Consequence Assessment for Complex Food Transportation Systems Facing Catastrophic Disruptions

Yu Zhang and Alan Erera

ABSTRACT

This white paper describes our research on vulnerability assessment for complex transportation system facing catastrophic disruptions. The proposed methods attempt to understand the consequences of disruptions to major freight transportation systems, where the consequences are measured here in the limited sense of increased supply chain costs. A case study applying the ideas to the US corn export supply chain is provided. The paper explains how the dataset for the corn network is constructed from public data sources and presents the results of an example assessment, focusing on a set of dams and locks on the Mississippi River System.

INTRODUCTION

The United States is one of the largest grain producers and top grain exporting countries in the world. For the three primary export field crops – corn, wheat and soybean – total exports in 2007 measured 110 million metric tons (mmt) with a total value of $13-17 billion.[1] On the basis of value alone, the revenue from grain exports is critical to the economic health of US grain producers and related industries.

Export flows for grains rely on three freight transport modes – truck, railroad and inland water – while moving through the mainland US en route to an export port. From the export port, the grains are shipped to destination countries by bulk ocean vessel, with the exception of exports to Mexico and Canada. In this paper, we focus on the domestic long-haul segment of the grain export transportation chain, i.e., the portion of transportation conducted by railroad and barge.

Currently, the US grain export supply chain faces large challenges due primarily to enormous freight volume and relatively tight transport capacity. Moreover, the supply chain is often affected by various disruptions, arising from natural hazards, some recent examples of which have been catastrophic. For example, Hurricane Katrina hit the Gulf of Mexico in 2005, resulting in a major disruption to grain transportation. Barge and rail traffic was slowed, because of serious damage to transportation facilities and displacement of employees.[2]

Our research aims to identify and determine how to understand the potentially severe supply chain cost risks present in complex transportation systems supporting US food supply chains, with the intent of enabling significant improvement in food supply chain security, preparedness and resiliency. Models are developed to assess the vulnerability of critical infrastructure and key resources (CI/KR) in the transportation system, where vulnerability in this case is measured by the potential for large supply chain cost increases given disruption. Understanding vulnerabilities in the system is important for the effective allocation of protection investment.

TECHNICAL DETAILS: MODEL AND DATA COLLECTION

CONSTRUCTION OF GRAIN EXPORT SUPPLY CHAIN NETWORK

The grain export supply chain is modeled as a network. Each node in the network represents a Business Economic Area (BEA) in the United States.[3] Transport routes between nodes, mainly railroads and inland waterways, are modeled as arcs. Critical infrastructure in the transportation system, such as locks and dams on rivers, are included in this set of arcs. The goal of the network model is to predict how grain flows will move between production sources and export ports, given the relative costs and capacities of the underlying transportation infrastructure. In this initial research, we assume that costs can be modeled as linear in total freight flow along arcs, but that arcs have limited capacity for flow. When arc capacities are reduced due to a disruption, such a model can be used to predict how freight will be move post-disruption, and provide a measure of potential supply chain cost impact. The resulting optimization problem is a Minimum Cost Flow (MCF) problem, which can be solved efficiently.[4] System behavior over time can be simulated by using a time-space network, an expansion of the static network over the time horizon. Figure 1 illustrates a sample network and its time-space version.[5]

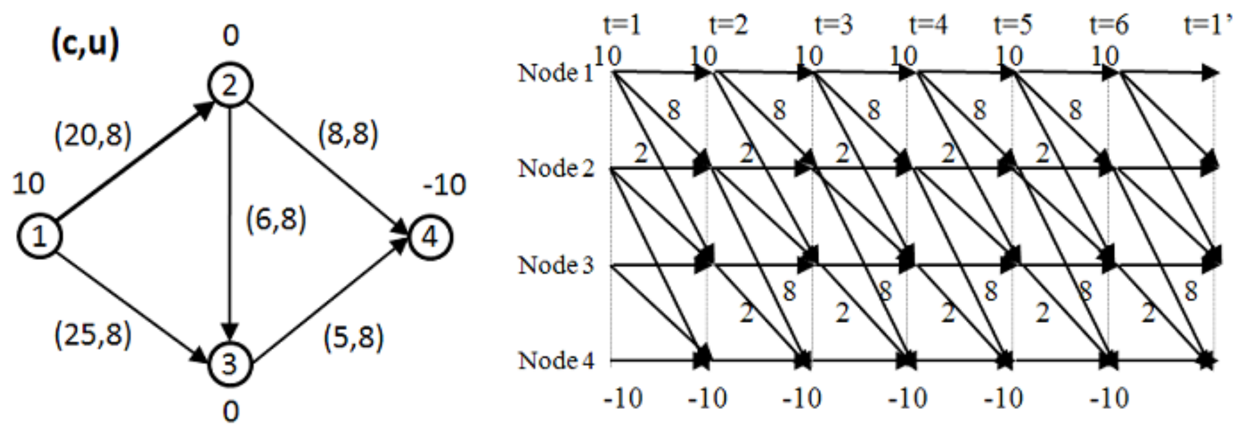


Figure 1. A Sample Network

DATA COLLECTION

Our vulnerability assessment methodology is applied to the US corn export supply chain. Figure 2 shows an overview of the transportation network for exporting corn. Corn is mainly grown in the "Corn Belt," the dark green region in this figure. The primary destinations of export flows within the US are the Gulf of Mexico and Pacific-northwest (PNW). Corn is shipped to New Orleans by barge and railroad and shipped to PNW by railroad. Barge is preferred if available because of its lower cost.

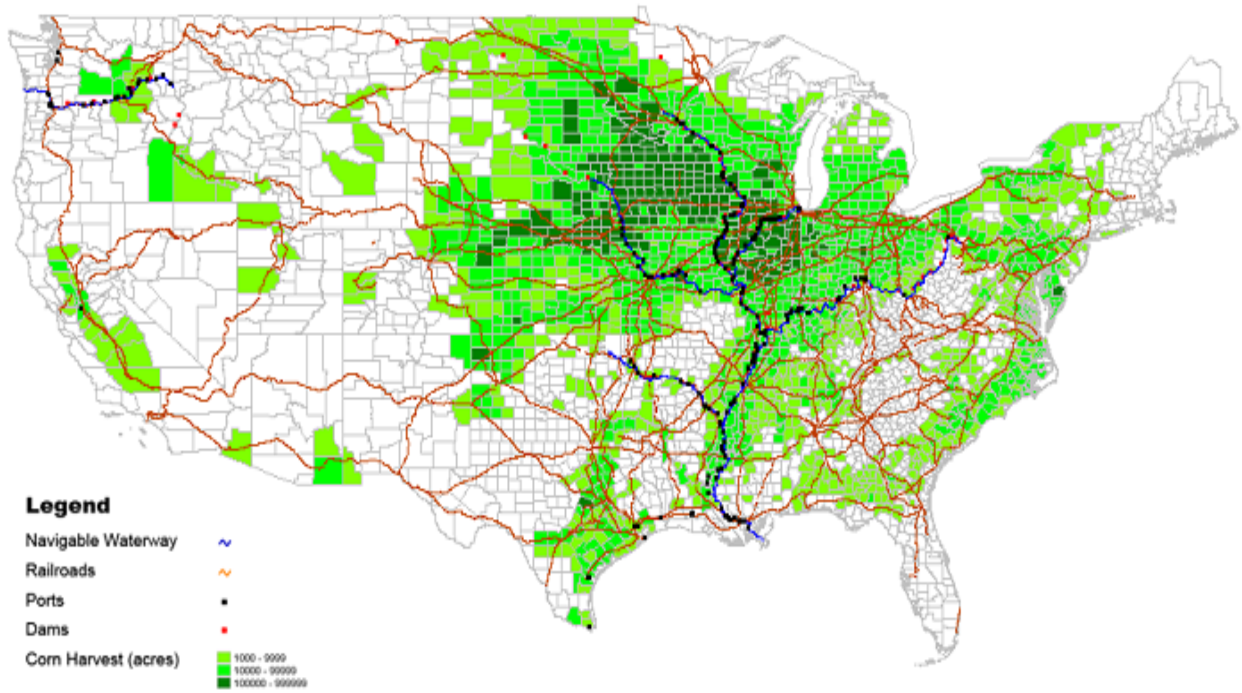
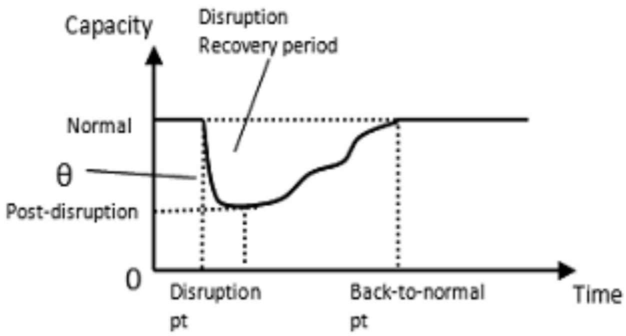


Figure 2. Map of Corn Export Supply Chain

All data for our example case study was collected from public sources, such as the US Department of Agriculture (USDA), The US Department of Transportation (USDOT), and the US Army Corps of Engineers (USACE). Technically, the data is collected separately for the two modes: inland water and railroad. In the inland water sub-network, each node represents a Business Economic Area (BEA) along the Mississippi River System.[6] Arcs connect two BEA along the rivers. Locks and dams limit the capacity of corresponding arcs. The inland water data was obtained primarily from the Grain Transportation Report (GTR).[7] In the railroad sub-network, each BEA is again represented by one node. Ninety-one BEA that have rail transportation activities related to corn export are involved, as determined from the Public Use Waybill (2007).[8] The two sub-networks are connected by arcs representing intermodal transportations between proper nodes. Supply and demand in the network are also determined from the GTR.[9]

MODELING DISRUPTIONS

A disruption can be modeled as reduction of arc capacity in the network. The general disruption-recovery process, illustrated in Figure 3, can also be modeled in time-space network. In this figure, the affected component is disrupted at the time “disruption point.” As the magnitude of disruption increases, the capacity of the affected arc drops to minimum. Subsequently, the effect of disruption diminishes and the arc capacity recovers slowly to the normal state at the time “back-to-normal point".



$$\text{Min} \sum_{(i,j)\in E} c_{ij}x_{ij}$$

$$\text{s.t.} \sum_{j\in N} x_{ij} - \sum_{j\in N} x_{ji} = b_i, \forall i \in N$$

$$0 \le x_{ij} \le u_{ij} - \theta d_{ij}, \forall (i,j) \in E$$

Figure 3. General Recovery Process and MCF Model with Disruption

Figure 3 also provides a simple formulation of the mathematical optimization problem given a disruption. The notation used is standard MCF notation.[10] Additionally, θ represents the maximum magnitude of the disruption and reflects the relative effect that disruption exerts on arc (i,j).

The relationship between total supply chain cost and magnitude of disruption reflects the impact of disruption to the system. It is described by a so-called **Impact Curve**. We prove that the impact curve resulting from our model is a convex, piecewise linear, non-decreasing function of disruption magnitude, illustrated in Figure 4. Given the impact curves of all network components, their vulnerability can be compared. But the vulnerability of one component may not dominate that of another, as shown in the right part of Figure 4, where component 1 is more vulnerable to smaller disruptions, but component 2 becomes more vulnerable as the disruptions grow larger.

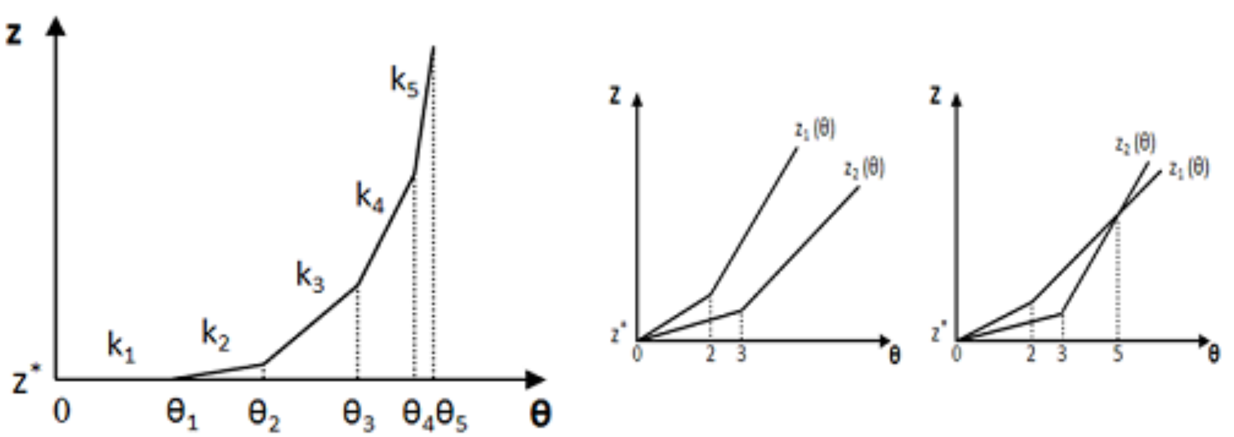


Figure 4. Impact Curves

VULNERABILITY ASSESSMENT ALGORITHM

An impact curve can be determined by a series of breakpoints and slopes between two breakpoints. Based on the observation, the **Dual Network Simplex Algorithm** is used to determine the impact curves for a selection of arcs in a network.[11] An outline of the procedure is as follows:

- Start from the optimal flow x of the nominal problem with no disrupted arcs;
- For each arc selected , do:
- If , then the assessment result is ; Go to the next arc;
- Set the arc flow and capacity to zero, resulting in excess and deficit at its tail i and head j;
- Perform dual pivots until excess/ deficit is zero or infeasibility is detected;
- Record pivot history, represented by

RESULTS OF VULNERABILITY ASSESSMENT

STATIC VULNERABILITY ASSESSMENT

The dams and locks on the Mississippi River System play a critical role in the corn export supply chain. Thus, we choose six representative dams and locks for assessment and number them from 1 to 6, hiding their actual names in this document. Since the static assessment model is developed using annual freight volume parameters and capacities, the impact curves represent a rough estimate of the annual impact to total supply chain cost due to a disruption. The impact curves are shown in the left graph of Figure 5. The right graph is the zoomed version.

In Figure 5, since the impact curves of Dams No. 5 and 4 are the steepest, the two locks are the most vulnerable. However, neither of the two dominates the other in vulnerability. By similar arguments, Dam No. 1 is the least vulnerable (except Dam No. 6). The vulnerability of Dam No. 1 is close to that of Dams No. 5 and 4. For Dams No. 2 and 3, the two curves intersect. Dam No. 3 is more vulnerable for small disruptions while Dam No. 2 is more vulnerable for large disruptions. Due to limited economic impact, Dam No. 6 is less vulnerable than the other targets, seen in the zoomed graph. As we can see, it is a little counter-intuitive that the dam on the downstream, which has more volume going through it, is not always more vulnerable.

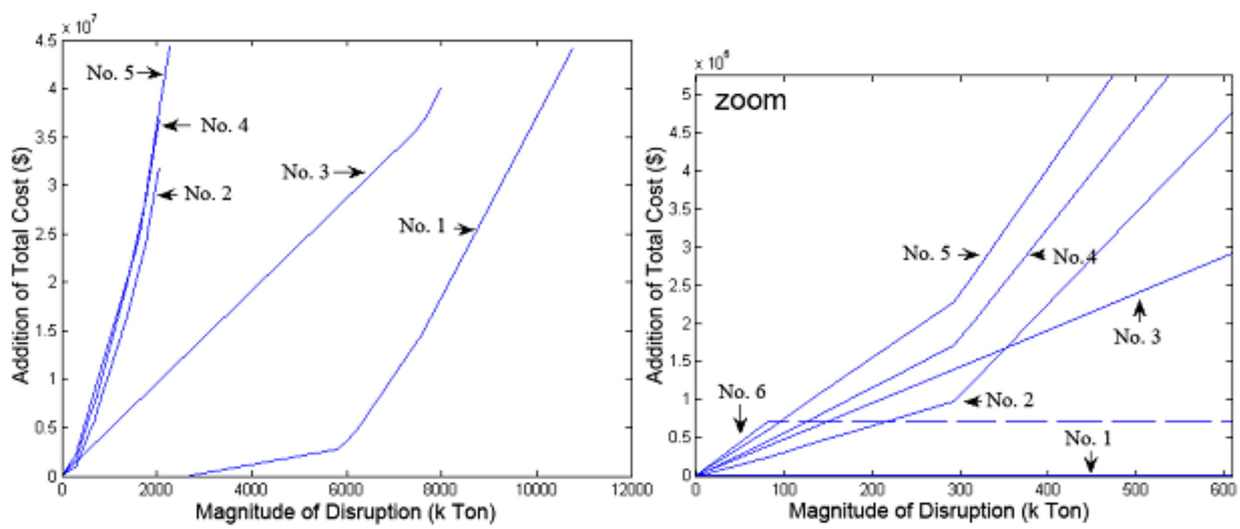


Figure 5. Static Vulnerability Assessment

DYNAMIC VULNERABILITY ASSESSMENT

The same selection of targets is used in dynamic assessment; however, each target corresponds to a set of transportation arcs originating at different time periods in the time-space network. The result is illustrated in Figure 6. The upper left graph shows the impact curves of all selected targets at all time periods; the upper right graph only shows the most vulnerable ones; the lower ones are the zoomed versions of the upper right graph.Besides identifying the most vulnerable targets, the dynamic assessment also provides the critical time for each target, i.e., the time at which the target is most vulnerable. Simply stated, Dam No. 5 is most vulnerable around week twenty-seven of the year, since the harvest peak in its vicinity is around week twenty-seven. Dam No. 4 is most vulnerable around week seventeen. Dam No. 2 is most vulnerable around week forty-five. Dam No. 1 does not appear in the list of most vulnerable targets because it has redundant capacity that can absorb small disruptions. Dam No. 3 does not appear in the list, since there is a railroad hub nearby and there are good alternative routes available when the dam is disrupted.

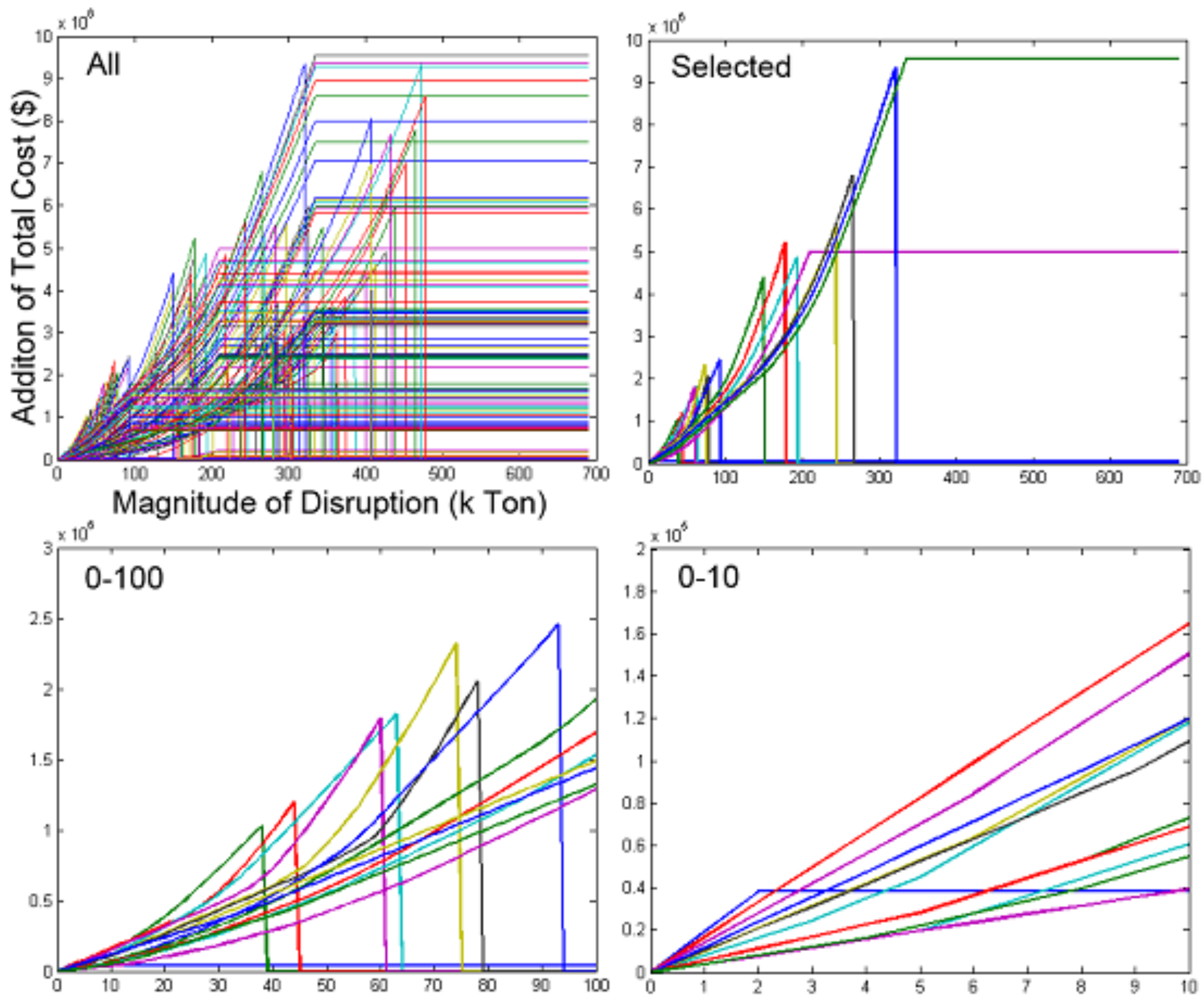


Figure 6. Dynamic Vulnerability Assessment

CONCLUSION

Based on the assessments, the vulnerability of a target is closely related to three factors: redundancy, alternative routes, and time. For example, Dams No. 5 and 4 are the most vulnerable among the six targets, because of high utilization and lack of good alternative routes. Dam No. 3 is less vulnerable than Dam No. 2 because the former one has more alternative routes. Dam No. 1 is less vulnerable because its capacity is not fully utilized and the slack capacity can absorb small disruptions. Dam No. 6 has a limited impact if disrupted due to its small capacity and good alternative routes. In addition, the time when the disruption occurs is also an important factor for determining the vulnerability. If the disruption occurs near the peak season for transportation, the economic impact of the disruption is high.

Hence, the following suggestions are given to reduce the vulnerability of the corn export supply chain: in the long run, decision-makers need to consider expanding the capacity of the critical infrastructure components; in the short run, identifying and establishing good alternative (backup) routes for vulnerable routes and making emergency plans can improve the responsiveness of the system and can reduce the economic loss when disruption occurs.

ABOUT THE LEAD AUTHOR

Yu Zhang *is a PhD student in the School of Industrial and Systems Engineering (ISyE) at the Georgia Institute of Technology. He received his Bachelor of Science in Engineering from Huazhong University of Science and Technology (Wuhan, China). He currently serves as a research assistant at ISyE's Supply Chain and Logistics Institute. Yu Zhang's research focuses primarily on transportation and logistics systems planning and control, with a focus both on innovative modeling and solution methodologies, and on challenging application areas including robust service network design, integrating security and efficiency in logistics systems. He may be contacted at zhangyu@gatech.edu.*

[1] United States Department of Agriculture, *Agriculture Statistics 2007* (Washington, DC: National Agriculture

[2] United States Department of Agriculture. *Grain Transportation Report* 2 (November 2005): 1-5.

[3] K. Johnson and J. Kort, "2004 Redefinition of the BEA Economic Areas," *Survey of Current Business* (November 2004): 68-75.

[4] R. Ahuja, T. Magnanti, and J. Orlin, *Network Flows: Theory, Algorithms, and Applications* (Englewood Cliffs, NJ: Prentice Hall, 1993).

[5] For more details, see A. Erera and Y. Zhang, *Methodology Report: Vulnerability Assessment of Supply Chain*. (Georgia Institute of Technology, Unpublished Report 2009).

[6] Johnson and Kort, "2004 Redefinition of the BEA Economic Areas."

[7] United States Department of Agriculture. *Grain Transportation Report* 3 (November 2007a): 1-5.

[8] Surface Transportation Board, *Public Use Waybill* (Washington, DC: Surface Transportation Board, 2007).

[9] USDA, *Grain Transportation Report* 3 (November 2007).

[10] Ahuja, et al., *Network Flows*.

[11] For more details, please refer to Erera and Zhang, *Methodology Report*.