we use past shipments as a proxy for representative levels of demand.

## **6. Penalty Costs**

Our operator's model accounts for the costs to transfer coal onto and off of each mode of transport, as well as the cost to move it along each mode of transport. The model, however, is also driven by two additional penalty costs. We impose one (large) per-ton penalty cost if the system is unable to satisfy demand (i.e., deliver coal) at a terminal when it is needed. We set this penalty cost sufficiently high so that the system will find a (possibly expensive) path to deliver coal if it is feasible to do so. In our analysis, however, this penalty is arbitrary and does not reflect an actual cost. In practice, one could perform in-depth analysis of the economic or other “downstream” implications (e.g., impact on other infrastructures or industries) of not having coal when it is needed. When used as inputs to the operator's model, these more realistic penalty costs allow for the assessment of when it makes sense to pay a premium to find other ways of getting coal or make defensive investments in the infrastructure, as opposed to simply allowing the system to “fail” in delivering coal.

We include a second (smaller) per-ton penalty cost that is imposed when the system does not satisfy (i.e., “breaks”) a contracted flow between origin and destination. As evidenced by the origin-destination flows in Table 1, the Port of Pittsburgh has the same coal moving in opposite directions along the river. This is because these flows represent the contracts between different shippers and consumers. A perfectly integrated and efficient system would not allow such crossing flows; rather, it would satisfy demand for coal at each terminal at the lowest cost because distance is a big component of cost. This would likely mean that coal demand would be satisfied locally, without regard to the actual buyer or seller. This additional per-ton penalty discourages this by imposing an additional cost on non-contracted, origin-destination pairs, so that the lowest-cost shipment in the system is the contracted one. In our analysis, this penalty is arbitrary in the sense that it does not reflect an actual cost. Rather, we set this penalty high enough so



that contracted flows are maintained during normal operation, but low enough that it makes sense for the system to break contracts in order to reroute flows and avoid shortages at demand points. Again, additional data on the actual costs of breaking contracts could be included in these penalty costs. This would then make it possible to use the operator's model to explore the real trade-offs between allowing the system to "fail" in delivering coal vice finding a way to deliver coal "at any cost."

Our operator's model allows us to set the shortfall penalties individually by commodity type at each terminal. In our analysis here, we set the shortfall penalties uniformly at \$10,000 per ton for each type of coal. We also set the penalties for breaking contracts uniformly at \$0.75 per ton.

### **C. ANALYSIS OF THE MONONGAHELA RIVER**

Following Onuska (2012), we focus attention on the Monongahela River, which carries a significant amount of coal through our system. This reduced system has 8 pools, 24 terminals, 9 rail bridges, and 12 road bridges. The time horizon for this analysis is limited to a single week in which there is a total contracted flow of 167,032 tons of coal. In the absence of any disruption, the system is able to satisfy all contracts at a total baseline cost of \$225,450. Of this cost, \$153,416 comes from the transport of over 19 million ton-miles of coal on the river and \$74,034 in transfer costs on and off the river.

The operator's model allows us to consider the consequence on system performance of any change in system inputs, and to do this in a systematic manner. When considering risks to the MTS, we are particularly interested in changes that reduce the connectivity, capacity, or capability of the system. We first consider the possible disruptions to the "waterside" of the system. If the system had a dam fail, we assume that the pool that it supports would become unnavigable; in terms of the model, this means that barges could not transit that pool. If a lock were to become inoperable, then we assume that barges could not transit between its adjacent pools. If a river terminal were to become inoperable, then we assume that coal could not be transferred on or off the river at that location.

Not surprisingly, the single most costly attack is to Pool 60 (see Figure 5) at the intersection of the Three Rivers in Pittsburgh itself. This essentially cuts off all river traffic into and out of the Monongahela River, and it also stops the local river transport of coal through that pool. This forces the operator to move the majority of coal by rail to its destination. This disruption causes a decrease in river transport, because a large amount of cargo is shipped from the Monongahela River to destinations outside of the Monongahela River and a large amount of cargo is shipped from origins outside of the Monongahela River to destinations on it. This yields more than twice the operating costs, at \$559,204. Coal is now primarily delivered via rail, and transfer costs have increased nearly 40%, to \$100,513.

Figure 12 compares the top 15 largest-consequence “waterside” attacks. Baseline operations are highlighted in green and the most impactful attacks are listed in descending order. The first four worst attacks are attacks on dams. The next most impactful attack occurs at a lock.

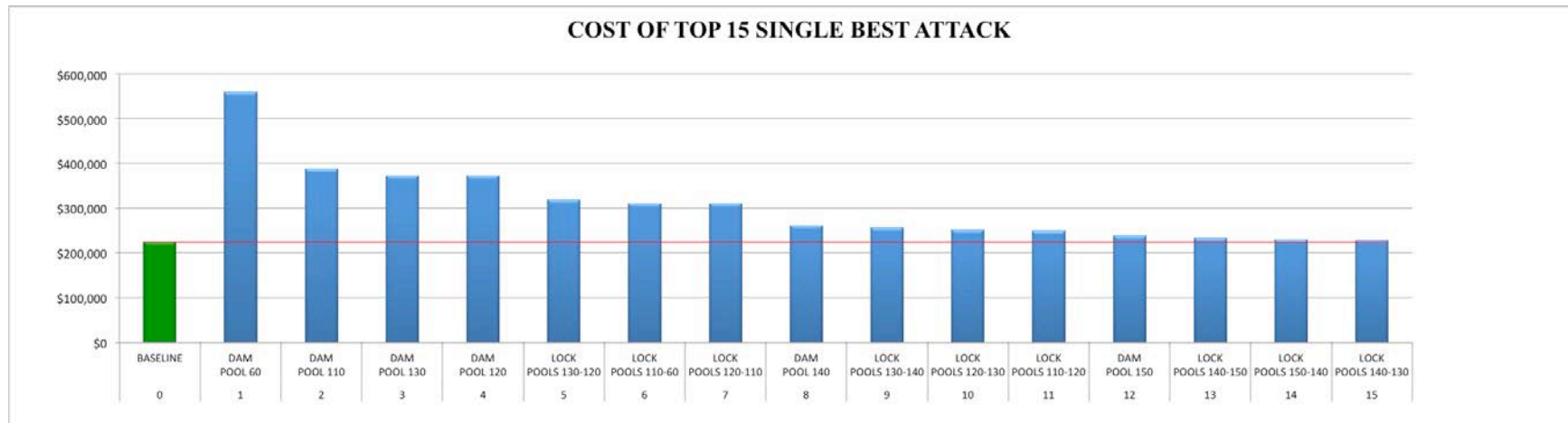


Figure 12. Baseline operating costs (left-most, green) and the cost of the best 15 single attacks to the Monongahela River. Dams are attacked first, restricting navigation through pools. Locks are then attacked, restricting the ability to transit between pools.

Simultaneous disruptions may occur at multiple, separate locations. These simultaneous attacks have the potential to increase costs above the cost of a single, worst-case disruption. The worst-case scenario for two simultaneous attacks occurs at Pool 60 and Pool 130 (see Figure 5). This attack causes total operating costs to rise to \$598,421. In this case, the operator must ship the majority of coal via rail, while some is still moved via river. We observe that, in this case, transfer costs actually decrease from the single attack scenario because the operator chooses to ship directly from source to destination via rail, rather than transferring coal to the river, partly using the river, and then transferring to rail for the remainder of the trip. With two simultaneous attacks, the operator avoids multiple loading and offloading transfers. Table 4 displays these statistics.

# attacks	components attacked	mode	TON-MILES	MODAL COST	TOTAL COST
0	none	river	19,176,963	\$153,416	\$225,450
		rail			
		road			
		transfer	320,151	\$72,034	
1	POOL 60	river	4,438,750	\$35,510	\$559,204
		rail	8,463,616	\$423,181	
		road			
		transfer	446,724	\$100,513	
2	POOL 60, POOL 130	river	894,238	\$7,154	\$598,421
		rail	10,208,468	\$510,423	
		road			
		transfer	359,304	\$80,844	
3	POOL 60, POOL 130, POOL 140	river	380,250	\$3,042	\$602,145
		rail	10,441,424	\$522,071	
		road			
		transfer	339,755	\$76,445	
4	POOL 60, POOL 120, POOL 150, LOCK 130-140	river	394,688	\$3,158	\$602,824
		rail	10,346,108	\$517,305	
		road			
		transfer	349,711	\$78,685	
5	POOL 60, POOL 110, POOL 130, LOCK 120-130, POOL 160	river	178,500	\$1,428	\$620,824
		rail	10,526,962	\$526,348	
		road	6,206	\$621	
		transfer	320,151	\$72,034	

Table 4. Most impactful simultaneous attacks: 0 through 5. For two simultaneous attacks, 213,250 tons of coal is transported via river and 153,742 tons of coal is transported via rail. The cost to operate the system becomes \$598,421.

We maintain this standard of conveying operating results throughout the remainder of this analysis. As the number of attacks increases, barge use decreases, and rail car and truck use increases. Table 4 deconstructs the costs associated with each mode of transport, beginning with zero attacks and ending with five simultaneous attacks. Looking at the MODAL COST in Table 4, it becomes apparent that transportation costs rise dramatically following the initial attack(s). In the case when all waterside assets are vulnerable, attacks on dams result in worst-case increase in cost, even after river operations adjust flows to minimize transport costs. Details of the specific pools, locks, and terminals that constitute each worst-case attack are available in Onuska (2012).

Figure 13 illustrates how the overall system cost increases with additional attacks. In practice, we often refer to this figure as the *resilience curve*, because it characterizes the ability of the system to function in the presence of increasing disruption (see Alderson et al. 2012 for a detailed discussion of resilience curves). In this context, we use number of simultaneous attacks to characterize the size of the disruption. For this reason, we can also interpret this figure as the attacker's *return on investment (ROI)* curve.

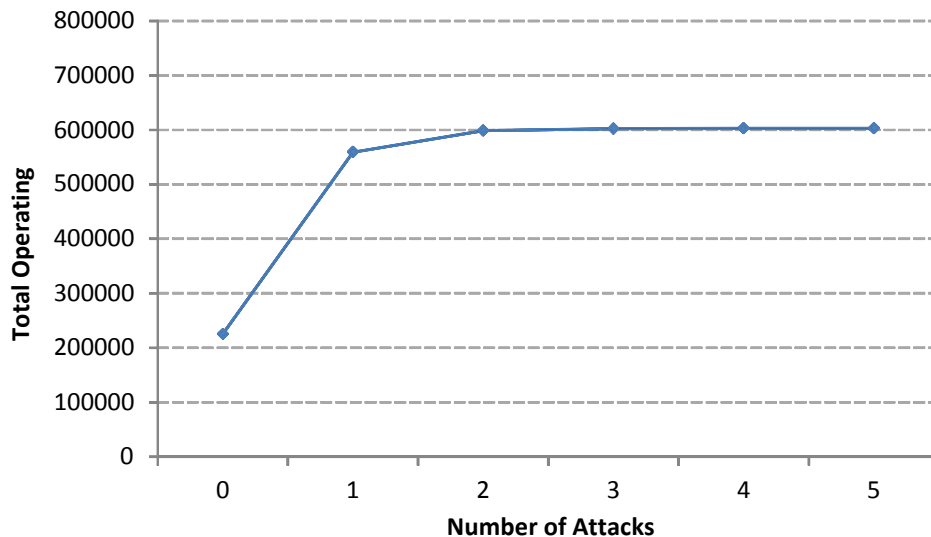


Figure 13. The resilience curve for coal transport on the Monongahela River in the absence of defenses. With only one or two coordinated attacks, the total operating cost of the system dramatically increases. The addition of a third, fourth, or fifth attack on water assets does little to further increase the operating cost.

The shape of Figure 13 quantifies what stakeholders in the Port of Pittsburgh have intuitively known for a long time: namely that the loss of only a small number of water

assets can inflict significant pain on the transport of coal. The next natural question is: how does the protection of assets on the river mitigate these potential disruptions?

Imagine that the USCG, perhaps in coordination with the USACE, could perfectly protect dams so that they would never fail and are invulnerable to attack. Under these conditions, an observant and intelligent attacker knows that targeting dams has no effect and therefore turns attention elsewhere. Not surprisingly, the worst-case attack is now on locks instead of dams, and the attacker's ROI is reduced. Figure 14 illustrates how the resilience curve changes in the presence of different defensive efforts. Specifically, perfect defense of dams significantly reduces the total operating cost in the presence of one or more attacks. In this case, the resilience curve shifts down, indicating that consequences of a worst-case attack are less than before.

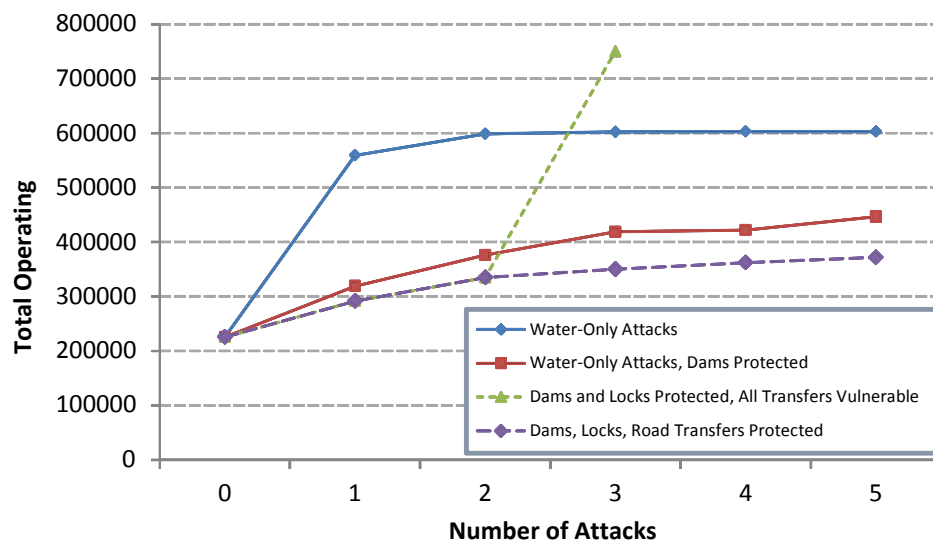


Figure 14. Resilience curves for coal transport in the presence of different defensive efforts. Perfect defense of dams lowers the curve (from circles to squares). Defense of dams and locks causes an attacker to consider landside assets. If an attacker can isolate a terminal by interdicting all three transfers (to river, road, and rail), then the operating cost becomes arbitrarily high (triangles). If we assume that coal can always be transported by road and that locks and dams can be perfectly protected, then the worst case disruption is more modest, even in the presence of multiple losses (diamonds).

Continuing this thought experiment, imagine that the USCG could perfectly defend both locks and dams. In this situation, the intelligent attacker will shift attention to terminals and their ability to transfer coal to and from river, rail, and road networks. Attacking the ability to transfer coal on or off the river results in less overall cost

increase, unless an attacker can isolate a terminal by completely interdicting its ability to send or receive coal. In this case, the resulting “cost” of that isolation can be arbitrarily high, depending on the penalty costs chosen to reflect the economic consequences at that terminal. In the scenario here, these penalties are such that isolating a terminal yields a higher cost than disabling a dam (see Figure 14).

This study considers only a single penalty cost that is the same for all terminals; thus, the terminals targeted are the ones that move the largest volumes of coal. A closer look at the individual consumers of coal in the region (e.g., electricity generators and steel manufacturers) would likely reveal, however, that the consequence associated with not having coal at some terminals is higher than at others. Again, the penalty costs in our model allow the analyst to specify these in the context of different “what-if” scenarios.

In practice, roads can be rebuilt in relatively short time, and so it might be unrealistic to think it is possible to completely isolate a terminal for a long period of time. So, we consider a final scenario in which dams and locks are perfectly defended on the water and where transfers to the road network are invulnerable to attack. Figure 14 shows the value associated with this level of resilience: while attacks increase the total operating cost to move coal, it is significantly less than it would be otherwise.

A decision to protect locks and dams, if such defenses are even possible, is not without cost. Quantifying resilience in this manner allows for a specific type of cost-benefit analysis: does the improvement in resilience, as measured by the shift in curves in Figure 14, justify the associated costs? This report does not pursue a detailed cost analysis of defensive actions, but such efforts are natural next steps in an assessment of operational resilience for the Port of Pittsburgh or other ports.

#### **D. ANALYSIS NOT (YET) PERFORMED**

Our model for the operation of coal transport in the Port of Pittsburgh contains features that we have not exercised, but that we perceive are important for future analysis in Pittsburgh and other ports.

## **1. Multiperiod Analysis**

Our analysis of the resilience of coal transport considers a time horizon of only a single, week-long time period. Our model, however, allows us to consider the transport of coal over a much longer time horizon, and more time periods, which is important for several reasons.

First, it is natural, in this context, to measure repair times for critical infrastructure in weeks. Our model allows us to incorporate domain-specific knowledge about the actual repair times. For example, we might know that transfer equipment (i.e., conveyors or cranes) takes two weeks to repair. Because locks are uniquely constructed and their repairs are labor-intensive tasks, however, we might assume their repairs take four or more weeks each. Moreover, because dams require the most time-consuming repairs, we might assume that these take 13 or more weeks each. Furthermore, we might assume that roads and rail lines can be repaired within one week; if so, then their repair times might be negligible, as these repairs can be accomplished within a single time period.

Second, because of the severe consequences of running out of coal, individual coal consumers tend to keep a reserve inventory on hand to use if coal shipments are disrupted for some period of time. Thus, assessing the situations under which there are shortfalls depends on both the actual inventories and the actual repair times.

Given coal inventories and repair times, then the loss of a dam, lock, or transfer capacity at a terminal can result in a disruption that lasts for several weeks. The solution of the operator's model reveals the best way to transport coal over the entire planning horizon, to include a means for working around damaged components and then resuming their use when they become available for use again. In the case where we consider an unannounced (surprise) loss of infrastructure, running the operator's model identifies how best to respond by rerouting coal flows and using coal inventories judiciously, and the resulting cost provides a more realistic estimate of the actual consequences.

We can also use the multiperiod planning feature in our model to consider the potential consequence of a planned future interruption of system function; for example, from the planned shutdown of a lock for preventative maintenance. We can think of a future outage as an "attack" that is announced in advance; in this case, the solution to the operator's model will reveal how to plan anticipatory shipments and preposition coal



storage. Thus, we can use the operator's model as a planning tool to assess the impact of proposed closures on key infrastructure assets, and measure the consequences of such proposed closures in units that are relevant to system function.

## **2. Including More Detailed Rail and Road Systems**

In this analysis, we include only the simplest representation of the rail and road networks. Specifically, we assume that there is sufficient path diversity on land that the only potential sources of disruption of these networks are the bridges over the rivers. In practice, the local terrain contains hills and valleys that often funnel rail lines and roads through areas that create bottlenecks and could serve as a serious potential disruption, either in isolation or in conjunction with a disruption on a river. The data for these rail and road networks are readily available, but incorporating it at an appropriate level of detail for use in our model will require time on the part of analysts. Before doing so, we recommend a preliminary assessment to determine whether we believe this additional level of detail has the potential to change the basic insights of this analysis.

## **3. Expanding the Scope to the Rest of the Three Rivers**

Our analysis of the Monongahela River can be extended in a straightforward manner to include the Allegheny River and upper portion of the Ohio River. To do this requires additional effort to development raw data into a form that can be used as input to the operator's model. It will also require additional effort to exercise the model through the various "what-if" scenarios necessary to gain insight about coal transport in this broader area. Even though the Monongahela River carries some of the highest coal volumes for local traffic, nearly all of the coal that enters or exits the Three Rivers region does so via the Ohio River. So it is possible that the worst-case disruption is, in fact, downstream from Pittsburgh. The idea that the worst-case disruption to a system can be one that is far away is something that we have observed in many studies of infrastructure.

## **E. PERFORMING THIS ANALYSIS FOR OTHER RIVER PORTS**

Our design of the operator's model is generic, in the sense that it can be applied to the movement of any continuous commodities through any ports on a river system. In this study, we focus on different types of coal moving through Pittsburgh, but the same

basic model could be applied, for example, to the movement of grain, fertilizer, or potash in the Port of Louisville, Kentucky. Although the mathematical model is ready for such application, the biggest “expense” in studying another river port will be in data development. We comment briefly on this.

We anticipate that we can use the same USACE shipment data as a starting point for identifying the most significant origins and destinations for each type of cargo. Again, although historical data is not a perfect proxy for future contracted shipments, it serves as a reasonable and defensible starting point for looking at the potential disruption of historical shipments. This first level of analysis, as performed in Section II of this report, does not require the use of the operator’s model, and the data development requirements are considerably less. It is possible that by simply understanding the aggregate cargo movements in a comprehensive way, one obtains sufficient insight into the relative importance of different facilities along the river, and that this insight is enough to inform Coast Guard decision making on the allocation of resources in advance of a disruptive event.

The development of data and its use in an operator’s model, as in Section III of this report, provides a more detailed and comprehensive means to consider “what-if” scenarios. We can explore how the system will respond to specific damage in scenarios of concern, whether deliberately inflicted or not. By using our hypothetical attacker, we can identify worst-case disruptions and assess whether the best-case response of the system as it currently stands would be sufficient. If we discover that the system will not function adequately, then we can consider specific investment or prepositioning measures that would mitigate this.

Having an operator’s model and input data for a specific river port, however, also puts us in position to respond to emergent events, by allowing us to quickly consider different courses of action following a disruption. That is, we can use the operator’s model to help coordinate (or at least advise) the activities of the port or broader river system in an integrated manner. This could be useful not only to the Coast Guard, but to emergency responders and executive decision makers at the local, state, and federal levels.

## **F. DISCUSSION**

The DAD decision support model described in this report is qualitatively different from the risk-based models currently in use by the USCG. Our models do not require probabilistic risk assessment of any attacker intent, nor do we require any probabilistic assessment of vulnerability to attack. Following standard military planning doctrine, we plan based on attacker capabilities, not intent. We note that the only situation where military planners might assess attacker intent is when the time horizon is very short and intelligence is very strong. This is a rare situation that we cannot rely on for continued, routine planning to defend our infrastructure. Further, even if we do assess these probabilities of intent and vulnerability, they are obviously not independent as is customarily assumed (i.e., an attacker will surely change his probability in response to any change in vulnerability). We avoid these complications, and the requirement that such probabilities be stated for some fixed time epoch.

We reiterate that our attacker model is not intended to represent the actual decision process of any specific adversary (e.g., Al Qaeda), rather we use it as a mechanism to discover worst-case disruptions to system function. Real terrorists might not have the ability to identify the combination of terminals, locks, and dams that yield the worst-case disruption of the transport of coal. Given the growing sophistication of adversaries everywhere, along with the possibility of an “insider threat,” we argue that it would be imprudent to assume that they are not able to do so.

Our model does not require consequence values associated with the loss of individual components, nor do we assume that the consequences associated with losing multiple components is merely additive. By explicitly representing the interaction between components and how they behave as a system, we can solve for the disruption to function associated with the loss of sets of components and then find the sets that are most critical.

In practice, system operators need to maintain function, no matter the source of disruption. So if a “perfect storm” of unlikely events involving a combination of scheduled maintenance, component failure, and human error could suddenly lead to loss three critical components, we want to know this in advance, and how to respond to it.

The USCG already maintains systems that collect information about infrastructure components of the MTS. These are ideal to use in support of the DAD decision support system we describe. Much of the required data are already collected and tended, but additional work is required to leverage these investments for use in the models described here.

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## IV. SUMMARY AND CONCLUSIONS

Rivers are an extremely important part of the MTS, and the Port of Pittsburgh offers a valuable target to an adversary looking to cause deliberate harm to coal transport. With approximately \$9 billion in annual commerce, the second-largest inland port in the United States could be significantly impacted with just a single attack, causing operating costs to rise nearly 150%. Adversaries are plotting to disrupt commerce, as evidenced by the recent planned attack on a bridge in neighboring Ohio (Barrett 2012). The use of system interdiction techniques allows us to identify the most critical infrastructure in our system; in our case, this is the dams that support pool navigability. This modeling method allows us to quantify impacts to operating costs and consider various alternate scenarios concerning defense tactics and schemes.

The analysis in this report provides one view on the resilience of the Port of Pittsburgh, specifically in terms of its coal transport operations. This analysis also suggests a general technique for assessing the operational resilience of the Inland MTS more broadly. The benefits of this technique, however, need to be weighed carefully against resource requirements, because the Coast Guard faces key decisions about the use of limited resources, both for the execution of its PWCS mission and also for analysis in support of this mission.

The DAD technique in this report is distinctly different from the currently fashionable, risk-based models for assessing the criticality of infrastructure. It does not suffer from the need to guess at adversary intent, nor does it presume to know in advance the consequence from losing a combination of infrastructure assets. It focuses instead on what we do know: how our infrastructures function on a day-to-day basis. By explicitly modeling the function of the system as managed by an operator, the model allows for an assessment of consequences that is operationally relevant, realistic, and defensible. It has the potential to serve as an important tool for assisting the Coast Guard with its planning, both before and after disruptions to the MTS.

The analysis in this report has taken a limited view of “defensive investment,” but the model and technique can be extended to consider a comprehensive formulation in which one considers a list of possible investment options, ranging from hardening to

redundancy to capacity expansion, each with its own cost. Then, given a fixed limited investment, the DAD model will identify the combination(s) of investment that yield the most resilient system. Moreover, it then becomes possible to consider how different levels of investment lead to improved resilience. Such defensive “return on investment” trade-offs will be an important avenue for future work.

The specific DAD model in this report was designed so that it could be used to assess the operational resilience of transporting any commodities through any river port over a long time horizon. The application of the model to a new port, however, will require considerable time to develop available raw data into a form suitable for use as model input. In addition, we anticipate that it will take considerable effort to exercise the model to analyze the “what if” scenarios for disruptions. The DAD model is not a software tool that can simply be “rolled out” on a regional or national basis.

Thus, the development of DAD models for assessing the operational resilience of individual ports represents a nontrivial investment, but it is one that can provide benefits beyond the near term. Because infrastructure tends to change on relatively slow time scales, we anticipate that, for example, the locks and dams in the Port of Pittsburgh will remain relatively unchanged over the next several years, or even decades. This means that an operator’s model of port operations can be helpful not only with planning today, but also in the future, as emergent situations arise. A key issue is how to manage the ongoing development, use, and custody of these models.

At this moment and in the foreseeable future, the Coast Guard must rely on personnel at the Naval Postgraduate School to exercise DAD models using a combination of customized and commercial software. We suggest that a natural, long-term objective should be to transition the software and analysis to Coast Guard personnel so they can use it independently. The means by which the Coast Guard develops the capability and resources to receive decision support models, such as DAD, remains an important topic of conversation.

## APPENDIX A. COAL SHIPMENT DATA

week	POOL 0			POOL 10			POOL 20		
	thru	on	off	thru	on	off	thru	on	off
1	71925	31358	40567	74507		2582	74507		
2	214496	147612	66884	240947		26451	250599	9652	
3	244869	107664	137205	257121		12252	259940	2819	
4	211047	120649	90398	218575		7528	227024	8449	
5	179949	117030	62919	198037		18088	214504	16467	
6	190628	105060	85568	207219		16591	218505	11286	
7	232285	103283	129002	246733		14448	251755	5022	
8	249145	116176	132969	263132		13987	275014	11882	
9	235023	130383	104640	244959		9936	247805	2846	
10	191377	115128	76249	199551		8174	215611	16060	
11	151953	112181	39772	161857		9904	178612	16755	
12	145744	101563	44181	158775		13031	170412	11637	
13	112519	69604	42915	121123		8604	126614	5491	
14	208390	107304	101086	224442		16052	226790	2348	
15	170943	79512	91431	190424		19481	203673	13249	
16	175407	70058	105349	185137		9730	197184	12047	
17	146250	50891	95359	167717		21467	175606	7889	
18	144057	40796	103261	154082		10025	154082		
19	157255	59856	97399	164723		7468	164723		
20	118176	55671	62505	118176			129906	11730	
21	145466	61252	84214	145466			148454	2988	
22	211721	69461	142260	211721			214771	3050	
23	219278	58545	160733	219278			220760	1482	
24	174788	55068	119720	174788			183752	8964	
25	213476	53758	159718	213476			229947	16471	
26	186221	62105	124116	186221			190662	4441	
27	195139	79398	115741	195139			202513	7374	
28	183706	87531	96175	183706			191264	7558	
29	158436	64003	94433	158436			166258	7822	
30	135916	60556	75360	135916			135916		
31	141171	78468	62703	141171			144093	2922	
32	178789	97899	80890	178789			192508	13719	
33	107217	72633	34584	107217			108811	1594	
34	193211	100040	93171	193211			205746	12535	
35	196712	73545	123167	196712			197721	1009	
36	200046	71260	128786	200046			207269	7223	
37	175228	87052	88176	183224		7996	183224		
38	172079	77693	94386	183445		11366	198418	14973	
39	162918	63106	99812	164629		1711	175751	11122	
40	178367	73452	104915	178367			178367		
41	177225	79239	97986	177225			177225		
42	170842	65237	105605	170842			170842		
43	143754	92685	51069	143754			160363	16609	
44	134892	86280	48612	134892			139608	4716	
45	162160	88072	74088	162160			162160		
46	174583	95939	78644	174583			183066	8483	
47	218587	94393	124194	218587			222904	4317	
48	160981	69726	91255	160981			162031	1050	
49	183817	97282	86535	183817			187906	4089	
50	183513	76706	106807	183513			192079	8566	
51	182621	74168	108453	182621			191969	9348	
52	127114	73339	53775	127114			135422	8308	
53	160401	75014	85387	160401			162168	1767	
TOTAL	9261813	4356684	4905129	9528685	0	266872	9886814	358129	0



	POOL 30			POOL 40			POOL 50		
week	thru	on	off	thru	on	off	thru	on	off
1	98481		23974	120102	21621		120102		
2	276182		25583	336807	57257	3368	336807		
3	271650		11710	328832	50401	6781	328832		
4	247530		20506	289077	40466	1081	289077		
5	234928		20424	299526	55688	8910	299526		
6	243229		24724	295965	47251	5485	295965		
7	257977		6222	311949	46178	7794	311949		
8	303714		28700	354902	43409	7779	354902		
9	266842		19037	313481	45552	1087	313481		
10	223381		7770	317521	94140		317521		
11	178612			254578	75966		254578		
12	170412			218039	47627		218039		
13	126614			177360	43983	6763	177360		
14	226790			258861	27624	4447	258861		
15	204809	1136		228008	18561	4638	228008		
16	213627	16443		251719	33772	4320	251719		
17	187346	11740		228885	33824	7715	228885		
18	170540	16458		223077	42639	9898	223077		
19	173843	9120		207092	22331	10918	207092		
20	166380	36474		202401	34934	1087	202401		
21	184468	36014		240409	48325	7616	240409		
22	238167	23396		285965	46732	1066	285965		
23	228908	8148		265658	26531	10219	265658		
24	195143	11391		240936	34857	10936	240936		
25	249816	19869		299811	42316	7679	299811		
26	202134	11472		265138	55490	7514	265138		
27	236609	34096		278214	31629	9976	278214		
28	201727	10463		248276	35849	10700	248276		
29	170362	4104		183959	3800	9797	183959		
30	165443	29527		167378	896	1039	167378		
31	149311	5218		179598	30287		179598		
32	209024	16516		234244	25220		234244		
33	119175	10364		156751	37576		156751		
34	205746			259039	46655	6638	259039		
35	210321	12600		251092	38524	2247	251092		
36	235793	28524		273477	29150	8534	273477		
37	200262	17038		233788	31409	2117	233788		
38	198418			238973	40555		238973		
39	175751			196173	19371	1051	196173		
40	178367			202105	15477	8261	202105		
41	177225			203341	26116		203341		
42	170842			187659	16817		187659		
43	166579	6216		169429	2850		169429		
44	139608			143597	2850	1139	143597		
45	162160			176678	8796	5722	176678		
46	183066			218806	26946	8794	218806		
47	222904			249789	22424	4461	249789		
48	162031			187553	25522		187553		
49	187906			220724	32818		220724		
50	192079			211303	12577	6647	211303		
51	191969			221297	26013	3315	221297		
52	135422			167017	25041	6554	167017		
53	162168			179879	13331	4380	179879		
TOTAL	10451791	0	564977	12456238	1765974	238473	12456238	0	0

week	POOL 60			POOL 70			POOL 80		
	thru	on	off	thru	on	off	thru	on	off
1	123337		6715	5641			5641		5641
2	341222		27175	22777			22777		22777
3	333513		24617	24118			24118		20946
4	298023		28860	18023			18023		18023
5	300831		25918	20000			20000		20000
6	307337		26595	14664			14664		14664
7	326231		29467	14891			14891		14891
8	364034		29164	18560			18560		18560
9	334378		33058	27295			27295		25759
10	323878		28640	33509			33509		33509
11	260367		31603	22351			22351		20844
12	218039		16472	24334			24334		24334
13	185222		15411	21733			21733		20178
14	273568		30447	29754			29754		28247
15	229060		19335	24848			24848		24848
16	251719		22984	32652			32652		31145
17	234466		18482	2015			2015		2015
18	236410		13333	20117			20117		20117
19	211324		18211	23483			23483		21988
20	203512		18657	13631			13631		13631
21	249552		23198	13030			13030		11471
22	293701		26971	8643			8643		8643
23	278387		22399	5648			5648		5648
24	246929		19996	9692			9692		9692
25	299811		21480	16886			16886		16886
26	275091		27720	21604			21604		20049
27	278214		19823	12703			12703		12703
28	254618		23743	16636			16636		15110
29	191352		15215	27776			27776		26114
30	175281		13729	23250			23250		23250
31	187203		16973	23012			23012		21505
32	235916		36604	24351			24351		22792
33	165347		15239	26127			26127		26127
34	262159		27291	35477			35477		35477
35	260697		18555	27567			27567		27567
36	284002		25339	31929			31929		28820
37	245438		22881	35994			35994		35994
38	238973		23476	22811			22811		22811
39	196173		16080	19263			19263		19263
40	214617		22339	19025			19025		17466
41	213070		27680	13635			13635		10566
42	196626		20742	2915			2915		2915
43	169429		25269	19193			19193		19193
44	143597		10016	14356			14356		14356
45	190451		19117	24217			24217		24217
46	222527		26160	28644			28644		25609
47	258506		25381	18178			18178		16623
48	194824		12968	25845			25845		25845
49	228742		28716	24211			24211		24211
50	211303		22619	25222			25222		25222
51	224501		18502	34364			34364		31041
52	173656		17772	26328			26328		26328
53	188460		19983	23515			23515		23515
TOTAL	12805624	0	1179120	1116443	0	0	1116443	0	1079146

week	POOL 90			POOL 100			POOL 110		
	thru	on	off	thru	on	off	thru	on	off
1	5641			5641			125498	1431	25262
2	18015			18015			351911	1517	96773
3	18510			18510	3172		329828	494	79241
4	12323			12323			294585		93105
5	15250			15250			286718	4053	80131
6	10708			10708			298866	2708	63928
7	11091			11091			318337	8200	71265
8	14760			14760			354962	8340	71193
9	22395			22395	1536		336640	5435	79258
10	27156			27156			322398	5412	65694
11	19818			19818	1507		251674	10870	71437
12	23384			23384			231660	14249	67021
13	16983			16983	1555		186796	9713	54744
14	25954			25954	1507		287398	3922	78307
15	21048			21048			248426	10759	69254
16	31702			31702	1507		276500	5226	56932
17	2015			2015			242548	6807	53166
18	17223			17223			260751	6504	41804
19	19683			19683	1495		210238	5016	33216
20	13631			13631			219487		56939
21	6351			6351	1559		251783	1594	55005
22	1993			1993			279788		56228
23	4698			4698			292152		64709
24	7790			7790			238814	1611	33484
25	13148			13148			307961		47199
26	14064			14064	1555		270831	1553	42257
27	2957			2957			251602		46268
28	1526			1526	1526		239286		76163
29	21288			21288	1662		214605	3185	65454
30	22320			22320			190845		42197
31	20091			20091	1507		202085		61870
32	17516			17516	1559		229206	1574	78902
33	19228			19228			180571	1708	60970
34	29777			29777			290122	4221	91048
35	21836			21836			277487	6723	62068
36	25279			25279	3109		281599	11499	52694
37	31244			31244			270538	12706	65717
38	17111			17111			246729		74548
39	15463			15463			191756	8126	52587
40	14275			14275	1559		211197	6551	50244
41	10785			10785	3069		196916	13809	49949
42	2915			2915			193154	6791	41455
43	16343			16343			166394	5574	75933
44	11506			11506			142237	5798	52316
45	23267			23267			209366	1338	57307
46	25794			25794	3035		237337	10062	72727
47	18178			18178	1555		276595	14562	76231
48	24176			24176			211634		47186
49	24211			24211			232255		61202
50	24220			24220			211902	3047	44938
51	29360			29360	1555	1768	226913	3275	41974
52	22412			22412			181019		48586
53	19529			19529			192601	3146	43326
TOTAL	907941	0	0	907941	35529	1768	13032501	239109	3201412

	POOL 120			POOL 130			POOL 140		
week	thru	on	off	thru	on	off	thru	on	off
1	103916	988	10824	101434	20170		106598	74847	31968
2	290342	1950	77614	241608	85453		229823	139740	83028
3	259786		25649	250416	56390		275332	198045	87041
4	219293		30965	202285	59987	1694	209109	144072	80593
5	207674		30021	190541	57965	1802	199726	117386	89435
6	238556		39724	269903	123772	1668	256823	124298	121116
7	239957		20088	276637	122708	1802	255424	135353	121046
8	280326		41730	301977	118643		307817	185467	120373
9	261803		49931	247007	100129	1735	207109	117094	76168
10	257428		47465	219933	66570	1882	165002	59687	62878
11	177746	9749	42195	131331	40903		126861	38759	73005
12	171844	10010	50056	177680	90959		173884	46656	88599
13	138167		28630	171550	93224		170219	49476	91813
14	217595		25683	234229	105589		214690	133502	66238
15	195021	2929	28052	216160	98565		217007	132636	87022
16	236407	1900	24254	252011	93823		256956	164943	98821
17	201543	992	7309	226020	84403		216952	126139	84855
18	222455		7060	248865	88453		245368	156045	95165
19	176974		10090	193014	75059		177042	114856	55489
20	184342		7469	228859	69771		257699	148138	87762
21	218706		14873	234232	68417		228159	138562	79139
22	239484		11236	249318	79596		230429	154265	73774
23	252806		11011	286507	110623		245013	165211	54790
24	204677		8063	221945	61773		221830	139063	64525
25	283101		12203	292118	81022		273029	171405	76217
26	250487		21232	266393	81272		266425	163344	97444
27	220231		27329	237623	58852		256647	171700	83564
28	183930		12335	179594	12239		222639	166126	83869
29	168866		18761	153406	31552		121854	114923	
30	157835		15887	154995	50459		108396	93622	4903
31	160937		24599	157803	57207		125103	71979	35757
32	180296		23148	169161	57057		150063	104844	52885
33	133830	1926	16449	135981	55311		121968	61191	52293
34	230401	950	22920	259597	94409	1618	269301	152604	121299
35	227632	4754	19302	241491	85343	1713	233610	135222	102387
36	226420	1900	13980	234052	67332	4433	222992	163099	75018
37	212257	7668	22868	215262	43638	20985	232236	168574	89099
38	194229	24154	10728	194321	21109	30412	225713	166005	91899
39	132174	1522	6692	153961	26312	27887	150621	126809	38543
40	157760		10539	181204	43733	20913	195416	148605	68527
41	137604	12555	13050	129138	41179		123047	71789	46080
42	160001	5497	21074	173874	99396		137134	66015	78363
43	97737		19421	112857	84857	9869	76712	36731	48712
44	89487	1974	22052	102515	49446	14768	122566	72466	73047
45	155628	22358	19604	161637	85631	22033	148187	83947	86590
46	175908	7301	26034	185580	45680	22149	212395	140646	101173
47	210477		21792	228033	65423	22074	224575	164558	93087
48	165431		6328	200021	60797	18589	202174	125998	98324
49	178017	4161	13921	201032	41562	29846	239479	156802	125341
50	172989	1338	21150	192316	59243	20215	167434	122435	49739
51	192395		24114	232713	65144	27307	245343	162153	102841
52	137547		14014	163763	38499	25668	193922	123489	89654
53	154589		18478	196741	66062	25217	179304	117497	40536
TOTAL	10345044	126576	1169996	10880644	3642711	356279	10643157	6628818	4081834

week	POOL 150			POOL 160			POOL 170		
	thru	on	off	thru	on	off	thru	on	off
1	20898	1053		27454	15564	19499			
2	66418	8133		71302	31329	41241	11749		11749
3	55273	13990		63460	29052	56585			
4	46952	10264		72860	48949	60083			
5	54109	13489		73173	40648	65078			
6	60129	9479		71827	34054	57845			
7	47717	6859		85586	58829	70407			
8	69053	11114		91879	47083	77659			
9	50534	10979		81855	55405	68750			
10	60431	12858		77398	30661	61656	6599		6599
11	53591	7860		79676	42885	62154	6521		6521
12	76522	14733		97681	48498	75362	6876		6876
13	76798	14629		79104	37631	51316	4932		4932
14	64567	8493		87434	37562	74996	2348		2348
15	52952	9645		79329	46294	63173	3780		3780
16	55493	12752		69190	33168	59218			
17	52296	11489		63844	31387	51713			
18	46601	3879		68544	36107	57302			
19	44622	4645		50270	20602	39961			
20	70328	2807		80577	27553	66080			
21	46193	4795		63918	35238	51200			
22	47972	4708		66674	37923	52161			
23	55105	966		87645	47725	73426			
24	55527	4866		72443	32915	61310			
25	68239	7116		77792	41812	52649			
26	63176	5170		77123	36557	59683			
27	49435	4014		52876	28432	31899			
28	22031	7972		23034	20883	11126			
29	6931	1065		6850	6850	984			
30	9871	4102		13947	9191	12934			
31	31037	1104		52495	30104	44953			
32	29187	3254		44898	35237	28626			
33	35655	2916		65169	39385	58214			
34	55554	4296		74334	40581	56829			
35	46562	3892		75350	64312	43718			
36	31082	3900		31133	21370	13714			
37	32924	4988		30020	24470	7634			
38	17975	1981		15994	14575	1419			
39	7258			7258	7258				
40	26517	979		25538	19193	6345			
41	27573	2824		25702	10693	15962			
42	24673	2009		30926	23790	15398			
43	19418	1868		21460	19939	5431			
44	29628	5830		25748	17322	10376			
45	26858	1906		24952	20791	4161			
46	23198	3699		20465	20465	966			
47	16611			20742	20742	4131			
48	19456	1984		18629	16619	2184	983	983	
49	33058	2802		30256	29224		1032	1032	
50	17093	935		16158	10225	1834	4099	4099	
51	31729	4123		33565	24561	12994	1969	1969	
52	39989	6749		43562	30405	23479			
53	42943			48442	18973	34968			
TOTAL	2215742	295963	0	2797541	1611021	1980786	50888	8083	42805

Table 5. Total flow of coal (in tons) that go on, off, and through a specific pool, by week, in Calendar Year 2009.

## APPENDIX B. MATHEMATICAL FORMULATION

### A. THE OPERATOR'S MODEL

Here we repeat the operator's model for coal movement in the Port of Pittsburgh, first presented in Onuska (2012), in NPS standard form.

Index Sets [~cardinality]:

$n \in N$	nodes [~100]
$r \in R \subseteq N$	transshipment nodes (alias $i, j$ )
$d \in D \subseteq N$	terminal nodes (alias $o, s$ ) $R \cap D = \emptyset$ ; $R \cup D = N$
$m \in M$	modes of transport; $M = \{\text{river, rail, road, transfer}\}$
$mx \in MX = M \setminus \text{'transfer'}$	
$\{m, i, j\} \in A \subseteq M \times N \times N$	directed arcs (from node $i$ to node $j$ using mode $m$ ) [~500]
$\{m, i, j\} \in U \mid \{m, i, j\} \in A \vee \{m, j, i\} \in A$	undirected arcs [~250]
$w \in W$	time periods (alias $wd$ ) [weeks, ~50]
$\{w, wd\} \in FORE\_LOG$	time periods $w$ during which shipments can be made for contracts due in time period $wd$ ( $w \leq wd$ ) [~50]
$\{m, i, j, w\} \in ARC\_I$	if arc $\{m, i, j\}$ is damaged, it is still inoperable during time period $w$ [~500]
$c \in C$	cargo type [~2]
$\{c, d, wd\} \in COM$	contract commodity [~1,000]

Input Data [units]:

$contract_{o,c,d,wd}$	amount of cargo type $c$ originating at node $o$ contracted for delivery to node $d$ during time period $wd$ [tons]
$cost_{m,i,j}$	cost per unit flow for using arc $\{m, i, j\} \in A$ [cost]
$cpen_{o,c,d,wd}$	per-unit penalty for failing to deliver contract volume [cost/ton]
$hcost_s$	holding cost for inventory at terminal $s$ [cost/ton]
$inv\_cap_s$	inventory capacity at terminal $s$ [tons]

$spen_{s,c}$	per-unit demand shortfall penalty at node $s$ of cargo type $c$ [cost/ton]
$\overline{ATTACK}_{m,i,j}$	binary indicator as to whether arc $\{m,i,j\} \in A$ is damaged; = 1 if arc $\{m,i,j\}$ is damaged, = 0 otherwise [binary]
$q_{m,i,j}$	per unit flow penalty for using arc $\{m,i,j\} \in A$ if damaged [cost]
$cap_{m,i,j}$	directed capacity of arc $\{m,i,j\} \in A$ [tons]
$ucap_{m,i,j}$	undirected (shared) capacity of arcs $\{m,i,j\} \in A$ and $\{m,j,i\} \in A$ , $i < j$ [tons]

Computed Data:

$demand_{c,d,wd}$	demand for cargo type $c$ at node $d$ at during time period $wd$ [tons]
$demand_{c,d,wd} = \sum_{o \in N} contract_{o,c,d,wd}$	

Nonnegative Decision Variables [units]:

$F_{o,w,c,d,wd}$	flow from mine $o$ during time period $w$ of contract cargo $\{c,d,wd\}$ [tons]
$Y_{m,i,j,w,c,d,wd}$	flow along arc $\{m,i,j\} \in A$ during time period $w$ of contract cargo $\{c,d,wd\}$ [tons]
$IN_{s,w,c,d,wd}$	inventory at node $s$ at <u>start</u> of time period $w$ of contract cargo $\{c,d,wd\}$ [tons]
$A_{s,w,c,d,wd}$	transfer node $s$ shortage at start of time period $w$ of contract cargo $\{c,d,wd\}$ [tons]
$R_{s,w,c,d,wd}$	transfer node $s$ excess at start of time period $w$ of contract cargo $\{c,d,wd\}$ [tons]

### Formulation 1: Defender Model (D)

$$\begin{aligned}
\min_{F, Y, IN, A, R} \quad & \sum_{\substack{\{m,i,j\} \in A, \\ w \in W}} \left[ cost_{m,i,j} + q_{m,i,j} (\overline{ATTACK}_{m,i,j} \mid_{\{m,i,j,w\} \in ARC\_I} + \overline{ATTACK}_{m,j,i} \mid_{\{m,j,i,w\} \in ARC\_I}) \right] \\
& + \sum_{\substack{\{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} Y_{m,i,j,w,c,d,wd} \\
& + \sum_{\substack{o \in D, \\ \{c,d,wd\} \in COM}} cpen_{o,c,d,wd} (contract_{o,c,d,wd} - \sum_{\{w,wd\} \in FORE\_LOG} F_{o,w,c,d,wd}) \\
& + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} hcost_s IN_{s,w,c,d,wd} \\
& + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} spen_{s,d} A_{s,w,c,d,dw} + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} spen_{s,d} R_{s,w,c,d,dw} \quad (S0)
\end{aligned}$$

$$\begin{aligned}
\text{s.t.} \quad & \sum_{\{w,wd\} \in FORE\_LOG} F_{o,w,c,d,wd} = contract_{o,c,d,wd} \quad \forall o \in D, \{c,d,wd\} \in COM \quad (S1) \\
& -F_{s,w,c,d,wd} - IN_{s,w,c,d,wd} \\
& - \sum_{\{'transfer',d,s\} \in A} Y_{'transfer',d,s,w,c,d,wd} + \sum_{\{'transfer',s,d\} \in A} Y_{'transfer',s,d,w,c,d,wd} \\
& + IN_{s,w+1,c,d,wd} \mid_{\{w+1,wd\} \in FORE\_LOG} \\
& + A_{s,w,c,d,wd} - R_{s,w,c,d,wd} = -demand_{c,d,wd} \mid_{d=s \wedge w=wd} \quad \forall s \in D,
\end{aligned}$$

$$\begin{aligned}
& mx \in MX, \{w,wd\} \in FORE\_LOG, \\
& \{c,d,wd\} \in COM \quad (S2)
\end{aligned}$$

$$\begin{aligned}
& - \sum_{\{mx,i,o\} \in A} Y_{mx,i,o,w,c,d,wd} + \sum_{\{mx,o,j\} \in A} Y_{mx,o,j,w,c,d,wd} \\
& - \sum_{\{'transfer',s,o\} \in A} Y_{'transfer',s,o,w,c,d,wd} + \sum_{\{'transfer',o,s\} \in A} Y_{'transfer',o,s,w,c,d,wd} \\
& = 0 \quad \forall mx \in MX, o \in D,
\end{aligned}$$

$$\begin{aligned}
& w \in W, \{w,wd\} \in FORE\_LOG, \\
& \{c,d,wd\} \in COM \quad (S3)
\end{aligned}$$

$$\begin{aligned}
& \sum_{\substack{\{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} Y_{m,i,j,w,c,d,wd} \leq cap_{m,i,j} \quad \forall (m,i,j) \in A, \forall w \in W \quad (S4)
\end{aligned}$$

$$\begin{aligned}
& \sum_{\substack{\{w,wd\} \in FORE\_LOG, \\ \{c,d,wd\} \in COM}} (Y_{m,i,j,w,c,d,wd} \mid_{\{m,i,j\} \in A} \\
& + Y_{m,j,i,w,c,d,wd} \mid_{\{m,j,i\} \in A}) \leq ucap_{m,i,j} \quad \forall \{m,i,j\} \in U, \forall w \in W \quad (S5)
\end{aligned}$$

$$\begin{aligned}
& \sum_{\{c,d,wd\} \in COM} IN_{s,w,c,d,wd} \leq cap\_inv_s \quad \forall s \in D, w \in W \quad (S6)
\end{aligned}$$



The objective (S0) measures the total transit, transfer and inventory holding cost, plus any penalties for shortfalls or contract violations. The “attack” terms will be discussed in a following section, but here merely represent arcs whose costs have risen so dramatically that they will not be used. Each constraint (S1) ensures for some contract that total flows from the source mine meet the contract amount. Note that in case of anticipated disruptions, flows may leave the mine earlier than the delivery contract week to be stored in intermediate inventory somewhere and conveyed to the customer later. Each constraint (S2) accounts for balance of flow at some transfer node at the start of a planning period for some commodity. Each constraint (S3) accounts for intermodal transfers at some terminal node of some commodity, including inventory, shortfall, supply, and demand. Constraints (S4) and (S5) enforce directed and undirected capacity on arcs, respectively. Each constraint (S6) limits inventory held at some terminal at the start of some planning period.

This model finds the minimum-cost means of delivering the contracted amount from each source to each destination, using any of three modes of transport, each having its own costs and capacities. An interdiction on an arc increases its usage cost, so if there is a disruption in one system (e.g., river), then the model looks for a low-cost alternative route (e.g., river, rail, or road). There is a penalty ( $cpen_{cod}$ ) for violating delivery of contracted amounts (e.g., by satisfying a customer from an alternative supplier), but, in general, this penalty is less than the penalty for incurring a customer shortfall ( $spen_{sc}$ ).

The model has the flexibility to move and store coal in advance of its contract delivery date. This is advantageous when planning for scheduled maintenance or when buffering inventories to reduce the impact of unplanned disruptions. This functionality is controlled by the FORE\_LOG mechanism in the formulation, which maintains an aspect of realism in delivery planning by limiting the model’s forecasting ability. A reasonable use of this mechanism might be to allow the model to plan ahead and move coal up to four weeks in advance. This prevents the model from transporting all coal in the first week of operations, limited only by infrastructure capacity. This unrestricted movement of coal is inconsistent with industry practice, which is more similar to a just-in-time system.

## B. THE ATTACKER'S MODEL

Repeating the presentation in Onuska (2012), the attacker's model follows directly from the operator's model formulation, by replacing the input data  $\overline{ATTACK}_{m\bar{j}}$  with a decision variable  $X_{mij}$ .

### Additional Data

$num\_attacks$                       Number of allowable attacks

### Additional Variables

$X_{mij}$                                   Disrupt Flow on arc  $(m,i,j)$ ,  
    binary indicator as to whether arc  $(m,i,j) \in A$  is damaged;  
    = 1 if arc  $(m,i,j)$  is damaged,  
    = 0 otherwise

### Formulation 2: Attacker-Defender Model (AD)

$$\begin{aligned}
 \max_X \min_{F,Y,IN,A,R} \quad & \sum_{\substack{\{m,i,j\} \in A, \\ w \in W}} \left[ cost_{m,i,j} + q_{m,i,j} (X_{m,i,j} \mid_{\{m,i,j,w\} \in ARC\_I} + X_{m,j,i} \mid_{\{m,j,i,w\} \in ARC\_I}) \right] \\
 & + \sum_{\substack{\{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} Y_{m,i,j,w,c,d,wd} \\
 & + \sum_{\substack{o \in D, \\ \{c,d,wd\} \in COM}} cpen_{c,o,d} (contract_{o,c,d,wd} - \sum_{\{w,wd\} \in FORE\_LOG} F_{o,w,c,d,wd}) \\
 & + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} hcost_s IN_{s,w,c,d,wd} \\
 & + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} spen_{s,c} A_{s,w,c,d,dw} \\
 & + \sum_{\substack{s \in D, \\ \{c,d,wd\} \in COM, \\ \{w,wd\} \in FORE\_LOG}} spen_{s,c} R_{s,w,c,d,dw}
 \end{aligned} \tag{A0}$$

s.t. (S1), (S2), (S3), (S4), (S5)

$$X_{mij} = X_{mji} \quad \forall (m,i,j) \in A \tag{A6}$$

$$\sum_{(m,i,j) \in A} X_{mij} \leq 2 \times num\_attacks \tag{A7}$$

$$X_{mij} \in \{0,1\} \quad \forall (m,i,j) \in A \tag{A8}$$

The objective function (A0) replaces (S0) and now takes a bi-level max-min form, with decision variables  $X_{mij}$  replacing data  $\overline{ATTACK}_{mij}$ . Operating constraints (S1)-(S5) apply as before. Constraints (A6) make sure that any attack on a directed arc also affects its reverse arc. Constraints (A7) enforce the attacker’s “budget.” Constraints (A8) enforce the binary nature of attacks.

We implement the Attacker’s Model using the General Algebraic Modeling System (GAMS 2012), and solve it with Bender’s Decomposition (see Wood 2011 for details on the use of this technique to solve bi-level network interdiction problems) using the CPLEX Optimization Solver (International Business Machines 2012).

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