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Barge Prioritization, Assignment, and Scheduling During Inland Waterway Disruption Responses

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Barge Prioritization, Assignment, and Scheduling During Inland Waterway Disruption
Responses

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Engineering

by

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Abstract

Inland waterways face natural and man-made disruptions that may affect navigation and infrastructure operations leading to barge traffic disruptions and economic losses. This dissertation investigates inland waterway disruption responses to intelligently redirect disrupted barges to inland terminals and prioritize offloading while minimizing total cargo value loss. This problem is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP). A previous study formulated the CPTAP as a non-linear integer programming (NLIP) model solved with a genetic algorithm (GA) approach. This dissertation contributes three new and improved approaches to solve the CPTAP.

The first approach is a decomposition based sequential heuristic (DBSH) that reduces the time to obtain a response solution by decomposing the CPTAP into separate cargo prioritization, assignment, and scheduling subproblems. The DBSH integrates the Analytic Hierarchy Process and linear programming to prioritize cargo and allocate barges to terminals. Our findings show that compared to the GA approach, the DBSH is more suited to solve large sized decision problems resulting in similar or reduced cargo value loss and drastically improved computational time.

The second approach formulates CPTAP as a mixed integer linear programming (MILP) model improved through the addition of valid inequalities (MILP'). Due to the complexity of the NLIP, the GA results were validated only for small size instances. This dissertation fills this gap by using the lower bounds of the MILP' model to validate the quality of all prior GA solutions. In addition, a comparison of the MILP' and GA solutions for several real world scenarios show that the MILP' formulation outperforms the NLIP model solved with the GA approach by reducing the total cargo value loss objective.

The third approach reformulates the MILP model via Dantzig-Wolfe decomposition and develops an exact method based on branch-and-price technique to solve the model. Previous approaches obtained optimal solutions for instances of the CPTAP that consist of up to five terminals and nine barges. The main contribution of this new approach is the ability to obtain optimal solutions of larger CPTAP instances involving up to ten terminals and thirty barges in reasonable computational time.

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Dedication

Dedicated to my mother, Lilia Omaira Hidalgo Galvis, the strongest and most loving woman I know; and to the memory of my father, Bernardo Delgado Santander, who left at the beginning of this journey and who would have been the happiest person in the world with this achievement. This is the result of their sacrifice. I love you both.

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List of Papers

Chapter 2 - Section 2.3:

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Chapter 3

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Chapter 4

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1 Introduction

This work investigates how to assign disrupted barges and prioritize their offloading at accessible terminals to minimize the cargo value loss during inland waterway disruption response. Maritime transportation researchers can use our techniques to develop decision support tools that assist inland waterway decision makers with assigning and prioritizing barge offloading to mitigate the total cargo value loss during disruption response. The decision makers who can benefit with the methods provided in this research include maritime transportation researchers and federal, state and local government agencies including the U.S. Department of Transportation, U.S. Coast Guard, and U.S. Army Corps of Engineers.

1.1 Research Motivation

The inland waterway system is comprised of navigable rivers linked by more than 12,000 miles of commercially navigable channels. The six major corridors are the Upper Mississippi River, Lower Mississippi River, Ohio River, Gulf Intracoastal Waterway, Illinois River, and Columbia River system (Figure 1.1). The infrastructure of the inland waterway transportation system consists of channels, lock and dam systems, channel training structures, dredged material placement facilities, tow marshalling areas, berthing facilities, navigation aids, cranes, and storage yard (Walsh, 2012). The primary commodities transported on inland waterways are coal, petroleum and petroleum products, food and farm products, chemicals and related products, and crude materials.



Figure 1.1. Inland and intracoastal waterways system (TRB, 2015)

Freight in the United States (U.S) is transported mainly by truck. In 2015, trucks carried 11.5 billion tons representing 64% of the total freight shipments in the U.S. (Bureau of Transportation Statistics, 2017). By 2045, the U.S. Department of Transportation (USDOT) forecasts an increase of 43% in freight movements by truck (Bureau of Transportation Statistics, 2017).

Nearly 5,560 miles of the 222,743 miles of the national highway system (NHS) carry more than 8,500 trucks per day where at least every fourth vehicle is a truck (Bureau of Transportation Statistics, 2017). The limited capacity of these roadways hinders traffic flow for more than 2,400 miles. Without intervention, this congestion is expected to increase more than 600% by 2045 (Bureau of Transportation Statistics, 2017).

If passenger vehicles are considered, the congestion issues reduce the vehicle speed below posted speed limits on 12,200 miles and cause frequent stops on 7,000 miles of the NHS

where at least every fourth vehicle is a truck. These number of miles are forecast to increase by 86% and 697% by 2045 respectively if roadway capacity and freight demand remains the same (Bureau of Transportation Statistics, 2017). Shifting cargo to the inland waterways transportation may relieve roadway congestion issues, considering that the standard cargo capacity of one dry bulk barge is 1,750 tons, while capacity of a bulk rail car is 110 tons, and only 25 tons for a truck trailer (Kruse, Warner, & Olson, 2017).

An additional benefit of inland waterways transportation is the system is more environmental friendly compared to other type of freight transportation modes. Inland towing is 36% more fuel efficient than railroad freight and 346% more fuel efficient than truck freight (Kruse et al., 2017). Furthermore, the inland towing sector spilled 64.3% less gallons per hazardous material ton-miles than the rail sector and 64.9% less gallons than the truck sector (Kruse et al., 2017). Similarly, inland waterway transportation is safer than the road and rail transportation modes. From 2001 to 2014, for each ton-mile transported, there were 2.2×10^{-5} fatalities in the inland towing sector, 48.0×10^{-5} fatalities in the railway sector, and 174.4×10^{-5} in the truck sector. Likewise, for each ton-mile transported during this time, there were 5.9×10^{-5} injuries in the inland towing sector, 474.6×10^{-5} injuries in the railway sector, and $4,086.1 \times 10^{-5}$ injuries in the truck sector (Kruse et al., 2017).

The benefits of the inland waterways show the importance of considering this transportation mode as the system under study for this research. The U.S. inland waterways transportation system has been subject to multiple disruptions in the last two decades. Table 1.1 summarizes common disruptions of inland waterway transportation including the type of disruption and its consequences. The occurrence of disruptions and their significant losses in terms of negative societal, economic, and productivity impacts show the importance of additional research on inland waterway disruption response. This field has attracted the attention of other researchers as discussed in Delgado-Hidalgo and Nachtmann (2016). However, limited

decision support techniques have been developed to support inland waterway disruption response.

When disruption events halt barge traffic, responsible parties need to transfer the cargo to an alternative transportation mode for transport to its final destination. Barges that need to traverse the section of the waterways where the disruption occurred must be rerouted to accessible terminals where the cargo can be offloaded. The motivation of this dissertation is to support maritime transportation researchers and inland waterways disruption response decision makers with information and methods that could be implemented to mitigate cargo value loss impacts after a disruption. This dissertation provides methodological contributions to support transportation planners with making quick, efficient, and effective cargo prioritization and barge-terminals allocation and scheduling decisions during inland waterway disruption response.

Table 1.1. Inland waterways disruptions cases. Adapted from Güler, Johnson, and Cooper (2012)

Disruption	Date	Consequences	Reference
Flood on Ohio River	1997	A barge company shut down for 1 week. 2,400 people evacuated. 14,000 damaged or destroyed. Over 20,000 home and business owners applied for disaster relief. Damage estimated at \$500 million. 33 dead people and hundreds of injuries	Güler et al. (2012), U.S. Department of Commerce (1998)
Icing on Illinois River	1999	Halted barge traffic. Increase in shipping costs. 48 hours lockage delays	Boyd (1999), Güler et al. (2012)
John Day Lock gate failed and cracked lock monoliths	2002 and 2004	Halted barge traffic. Gate repairs took eight months in 2002 and well over \$1 million in funds. one-month closure in March and daily 12-hour closures for two months thereafter during 2004.	Grier (2005)

Table 1.1. Inland waterways disruptions cases (Cont.). Adapted from Güler et al. (2012)

Disruption	Date	Consequences	Reference
A barge struck the I-40 bridge crossing the Arkansas River	2002	Killed fourteen people and shut down barge traffic for over 2 weeks	Pant, Barker, and Landers (2015), Volpe (2008)
Greenup Main Lock Closure for emergency repairs	2003	\$2 million on alternative routes, disruption for 52 days. The total cost was estimated to be \$41.9 million	The Planning Center of Expertise for Inland Navigation (2005b)
McAlpine Lock and Dam on the Ohio River was closed for repairs	2004	The total economic loss was estimated to be \$9 million. The closure lasted 10 days	The Planning Center of Expertise for Inland Navigation (2005a)
Lock & Dam 27 Main Chamber in the Upper Mississippi River closed for repairs	2004	Delays of up to 40 hours per tow. Three week closure	Grier (2005)
Drought on Mississippi and Ohio rivers	2005	Several barges ran aground, more than 60 boats and 600 barges were stopped. Delays caused \$10,000 loss per day	Güler et al. (2012)
Barges crashed into Belleville Lock in Reedsville	2005	Shutdown cost \$4.5 million a day. General Electric closed its plant	Güler et al. (2012)
I-35W bridge spanning the Mississippi River collapsed into the river	2007	Killed thirteen people and injured approximately 147 others	Volpe (2008)
Chemical run-off into the port of Catoosa	2009	The fire spread and consumed the entire complex. Environmental cleanup was required	Harper (2009)
Mississippi River record breaking low water level	2012	Halted barge traffic. Delayed movement of \$7 billion in commodities	Keen (2012)

1.2 Research Objective

The problem studied in this research is known in previous literature as the cargo prioritization and terminal allocation problem (CPTAP) (Tong & Nachtmann, 2017). The CPTAP assigns barges and prioritizes offloading at accessible terminals to mitigate the negative impacts during inland waterway disruptions. The overall goal of this research is to improve post-disaster outcomes, specifically the cargo value loss during inland waterway disruption response by developing new methods to solve the CPTAP.

Research Objective 1 is to reduce the time to provide a solution for large size instances of CPTAP that involve fifteen terminals and fifty disrupted barges. To achieve this objective, this dissertation develops a decomposition based sequential heuristic (DBSH) solution approach that solves the CPTAP in a nonintegrated manner by dividing the problem into three subproblems: cargo prioritization, barge assignment, and barge offloading scheduling. The DBSH solution approach is based on the Analytic Hierarchy Process (AHP) and linear programming. The DBSH prioritizes disrupted cargo and assigns barges to alternative terminals to minimize the cargo value loss during inland waterway disruption response. Reducing the time to provide a solution for a disaster enables inland waterway decision makers to implement disruption response promptly, thus minimizing the negative impacts of a disaster.

Research Objective 2 is to reduce cargo value loss during inland waterway disruption response by developing a pure mathematical approach that integrates barge-terminal assignment and scheduling decisions. Unlike Research Objective 1 in which the DBSH solves the CPTAP in a nonintegrated manner, Research Objective 2 explores solution improvement through a new integrated formulation to solve the CPTAP. The purpose of this research objective is to assess if solving the problem in an integrated manner, considering the assignment and scheduling decisions in one single model, results in solution improvement. The CPTAP is

formulated as a mixed integer linear programming (MILP) model which is improved through the addition of valid inequalities. The lower bounds (LBs) of the improved MILP model are used to validate the quality of the solutions obtained by Tong and Nachtmann (2017), which were not validated due to the nonlinearity of their proposed model.

Research Objective 3 is to reduce cargo value loss during inland waterway disruption response by developing an exact method to optimally solve new instances of the CPTAP. For this research objective, the MILP model is reformulated via Dantzig-Wolfe decomposition. Due to its complexity, previous approaches use heuristics to solve the CPTAP resulting in potential suboptimal solutions. This dissertation explores the structure of the model in Research Objective 2 to develop an exact solution method that decomposes the problem into subproblems more tractable to solve. The exact method is based on a branch-and-price algorithm which obtains optimal solutions for CPTAP instances involving up to ten terminals and thirty disrupted barges.

1.3 Research Methodology

The methodology starts with a literature review in the field of inland waterway transportation system to introduce the reader to the system under study, the research problem, and the theories and techniques proposed to solve the problem. The remaining of the methodology is organized around three research objectives.

- We conduct a comprehensive literature review in the field of systems optimization for inland waterway transportation to establish the existing body of knowledge and outline gaps in previous research. Our literature review shows inland waterway disruptions as a promising research field. The literature review consists of four sections that

start with a broad content in U.S. inland waterway transportation system. Next we present narrowed content including systems optimization techniques to solve planning problems for marine transportation system, specific inland waterway transportation planning literature examining: operations, decision problems, and disruptions response literature. Finally, we review literature for the berth allocation problem which has similarity with the problem studied in this research.

- Research Objective 1 is presented in Chapter 3. We aim to reduce the time to provide a solution for large size instances of the cargo prioritization and terminal allocation problem (CPTAP) (Tong & Nachtmann, 2017) that involve fifteen terminals and fifty disrupted barges by developing a heuristic to redirect barges and prioritize their offloading, while minimizing cargo value loss. To achieve this objective, we develop a decomposition based sequential heuristic (DBSH) solution approach based on an integrated Analytic Hierarchy Process (AHP) and mathematic model. We use the DBSH to solve realistic instances of the problem in a reasonable computational time. The DBSH consists of three components: cargo prioritization, assignment subproblem, and scheduling subproblem. The cargo prioritization subproblem determines the priority index of each barge cargo. These priority indexes are obtained from an AHP approach. The second subproblem, assignment of barges to terminals, is formulated as an integer linear programming (ILP) model that minimizes cargo value loss for assignment decisions. The assignment of barges to terminals considers the cargo priority, volume of the barge, capacity and water depth of each terminal, draft depth of each barge, and a safety level to assure that the barges safely travel into the terminals. The third subproblem, scheduling of barges assigned to a terminal, is formulated as a mixed integer linear programming (MILP) model that minimizes total value loss. The assignment subproblem and the scheduling subproblem are linked through the priority index associated to each type of cargo.

- Research Objective 2 is presented in Chapter 4. We aim to reduce cargo value loss during inland waterway disruption response by developing a pure mathematical approach that integrates barge-terminal assignment and scheduling decisions. To achieve this objective, we formulate a MILP model that integrates assignment and scheduling decisions to solve the CPTAP during inland waterway disruption response. The MILP is obtained when the problem is reformulated as a heterogeneous vehicle routing problem where the vehicles correspond to the inland terminals and the customers represent the barges that need to be serviced at the terminals. We also improve our initial MILP formulation through the addition of valid inequalities. A previous study formulated the CPTAP as a nonlinear integer programming (NLIP) model, which was solved with a genetic algorithm (GA) approach. We use the lower bounds (LBs) obtained with the linear relaxation of our improved MILP model to validate the quality of the solutions obtained with the GA approach. In this dissertation, we present a comparison between the CPTAP solutions obtained with the improved MILP model and GA for several scenarios to determine the solution approach with better performance.
- Research Objective 3 is presented in Chapter 5. We aim to reduce cargo value loss during inland waterway disruption response by developing an exact method to optimally solve new instances of the CPTAP. To achieve this objective, we reformulate the MILP model via Dantzig-Wolfe decomposition approach. The reformulated model allow us to decompose the problem into an upper level master problem and lower level subproblems that are more tractable to solve. We develop an exact method based on a branch-and-price algorithm to solve these problems. The purpose of this research objective is to exploit the effectiveness of the linear programming formulation and structure of the model developed in our Research Objective 2 to obtain improved solutions of the CPTAP.

1.4 Research Contribution

The problem studied in this research is known in previous literature as the cargo prioritization and terminal allocation problem (CPTAP) (Tong & Nachtmann, 2017). The CPTAP assigns barges and prioritizes offloading at accessible terminals to mitigate the negative impacts during inland waterway disruptions. In this research, we contribute information and methods to improve inland waterway post-disaster by reducing the total cargo value loss. Our methodological contributions are three different post-disaster response planning models to solve the CPTAP. Maritime transportation researches can integrate our methodological contributions with user friendly interfaces in order to develop disruption response decision support systems to assist decision stakeholders within the U.S. Department of Transportation, U.S. Army Corps of Engineers, and U.S. Coast Guard.

The work described in Chapter 2 contributes to the body of knowledge through a literature review in the fields of U.S. inland waterway transportation system and planning problems, techniques and methodologies used to solve the CPTAP and inland waterway disruption response. The manuscript “A Survey of the Inland Waterway Transportation Planning Literature,” published in the *Proceedings of the 2016 Industrial and Systems Engineering Research Conference*, is part of the literature review presented in Chapter 2.

When natural and man-made events disrupt barge traffic, responsible parties need to transfer the cargo to an alternative transportation mode for transport to its final destination. Chapter 3 contributes to the improvement of the response time to provide a solution for CPTAP large size instances that involve fifteen terminals and fifty disrupted barges. In addition, unlike a previous approach, the heuristic developed in Chapter 3 is able to solve all generated large size instances that involve twenty terminal and seventy disrupted barges. The heuristic reduces computational time by solving the problem in two stages. The first

stage considers the priority of the cargo to redirect disrupted barges to available terminals while minimizing the cargo value loss for assignment decisions. The second stage prioritizes cargo offloading of barges assigned to each terminal to minimize cargo value loss during inland waterway disruption response. The main contributions of Chapter 3 are: (1) a DBSH that redirects disrupted barges and prioritizes barge offloading to minimize cargo value loss during inland waterway disruption response, (2) a DBSH that has similar performance compared to a previous approach with a drastically improved computational time when solving large problem instances involving fifteen terminals and fifty disrupted barges, (3) a DBSH that is not only able to find solutions for all generated larger size instances consisting of twenty terminals and seventy disrupted barges, but also improves the cargo value loss and computational time compared to a previous approach.

Chapter 4 contributes to the improvement of inland waterway post-disaster cargo value loss by providing a pure mathematical approach that defines an inland waterway disruption response. The mathematical approach reduces cargo value loss by integrating the two stages that were solved separately in the heuristic presented in Chapter 3 into one single model formulated as a mixed integer linear program (MILP). Our mathematical approach redirects disrupted barges and prioritizes cargo offloading for transport to its final destination via an alternative transportation mode. The main contributions of Chapter 4 are: (1) a technique that redirects disrupted barges and prioritizes barge offloading to minimize cargo value loss during inland waterway disruption response, (2) a new solution method that reduces the total cargo value loss during inland waterway disruption response in comparison to the previous approach, (3) a tighter CPTAP formulation that provides more accurate lower bounds and reduce the computational time to solve the CPTAP, and (4) the validation of the quality of the NLIP and GA solutions for all size instances.

Chapter 5 contributes to the improvement of inland waterway post-disaster cargo value loss

by developing an exact method to optimally solve new instances of the CPTAP. Due to its complexity, previous approaches use heuristics to solve the CPTAP resulting in potential suboptimal solutions. On the other hand, pure mathematical approaches provide optimal solutions but are capable of solving only small sized problems. For our next approach, in Chapter 5, we reformulate the MILP model presented in Chapter 4 via Dantzig-Wolfe decomposition, and we contribute the first known exact method to solve the CPTAP. We explore the structure of the model formulated in Chapter 3 to develop an exact solution method that decomposes the problem into subproblems that are more tractable to solve. This solution method provides a disruption response that exploit the effectiveness of the model proposed in Chapter 3, while the decomposition method reduces the average computational time to solve CPTAP instances involving up ten terminals and thirty disrupted barges. The main contributions of Chapter 5 are: (1) a new decision support technique to redirect disrupted barges and prioritize offloading at accessible terminals during disruption response, (2) a new mathematical model for the CPTAP based on Dantzig-Wolfe decomposition approach, which in comparison to previous models, our model is tighter and yields better lower bounds, and (3) a first known exact method which provides optimal solutions for new instances of the CPTAP involving ten terminals and up to thirty disrupted barges in reasonable computational time.

1.5 Organization of Dissertation

This dissertation consists of five chapters. Chapter 1 introduces the dissertation topic by presenting the motivation of conducting research on inland waterway disruption response and the research objectives and contributions.

Chapter 2 is a comprehensive literature review on the field of inland waterway disruption

response and topics related to the modeling and solution of the problem under study. The manuscript “A Survey of the Inland Waterway Transportation Planning Literature” published in the *Proceedings of the 2016 Industrial and Systems Engineering Research Conference* is part of the literature review presented in Chapter 2.

Chapter 3 is the manuscript titled “A Heuristic Approach to Managing Inland Waterway Disruption Response” submitted to the *Engineering Management Journal*. This paper describes the decomposition based sequential heuristic (DBSH) to solve the cargo prioritization and terminal allocation problem (CPTAP). An earlier version of this chapter was presented and published as a conference paper, “Analytic Hierarchy Approach to Inland Waterway Cargo Prioritization and Terminal Allocation” at the American Society for Engineering Management 2015 International Annual Conference. The complete work was presented at the INFORMS annual meeting 2015.

Chapter 4 is the manuscript “A Computational Comparison for the Cargo Prioritization and Terminal Allocation Problem Models” submitted to the *Computers and Operation Research* journal. This paper extends previous research conducted by Tong and Nachtmann (2017) by validating their genetic algorithm (GA) solutions for all size instances of the CPTAP. To do so, we use the lower bounds obtained with the solution of the relaxed mixed integer linear programming (MILP) model. Our paper shows how the MILP model outperforms the GA approach.

Chapter 5 is the manuscript “An Exact Algorithm for the Cargo Prioritization and Terminal Allocation Problem” to be submitted to the *Computers and Industrial Engineering* journal. Chapter 5 presents the reformulation of the MILP model via Dantzig-Wolfe decomposition and the development of an exact method to solve the reformulated model. This manuscript presents optimal solutions of CPTAP instances involving up to ten terminals and thirty

barges in reasonable computational time.

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2 Literature Review

Our literature review begins by introducing the reader to the United States inland waterway transportation system in Section 2.1. In Section 2.2 we overview the system optimization techniques that have been applied to maritime transportation systems. Then in Section 2.3 we narrow the focus of our review to literature related specifically to inland waterway transportation planning and disruption response. Finally, due to the similarity between the problem we are investigating and the berth allocation problem (BAP), in Section 2.4 we summarize the relevant literature that addresses the BAP.

2.1 Inland Waterways in the United States

2.1.1 System Overview

This section provides a general background of the United States (U.S.) inland waterway system and is primarily based on the information obtained by the Transportation Research Board (TRB, 2015). The inland waterways navigation system is part of the U.S. marine transportation system (MTS). The MTS consists of navigable waterways, public and private ports, and a network of inland waterways including inland highway and rail connections. The MTS enables access to the water for shippers and customers in all fifty states (CMTS, 2008) and forty-one of the states are directly served by the inland and intra-coastal waterways (Clark, Henrickson, & Thoma, 2005).

The navigable rivers in the U.S. are connected through a series of major canals. The inland waterway infrastructure includes lock and dam systems that enable the upstream and down-

stream movement of cargo. The majority of locks in the U.S. are more than 50 years old. The maintenance of locks and dams is the major expense in inland waterway infrastructure, which is managed by the U.S. Army Corps of Engineers (USACE) and funded by Congress through the USACE civil appropriations for the inland navigation budget.

Figure 2.1 shows a representation of the inland and intra-coastal waterway system (TRB, 2015). Inland waterways consist of more than 12,000 miles of commercially navigable channels and 240 lock systems. The Mississippi is the largest river with about 1,800 miles (TRB, 2015).



Figure 2.1. Inland and intracoastal waterways system (TRB, 2015)

Based on the water depth, the waterways are classified as deep draft, shallow draft, waterways suited for shallow and deep draft, or non-navigable waterways. Table 2.1 presents the length and depth of each category.

Table 2.1. Summary characteristics of the inland waterways network (TRB, 2015)

Inland Geographic Class	Length of Waterway (miles)	Average Control Depth (feet)
Deep draft navigation	1,901	35
Shallow draft navigation	21,218	10
Both (deep and shallow draft)	13,205	28
Total	36,324	

Regarding to freight traffic, based on the cargo ton-miles transported, the waterways can be classified as low, moderate, and high use (Figure 2.2). The high use category transports 75 percent of the cargo ton-miles along the navigable waterways that represent the 22 percent of the total inland waterway miles (TRB, 2015).

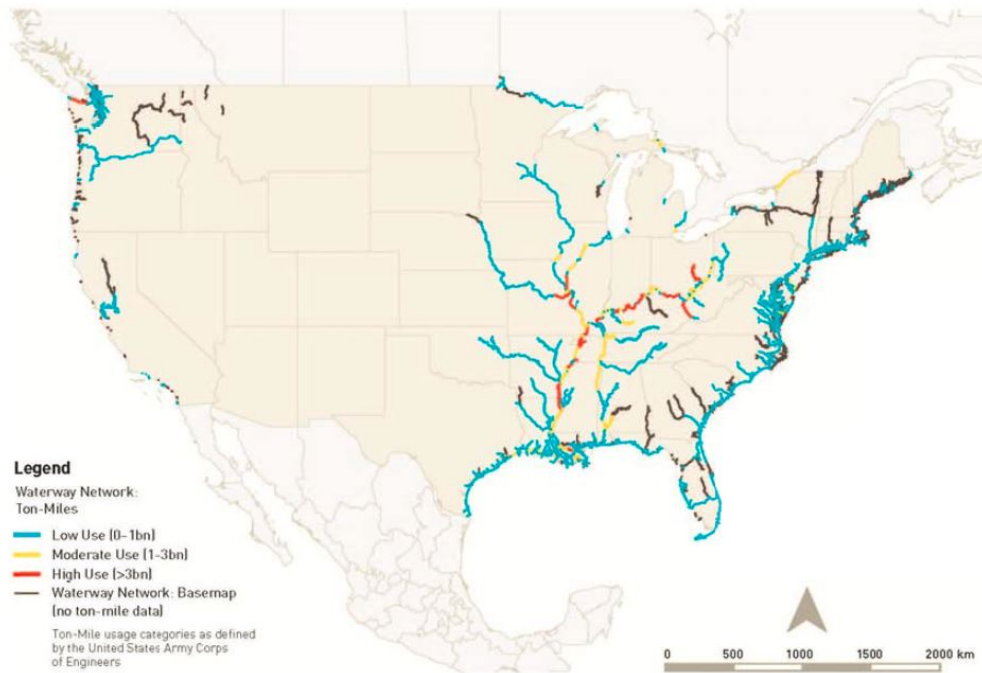


Figure 2.2. High, moderate, and low-use river segments (TRB, 2015)

The inland waterways system has carried about half of domestic waterborne commerce, and moves six to seven percent of all domestic cargo in terms of total ton-miles, primarily consisting of coal, petroleum and petroleum products, food and farm products, chemicals and related products, and crude materials. Table 2.2 presents the barge traffic freight for

2012 classified by commodity and waterway type.

Table 2.2. Barge freight traffic summary for 2012 (TRB, 2015)

Commodity	Total Barge	Coastwise or Lakewise	Inland (Internal)	Intraport or Intraterritory	All Traffic (barge and non-barge)	Percent Barge	Percent of All Domestic Traffic That Is Inland Barge (Internal)	Percent of Barge Traffic That Is Inland Barge (Internal)
Total	737.6	101.1	557.6	79.1	884.8	83%	63%	76%
Coal	182.7	4.0	169.0	9.7	200.0	91%	85%	93%
Petroleum and petroleum products	252.4	55.5	149.2	47.7	311.1	81%	48%	59%
Chemicals and related products	70.4	8.7	50.7	11.0	72.8	97%	70%	72%
Crude materials	111.5	16.9	85.9	8.7	165.7	67%	52%	77%
Primary manufactured goods	31.0	3.9	26.2	0.9	32.4	96%	81%	85%
Food and farm products	76.1	1.9	73.7	0.5	79.1	96%	93%	97%
All manufactured equipment	12.2	10.0	1.8	0.4	22.3	55%	8%	15%
Other	1.3	0.0	1.0	0.3	1.5	100%	67%	77%

The six major corridors in the inland waterway system are: the Upper Mississippi River, the Lower Mississippi River, the Ohio River, the Gulf Intracoastal Waterway (GIWW), the Illinois River, and the Columbia River system. Table 2.3 summarizes the freight traffic for these corridors. In the next section we provide general information about the infrastructure of the inland waterway system.

Table 2.3. Freight traffic for six major U.S. inland waterways, 2012 (TRB, 2015)

Waterway Description	Commodities	Short Tons (millions)	Percent of Total
Upper Mississippi River (Minneapolis, Minnesota, to mouth of Ohio River)	Total	110.1	100
	Coal	24.1	21.9
	Petroleum and petroleum products	12.8	11.6
	Chemicals and related products	11.4	10.3
	Crude materials	16.7	15.2
	Primary manufactured goods	9.8	8.9
	Food and farm products	35	31.7
	All manufactured equipment	0.3	0.3
	Other	0	0
Lower Mississippi River (mouth of Ohio River to Baton Rouge, Louisiana)	Total	186.3	100
	Coal	37.3	20
	Petroleum and petroleum products	20.1	10.8
	Chemicals and related products	22.3	11.9
	Crude materials	31	16.6
	Primary manufactured goods	12.8	6.9
	Food and farm products	62.5	33.6
	All manufactured equipment	0.4	0.22
	Other	0	0
Ohio River system	Total	239.1	100
	Coal	140.2	58.5
	Petroleum and petroleum products	14.4	6
	Chemicals and related products	10.5	4.4
	Crude materials	51.9	21.7
	Primary manufactured goods	8.7	3.6
	Food and farm products	13.4	5.6
	All manufactured equipment	0.1	0.04
	Other	0	0
Gulf Intracoastal Waterway (from Florida to Texas)	Total	113.7	100
	Coal	2.5	2.2
	Petroleum and petroleum products	65.8	57.8
	Chemicals and related products	21.2	18.7
	Crude materials	16.7	14.7
	Primary manufactured goods	4.6	4.1
	Food and farm products	1.4	1.3
	All manufactured equipment	0.8	0.7
	Other	0.6	0.5

2.1.2 Inland Waterway Infrastructure

This section focuses on the six major U.S. inland waterways corridors and lock and dam systems. We construct Table 2.4 based on information provided in TRB (2015) which presents the length and depth of each river and the number of lock and dam systems in each corridor. In Figure 2.3 (TRB, 2015) we present the inland waterway navigation lock and dam usage given as a percentage of lockages in the inland waterway system (data of 2013).

Table 2.4. Six major U.S. inland waterways (TRB, 2015)

River	Navigable Length (miles)	Waterway Depth (feet)	Number of Lock and Dams
Upper Mississippi	858	9	27
Lower Mississippi	956	-	0
Ohio	981	9	20
Gulf Intracoastal	1,109	12	10
Illinois	292	9	7
Columbia	465	14, 40	4

2.2 Systems Optimization Applied to Maritime Transportation

This section presents a summary of several systems optimization techniques applied to enhance different MTS operations. Based on the planning horizon, the maritime transportation planning problems can be categorized as strategic, tactical, and operational problems. We construct Table 2.5 based on the maritime transportation planning problems identified by Christiansen, Fagerholt, Nygreen, and Ronen (2007). For each problem, we provide a reference of a relevant study associated with the specific planning problem.



Figure 2.3. Summary inland waterway navigation lock and dam usage (TRB, 2015)

Table 2.5. Maritime transportation planning problems

Type	Problem	Description	Studies
Strategic	Ship design	Structural and stability issues, materials, on-board mechanical and electrical systems, cargo handling equipment, ship size and speed (single ship) (Christiansen et al., 2007)	Cullinane and Khanna (2000)
Strategic	Fleet size and mix decisions	Optimal size and composition of a fleet. ships to include in the fleet, their sizes, and the number of ships of each size (Christiansen et al., 2007)	Pantuso, Fagerholt, and Hvattum (2014)
Strategic	Network design in liner shipping	Design of liner routes and the associated frequency of service, Hub and spoke networks, Shuttle services (Christiansen et al., 2007)	Zheng, Meng, and Sun (2015)

Table 2.5. Maritime transportation planning problems (Cont.)

Type	Problem	Description	Studies
Strategic	Maritime transportation system design	Number and size of ships to charter in each time period during the planning horizon, the number and location of transshipment ports to use, and transportation routes from the transshipment ports to the customers (Christiansen et al., 2007)	Mehrez, Hung, and Ahn (1995)
Strategic	Evaluation of long-term contracts	Deciding whether to accept a specified long-term contract or not (Christiansen et al., 2007)	Ladany and Arbel (1991)
Tactical	Adjustments to fleet size and mix	A fleet of ships is given and the focus is on the best way of using the available ships in order to meet the transportation demand (Pantuso et al., 2014)	Pantuso et al. (2014)
Tactical	Fleet deployment	Assignment of vessels to established routes or lines (Christiansen et al., 2007)	Bakkehaug, Rakke, Fagerholt, and Laporte (2015)
Tactical	Ship routing and scheduling	Select the route and the schedule of ships	Nishi and Izuno (2014)
Tactical	Inventory ship routing	Find routes and schedules that minimize the transportation cost without interrupting production or consumption (Christiansen et al., 2007)	Christiansen et al. (2007)
Tactical	Berth scheduling	How to allocate vessels to berths	Bierwirth and Meisel (2015)
Tactical	Crane scheduling	How to schedule the cranes for loading and unloading vessels	Fu and Diabat (2015)
Tactical	Container yard management	Storage yard operations at container terminals	Carlo, Vis, and Roodbergen (2014)
Tactical	Container stowage Planning	Stowage plans	Ding and Chou (2015)
Tactical	Ship management	Crew scheduling, maintenance scheduling, positioning of spare parts, and bunkering, among others (Christiansen et al., 2007)	John and Gailus (2014)

Table 2.5. Maritime transportation planning problems (Cont.)

Type	Problem	Description	Studies
Tactical	Distribution of empty containers	Repositioning empty containers	Francesco, Lai, and Zud-das (2013)
Operational	Cruising speed selection	Selection of the speed of the vessel	Fagerholt (2001)
Operational	Ship loading	Prevent loss of the ship or damage to the cargo (Christiansen et al., 2007)	Avriel, Penn, Shpirer, and Witteboon (1998), Ji, Guo, Zhu, and Yang (2015)
Operational	Environmental routing	Selecting routes that mitigate the currents, tides, waves, and winds effects (Christiansen et al., 2007)	Papadakis and Perakis (1990)

The government agency that manages the U.S. MTS infrastructure is the U.S. Army Corps of Engineers (Corps). The navigation mission of the Corps is to “provide safe, reliable, efficient, effective and environmentally sustainable waterborne transportation systems for movement of commerce, national security needs, and recreation.” Systems optimization applications within the Corps’ navigation efforts are sediment management in coastal systems and across watersheds, lock and dam operations and maintenance, and dredge scheduling and sequencing (Nachtmann & Mitchell, 2012). Some of the objectives that systems optimization applications aim to improve in the case of inland waterways planning are related with cost, risk, reliability, throughput, among others. In the next section we focus our review on the inland waterway transportation planning literature and highlight inland waterway disruption response as a promising research field. Section 2.3 is the manuscript “A Survey of the Inland Waterway Transportation Planning Literature” (Delgado-Hidalgo & Nachtmann, 2016).

2.3 A Survey of the Inland Waterway Transportation Planning Literature

Most studies related to resource planning problems for the maritime transportation system have focused on coastal port operations. In this section, we focus on resource planning within the inland waterway transportation system. In order to support the development of a planning decision tool for inland waterway operations and disruptive events, this paper reviews the current literature related to resource planning problems in inland waterway transportation operations and disruptions. First, we provide an overview of the strategic and operational decisions related to the inland waterway transportation system. Next, we characterize the relevant literature in terms of the planning problem studied and the techniques used to solve the problem. This paper also presents evidence of resource planning for inland waterway disruption events as a promising research field.

2.3.1 Introduction

The inland waterway transportation system of the United States is comprised of more than 12,000 miles of commercially navigable channels. The six major corridors are the Upper Mississippi River, the Lower Mississippi River, the Ohio River, the Gulf Intracoastal Waterway, the Illinois River, and the Columbia River system. The inland waterway transportation system consists of navigable channels, lock and dam systems, bridges, and inland ports serving thirty-eight States. The primary commodities transported on the inland waterways are coal, petroleum and petroleum products, food and farm products, chemicals and related products, and crude materials (TRB, 2015). The inland waterway transportation system is an important component part of the maritime transportation system. Other papers have surveyed planning problems for maritime transportation (Christiansen et al., 2007; Davarzani, Fahimnia, Bell, & Sarkis, 2016; Pantuso et al., 2014; Stahlbock & Voß, 2008). However,

our review indicates that only one paper specifically reviews the literature related to inland waterway transportation (Li, Negenborn, & Lodewijks, 2013). We update the literature given in Li et al. (2013) and consider additional planning problems such as the dredging scheduling and lock scheduling problems. In this paper, we review seventeen relevant papers. Twelve papers (An, Hu, & Xie, 2015; Arango, Cortés, Muñuzuri, & Onieva, 2011; Fazi, Fransoo, & Woensel, 2015; Grubišić, Hess, & Hess, 2014; Khodakarami, Mitchell, & Wang, 2014; Nachtmann, Mitchell, Rainwater, Gedik, & Pohl, 2014; Pap, Bojanić, Bojanić, & Georgijević, 2013; Passchyn, Briskorn, & Spieksma, 2016; Tan, Li, Zhang, & Yang, 2015; Tong & Nachtmann, 2015; Verstichel, Kinable, Causmaecker, & Berghe, 2015; Wu & Peng, 2013) study various planning problems for the inland waterway transportation system. The other papers (Baroud, Barker, Ramirez-Marquez, & Rocco, 2015; Marufuzzaman & Eksioğlu, 2014; Pant et al., 2015; Tong & Nachtmann, 2015; Whitman, Baroud, & Barker, 2015; Wu, Rahman, & Zaloom, 2014) focus on inland waterway disruption response. A disruption is a system's natural or manmade perturbation that negatively impacts the functionality of the system. Disruption to inland waterway transportation may affect the waterway such as ice, droughts, floods, collision of vessels, or it may affect the inland infrastructure, such as emergency repairs or earthquakes. When a disruption occurs, it is necessary to implement a response which consists of implementing pre-disaster preparation and/or after-disaster response activities aiming to mitigate the negative impacts of a disaster. The remainder of this paper is organized as follows. Section 2.3.2 overviews strategic and operational decision problems related to the inland waterway transportation system. In Section 2.3.3, we provide a summary of the decisions, objectives, and techniques for each paper described in Section 2.3.2. Section 2.3.4 discusses the literature related to inland waterway disruption response, and we conclude by identifying this area as a promising research field.

2.3.2 Operations and Decision Problems for Inland Waterway Transportation System

The primary vessels used in inland waterway freight transportation are barge tows. A barge is a flat-bottomed boat that is generally pushed or towed by a towboat. Typically, a single towboat pushes between nine and fifteen barges. The inland waterway transportation system infrastructure that allows barge tows to navigate is comprised of navigable channels, lock and dam systems, bridges, and inland waterway ports. A strategic decision problem we identify in this paper is maintenance and construction planning of the inland waterway transportation infrastructure. Determining which sections of the river are well-suited for navigation purposes and which sections can be adapted to be part of the navigation system is one of the first decisions associated with the deployment of the transportation network. Defining where to locate infrastructure such as lock and dam systems and inland waterway ports is also an important component of this strategic decision. In addition to the location of inland waterway ports, it is necessary to define the capacity and service level that the port will offer. The management of berths, yards, quay cranes, and other unloading/offloading equipment, as well as the scheduling of labor force, are other important planning decisions that need to be made. Maintenance of existing infrastructure is another critical set of operational decisions related to the inland waterway transportation system. To maintain inland waterway navigable channels, dredging operations consisting of removing sediment from navigation channels to increase the channel depth are required. The key decisions related to dredging operations are determining the optimum dredged depth and assigning and scheduling dredge vessels to navigation projects. The maintenance of lock and dams also needs to be considered, specifically how to prioritize maintenance projects and how much to invest in each project subject to a limited budget.

Once the inland waterway transportation system infrastructure is built, the inland shipping

routes to transport the cargo need to be defined. Unlike marine shipping routes in which a route is defined by calling ports and the calling sequence, inland shipping routes are defined only by the calling ports. This occurs because all ports are located across a single river axis (An et al., 2015). The decision problems related to defining the routes of the barges are known as barge routing, barge scheduling, barge rotation, and barge dispatching. One of the key operations within the inland terminal is barge loading. This operation requires solving decision problems such as the assignment of the barges to the available inland terminal berths. It also requires selecting the handling equipment and the means in which the equipment will be used. Some of the most well-known related decision problems are ship loading, barge handling, Berth Allocation Problem (BAP), and quay crane assignment and scheduling. Since barges are not generally self-propelled, another decision problem is related to the assignment of barges to the towboats that will tow/push them. This decision problem is known as barge scheduling and barge dispatching. During the navigation, barges pass through multiple lock and dam systems. These systems allow the barges to move through sections of the rivers with varying water levels. A lock is comprised of one or more chambers that hold water between two gates. The main decisions related to lock and dam management are scheduling of lockages, assignment of barges to chambers, and positioning of barges inside the chambers. This problem is generally known as the lock scheduling problem. Finally, the operations related with arrivals of barge tows to the calling inland port are similar to the operations for dispatching of barge tows from their origin inland port. Berth allocation and assignment and scheduling of the handling equipment are decisions that need to be solved. Table 2.6 presents a summary of planning problems in inland waterway transportation and the associated references identified in our literature review.

Table 2.6. Summary of planning problems in inland waterway transportation

Problem	Description	Studies
Dredge scheduling	Schedule dredge equipment for the removal of sediment from navigation channels	Khodakarami et al. (2014), Nachtmann et al. (2014)

Table 2.6. Summary of planning problems in inland waterway transportation (Cont.)

Problem	Description	Studies
Lock scheduling	Schedule the time for each barge to begin a lockage; Locating barges to lock chambers	Passchyn et al. (2016), Verstichel et al. (2015)
Location and capacity of ports	Selection of the location and capacity of the inland port	Tan et al. (2015), Wu and Peng (2013)
Barge scheduling, Barge Rotation	Determining the upstream and downstream calling sequence and the flow transported between each pair of ports	An et al. (2015), Fazi et al. (2015)
Berth Allocation Problem	Assignment of berths to incoming ships for their cargo handling	Arango et al. (2011), Grubišić et al. (2014), Tong and Nachtmann (2015)
Quay Crane Scheduling	Determining quay cranes, time and sequence of movements	Pap et al. (2013)

2.3.3 Literature Review: Decisions, Objectives, and Techniques

In this section, we review the decisions, objectives, and techniques for each paper described in Section 2.3.2. This information is summarized in Table 2.7.

Table 2.7. Decision, objectives, and techniques

Paper	Decision	Objectives	Techniques
An et al. (2015)	Assignment and scheduling of ships to routes, number of loaded and empty containers at each route, frequency of each route	Minimize system cost	Genetic Algorithm (GA)
Nachtmann et al. (2014)	Assignment and scheduling of dredge equipment for the navigation portfolio of projects	Maximize the cumulative cubic yards dredged	Mixed Integer Programming (MIP), Constrained Programming, decomposition

Table 2.7. Decision, objectives, and techniques (Cont.)

Paper	Decision	Objectives	Techniques
Khodakarami et al. (2014)	Define the depth of dredging for river segments, flow of commodity, increased hours of lock operation; Assignment of segments to be dredged.	Maximize the total value of all origin-destination flow accommodated by the system; Maximize the total weighted benefit	MIP, Probabilistic Operations Research models for Dredging, Benefit-Cost and only benefit based heuristic
Verstichel et al. (2015)	Selection of lockages, assignment and scheduling of ships to each lockage; Assignment and scheduling of lockages to chambers, location of the ships in a chamber	Minimize the number of lockages, the sum of all ships departure time from the lock, and the maximum waiting time of a ship at the lock	Master Problem as a Mixed Integer Linear Programming (MILP), Subproblem as a Integer Programming, Bender's Decomposition
Passchyn et al. (2016)	Assignment of ships to lock movements, starting time of lockage of each lock, completion time of each ship	Minimize total flow time; Minimize total emission	Two MIP, CPLEX, Heuristic Repeated Iterations of Single Lock Scheduling
Wu and Peng (2013)	Assess the capacity and service level of Kwan Sting Container Terminals for ocean vessels and barges	Evaluate the capability of the port when the demand is increased	Simulation model, Arena
Tan et al. (2015)	Selection of port location, service charge and service capacity; Selection of either road or waterway transportation mode	Maximize the profit of the port operator	Analytic approach for hoteling's model framework, M/M/1, location dependent non-linear cost functions
Fazi et al. (2015)	Assignment of containers to either barges or trucks, routing of barges and trucks	Minimize the cost for transportation, the penalty for docking a barge at more than one quay, and the penalty for under-utilization of barges	Heterogeneous Vehicle Routing Problem, Variable Size Bin Packing Problem, and Metropolis algorithm

Table 2.7. Decision, objectives, and techniques (Cont.)

Paper	Decision	Objectives	Techniques
Arango et al. (2011)	Assignment of barges to berths, scheduling of barges, start time of handling operations	Minimize the sum of each ship's service time	MIP, Simulation, Arena, GA, VBA
Grubišić et al. (2014)	Assignment of vessels to berths per location and time period, convoy departure time, and berthing waiting time	Minimize vessels make span and trans-shipment workload at port	MILP, LINGO
Tong and Nachtmann (2015)	Cargo prioritization, assignment and scheduling of barges to inland terminals	Minimize total value loss	Mixed integer nonlinear programming (MINLP) and GA, Tabu Search
Pap et al. (2013)	Scheduling of rail mounted quay gantry crane used for barge reloading in river container terminals	Maximize the handling time savings	Dynamic programming algorithm

2.3.4 Inland Waterway Disruption Response

The most common transportation modes used to transport freight (as measured in % of total tons transported) in the United States are truck (70%), rail (11%), and water (3%) (U.S. Department of Transportation, 2015). Road transportation is the most frequently used freight transportation mode. More than 8,500 trucks per day travel along the nearly 14,530 miles of the National Highway System (NHS). This number of NHS miles carrying freight is expected to increase more than 175% by 2040 (Strocko, Sprung, Nguyen, Rick, & Sedor, 2014). If the network capacity is not significantly increased, recurring peak-period congestion is forecasted to increase to 34% of the NHS in 2040 compared to 10% in 2011 (Strocko et al., 2014). Congestion issues are not only a concern for roadway transportation. The demand

for Class 1 freight railroads increased by 50% between 1960 and 2000. The freight volume is reaching its capacity on the mainline railroad network. The limited capacity, seasonal surges in freight demand, disruptions, and maintenance activities cause congestion in the mainline railroad network (USDOT, 2015). The U.S. Department of Transportation through its U.S. Maritime Administration division has identified the inland waterways as a freight alternative to alleviate roadway and railway congestion (Maritime Administration, U.S. Department of Transportation, 2011). A primary reason that inland waterways could significantly mitigate landside congestion is its capacity to carry freight. One single barge can carry 1,750 short tons of dry cargo; while 70 semi-tractor trailers or sixteen railcars are needed to transport the same amount of cargo. The capacity of fifteen barge tow is equivalent to the capacity of 1,050 trucks or the capacity of two unit trains (U.S. Maritime Administration and National Waterways Foundation. Centers for Ports and Waterways., 2007).

In addition to potentially relieving landside congestion, inland waterway transportation has other benefits such as being less expensive and more fuel-efficient. A barge tow carrying one ton of cargo can travel 576 miles per gallon; while only 155 miles can be traveled by truck and 413 by rail per gallon of fuel. Inland waterway transportation also has additional safety and environmental benefits. The ratio of inland waterway transportation fatalities is 155 to 1 for highway and 22.7 to 1 for rail. The ratio of inland waterway injuries is 2,171 to 1 for highway and 125 to 1 for rail. The number of spills in gal/million ton miles is 6.06 for highway, 3.86 for rail, and 3.60 for inland waterways (U.S. Maritime Administration and National Waterways Foundation. Centers for Ports and Waterways., 2007). Due to these benefits, the inland waterway transportation system has attracted the interest of transportation researchers who have studied different planning problems associated with this system (see Table 2.6).

An area of study not discussed in Section 2.3.2 is inland waterway disruption response. Common natural disruptions of inland waterway transportation are floods and droughts,

which can negatively affect the river levels. Examples of real-world natural and man-made disruptions are discussed next. In May 2002, an Interstate 40 bridge spanning the Arkansas River collapsed when a barge struck a pylon, the barge traffic was negatively impacted for two weeks (Pant et al., 2015). In 2003, the main lock chamber of the Greenup Lock and Dam on the Ohio River was closed to navigation traffic for emergency repairs. Initial planning indicated that the closure was predicted to last eighteen days. However, the closure lasted 52 days, and the total economic loss was estimated to be \$41.9 million (The Planning Center of Expertise for Inland Navigation, 2005b). In 2004, the McAlpine Lock and Dam on the Ohio River was closed for ten days to repair extensive cracking in its miter gate. The total economic loss was estimated to be \$9 million (The Planning Center of Expertise for Inland Navigation, 2005a). A fire at a fertilizer company in early 2009 led to chemical run-off into the port of Catoosa, which required environmental cleanup before it spread (Pant et al., 2015). In 2012, the Mississippi River suffered a record breaking low water level which negatively impacted barge traffic for an extended amount of time. These disruption events, the fact that the inland waterways have been identified as an alternative to reduce landside congestion, and the economic, fuel-efficient, and environmental benefits of the inland waterway transportation system show the importance of inland waterway disruption response as a promising research field. The literature shows an increasing interest of authors publishing research on this topic. Table 2.8 presents summaries of the model and objectives from the reviewed papers in this area.

Table 2.8. Summary of inland waterway disruption response models

Model	Objectives	Paper
MINLP, GA, TS	Assign and schedule disrupted barges to inland terminals to minimize total value loss during a disruption event	Tong and Nachtmann (2015)
Dynamic framework – simulation	Assessing multi-regional, multi-industry losses due to disruptions on the waterway networks including ports and waterway links; Quantify the effect of disruptions on industry inoperability	Pant et al. (2015)

Table 2.8. Summary of inland waterway disruption response models (Cont.)

Model	Objectives	Paper
MINLP, rolling horizon algorithm, Benders Decomposition	Design a cost-efficient and reliable supply chain networks for biomass delivery to biofuel plants; Evaluate the impact of disruption in the biofuel supply chain network	Marufuzzaman and Eksioglu (2014)
Simulation	Evaluating how increased or decreased traffic affects the probabilities of collisions and groundings along three proposed routes in the Sabine–Neches Waterway	Wu et al. (2014)
Metrics of network resilience, Stochastic approach, simulation	Compute three metrics of resilience after a disruption event; loss of service cost, total network restoration cost, and cost of interdependent impacts	Baroud et al. (2015)
Integrated dynamic risk-based interdependency model with TOPSIS	Evaluate dock-specific discrete resource allocation alternatives to improve port preparedness	Whitman et al. (2015)

2.3.5 Conclusions

The inland waterway transportation system has been identified as an alternative mode to alleviate the dramatically increasing landside congestion. Moreover, inland waterway transportation has proven to be an economic, fuel-efficient, reliable, and environmental friendly transportation mode. The interest of researchers to study inland waterway disruption response and planning has increased. However, this research field still lacks of maturity. In this paper, we surveyed seventeen papers related to inland waterway transportation planning problems and disruption response. We categorized the reviewed references in terms of the planning problem studied and the decision, objectives, and techniques used to solve the problem. Some papers (Arango et al., 2011; Grubišić et al., 2014) focus specifically on the assignment and scheduling of barges to terminals (BAP). Others (Baroud et al., 2015; Marufuzzaman & Eksioglu, 2014; Pant et al., 2015; Whitman et al., 2015; Wu et al., 2014)

focus specifically in evaluating and minimizing the negative impacts of a disruption. Only Tong and Nachtmann (2015) studies the BAP in the context of a disruptive event. Among the reviewed papers, only Tong and Nachtmann (2015) and Whitman et al. (2015) consider prioritization. However, in Whitman et al. (2015) prioritization is related to the resource allocation investment alternatives, while in Tong and Nachtmann (2015) the cargo is prioritized based on its features. Among the BAP papers, (i) only Tong and Nachtmann (2015) aims to minimize the total value loss while considering subjective characteristics of the cargo, and (ii) only Grubišić et al. (2014) solves a mixed integer linear program. However, Grubišić et al. (2014) does not solve a real world scenario. This review is part of an undergoing work addressing the development of a response model to support inland waterway disruptive events, in which we plan to extend Tong and Nachtmann (2015) by formulating a MILP to solve more realistic problems with a computational efficient approach.

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Appendix 1



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“A Survey of the Inland Waterway Transportation Planning Literature”

2.4 Berth Allocation Problem ¹

Due to the similarity between the CPTAP and the BAP, we discuss the relevant and recent literature for the BAP. The literature classifies the BAP into three aspects: (i) vessel arrival process, (ii) berth layout, and (iii) nature of the parameters. The vessel arrival process categorizes the BAP as static or dynamic. The static BAP assumes the vessels are waiting at the port before the berth allocation plan starts (Imai, Nagaiwa, & Tat, 1997; Qin, Du, & Sha, 2016), while the dynamic BAP assumes that vessels continue arriving at the port while the berth allocation plan is in progress (Arango et al., 2011; Boile, Theofanis, & Golias, 2006; Buhrkal, Zuglian, Ropke, Larsen, & Lusby, 2011; Cordeau, Laporte, Legato, & Moccia, 2005; Grubišić et al., 2014; Imai, Nishimura, & Papadimitriou, 2001, 2003; Imai, Sun, Nishimura, & Papadimitriou, 2005; Imai, Zhang, Nishimura, & Papadimitriou, 2007; Monaco & Sammarra, 2007; Qin et al., 2016; Simrin & Diabat, 2015; Umang, Bierlaire, & Erera, 2017; Yan, Lu, Hsieh, & Lin, 2015).

The berth layout categorizes the BAP as discrete (DBAP), continuous (CBAP), or hybrid (HBAP). In the DBAP, the quay is partitioned into berths and only one vessel can be serviced at each berth (Arango et al., 2011; Boile et al., 2006; Buhrkal et al., 2011; Cordeau et al., 2005; Grubišić et al., 2014; Hu, 2015b; Imai et al., 1997; Imai et al., 2001, 2003; Imai et al., 2007; Kordić, Davidović, Kovač, & Dragović, 2016; Mauri, Ribeiro, Lorena, & Laporte, 2016; Monaco & Sammarra, 2007; Venturini, Iris, Kontovas, & Larsen, 2017). While in the CBAP, the quay is not partitioned and the vessels can berth in any position within the quay limits (Cenkşahin & Kuvvetli, 2016; Du, Chen, Lam, Xu, & Cao, 2015; Ernst, Oğuz, Singh, & Taherkhani, 2017; Imai et al., 2005; Mauri et al., 2016; Xu & Lee, 2018). On the other hand, the HBAP is a combination of DBAP and the CBAP. Similar to the DBAP, the HBAP partitions the quay into berths, however vessels can use more than one berth as in

¹Excerpted from Section 5.2 of Chapter 5

the CBAP (Kordić et al., 2016; Umang et al., 2017; Umang, Bierlaire, & Vacca, 2013).

The nature of the parameters classifies the BAP as deterministic (D-BAP) or stochastic (S-BAP). Most of the BAP papers study the D-BAP which does not consider uncertainty (Kordić et al., 2016), while the S-BAP research considers uncertainty primarily associated with vessel arrivals and handling times (Alsoufi, Yang, & Salhi, 2016; Budipriyanto, Wirjodirdjo, Pujawan, & Gurning, 2017; Golias, Portal, Konur, Kaisar, & Kolomvos, 2014; Umang et al., 2017; Ursavas, 2015; Ursavas & Zhu, 2016; Zhen, 2015; Zhen & Chang, 2012; Zhen, Lee, & Chew, 2011).

Other authors have studied berthing allocation decisions as part of other integrated problems including the integrated berth allocation and crane assignment problem (BACAP) (Han, Gong, & Jo, 2015; He, 2016; Hsu, 2016; Hu, 2015a; Iris, Pacino, & Ropke, 2017; Iris, Pacino, Ropke, & Larsen, 2015; Li, Hong, Geng, & Wang, 2017; Liu, Zheng, & Zhang, 2016; Liu, Wang, & Shahbazzade, 2018; Pratap, Nayak, Kumar, Cheikhrouhou, & Tiwari, 2017; Shang, Cao, & Ren, 2016; Song, Zhang, Liu, & Chu, 2018; Yuping, Yangyang, Yuanhui, Youfang, & Tianyi, 2018; Zhang, Wu, Qi, & Miao, 2018; Zhen, Liang, Zhuge, Lee, & Chew, 2017), the integrated berth allocation and quay crane assignment and scheduling problem (BACASP) (Agra & Oliveira, 2018; Expósito-Izquiero, Lalla-Ruiz, Lamata, Melián-Batista, & Moreno-Vega, 2016; Han, Lu, & Xi, 2010; Karam & Eltawil, 2016; Türkoğulları, Taşkın, Aras, & Altmel, 2016; Zhang, Zeng, & Yang, 2016), and the integrated berth allocation and yard assignment problem (BYAP) (Al-Hammadi & Diabat, 2017).

The BAP has been solved with multiple heuristics and metaheuristics (Kovač, Stanimirović, & Davidović, 2018) including tabu search (Cordeau et al., 2005; Emde, Boysen, & Briskorn, 2014), greedy randomized adaptive search procedure (Lee, Chen, & Cao, 2010), adaptive large neighborhood search heuristic (Mauri et al., 2016; Ribeiro, Mauri, de Castro Beluco,

Lorena, & Laporte, 2016), squeaky wheel Optimization (Umang et al., 2013), variable neighborhood search (Hansen, Oğuz, & Mladenović, 2008), simulated annealing (Kim & Moon, 2003), particle swarm optimization (Ting, Wu, & Chou, 2014), bee colony optimization (Kovac, 2013), ant colony optimization (Cheong & Tan, 2008), evolutionary algorithms (Cenkşahin & Kuvvetli, 2016), genetic algorithms (Alsoufi et al., 2016; Hu, 2015b; Pratap et al., 2017; Simrin & Diabat, 2015; Tsai, Lee, Wu, & Chang, 2017), memetic algorithms (Dulebenets, Golias, & Mishra, 2018), greedy algorithms (Umang et al., 2017), sedimentation algorithms (Kordić et al., 2016), and partial optimization metaheuristic under special intensification conditions (Lalla-Ruiz & Voß, 2016). Other authors have used simulation to study the BAP (Budipriyanto et al., 2017; Umang et al., 2017).

Bierwirth and Meisel (2015) stated that only a 24% of the papers they reviewed had solved the BAP with exact methods. In that percentage, Bierwirth and Meisel (2015) included papers that solve MILP and generalized set-partitioning (GSPM) (Buhrkal et al., 2011; Umang et al., 2013) models with CPLEX solver and papers that used an exact method to solve integrated problems that include the BAP (Chen, Lee, & Cao, 2012; Robenek, Umang, Bierlaire, & Ropke, 2014; Türkoğulları et al., 2016; Ursavas, 2014; Vacca, Salani, & Bierlaire, 2013). In addition, we found that Kordić et al. (2016) and Xu and Lee (2018) proposed exact methods to solve the BAP. Kordić et al. (2016) solved their model with an exact approach based on the model proposed by Rashidi and Tsang (2013). Xu and Lee (2018) developed an exact method based on a branch-and-bound approach, which incorporates a new lower bound with some heuristic and pruning techniques.

From our review, we note that some authors have studied the BAP considering vessels priority (Imai et al., 2003; Lalla-Ruiz, Expósito-Izquierdo, Melián-Batista, & Moreno-Vega, 2016; Pratap et al., 2017; Qin et al., 2016; Umang et al., 2017; Ursavas & Zhu, 2016), others have studied the BAP under disruption (Liu et al., 2016; Umang et al., 2017; Zhen et al.,

2011), and a few have studied the BAP for inland terminals (Arango et al., 2011; Grubišić et al., 2014; Lalla-Ruiz, Shi, & Voß, 2018; Qin et al., 2016). However, only Tong and Nachtmann (2017) and Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) have considered berth allocation decisions in conjunction with cargo prioritization, disruptions, and inland waterway shipping.

Tong and Nachtmann (2017) studied the cargo prioritization and terminal allocation problem (CPTAP) which is an extension of the BAP that considers cargo prioritization in the context of inland waterways disruptions. Tong and Nachtmann (2017) formulated their problem as a non-linear integer programming (NLIP) model that minimizes total cargo value loss. The authors were able to find optimal solutions with their NLIP model for small size instances considering up to five terminals and nine barges. Tong and Nachtmann (2017) developed a genetic algorithm (GA) approach to obtain solutions for larger size instances involving up to fifteen terminal and fifty barges. However, due to the difficulty of their NLIP, Tong and Nachtmann (2017) could validate the results for their GA only for small size instances.

Our research contributes a response model to support inland waterway disruptive events, in which we extend Tong and Nachtmann (2017) by formulating the CPTAP in a more suited way that allow us to solve more realistic problems. Our improved formulation allow us to validate the GA results obtained by Tong and Nachtmann (2017) for all size instances. In addition, this dissertation contributes the first exact method to solve the CPTAP. This exact method is based on a branch-and-price algorithm which we are able to obtain new optimal solutions for larger instances of the CPTAP.

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3 A Heuristic Approach to Managing Inland Waterway Disruption Response

Abstract

Inland waterways are a cost-effective and environmentally-friendly mode of freight transportation. Natural and man-made events can disrupt navigation and may halt barge traffic. Our research provides decision support during inland waterway disruption response to minimize value loss through development of a decomposition based sequential heuristic (DBSH). The DBSH integrates the Analytic Hierarchy Process and linear programming to prioritize cargo and allocate barges to terminals. Our findings show that compared to a previous approach the DBSH is more suited to solve large sized decision problems by reducing the cargo value loss and drastically improving computational time.

Keywords: Disruption Response, Freight Transportation, Cargo Prioritization, Inland Waterways, Analytic Hierarchy Process, Heuristic Optimization

EMJ Focus Areas: Operations Management, Quantitative Methods & Models

3.1 Introduction

Inland waterways are an important transportation mode to alleviate landside congestion and have proven to be economic, fuel-efficient, reliable, and environmentally-friendly (Kruse et al., 2017). The inland waterway transportation infrastructure consists of navigable channels, lock and dam systems, cargo handling equipment, dredged material placement facilities, and berthing facilities or inland ports. The primary vessels used in inland waterway transporta-

tion are barges, which are flat-bottomed boats grouped together and pushed or pulled by a towboat. The lock and dam systems are used to allow barges to navigate sections of the river at varying water depth levels.

The inland waterway transportation system of the United States (U.S.) is comprised of more than 12,000 miles of commercially navigable channels including the Upper Mississippi River, Lower Mississippi River, Ohio River, Gulf Intracoastal Waterway, Illinois River, and Columbia River system (Welch-Ross & Hendrickson, 2016). The U.S. inland waterway transportation system has 239 lock chambers operating at 193 sites and 1,930 cargo handling docks (USACE, 2016). In 2016, U.S. waterborne moved 876.6 million short tons of domestic traffic and 1,415.5 million short tons of foreign traffic for a total of 2,292 million short tons (USACE, 2016). The primary commodities transported on the U.S. inland waterways are coal, petroleum and petroleum products, food and farm products, chemicals and related products, and crude materials.

In addition to contributions to the U.S. economy, inland waterway transportation system offers other benefits in comparison to rail and land transportation modes including larger capacity to carry freight, fuel-efficiency, and safety. For dry cargo, the capacity of one barge is equivalent to the capacity of 16 railcars or the capacity of 70 semi-tractor trailers. For liquid cargo, the capacity of one barge is equivalent to the capacity of 46 railcars or the capacity of 144 semi-tractor trailers (Kruse et al., 2017). The average fuel efficiency in ton-miles per gallons is 647 for inland towing, 477 for railroads, and 145 for truck. The ratio of rail and truck to towing fatalities (per million ton-miles) is one fatality in the towing sector for every 21.9 in the rail sector and 79.3 in the truck sector. The ratio of rail and truck to towing injuries (per million ton-miles) is one injury in the towing sector for every 80.9 in the rail sector and 696.2 in the truck sector (Kruse et al., 2017).

Due to these benefits, the U.S. Department of Transportation considers the inland waterways as a freight alternative with potential to relieve roadway and railway congestion (Maritime Administration, U.S. Department of Transportation, 2011), and maintaining the availability and reliability of the inland waterway transportation system is prominent. However, the inland waterways system faces natural and man-made disruptions. Common disruptions to inland waterway freight transportation are ice, droughts, floods, vessel collisions, and infrastructure emergency repairs, which can negatively affect navigation infrastructure operations and channel water levels and cause system closures and thus economic losses. In September 2016, Lock and Dam No. 52 on the Ohio River required emergency repairs which halted the river traffic for more than fifteen hours. Tennessee Valley Towing, a towing industry, estimated their losses at \$80,000 due to the river closure (Kelley, 2016). In March 2014, a barge collision occurred in the Houston Ship Channel, which shut down the Houston-Galveston port for five days, causing thirty-seven tows to be delayed in the Gulf Intracoastal Waterway resulting in an economic loss of \$785,000 (Kruse & Protopapas, 2014).

When disruptions halt barge traffic, barges that need to traverse the disrupted segment of the waterway need to be rerouted to accessible terminals where the cargo is then offloaded for land transport to its final destination. Our research provides decision support to transportation planners and engineering managers during inland waterway disruption response to mitigate negative impacts. Our main motivation is to develop a methodology to solve large problem instances in a shorter amount of computational time in order to address real world-sized transportation system decisions. We present a decomposition based sequential heuristic (DBSH) approach that consists of three components: (1) cargo prioritization, (2) assignment of barges to terminals, and (3) scheduling of barges assigned to a terminal. The cargo prioritization component determines the priority index of each barge through the Analytic Hierarchy Process (AHP) (Saaty, 1980) approach. Barges with higher priority indices are given higher priority consideration to be offloaded. This paper modifies an initial version

on the AHP proposed by Tong and Nachtmann (2013) by using the weighted geometric mean method (WGMM) proposed by Xu (2000) as an aggregation method.

The second component, assignment of barges to terminals, is formulated as an integer linear programming (ILP) model that minimizes total cargo value loss during the assignment. An initial version of the assignment model, where the ILP minimizes transportation and handling times was published in the proceedings of the 2015 American Society for Engineering Management conference (Delgado-Hidalgo, Nachtmann, & Tong, 2015). The third component, scheduling of barges assigned to a terminal, is formulated as a mixed integer linear programming (MILP) model that minimizes total cargo value loss.

The remainder of this paper presents relevant background literature and our DBSH approach. We present the results for multiple problem instances and a comparison between DBSH and a previous approach (Tong & Nachtmann, 2017). Finally, we make concluding remarks and discuss future work.

3.2 Literature Review

Inland waterways transportation faces natural and man-made events resulting in significant economic losses and environmental damage. The frequency of common inland waterway disruptions such as droughts and floods is expected to increase as a result of climate change (Edenhofer et al., 2014). We summarize recent real world examples of inland waterway disruptions and their associated consequences in Table 3.1. Given the significant impacts of inland waterways disruptions, increased expected frequency of natural disruptions, inland waterways system benefits in comparison to other transportation modes, and the waterways' contributions to the U.S. economy, investigating pre- and post- disruption responses to sup-

port inland waterways seems to be crucial to maintaining a reliable transportation system. Next, we provide recent literature classified into three topics relevant for our research: inland waterway disruption response, cargo prioritization, and berth allocation problem. Finally, we conclude this section by discussing the contributions of our research.

Table 3.1. Inland waterway disruptions

Disruption	Year	Consequences	Reference
Drought on Mississippi and Ohio rivers	2005	Several barges ran aground. More than 60 boats and 600 barges were stopped. Delays caused \$10,000 loss per day	Güler et al. (2012)
Barges crashed into Belleville Lock in Reedsville	2005	Shutdown cost \$4.5 million a day. General Electric closed its plant	Güler et al. (2012)
Flooding in the Mississippi River	2011	River barge traffic, transporting billions in crops, were delayed. Riverboat casinos were closed for 6-8 weeks with an estimated loss of \$14 million	Amadeo (2016)
Collision occurred in the Houston Ship Channel	2014	Houston-Galveston port was shut down for 5 days. 37 tows were delayed in the Gulf Intracoastal waterway, which represented an estimated cost of \$785,000	Kruse and Protopapas (2014)
A tow vessel crashed into a barge fleet	2016	Spilling about 20 gallons of “residual petroleum-based product”. The incident shut down traffic in a three-mile portion of the river for more than 10 hours	Torres (2016)
Emergency repairs on dam 52	2016	River traffic stopped for 15 hours. Tennessee Valley Towing calculated a loss of \$80,000 due to the river closure	Kelley (2016)
Towing vessel allided with Lock and Dam 52	2017	The section of the river was closed. Queue was 12 vessels up-bound and 10 vessels down-bound. Corn costs at the Gulf rose by about 2 to 3 cents per bushel, partly in response to the slowed flow of grain.	gCaptain (2017)
Barge collided with Smothers Park	2017	Estimated half a million dollars to repair	O’Rourke (2017)

Table 3.2 summarizes the model and objectives from the reviewed papers in this area.

Table 3.2. Summary of inland waterway disruption response models

Model	Objectives	Paper
Integrated dynamic risk-based interdependency model with TOPSIS	Evaluate dock-specific discrete resource allocation alternatives to improve port preparedness	Whitman et al. (2015)
Metrics of network resilience, Stochastic approach, simulation	Compute three metrics of resilience after a disruption event; loss of service cost, total network restoration cost, and cost of interdependent impacts	Baroud et al. (2015)
Dynamic framework – simulation	Assessing multi-regional, multi-industry losses due to disruptions on the waterway networks including ports and waterway links; Quantify the effect of disruptions on industry inoperability	Pant et al. (2015)
Bayesian networks	Model infrastructure resilience as a function of capacity measured with three components: absorptive, adaptive, and restorative	Hosseini and Barker (2016)
Price-endogenous, spatial equilibrium, quadratic programming model and an input-output model	Estimate prices, economic surplus, and economic impacts of inland waterways disruptions on the U.S. corn and soybean transportation sector	Yu, English, and Menard (2016)
Simulation-based approach	Study the economic impacts of disruption duration estimation and commodity type on inland waterway disruption response	Oztanriseven and Nachtmann (2017)
Dynamic multi-objective transportation cost model	Select the optimal alternative (waiting or rerouting the cargo) given the expected duration of the disruption	Zhang, Lee, and Holmer (2017)
Nonlinear Integer Programming (NLIP), Genetic Algorithm (GA)	Assign and schedule disrupted barges to inland terminals to minimize total value loss during a disruption event	Tong and Nachtmann (2017)

Cargo Prioritization

Tong and Nachtmann (2013) presented a multi-attribute decision approach based on the AHP to prioritize cargo offloading during inland waterway disruptions. The authors assumed all barge cargo is assigned to the nearest terminal for offloading. Delgado-Hidalgo et al. (2015) extended Tong and Nachtmann (2013) approach by using the priority index associated to each type of cargo and obtained with the AHP approach as input to solve the assignment and scheduling of disrupted barges to available terminals. The authors formulated an ILP model that minimizes transportation and handling time to assign disrupted barges to terminals. The scheduling of the barges at each terminal was undertaken based on the priority index of the cargo.

Tong, Nachtmann, and Pohl (2015) studied cargo prioritization by developing a priority index denominated cargo value decreasing rate (CVDR). The CVDR is defined as “the rate at which the cargo’s economic and societal value diminishes as time elapses” (Tong, Nachtmann, & Pohl, 2015, p.73). Cargoes with higher CVDR are given higher priority. The authors used value-focused thinking approach to assess the CVDR. A review of cargo prioritization techniques within inland waterway transportation is presented in Tong and Nachtmann (2012).

Berth Allocation Problem

The barge terminal allocation component of the problem we are studying has a similar problem structure to the berth allocation problem (BAP). The BAP studies the assignment of a set of vessels to a given berth layout within a given time horizon (Umang et al., 2013). Like the BAP, the barge terminal allocation component of our problem studies the assignment of vessels to berths. In our case, vessels are disrupted barges and berths are inland waterway

terminals. Unlike most of the BAP research that focuses on ocean shipping, our problem focuses on inland waterway shipping. Inland waterway shipping differs from ocean shipping in three main aspects. The first aspect is related to the size of the vessels. Due to the shallow waterways, inland waterway shipping requires to use shallow vessels such as barges that can safely navigate in the waterways and berth in the inland terminals. The second different aspect is associated to the transportation system infrastructure. Inland waterways transportation infrastructure includes lock and dam systems that allow barge tows to navigate sections of the river at varying water levels. Lock and dam systems are critical to inland waterway shipping. Finally, the third different aspect is related to the definition of routes. Unlike ocean shipping routes that are defined by calling sequence and calling ports, inland waterway shipping routes are defined just by calling sequence since inland ports are located across a single river axis (An et al., 2015). In addition, unlike the BAP, our research problem explicitly considers and prioritizes the type of cargo that the barges carry.

The BAP for ocean shipping has been extensively studied as discussed in the BAP surveys developed by Bierwirth and Meisel (2010) and Bierwirth and Meisel (2015). On the other hand, our literature review identified two BAP papers that focus on inland waterways (Arango et al., 2011; Grubišić et al., 2014) and two other papers that study a similar problem on inland waterways (Lalla-Ruiz et al., 2018; Tong & Nachtmann, 2017). Arango et al. (2011) developed an integrated simulation and optimization model based on genetic algorithm (GA) approach to solve the BAP. Their model minimizes total service time for each ship and considers a first-come-first-served allocation strategy. Grubišić et al. (2014) formulated a MILP model to solve the BAP. Their model minimizes the total time of vessels' stay in port and transshipment operation workload. Lalla-Ruiz et al. (2018) studied the waterway ship scheduling problem (WSSP). Unlike the BAP, the WSSP assigns ships to waterways rather than berths. Lalla-Ruiz et al. (2018) formulated a MILP model to minimize the total time required for the ships to pass through the waterways. Their model was

solved with a greedy heuristic based on commonly used queue rules as well as a simulated annealing (SA) algorithm. Tong and Nachtmann (2017) studied the cargo prioritization and terminal allocation problem (CPTAP). The CPTAP studies the assignment and scheduling of disrupted barges to inland port for inland waterway disruption response. The authors formulated the CPTAP as nonlinear binary integer program (NLIP) and developed a GA approach to solve their model.

Research Contributions

The reviewed inland waterway disruption response literature motivates our research by providing different indicators that evidence the negative impacts of inland waterway disruptions measured as total cost (Baroud et al., 2015; Oztanriseven & Nachtmann, 2017; Pant et al., 2015; Whitman et al., 2015; Zhang et al., 2017), cargo price and economic surplus (Yu et al., 2016), and total cargo value loss (Tong & Nachtmann, 2017).

When barge traffic is halted due to inland waterway disruptions, two alternatives to face the disruption are: the waiting alternative, waiting at the location at the time of disruption until the waterways are navigable, and the rerouting alternative, rerouting the cargo to available inland terminals for transport to the final destination via an alternative transportation mode. Similar to our work, Delgado-Hidalgo et al. (2015), Hosseini and Barker (2016), Oztanriseven and Nachtmann (2017), Tong and Nachtmann (2013, 2017), Zhang et al. (2017) identified rerouting the cargo as a suitable resilience strategy for inland waterway disruption response.

In Zhang et al. (2017), if their model selects rerouting alternative as the optimal alternative, the authors assumed that the new routes correspond to the minimum cost path from the nearest available terminal. However, unlike our research, the assignment and scheduling of barges to terminals were not developed in their paper.

Oztanriseven and Nachtmann (2017) results suggested that the alternative that minimizes total disruption cost for manufactured equipment and machinery commodity is to transfer the cargo to an alternative transportation mode, which motivates the rerouting alternative considered in our research. The authors concluded that the selection of the disruption response alternative depends on the expected duration of the disruption.

From our inland waterway disruption response literature, only Whitman et al. (2015) and Tong and Nachtmann (2017) consider cargo prioritization. Tong and Nachtmann (2017) prioritized the cargo carried by the barges, while Whitman et al. (2015) prioritized alternatives that allocate resources to docks that handle specific type of cargo.

From our cargo prioritization literature, only Delgado-Hidalgo et al. (2015) used priority indexes to solve the assignment and scheduling of disrupted barges to inland ports during disruption response. In Delgado-Hidalgo et al. (2015), the scheduling of the barges at each terminal was undertaken based on the barge's cargo priority index; the higher the priority index, the earlier the barge is scheduled for offloading. However, this scheduling approach did not consider a disruption performance measure to guide the offloading sequence of the disrupted barges. We fill into this gap by formulating a MILP model that minimizes total cargo value loss to schedule barges to inland ports during disruption response. In addition, we modified the AHP approach proposed by Tong and Nachtmann (2013) by using the weighted geometric mean method (WGMM) proposed by Xu (2000) as aggregation method. The WGMM has proven to be an acceptable solution to derive weights from pairwise comparison matrices avoiding the known eigenvector method problems such as rank reversals (Barzilai, 1997).

From our BAP literature, only Tong and Nachtmann (2017) consider cargo prioritization in their allocation and scheduling of barges to terminals. In fact, like our research, only Tong

and Nachtmann (2017) consider cargo prioritization to assign and schedule disrupted barges to terminals for inland waterway disruption response. Tong and Nachtmann (2017) presented a non-linear model formulation to solve the CPTAP. There are two different components in their approach, assignment decisions and scheduling order, integrated into a single model. Their model requires the calculation of the actual contributing time defined as “the amount of time it takes for a disrupted barge to be transported by water to its assigned terminal, to incur any wait time until its prioritized offload order is reached, and to have its cargo offloaded” (Tong & Nachtmann, 2017, p.9). The actual contributing time of a barge depends on the actual contributing time of all the barges that have been served in the same terminal before that particular barge. Note that this calculation resembles a nested structure, non-linear in nature and computationally expensive. The non-linearity of their model led Tong and Nachtmann (2017) to use a GA heuristic to solve their model.

This research contributes a more computationally simple and efficient approach to model the CPTAP studied by Tong and Nachtmann (2017). The DBSH approach consists of linear models while the CPTAP formulation is a non-linear model. The decomposition used in our DBSH makes possible the use of off-the-shelf solvers to solve the linear models which allows for more efficient technology transfer into practice. Our approach can be more widely adopted by engineering managers in the maritime transportation community.

3.3 Problem Definition

Figure 3.1 depicts a section of the Arkansas River that was disrupted when the Arkansas and Missouri railroad bridge was damaged. This section contains five lock and dam (L/D) systems that enable barges to navigate across sections of the waterways that are at different levels. The upper waterway section includes three terminals and one barge tow which consists

of nine to fifteen barges. The lower waterway section includes seven terminals and seven barge tows. Based on the navigation direction, six of the eight barge tows (shaded in black) require crossing the point of disruption and therefore are disrupted barge tows. The other two barge tows (shaded in white) are not affected by the disruption.

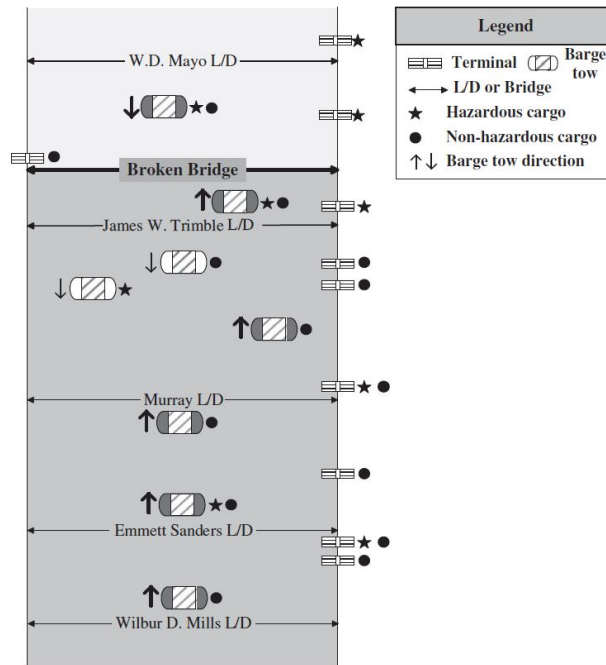


Figure 3.1. Arkansas river disruption (Tong & Nachtmann, 2017)

A disruption response needs to redirect disrupted barges to available terminals where their cargo is offloaded for transport to their final destination via an alternative transportation mode. We reasonably assume that each barge transports a single type of cargo whose volume is known. The limited capacity of the terminals prevents offloading more than one barge at the same time. The barge-terminal assignments take into account the volume of the cargo, capacity and water depth of each terminal, draft depth of each barge, and a clearance between the terminals' water depth and the barges' draft depth for safety purposes. Some disrupted barges may not be assigned to a terminal if there is not available offload capacity or the expected cargo value loss is greater than the maximum cargo value loss the customer

is willing to accept. Barges carrying non-hazardous cargo that are not assigned to a terminal are assumed to remain on the waterway to be collected at a later date which results in a total value loss of the cargo. Barges transporting hazardous cargoes must be assigned to a terminal and offloaded. Cargo loses value over time due to a variety of reasons including declining customer interest in the cargo as the delay increases and the perishable condition of the cargo. The value loss of the cargo depends on the volume of the cargo, the cargo value decreasing rate, and the total time it takes to deliver the cargo to its final customer.

3.4 Decomposition Based Sequential Heuristic

In this section, we describe our DBSH approach to assign and schedule disrupted barges during inland waterway disruption response. First, we present a general description of the DBSH, explaining how the three components of our heuristic including the cargo prioritization model, assignment model, and scheduling model are integrated into the DBSH. Next, we present an explanation of the three components of our approach. The first component is a modification of previous work conducted by Tong and Nachtmann (2013). In this article, we use the weighted geometric mean method (WGMM) as aggregation method (Xu, 2000) in the AHP approach. An initial version of the second component was proposed in previous work conducted by Delgado-Hidalgo et al. (2015).

3.4.1 Flow Diagram for the Decomposition Based Sequential Heuristic

Figure 3.2 describes the overall flow of our DBSH approach. The shaded rectangles represent the three main components of the DBSH: Cargo Prioritization (Model 1), Assignment (Model 2), and Scheduling (Model 3) of barges to terminals. The first step of the heuristic is to

determine the prioritization of each cargo (Step 1 in Figure 3.2). The Cargo Prioritization Model (Model 1 in Figure 3.2) also determines the priority index of each barge based on the cargo commodity it carries. We then decompose the set of barges into subsets of barges based on the hazardous condition and priority index p of each barge (Step 2 in Figure 3.2). The priority index for hazardous cargoes is set to $p = 1$, and we assume there is enough capacity to offload all the barges carrying hazardous cargo.

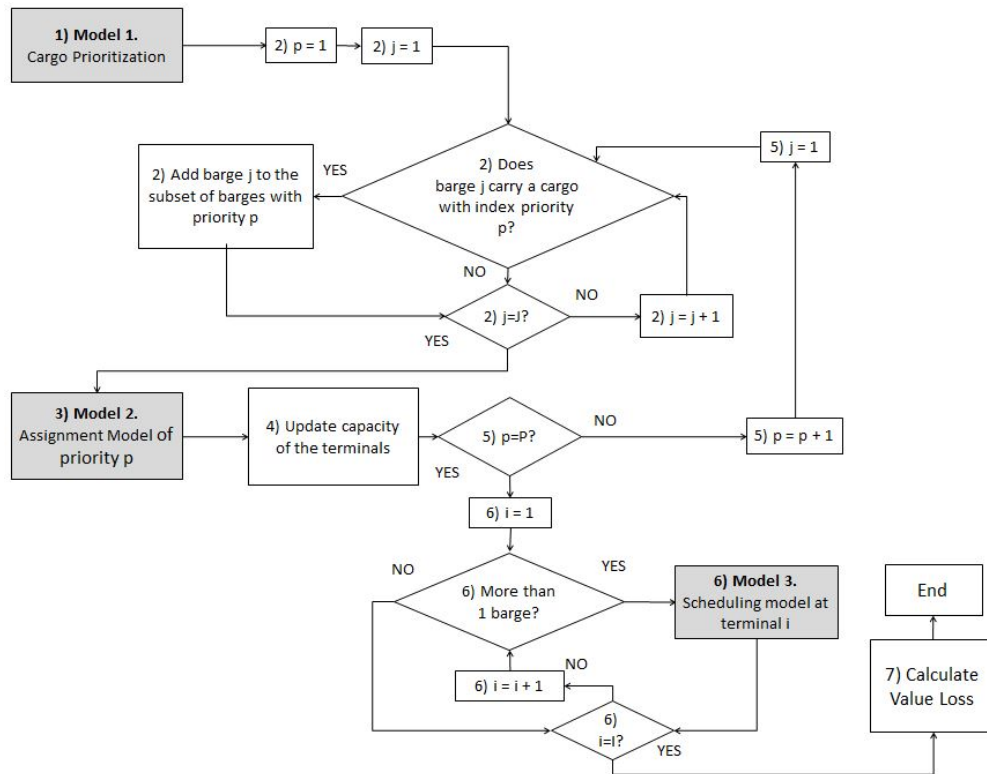


Figure 3.2. Flow diagram DBSH

A sequential use of the Assignment Model (Step 3 in Figure 3.2) is as follows: initially, only those barges carrying the cargo with the highest priority are considered for assignment. This assures that the capacity of the terminals is first consumed by barges with the most important cargo ($p = 1$). Hazardous cargoes are also included in the first run of the assignment model since hazardous cargo is not allowed to remain in the river and must be offloaded.

After running the Assignment Model (Model 2 in Figure 3.2) and knowing which terminals

receive cargo of the highest priority, we update the capacity of those terminals (Step 4 in Figure 3.2). In particular, the capacity available for each terminal to service barges carrying cargo with the second highest priority ($p = 2$) is strictly the remaining capacity after decreasing the capacity that was used by the barges with the highest priority. Once the capacity of the terminals has been updated, a second run of the Assignment Model is needed, this time including barges carrying cargo with the second highest relative priority.

This process continues until barges at all levels of priority (Step 5 in Figure 3.2) have been considered or there is no remaining capacity at the terminals. In the latter case, some non-hazardous barges may remain on the river and their total value is considered lost. The decision of leaving barges on the river to be salvaged at a later date is represented through the assignment of the barges to a dummy terminal.

At this point, all barges have been assigned to a terminal for offloading (or remain on the river for the case when the barges have been assigned to a dummy terminal). However, the sequence in which they will be handled has not been defined yet. Therefore except for the dummy terminal for which scheduling is not needed, in the cases where more than one barge has been assigned to a terminal, we then solve the Scheduling Model (Model 3 in Figure 3.2) at each terminal (Step 6 in Figure 3.2) considering the assigned barges to that particular terminal. Finally, we calculate the value loss derived from the assignment and scheduling decisions obtained with the DBSH (Step 7 in Figure 3.2). Next, we present an explanation of the three components of our approach.

3.4.2 Model 1: Cargo Prioritization Model

The first component of the DBSH deals with identifying the relative priority of each cargo type. The relative priority of each barge is based on pair-wise comparisons that take into account multiple important criteria of the decision makers as shown in Figure 3.3, which displays the four-level AHP decision hierarchy for this problem (Tong & Nachtmann, 2013). The first level of the decision hierarchy presents the global objective of minimizing the negative impacts of the inland waterway disruption. The second and third levels of the decision hierarchy present the cargo's attributes and subattributes, respectively. The fourth level of the decision hierarchy presents the alternatives to prioritize, which are the different types of cargo carried by the barges.

Below we summarize the steps undertaken to determine the relative priority of the cargo (and hence of each barge). For all these steps we use AHP, the WGMM proposed by Xu (2000), and the pair-wise comparison matrices used by Tong and Nachtmann (2013). The first step is to determine the priorities of the attributes shown in the second level of the decision hierarchy based on the aggregation method applied to the pair-wise matrix that makes comparisons between the attributes. There is no need to use AHP and WGMM to calculate the relative priority of the subattributes, since there are only two subattributes for the attributes classified into subattributes.

The next step is to calculate the relative priority of each cargo with respect to the associated subattribute/attribute. These calculations are based on the aggregation method applied to the pair-wise matrices that make comparisons between the alternatives (cargo type) with respect to each subattribute and with respect to the attributes *Value* and *Urgency* (because these attributes are not classified into subattributes).

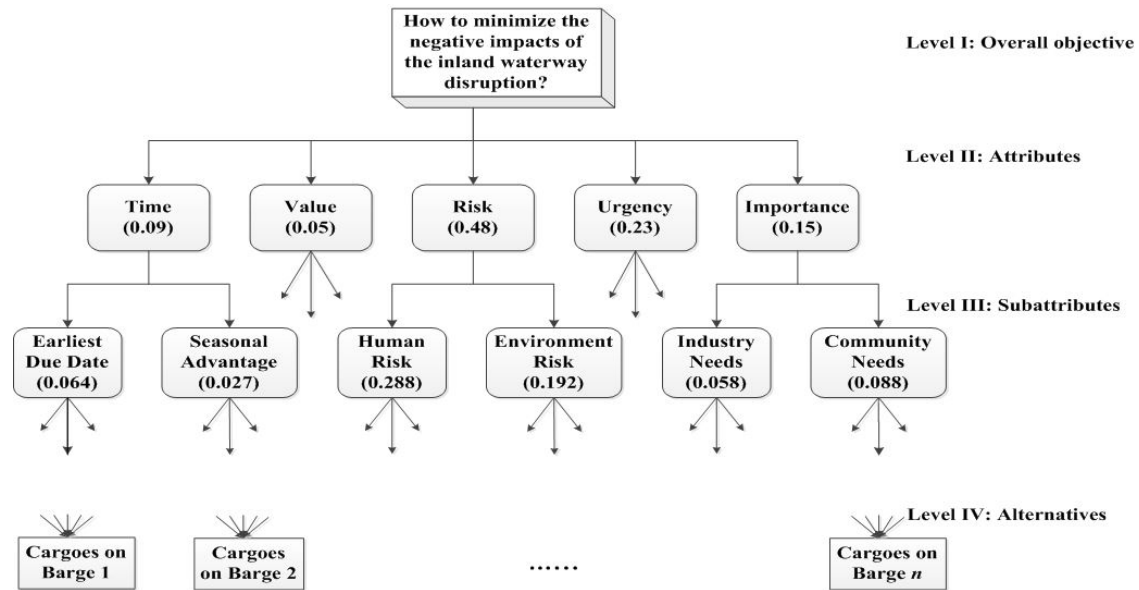


Figure 3.3. AHP decision hierarchy for cargo prioritization within inland waterway transportation (Tong & Nachtmann, 2013)

The priorities of each element at each hierarchy level with respect to the element at the associated higher hierarchy level are used to calculate the overall priorities for the alternatives shown in Table 3.3. The type of cargo with the highest priority (0.386) is Petroleum and the type of cargo with the lowest priority (0.091) is Coal.

Table 3.3. AHP based priority for cargo types

Alternatives (Cargo types)	Priority	Rank
Petroleum	0.386	1
Chemicals	0.178	2
Primary Manufactured Goods	0.126	3
Food and Farm Products	0.124	4
Crude Materials	0.094	5
Coal	0.091	6

3.4.3 Model 2: Assignment Model

The second component of our DBSH is the assignment of disrupted barges to the available terminals. The assignment problem is formulated as an ILP model. The decision variables are $y_{ij} \in \{0, 1\}$, which take value of 1 if barge j is assigned to terminal i ; and 0 otherwise. We use the following notation in our model (Delgado-Hidalgo et al., 2015):

- J is the set of barges carrying non-hazardous cargo
- H is the set of barges carrying hazardous cargo
- I is the set of real terminals
- D is the set of dummy terminals (one, which is used to represent the case when a barge is not assigned to a terminal)
- N is the set of commodity cargo types
- t_{ij} is the water transport time of barge $j \in J \cup H$ from its location at the time of disruption to terminal $i \in I$
- r_{ij} is the land transportation time of barge $j \in J \cup H$ from terminal $i \in I$ to its final destination
- h_{ij} is the handling time of barge $j \in J \cup H$ at terminal $i \in I$
- α_j is the value decreasing rate of barge $j \in J \cup H$ cargo per unit volume per unit time
- c_j is the cargo volume on barge $j \in J \cup H$
- v_j is the value of the cargo on barge $j \in J \cup H$
- e_{jn} is a binary parameter that takes value of 1 if barge $j \in J \cup H$ carries cargo $n \in N$; and 0 otherwise
- u_{in} is the offload capacity for cargo $n \in N$ at terminal $i \in I$ during the disruption response
- w_i is the water depth at terminal $i \in I$
- d_j is the draft depth of barge $j \in J \cup H$
- s is the safety level

p is the sinking threshold

Equation (3.1) corresponds to the objective function which is to minimize the total cargo value loss associated to the assignment decisions. The first part of the objective function consists of the cargo's value decreasing rate α_j , which describes how the cargo loses value as the time elapses and is given in units of volume and units of time, multiplied by the cargo's volume and the transportation time (water and land) plus the handling time. Note that the second part of the objective function is used to represent the cases when the barges carrying non-hazardous cargo cannot be assigned to a terminal. Those cases result in a total value loss equal to the cargo's total value.

$$\text{minimize } \sum_{j \in J \cup H} \sum_{i \in I} (t_{ij} + r_{ij} + h_{ij}) \times c_j \times \alpha_j \times y_{ij} + \sum_{j \in J} \sum_{i \in D} (v_j \times y_{ij}) \quad (3.1)$$

Subject to

$$\sum_{i \in I \cup D} y_{ij} = 1 \quad \forall j \in J \quad (3.2)$$

$$\sum_{i \in I} y_{ij} = 1 \quad \forall j \in H \quad (3.3)$$

$$\sum_{j \in J \cup H} c_j e_{jn} y_{ij} \leq u_{in} \quad \forall i \in I \cup D, n \in N \quad (3.4)$$

$$\sum_{i \in I \cup D} (w_i - d_j) \times y_{ij} \geq s \quad \forall j \in J \cup H \quad (3.5)$$

$$\sum_{i \in I} (t_{ij} + r_{ij} + h_{ij}) \times c_j \times \alpha_j \times y_{ij} \leq v_j \times p \quad \forall j \in J \cup H \quad (3.6)$$

$$y_{ij} \in \{0, 1\} \quad \forall i \in I \cup D, \quad \forall j \in J \cup H \quad (3.7)$$

Constraint set (3.2) ensures that each barge with non-hazardous cargo is assigned to a

terminal, including the dummy terminal as option when the barge is left on the river to be salvaged at a later date. Constraint set (3.3) assures that hazardous cargoes are assigned to a real terminal. Constraint set (3.4) imposes the capacity constraint. This will be the coupling constraint between the different runs of the assignment model (Model 2 in Figure 3.2) in the DBSH. For the first run of the assignment model, the right hand side of this constraint set will be equal to the given capacity of each terminal. Subsequent runs of the assignment model may face a reduction in the available capacity due to assignment decisions made by the previous runs of the assignment model. Constraint set (3.5) ensures that the safety level is observed for any assignment. Constraint set (3.6) is the sinking threshold requirement that assures the value loss for each type of cargo is less than the maximum cargo value loss the customer is willing to accept. Finally, constraint set (3.7) corresponds to the binary nature of the decision variables.

3.4.4 Model 3: Scheduling Model

The third component of our decomposition based sequential heuristic is the scheduling of disrupted barges assigned to a terminal. We formulate the scheduling problem as a MILP model defined on a graph $G = (V, A)$ where the set of vertices $V = B \cup \{o\} \cup \{d\}$ consists of a vertex for each barge in the set B of barges, as well as dummy vertices $\{o\}$ and $\{d\}$ that represent the first and last barge to be serviced at the terminal, respectively. The set of arcs A is a subset of $V \times V$. The decision variables are $x_{jk} \in \{0, 1\}$, $\forall (j, k) \in A$. x_{jk} takes value of 1 if barge j is serviced before barge k ; and 0 otherwise. We also use the decision variables s_j , $\forall j \in V$ to represent the starting service time of barge j . Since the scheduling model is solved at each terminal, the parameters handling time, water transportation time, and land transportation time used to solve the model are the ones associated with that particular terminal. We use the following additional notation in our model:

M is a parameter given a big number. Its function is to discard constraint set (3.13) for the cases when barge $j \in J \cup H$ is not serviced before barge k ($x_{jk} = 0$)

Equation (3.8) represents the objective function which minimizes the total value loss associated with the scheduling decisions. Note that unlike the assignment model objective function (equation 3.1) that assumes a starting service time equal to the water transportation time, the scheduling model defines the starting service time as a decision variable that considers the cases when the barges have to wait to be serviced after their arrival.

$$\text{minimize } \sum_{j \in B} \left[\left(s_j + h_j \sum_{k \in B} x_{jk} + r_j \right) \times c_j \times \alpha_j \right] \quad (3.8)$$

Subject to

$$\sum_{k \in B | (o,k) \in A} x_{ok} = 1 \quad (3.9)$$

$$\sum_{k \in B | (k,d) \in A} x_{kd} = 1 \quad (3.10)$$

$$\sum_{k \in B \cup \{d\} | (j,k) \in A} x_{jk} - \sum_{k \in B \cup \{o\} | (k,j) \in A} x_{kj} = 0 \quad \forall j \in B \quad (3.11)$$

$$\left(s_j + h_j \sum_{k \in B} x_{jk} + r_j \right) \times c_j \times \alpha_j \leq v_j \times p \quad \forall j \in B \quad (3.12)$$

$$s_j + h_j - s_k \leq (1 - x_{jk})M \quad \forall (j,k) \in A \quad (3.13)$$

$$s_j \geq t_j \quad \forall j \in B \quad (3.14)$$

$$x_{jk} \in \{0, 1\} \quad \forall (j,k) \in A \quad (3.15)$$

$$s_j \geq 0 \quad \forall j \in V \quad (3.16)$$

Constraint set (3.9) assures that there is only one barge serviced first. Constraint set (3.10)

assures that there is only one barge serviced last. Constraint set (3.11) is the flow balance constraint that assures there is only one barge serviced at a time, that is, each barge has only one predecessor and only one successor. Constraint set (3.12) is the sinking threshold requirement that assures the value loss for each type of cargo is less than the maximum value loss the customer is willing to accept. Constraint set (3.13) represents the sequence of the barges. Constraint set (3.14) assures that each barge has arrived to the terminal before start being serviced. Constraint sets (3.15) and (3.16) correspond to the nature of the decision variables.

3.5 Computation Results

3.5.1 DBSH Implementation

First, we solve a case study taken from Tong and Nachtmann (2017) which is illustrated in Figure 3.4 (Tong & Nachtmann, 2017). This case study is based on data collected from a 154-mile section of the Upper Mississippi River where a disruption occurs. The section of the river contains six lock and dam (L/D) systems enumerated from fourteen to nineteen. A disruption occurs at lock and dam sixteen which divides the section of the river into two subsections (upper, shaded in light gray; and lower, shaded in dark gray). The upper waterway section includes eight terminals and five barge tows. Based on the navigation direction, two of the five barge tows (shaded ovals) require crossing the point of disruption and therefore are disrupted barge tows. The lower waterway section includes eleven terminals and three disrupted barge tows among a total of eight barge tows.

For the disrupted barge tows, Figure 3.4 illustrates the barges carried by each barge tow. A notation of U or L is given to the barge number to specify if the barge is located at the

upper (U) or lower (L) section of the river respectively. An underlined barge number denotes that a barge is carrying hazardous cargo. The barge tow number, the barge tow location, the number of barges carried by each barge tow, the traveling direction of each barge tow, the section of the river where each barge tow is located at time of disruption, and the barge number carried by each barge tow are presented in Table 3.5.

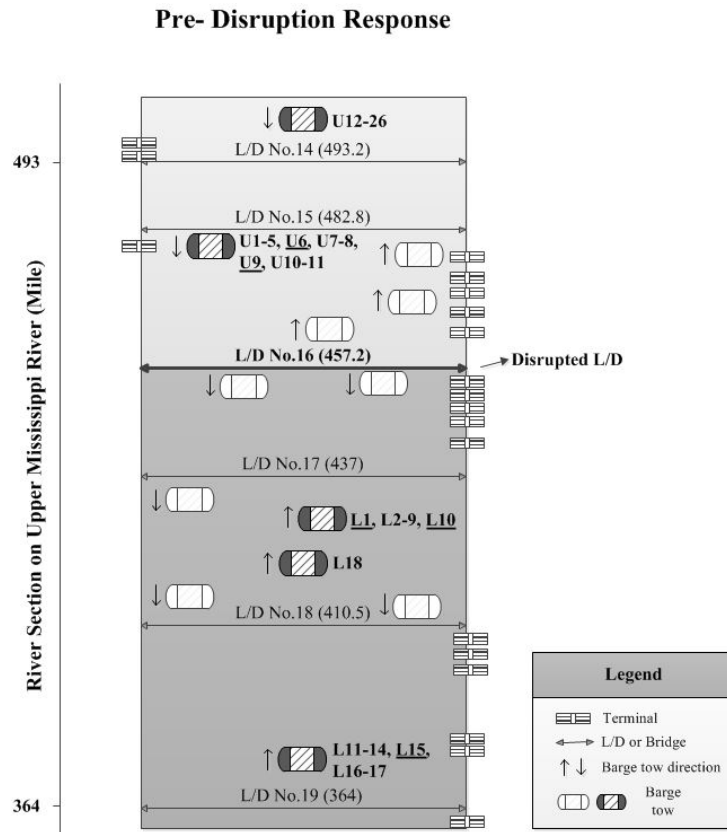


Figure 3.4. River disruption case study (Tong & Nachtmann, 2017)

The rows shaded in light gray and dark gray contain data for the disrupted barge tows in the upper and lower section of the river respectively. The total number of disrupted barges is twenty-six and eighteen for the upper and the lower section of the river respectively.

Table 3.5. Barge location. Updated from Tong and Nachtmann (2017)

Barge tow number	Barge tow location (River mile)	Number of barges	Direction	Section of the river	Barge number
1	373.287	7	up	Lower	L11-17
2	415.752	12	down	Lower	L19-30
3	416.198	15	down	Lower	L31-45
4	422.644	1	up	Lower	L18
5	427.628	10	up	Lower	L1-10
6	427.778	15	down	Lower	L46-60
7	454.999	15	down	Lower	L61-75
8	455.26	15	down	Lower	L76-90
9	461.48	1	up	Upper	U27
10	469.61	5	up	Upper	U28-32
11	476.22	2	up	Upper	U33-34
12	478.187	11	down	Upper	U1-11
13	502.731	15	down	Upper	U12-26

All data related to the case study is assumed to be known. The barge locations are uniformly distributed across the section of the river based on the location of the terminals. The type of cargo carried by each barge is defined based on the probability density function estimated from the tonnage data shown in Table 3.6. The volume of the cargo is assumed to be 1,000 tons per barge. Petroleum and fifty percent of the chemicals are considered hazardous cargo. The value decreasing rate per each cargo type is calculated per 1,000 tons and per hour based on data given in Table 3.6. The cargo value is calculated based on the estimated market price given in Table 3.6 and the cargo volume.

Water transportation time is calculated based on the barge and terminal locations, and the assumed barge average speed of 5 miles per hour. The handling time and land transportation time are uniformly distributed between 5-10 hours and 18-96 hours, respectively. The draft of the barges varies between 6 and 14 feet and is based on a probability density function estimated from the vessels draft data provided by U.S. Army Corps of Engineers Navigation Data Center (USACE, 2012). The water depth of the terminals ranges between 8 and 15 feet. The safety level is set to 1 foot. The capacity of the terminals is assumed to be 5,000

tons per each commodity. The sinking threshold is set to 90%.

Table 3.6. Commodity type data. Updated from Tong and Nachtmann (2017)

Two digit	Cargo Commodity type	Tonnage data	Value decreasing rate (\$ per 1,000 tons per hour)	Market price (\$/ton)
10	Coal, lignite and coal coke	10,288.25	100	36.29
20	Petroleum and petroleum products	1,238.20	600	403.39
30	Chemicals and related product	18,331.33	Hazardous: 600 Non-hazardous: 400	399.88
40	Crude materials, inedible, except fuels	11,364.99	400	134.61
50	Primary manufactured goods	7,843.58	300	396.45
60	Food and farm products	58,670.63	300	164.52

We implement our DBSH with Concert Technology C++ and solve the models with CPLEX 12.6. The DBSH is solved twice, one per each section of the river. We compare our results with the CPTAP results obtained by Tong and Nachtmann (2017). We use the DBSH to obtain the assignment and scheduling of the barges to terminals and calculate the total value loss of our solutions by using Equation 3.17 (Tong & Nachtmann, 2017).

$$\sum_{i \in I} \sum_{j \in J \cup H} \sum_{k \in K} \left[\left(\sum_{m \in J \cup H} \sum_{k' \in K | k' < k} a_{imk'} x_{imk'} + a_{ijk} + r_{ij} \right) \times c_j \alpha_j x_{ijk} \right] + \sum_{i \in D} \sum_{j \in J} \sum_{k \in K} v_j x_{ijk} \quad (3.17)$$

where a_{ijk} is the actual contributing time of barge $j \in J \cup H$ that is assigned to terminal $i \in I$ in the k^{th} order. r_{ij} is the land transportation time of barge $j \in J \cup H$ from terminal $i \in I$ to its final destination. c_j is the cargo volume on barge $j \in J \cup H$. α_j is the value

decreasing rate of barge $j \in J \cup H$ cargo per unit volume per unit time. v_j is the total value of barge $j \in J \cup H$ cargo. x_{ijk} are the decision variables that take value of 1 if barge $j \in J \cup H$ is assigned to terminal $i \in I$ in the k^{th} order; and 0 otherwise.

3.5.2 DBSH Results

We compare the DBSH results with the CPTAP results obtained by Tong and Nachtmann (2017). For the lower waterway section of the case study, our DBSH and the CPTAP approach both result in the same assignment and scheduling decisions as shown in Figure 3.5. Barges L4 and L16 remain on the waterway because their draft depths exceed the water level of the accessible terminals. The total value loss is found to be \$420,302. The solutions for the upper waterway section of the case study differ between the two approaches as shown in Figure 3.5.

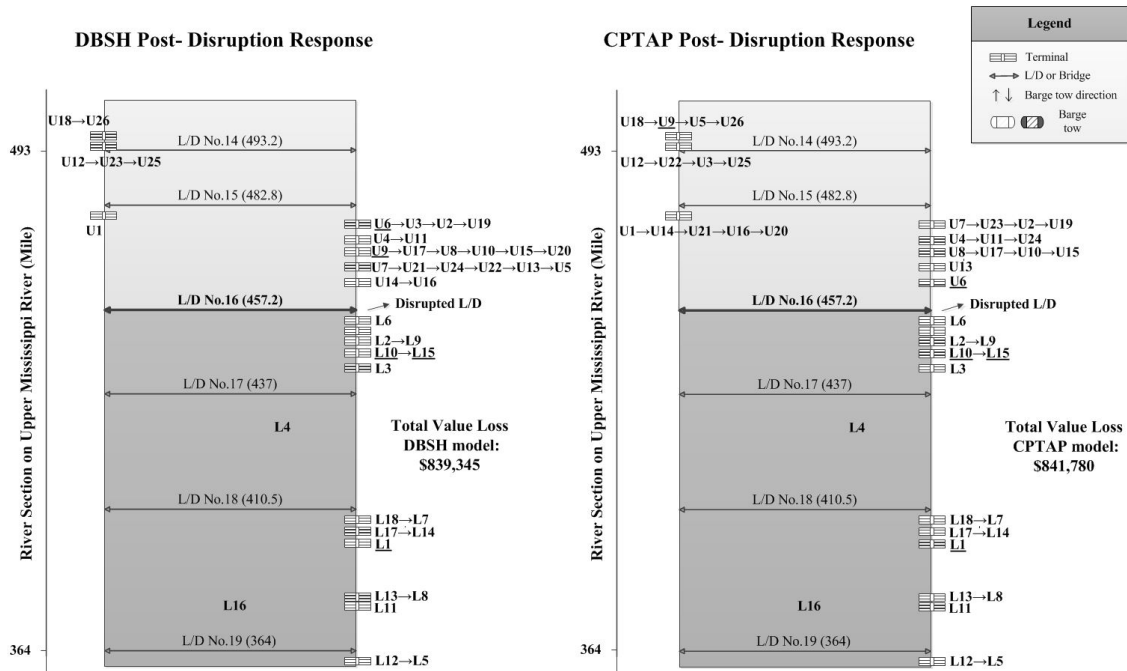


Figure 3.5. DBSH and CPTAP comparison results. Updated from Tong and Nachtmann (2017)

The value loss obtained with the DBSH approach is found to be \$419,043, while the value loss obtained with the CPTAP approach is found to be \$421,478. The total value loss is \$839,345 and \$841,780 obtained when the DBSH and the CPTAP are used respectively. DBSH shows an improvement in the value loss for the upper section of the river with a gap of 0.581% and an improvement in the total value loss with a gap of 0.29%. In addition to the case study, we use our DBSH to solve thirty-five test instances. Tong and Nachtmann (2017) classified these instances as large size because they consist of fifteen terminals and fifty disrupted barges. We focus on solving large size instances because these are the instances that best represent real world-sized transportation system decisions. Moreover, we want to be able to decrease the amount of computational time that is consumed by the CPTAP to solve these large size instances.

We present our results in Table 3.7, which shows the instance number, value loss obtained with CPTAP and DBSH respectively, the gap between these values, CPU time used with each approach, and the gap between the CPU required by CPTAP and DBSH. On average, the value loss obtained with the CPTAP is \$812,403, while the DBSH results in a value loss of \$815,553, which represents a gap of 0.4%. The maximum gap for the cases when CPTAP outperforms the DBSH is 6.42%.

For the computation time criteria, the DBSH outperforms the CPTAP for all instances. The CPTAP CPU time is 201.2 seconds on average, while the DBSH CPU time is 8.3 seconds on average. The gap between the CPTAP CPU time and the DBSH CPU time is -92.3% on average. The maximum gap for the cases when DBSH outperforms the CPTAP computational time is 99.8%. The reason the DBSH outperforms CPTAP in terms of computational time is that the CPTAP model requires the calculation of the actual contributing time of every barge for all possible combinations of terminal assignments, which is a non-linear calculation and computationally expensive.

Table 3.7. Results for large size instances (fifteen terminals and fifty barges)

Instance	Value Loss (\$)			CPU time (s)		
	CPTAP	DBSH	Gap	CPTAP	DBSH	Gap
1	836,646	845,700	1.08%	325.2	11.0	-96.6%
2	819,302	802,562	-2.04%	83.9	3.3	-96.0%
3	780,752	830,886	6.42%	94.6	62.1	-34.4%
4	838,204	841,876	0.44%	82.6	2.0	-97.6%
5	769,850	758,266	-1.50%	48.8	0.8	-98.3%
6	842,632	864,694	2.62%	439.7	7.3	-98.3%
7	749,468	751,568	0.28%	47.4	3.6	-92.3%
8	846,444	841,696	-0.56%	120.0	4.8	-96.0%
9	837,048	818,836	-2.18%	283.8	0.8	-99.7%
10	861,376	849,258	-1.41%	128.1	1.5	-98.8%
11	747,068	726,742	-2.72%	38.9	0.9	-97.7%
12	882,670	899,486	1.91%	200.0	7.7	-96.1%
13	821,966	856,166	4.16%	73.0	6.7	-90.8%
14	824,294	811,894	-1.50%	950.9	1.7	-99.8%
15	807,530	818,704	1.38%	514.9	0.8	-99.8%
16	742,138	764,032	2.95%	91.1	4.9	-94.6%
17	868,730	877,262	0.98%	338.1	4.1	-98.8%
18	781,740	763,284	-2.36%	47.8	0.8	-98.3%
19	893,724	908,046	1.60%	63.0	0.7	-98.9%
20	812,968	824,494	1.42%	140.7	11.0	-92.2%
21	810,704	826,424	1.94%	47.5	1.5	-96.9%
22	841,086	855,230	1.68%	93.0	2.2	-97.6%
23	736,554	722,758	-1.87%	173.9	1.7	-99.0%
24	750,782	735,134	-2.08%	557.1	6.7	-98.8%
25	799,256	804,740	0.69%	323.0	9.8	-97.0%
26	794,052	777,700	-2.06%	102.4	0.7	-99.3%
27	861,198	868,224	0.82%	52.2	0.9	-98.4%
28	896,548	903,080	0.73%	511.2	6.8	-98.7%
29	783,578	805,928	2.85%	196.8	55.3	-71.9%
30	800,514	782,118	-2.30%	59.1	1.6	-97.2%
31	888,756	890,172	0.16%	152.7	6.5	-95.8%
32	745,136	730,576	-1.95%	49.0	0.8	-98.5%
33	791,820	820,186	3.58%	64.0	58.4	-8.8%
34	818,462	822,586	0.50%	432.1	1.2	-99.7%
35	751,114	744,050	-0.94%	115.7	1.3	-98.8%
Mean	812,403	815,553	0.36%	201.2	8.3	-92.30%

We also generate twenty new larger instances of the CPTAP that consider twenty terminals

and seventy disrupted barges. We present the results in Table 3.8. The DBSH was able to solve all the instances, while the CPTAP solved only five out of twenty instances. Furthermore, for instances solved by both approaches, the DBSH reduces the cargo value loss compared to the CPTAP with an average gap of 0.5%. In addition, the DBSH outperforms on the computational time required to solve CPTAP with an average gap of 95.7%. These findings show the benefits of the DBSH to solve large sized decision problems supporting real disruptions.

Table 3.8. Results for larger size instances (twenty terminal and seventy barges)

Instance	Value Loss (\$)			CPU time (s)		
	CPTAP	DBSH	Gap	CPTAP	DBSH	Gap
1	-	1,252,378	-	-	6	-
2	1,087,728	1,076,766	-1.0%	1,202	3	-99.8%
3	-	1,197,990	-	-	9	-
4	1,177,900	1,199,136	1.8%	482	72	-85.0%
5	-	1,106,714	-	-	9	-
6	1,159,580	1,173,904	1.2%	1,846	28	-98.5%
7	-	1,149,226	-	-	19	-
8	-	1,094,372	-	-	15	-
9	-	1,288,792	-	-	23	-
10	-	1,160,520	-	-	65	-
11	-	1,131,440	-	-	117	-
12	1,190,124	1,145,892	-3.7%	656	17	-97.4%
13	-	1,140,460	-	-	14	-
14	-	1,158,238	-	-	18	-
15	-	1,127,432	-	-	18	-
16	-	1,112,616	-	-	14	-
17	1,154,710	1,146,138	-0.7%	725	16	-97.8%
18	-	1,198,044	-	-	17	-
19	-	1,079,994	-	-	75	-
20	-	1,299,602	-	-	24	-
Mean	1,154,008	1,161,983	-0.5%	1,046	28	-95.7%

In this article, we introduced the DBSH approach that solves multiple linear models, updating the remaining capacity after running the previous iterations (assignment model). The possible assignments for each iteration in the DBSH approach are made following a priority index, considering the barges carrying the cargo with the priority index associated with the current iteration. The scheduling component is handled outside the assignment linear models, and the barges are scheduled at each terminal based on the linear scheduling model.

The CPTAP modeling effort is therefore more computationally complex than that of the proposed DBSH. The capabilities of off-the-shelf solvers are better suited to solve linear models over non-linear models. Considering the results and ease of implementation, the use of the less complex and more efficient DBSH approach is recommended.

3.6 Implications for Engineering Managers

In this section, we highlight the implication of this study for engineering managers. Engineering managers require tools such as the DBSH to support their decisions during a disruption response in order to efficiently mitigate the negative impacts. Some disruptions may cause drastic losses not only in terms of either time or money losses but in terms of lives and environmental losses. The closure of the main lock chamber of the Greenup Lock and Dam on the Ohio River, due to emergency repairs in 2003, lasted 52 days and caused an estimated total economic loss of \$41.9 million (The Planning Center of Expertise for Inland Navigation, 2005b). The McAlpine Lock and Dam on the Ohio River closure due to repair extensive cracking in its miter gate lasted ten days and the total economic loss was estimated to be \$9 million (The Planning Center of Expertise for Inland Navigation, 2005a). In April 2017, the navigation on a section of the Mississippi River was closed after nine grain barges broke free from a tow and struck Lock and Dam 22. On the same month, a four-mile section

of the lower Ohio River was closed after a tow boat pushing twenty barges struck Lock and Dam 52. One of the barges was carrying 47,000 gallons of diesel, and the closure caused a queue of sixteen vessels. The waterway closures disrupted the navigation of grain barges from a large portion of the Midwest farm belt to Gulf Coast export terminals, which handle approximately sixty percent of U.S. corn, soybean and wheat export shipments. As a result, the corn cost increased by an estimated two to three cents per bushel (Plume, 2017). Other recent real world examples of inland waterway disruptions and their associated consequences are presented in Table 3.1. In these situations, it is necessary for engineering managers to make quick, efficient, and effective decisions on how best to redirect disrupted cargo in order to reduce negative impacts. Engineering managers in the maritime transportation field specifically need decision support tools to allocate and schedule disrupted barges to inland terminals available after the disruption. These decisions should consider the features of the cargo carried by the barges as hazardous cargo must be handled with a higher priority than non-hazardous and cargo types vary in value and perishability. In this article, we contribute a decision support tool that engineering managers can use to support their inland waterway disruption response efforts.

3.7 Conclusions and Future Work

This article studies the cargo prioritization and terminal allocation problem for inland waterway navigation under disruptive response. This problem integrates two decisions, the assignment of the disrupted barges to terminals where the cargo is offloaded and the scheduling and order in which the barges are served by the assigned terminals. To solve this problem, we propose a decomposition based sequential heuristic (DBSH) that consists of three decision components; a cargo prioritization model, an assignment model, and a scheduling model.

We assume that each barge strictly carries one type of cargo. Therefore, the cargo prioritization also determines the priority index of each barge. These priority indexes are obtained from an AHP approach. The second component, assignment of barges to terminals, is formulated as an ILP model that minimizes the total cargo value loss associated to the assignment decisions. The third component, scheduling of barges assigned to a terminal, is formulated as a MILP model that minimizes total value loss associated with the scheduling decisions. The allocation of barges to terminals is developed by using the ILP in a sequential manner. The ILP is executed for each set of barges carrying cargo with the same priority index. The barges carrying cargo with highest priority are considered in the first run of the model. The capacity is updated, and a second run of the model is executed for the barges carrying cargo with the next highest priority index. This process is repeated until either no capacity is available or all barges have been assigned. The third component of the decision, scheduling the barges offloading at each terminal, is addressed using a MILP model.

Initially, we implement our DBSH to solve thirty-five instances proposed by Tong and Nachtmann (2017) and compare our results with their CPTAP results obtained with a non-linear model and GA approach. We find that the results of our DBSH do not differ practically from the results obtained with the CPTAP approach in terms of the total value loss. However, the computational time is drastically improved with the DBSH. In addition, we generate twenty new and larger size instances to solve the DBSH. For this case, the DBSH was able to solve all instances, while the CPTAP was able to solve only five out of twenty instances. Furthermore, for the instances solved by both approaches, the DBSH outperforms the CPTAP in both cargo value loss and computation time.

Our solution approach consists of linear models, while the model proposed by Tong and Nachtmann (2017) is non-linear. Considering our findings, we conclude the DBSH may be used in order to obtain either similar or better results than the CPTAP approach while

less computational time is required. With this contribution, we have extended the AHP approach that Delgado-Hidalgo et al. (2015) and Tong and Nachtmann (2013) developed to assign a priority index to each cargo carried by the barges. We integrate a modified version of their AHP approach with mathematical models to allocate and schedule prioritized barges to terminals as part of disruption response in inland waterways.

Future work includes integrating the assignment and scheduling model in a single linear model as this would allow us to develop experimental comparison between the hierarchical and the integrated model in terms of the total cargo value loss and considering additional characteristics into the model to study more realistic problems such stochastic handling or transport time.

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Appendix 1



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This memorandum is to confirm that Liliana Delgado-Hidalgo is the first author of the following article and completed at least 51% of the work for the article.

“A Heuristic Approach to Managing Inland Waterway Disruption Response”

4 A Computational Comparison of Cargo Prioritization and Terminal Allocation Problem Models

Abstract

Inland waterway disruptions may interrupt barge tow navigation which can result in significant economic and environmental consequences. Disruption response needs to reroute disrupted barges to accessible terminals to offload their cargo to be transported on land. We investigate how to redirect disrupted barges and prioritize offloading at terminals to minimize the total cargo value loss during inland waterway disruption response. This problem is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP). A previous study formulated the CPTAP as a non-linear integer programming (NLIP) model solved with a genetic algorithm (GA) approach. In this paper, we formulate CPTAP as a mixed integer linear programming (MILP) model and improve its performance through the addition of valid inequalities, which we refer to as MILP'. Due to the complexity of the NLIP, the GA results were validated only for small size instances. We fill this gap by using the lower bounds of MILP' model to validate the quality of all GA solutions. In addition, we compare the MILP' and the GA solutions for several scenarios. The results show that the MILP' formulation outperforms the NLIP model and the GA approach by reducing the total cargo value loss.

Keywords: Disruption Response, Freight Transportation, Cargo Prioritization, Inland Waterways, Integer programming, Valid inequalities

4.1 Introduction

Compared to land and rail transportation modes, inland waterway transportation is safer, less expensive, and more fuel-efficient. Inland waterway transportation system has also a greater capacity to carry high volumes of freight. For dry cargo, the capacity of a fifteen-barge tow is equivalent to the capacity of 16 rail cars or the capacity of 70 truck loads. For liquid cargo, the capacity of a fifteen-barge tow is equivalent to the capacity of 46 rail cars or the capacity of 144 truck loads (Kruse et al., 2017).

Due to these benefits, the U.S. Department of Transportation recognizes inland waterways as a freight alternative to alleviate roadway and railway congestion (Maritime Administration, U.S. Department of Transportation, 2011). However, the inland waterway transportation system faces natural and man-made disruptions including bridge collapses, lock chamber emergency repairs, fires, and chemical run-offs. These disruptions may cause closures of the transportation system, resulting in million of dollars of economic loses as discussed in Delgado-Hidalgo and Nachtmann (2016).

When inland waterway disruptions halt barge tow traffic, barge tows that traverse the disrupted section of the river need to be rerouted. The disrupted barges are redirected to terminals where the cargo is offloaded for transport to its final destination via a land-based transportation mode. The problem of redirecting disrupted barges and prioritizing offloading at accessible terminals to minimize the total cargo value loss is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP) (Tong & Nachtmann, 2017).

A barge tow typically pushes between nine to fifteen barges. The CPTAP assumes that each individual barge transports only one type of cargo whose volume is known, the terminals have limited capacity to offload a single barge at a time, and some barges cannot be offloaded

at certain terminals that are unable to handle that cargo type. The assignment of barges to terminals considers the cargo and its volume, the capacity at each terminal, a clearance requirement between the terminal's water depth and the barge's draft depth, and a sinking threshold that represents the maximum value loss allowed before the customer considers the cargo unacceptable.

The cargo value loss depends on the cargo's value before the disruption occurs, the value decreasing rate, which represents how the cargo loses value as the time elapses; the time it takes the cargo to reach its final destination, and the cargo's volume. The total time associated with the delivering of the cargo consists of the water transportation time, the waiting time, the handling time, and the land-based transportation time.

The CPTAP is similar to another known problem in the literature: the berth allocation problem (BAP) (Imai et al., 1997). The BAP and the CPTAP study the assignment and scheduling of ships to ports. However, the BAP studies the assignment of a set of vessels to a given berth layout in a coastal port, while the CPTAP assigns disrupted barges to inland ports. Although ocean and inland waterway shipping have some similarities, inland waterway transportation has its own specific features and therefore it requires particular attention paid to these features when modeling the system. For instance, inland waterway transportation network contains lock and dam systems that allow barge tows to navigate sections of the river at varying water levels. Lock and dam systems and bridges are unique to the inland waterway transportation network. Another difference between ocean and inland waterway shipping is the size of the ships, since inland waterway transportation requires shallow-draft vessels such as barges to navigate the shallow waterways. Regarding to the shipping routes, unlike ocean shipping in which a route is defined by calling ports and the calling sequence, inland waterway shipping routes are defined only by the calling ports because all ports are located across a single river axis (An et al., 2015).

The BAP has been extensively studied by multiple authors (Bierwirth & Meisel, 2010; Boile et al., 2006; Buhrkal et al., 2011; Cordeau et al., 2005; Imai et al., 1997; Imai et al., 2001, 2003; Imai et al., 2005; Imai et al., 2007; Mauri et al., 2016; Monaco & Sammarra, 2007; Park & Kim, 2003; Umang et al., 2013). However, to the best of our knowledge, only Arango et al. (2011), Grubišić et al. (2014), and Lalla-Ruiz et al. (2018) have studied the BAP for inland waterway transportation system. Moreover, only Tong and Nachtmann (2017) have studied the CPTAP to date. Tong and Nachtmann (2017) formulated the CPTAP as a non-linear integer programming (NLIP) model which was solved with a genetic algorithm (GA) approach. Due to the non-linearity of their model and the complexity of the problem, Tong and Nachtmann (2017) validated the quality of their GA results only for small size instances (5 terminals and less than 9 barges). We aim to fill this gap by validating the quality of the GA solutions for all size instances proposed by Tong and Nachtmann (2017).

In this paper, we formulate CPTAP as a mixed integer linear programming (MILP) model. Based on optimization theory, the solution of a relaxed MILP model is a lower bound of the solution of the MILP model (for minimization objective function problem). We improve our initial formulation by adding valid inequalities, which increases the lower bounds of the MILP model up to 8.1%. This increase means that our improved model (MILP') yields a tighter formulation. In addition, we compare the cargo value loss obtained with the NLIP model, solved with the GA approach, with the cargo value loss obtained with our MILP' model. The results show evidence that the MILP' formulation outperforms the NLIP model solved with the GA approach.

In summary, this paper contributes a decision support technique to redirect disrupted barges and prioritize offloading at accessible terminals to minimize cargo value loss during inland waterway disruption response. Our main contribution is the reduction of the cargo value loss during inland waterway disruption response up to 8.5% in comparison to Tong and

Nachtmann (2017) results.

The structure of the paper is organized as follows. Section 4.2 presents relevant literature review associated with our problem. Section 4.3 presents the definition of the problem we are studying. Section 4.4 consists of three subsections. First, we present our MILP formulation to solve the CPTAP in Section 4.4.1. Then, we improve our initial MILP model through the addition of valid inequalities in Section 4.4.2. Finally, we show the equivalence between the MILP and the NLIP models in Section 4.4.3. Section 4.5 shows the computational results presented in two subsections. In Section 4.5.1, we compare the lower bounds of MILP and the MILP' models to show evidence of improvement resulting in a tighter formulation. In Section 4.5.2, we use the lower bounds of our MILP' model to validate the results obtained by Tong and Nachtmann (2017) with their NLIP and GA approach. In addition, we compare the total cargo value loss obtained when the GA and our MILP' model are used. Finally, we make concluding remarks and discuss future work in Section 4.6.

4.2 Literature Review

Due to the similarities between the CPTAP and the BAP, we review relevant BAP literature in this section. The BAP studies the assignment of a set of vessels to a given berth layout within a given time horizon (Umang et al., 2013). Authors have studied different variants of the BAP. The vessel arrival process characterizes the BAP as either static or dynamic. The static BAP assumes that all the vessels are at the port before starting the assignment of vessels to berths (Imai et al., 1997). On the other hand, the dynamic BAP assumes vessels continue arriving at the port while the vessels are assigned to berths (Imai et al., 2001). Another variant of the BAP depends on the berth layout. The discrete BAP partitions the quay into berths and only one vessel can be serviced at each berth (Imai et al., 2001). On

the contrary, the continuous BAP does not partition the quay and the vessels can berth in any position considering the quay limits (Imai et al., 2005). The hybrid BAP assumes a quay layout that has features of both the discrete and continuous BAP. Like the discrete BAP, the hybrid BAP partitions the quay into berths, however vessels may use more than one berth as in the continuous BAP (Umang et al., 2013).

Imai et al. (1997) were the first authors to introduce the static BAP. They formulated the BAP as a two-objective NLIP model, minimizing overall staying time and dissatisfaction on berthing order. The authors did not consider safety constraints related to the depth and length of the ships. Their model was solved with a weighting method. Later, Imai et al. (2001) extended their initial static variant of the BAP to the dynamic BAP, which was formulated as a mixed integer programming model (MIP). The objective of their model is to minimize the total of waiting and handling times for every ship. The authors solved their model with a heuristic procedure of sub-gradient optimization with lagrangian relaxation. In their formulation, Imai et al. (2001) assumed all berths have the same water depth. Nishimura, Imai, and Papadimitriou (2001) extended the dynamic BAP to consider berths with multiple water depths. The objective function of their NLIP model is to minimize the total service time. The authors developed a heuristic based on GA to solve their model.

The next extension for the dynamic BAP was proposed by Imai et al. (2003). The authors considered ship priorities depending on the service times including the waiting time for an idle berth. They solved their model with GA based heuristic. This model was next reformulated as a MILP model by Boile et al. (2006). The authors developed a heuristic approach based on the concept of online optimization with bounded migration to solve their model. Later, a different formulation for the dynamic BAP was proposed by Cordeau et al. (2005). The authors studied both variants of the BAP, the discrete and the continuous cases. They formulated the BAP as a multi-depot vehicle routing problem with time win-

dows (MDVRPTW). The objective function of their model is to minimize the weighted sum of the service time. Additional constraints were considered in their formulation including service time windows on the ships and availability time windows on the berths. The authors developed two tabu search (TS) heuristics to solve the discrete and continuous BAP.

The discrete and dynamic BAP formulation proposed by Imai et al. (2001) was the base of Monaco and Sammarra (2007) formulation. The authors formulated a MILP model based on the dynamic scheduling problem on unrelated parallel machines. They showed that their formulation is more compact and stronger than Imai et al. (2001) formulation. The authors assumed ships with the same priority and developed a Lagrangean heuristic algorithm to solve their model. The discrete and dynamic BAP model proposed by Imai et al. (2001) was also studied by Buhkal et al. (2011). The authors made a computational comparison between Imai et al. (2001) formulation, an improved version of Cordeau et al. (2005) model, and the generalized set-partitioning (GSP) model proposed by Christese and Holst (2008). They concluded that the GSP model outperforms the other two models.

Regarding to the continuous variant of the BAP, Imai et al. (2005) formulated the dynamic BAP as a non-linear model that minimizes the total service time. The authors assumed that the ship's handling time depends on the ship's berthing location in the quay. The authors solved their model with a two stages heuristic. First, the authors used their algorithm proposed before for the discrete BAP (Imai et al., 2001) to identify a solution given the number of partitioned berths. In a second stage, the authors used another procedure that relocates the overlapped or sparsely located ships resulting from the first stage.

For the dynamic hybrid variant of the BAP, Umang et al. (2013) studied the BAP in bulk ports considering the cargo type on the vessel. The authors formulated two models: a MILP and a GSP. The objective of their models is to minimize the total service time of the vessels.

They also proposed a heuristic algorithm based on squeaky wheel optimization approach to solve larger instances of the problem. Additional BAP literature can be found in the surveys made by Bierwirth and Meisel (2010) and Bierwirth and Meisel (2015).

Unlike Boile et al. (2006), Buhrkal et al. (2011), Christese and Holst (2008), Cordeau et al. (2005), Imai et al. (1997), Imai et al. (2001, 2003), Imai et al. (2005), Monaco and Sammarra (2007), Nishimura et al. (2001), Umang et al. (2013) who studied the BAP for ocean shipping, we investigate the BAP decisions for inland waterway shipping. To the best of our knowledge, only Arango et al. (2011), Grubišić et al. (2014), and Lalla-Ruiz et al. (2018) have studied the BAP for inland waterway transportation system. Arango et al. (2011) studied the discrete and dynamic BAP. They proposed an integrated simulation and optimization model which considers a first-come-first-served allocation strategy and minimizes the total service time for each ship. The authors developed a heuristic procedure based on a GA approach to solve their non-linear problems. On the other hand, Grubišić et al. (2014) solved the dynamic and hybrid BAP under two different scenarios of berth and terminal designs. They proposed a MILP model that minimizes the total time of vessels' stay in port and transshipment operations workload. However, the authors presented the solution of a case example with only five berths and eleven vessels. Lalla-Ruiz et al. (2018) studied the waterway ship scheduling problem (WSSP). The WSSP differs from the BAP in that the WSSP assigns ships to waterways rather than berths. The authors formulated their model as a MILP that minimizes the total time required for the ships to pass through the waterways. Lalla-Ruiz et al. (2018) proposed a greedy heuristic based on commonly used queue rules as well as a simulated annealing (SA) algorithm to solve their problem.

Like Arango et al. (2011), Grubišić et al. (2014), and Lalla-Ruiz et al. (2018) our paper focuses on the BAP decisions for inland waterway transportation system. However, we consider three additional components: cargo prioritization, inland waterway disruption events,

and cargo value loss during disruption response. The BAP decisions and these three components define the CPTAP studied by Tong and Nachtmann (2017). The authors formulated the CPTAP as a NLIP model and developed a GA approach to solve three cases classified as small, medium, and large size instances. Due to the complexity of their model, Tong and Nachtmann (2017) validated the quality of their GA solutions only for small size instances. In this paper, we fill this gap by validating the GA solutions for medium and large size instances and reducing the total value loss obtained by Tong and Nachtmann (2017). To achieve this purpose, we formulate the CPTAP as a MILP model that later is improved through the addition of valid inequalities resulting in the MILP' model. We use the lower bounds of the MILP' model to validate the quality of the GA solutions for all size instances proposed by Tong and Nachtmann (2017).

4.3 Problem Definition

In this section we describe the CPTAP by using an inland waterway disruption event occurred on January 20, 2014. Figure 4.1 shows the Arkansas and Missouri railroad bridge located in Fort Smith. This bridge has a system of cables that are used to vertically lift the center of the bridge to allow river traffic to pass beneath. Due to a malfunction, the Arkansas and Missouri railroad bridge became stuck halting barge tows traffic on the Arkansas River (McGeeny & Magsam, 2014).



Figure 4.1. Arkansas and Missouri railroad bridge (McGeeny & Magsam, 2014)

Figure 4.2 graphically represents the Arkansas River disruption. The disrupted section of the river has five lock and damn (L/D) systems (Figure 4.2). L/D are unique systems to inland waterway transportation network and allow barge tows to navigate sections of the river at varying water levels. The inland waterway disrupted section has ten inland terminals or inland ports located along both sides of the river (Figure 4.2). Inland terminals have multiple water depths, limited capacity, and equipment to handle specific type of commodities. Figure 4.2 also shows eight barge tows which commonly carry between nine to fifteen barges each. Barges are flat-bottomed boats with varying draft depths that are used to transport cargo. Among the barge tows navigating the section of the river at time of disruption, two barge tows (shaded in white) have already passed beneath the broken bridge and are not impacted by the disruption. The other six barge tows (shaded in black), which consist of approximately sixty barges, require passage beneath the broken bridge and are therefore affected by the disruption.

The disrupted barges are no longer able to continue their original travels and their cargo need to be transferred to a land-based transportation mode for transport to its final destination. The CPTAP redirects disrupted barges and prioritizes offloading at accessible terminals and aims to minimize total cargo value loss during disruption response to mitigate inland waterways post-disaster outcomes.

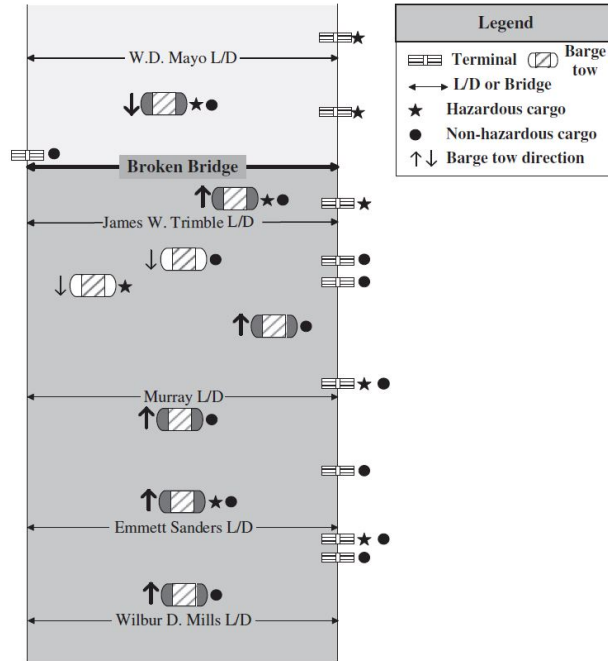


Figure 4.2. Arkansas river disruption (Tong & Nachtmann, 2017)

The cargo losses value depending on the cargo’s volume, its value decreasing rate, and the time it takes the cargo to reach its final destination. The value decreasing rate is the “rate at which the cargo’s economic and societal value diminishes as time elapses” (Tong & Nachtmann, 2017, p. 6). A cargo with higher rate losses value faster than a cargo with a lower value decreasing rate. Therefore, CPTAP considers the cargo’s value decreasing rate to assign higher offloading priorities to cargo with higher rates.

The total time to deliver the cargo consists of the water transportation time, waiting time, handling time, and land-based transportation time. The water transportation time is the time spent traveling from the location of the barge when the disruption occurs to the terminal where the barge is reassigned. The waiting time occurs since a barge arrives to its assigned terminal until the completion service time of its predecessor barge. The handling time to process and offload the cargo depends on the cargo itself, the barge, and the terminal. The land transportation time is the time spent traveling from the terminal where the barge is offloaded to the cargo’s final destination.

The CPTAP assumes that each barge carries only one type of cargo that can be hazardous/non-hazardous and whose volume is known. If a barge carries a hazardous cargo, it must be assigned to a terminal. However, if the barge carries non-hazardous cargo, it may be left on the waterways to be salvaged at a later date if (1) there are terminal limitations that do not allow to handle the cargo or (2) the customer considers that the value loss when the cargo would reach its final destination is not acceptable. CPTAP represents the customer's maximum allowable cargo value loss by using a sinking threshold coefficient. The decision of leaving cargo on the waterways is represented through the assignment of the barge to a dummy terminal in which case the cargo value loss is the total value of the cargo.

The CPTAP assumes the terminals have limited capacity to offload a single barge at a time and some barges cannot be offloaded at certain terminals that are unable to handle that cargo type. The assignment of barges to terminals considers the cargo and its volume, the capacity at each terminal, and a clearance requirement between the terminal's water depth and the barge's draft depth to assure the barges safely travel into the terminals.

4.4 Models for the Cargo Prioritization and Terminal Allocation Problem

The original CPTAP formulation is the NLIP model proposed by Tong and Nachtmann (2017), which is described in the Appendix. In this section we describe an alternative CPTAP formulation in the form of a mixed integer linear programming (MILP). Then, we present an improvement to the MILP formulation through the addition of valid inequalities. This improvement results in the MILP' model which is a tighter formulation that requires less computational time. Finally, we show equivalence between the MILP and the NLIP models.

4.4.1 Mixed Integer Linear Programming Formulation (MILP)

In this section, we reformulate the CPTAP as a MILP model. The MILP is obtained when we reformulate the CPTAP as a heterogeneous vehicle routing problem with time windows (HVRPTW), where the vehicles correspond to the inland terminals and the customers represent the barges that need to be serviced at the terminals. The problem is defined on a graph $G = (V, A)$ where the set of vertices $V = B \cup \{o\} \cup \{d\}$ consists of a vertex for each barge in the set B of barges, as well as dummy vertices $\{o\}$ and $\{d\}$ used to represent the first and last barge to be serviced at a terminal respectively. The set of arcs A is a subset of $V \times V$. The notation used in the MILP model is the following:

Sets

- B set of barges
- NH set of barges carrying non-hazardous cargo
- H set of barges carrying hazardous cargo
- K set of real terminals
- D set of dummy terminals (one)
- N set of commodity cargo types
- V nodes in the network. $V = B \cup \{o\} \cup \{d\}$. Where $\{o\}$ is a dummy source node, and $\{d\}$ is a dummy sink node
- A arcs (i, j) in the network. Where $i \in B \cup \{o\}$, $j \in B \cup \{d\}$, and $i \neq j$

Parameters

t_i^k	water transport time of barge $i \in B$ from its location at the time of disruption to terminal $k \in K$
l_i^k	land transportation time of barge $i \in B$ from terminal $k \in K$ to its final destination
h_i^k	handling time of barge $i \in B$ at terminal $k \in K$
c_i	cargo volume on barge $i \in B$
α_i	value decreasing rate per unit of volume and per unit of time of cargo carried by barge $i \in B$
v_i	total value of barge $i \in B$ cargo
e_{in}	1 if barge $i \in B$ carries cargo $n \in N$; 0 otherwise
u_{kn}	offload capacity for cargo $n \in N$ at terminal $k \in K$ during the disruption response
w_k	water depth at terminal $k \in K$
d_i	draft depth of barge $i \in B$
s	safety level/clearance
b_i	latest time at which a cargo $i \in B$ must be delivered to its final customer because after that time the cargo value loss is not acceptable by the customer
M_{ij}^k	defined as the $\max\{b_i + h_i^k - t_j^k, 0\}$ such that $(i, j) \in A$ and $k \in K$

Decision Variables

$y_i^k \in \{0, 1\}$	1 if barge i is assigned to terminal k ; 0, otherwise, where $i \in B$ and $k \in K \cup D$
$x_{ij}^k \in \{0, 1\}$	1 if barge i is serviced before barge j at terminal k ; 0, otherwise, where $(i, j) \in A$ and $k \in K \cup D$
T_i^k	starting service time of barge i at terminal k , where $i \in V$ and $k \in K$

MILP

$$\text{minimize } \sum_{k \in K} \sum_{i \in B} [(T_i^k + (h_i^k + l_i^k) y_i^k) c_i \alpha_i] + \sum_{k \in D} \sum_{i \in NH} v_i y_i^k \quad (4.1)$$

Subject to:

$$\sum_{k \in K \cup D} y_i^k = 1 \quad \forall i \in B \quad (4.2)$$

$$\sum_{k \in K} y_i^k = 1 \quad \forall i \in H \quad (4.3)$$

$$\sum_{j \in BU\{d\} | (o,j) \in A} x_{oj}^k \leq 1 \quad \forall k \in K \quad (4.4)$$

$$\sum_{i \in BU\{o\} | (i,d) \in A} x_{id}^k \leq 1 \quad \forall k \in K \quad (4.5)$$

$$\sum_{j \in BU\{d\} | (i,j) \in A} x_{ij}^k - \sum_{j \in BU\{o\} | (j,i) \in A} x_{ji}^k = 0 \quad \forall k \in K, i \in B \quad (4.6)$$

$$\sum_{j \in BU\{d\} | (i,j) \in A} x_{ij}^k = y_i^k \quad \forall k \in K, i \in B \quad (4.7)$$

$$\sum_{i \in B} c_i e_{in} y_i^k \leq u_{kn} \quad \forall k \in K, n \in N \quad (4.8)$$

$$\sum_{k \in K} (w_k - d_i) y_i^k \geq s \left(1 - \sum_{k \in D} y_i^k \right) \quad \forall i \in B \quad (4.9)$$

$$T_i^k \geq t_i^k y_i^k \quad \forall k \in K, i \in B \quad (4.10)$$

$$\sum_{k \in K} (T_i^k + (h_i^k + l_i^k) y_i^k) \leq b_i \quad \forall i \in B \quad (4.11)$$

$$T_i^k + h_i^k - T_j^k \leq (1 - x_{ij}^k) M_{ij}^k \quad \forall k \in K, (i, j) \in A \quad (4.12)$$

$$T_i^k \geq 0 \quad \forall k \in K, i \in B \quad (4.13)$$

$$y_i^k \in \{0, 1\} \quad \forall k \in K \cup D, i \in B \quad (4.14)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall k \in K \cup D, (i, j) \in A \quad (4.15)$$

Equation (4.1) is the objective function which minimizes total cargo value loss. The first part of the objective function is associated with barges, carrying hazardous or non-hazardous cargo, which are assigned to a real terminal. As stated previously, the value loss depends on the cargo value, the cargo volume, the cargo value decreasing rate, and the time it takes the cargo to arrive to its final destination. This time consists of the barge starting service time, the handling time of the barge at that particular terminal, and the land transportation time from the assigned terminal to the cargo's final destination. The barge starting service time consists of the water transportation time from the location of the barge at time of disruption to the assigned terminal plus the barge waiting time to be serviced. The second part of the objective function represents the case in which barges carrying non-hazardous cargo are allowed to remain on the waterway to be salvaged at a later date. This decision is represented through the assignment of the barges to the dummy terminal D . For this case, the value loss is the total value of the cargo.

Constraint set (4.2) ensures that each barge is assigned to a terminal, including the dummy terminal. Constraint set (4.3) assures that barges carrying hazardous cargo are assigned to a real terminal. Constraint set (4.4) and (4.5) establish that at each real terminal there is only one barge serviced first and only one barge serviced last, respectively. Constraint set (4.6) is the flow balance conservation constraint, which ensures that each barge assigned to a real terminal has a predecessor barge (including the dummy source barge $\{o\}$) and a successor barge (including the dummy sink barge $\{d\}$) serviced at the same terminal. Constraint set (4.7) represents the link between the decision variables x_{ij}^k and y_i^k . Constraint set (4.8) imposes the capacity constraint for each cargo at each terminal. Constraint set (4.9) imposes a clearance between the terminal's water depth and the barge's draft depth to guarantee the barges safely travel into the terminals. Constraint sets (4.10) and (4.11) enforce the time windows requirements. Constraint set (4.10) assures that a barge starting service time occurs after the barge's arrival to the terminal. Constraint set (4.11) imposes the upper bound of

the time windows constraint. It is the latest delivery time before the customer considers the cargo unacceptable due to its value loss. Constraint set (4.12) assures the time sequence of barges serviced at each real terminal. We define M_{ij}^k as $M_{ij}^k = \max\{b_i + h_i^k - t_j^k, 0\}$, the explanation is the following:

- When $x_{ij}^k = 0$ and $M_{ij}^k = 0$, constraint set (4.12) becomes $T_i^k + h_i^k \leq T_j^k$. Since $M_{ij}^k = \max\{b_i + h_i^k - t_j^k, 0\}$, $M_{ij}^k = 0$ means that $t_j^k \geq b_i + h_i^k$. From constraint set (4.10), $T_j^k \geq t_j^k$, therefore $T_j^k \geq b_i + h_i^k$. Also, from constraint set (4.11), $b_i \geq T_i^k$, therefore $T_j^k \geq T_i^k + h_i^k$ holds.
- When $x_{ij}^k = 0$ and $M_{ij}^k = b_i + h_i^k - t_j^k$, constraint set (4.12) becomes $T_i^k + h_i^k \leq T_j^k + b_i + h_i^k - t_j^k$ or equivalently $T_i^k - b_i \leq T_j^k - t_j^k$, which always holds since $T_i^k \leq b_i$ (constraint set 4.11) and $T_j^k \geq t_j^k$ (constraint set 4.10)

Finally, constraint set (4.13), (4.14), and (4.15) correspond to the nature of the decision variables.

4.4.2 Improved Formulation with valid inequalities (MILP')

In this section we improve our initial MILP formulation for the CPTAP by adding valid inequalities. The resulting MILP' model is a tighter formulation that reduces the computation time to solve the CPTAP. We note that the continuous decision variables T_i^k are a main component in the objective function (Equation (4.1)) with lower and upper bounds given in Equations (4.10) and (4.11) respectively. Since the MILP model has a minimization objective function, we expect a barge starts being serviced as soon as the terminal is available (after completion service time of its predecessor barge) and the barge has arrived

to the assigned terminal (i.e. unnecessary waiting time is not allowed). Therefore, the value of the T_j^k decision variable in an optimal solution is given by $T_j^k = \max\{T_i^k + h_i^k, t_j^k\}$, where i is the predecessor barge and j is the successor barge. Because $T_i^k \geq t_i^k$ (equation 4.10), then $T_j^k \geq \max\{t_i^k + h_i^k, t_j^k\}$, where $t_i^k + h_i^k$ represents the minimum possible completion time of the predecessor barge i at terminal k . Moreover, constraint sets (4.4)-(4.6) impose that each barge has only one predecessor and only one successor (including the source and sink dummy barges), which means that for each successor barge j and each terminal k , only one x_{ij}^k decision variable is active in the optimal solution. Therefore, we add constraint set (4.16) as a set of valid inequalities.

$$\sum_{i \in B \cup \{o\} | (i,j) \in A} (t_i^k + h_i^k) \times x_{ij}^k \leq T_j^k \quad \forall k \in K, \forall j \in B \cup \{d\} \quad (4.16)$$

For the cases where the minimum possible completion time of a predecessor barge i is greater than the arrival time of a successor barge j , ($t_i^k + h_i^k > t_j^k$), the addition of constraint set (4.16) results in a tighter formulation because these valid inequalities remove solutions where the starting service time of the successor barge j is greater than its arrival time but it is less than the minimum possible completion time of its predecessor barge i , ($t_j^k \leq T_j^k < t_i^k + h_i^k$). This means that the valid inequalities cut out solutions where the starting service time of the successor barge j , T_j^k , falls into the interval $[t_j^k, t_i^k + h_i^k)$.

Buhrkal et al. (2011) proposed a similar valid inequality for the case when time windows for berths are also considered. We define the resulting model after adding the valid inequalities, Equations (4.1)-(4.16), as MILP' model. In the results section, we present a comparison between the MILP and the MILP' models to show evidence that the valid inequalities improve the original formulation.

4.4.3 Equivalence between MILP and NLIP models

We provide insights regarding the equivalence between our MILP model and the NLIP model (see Appendix) proposed by Tong and Nachtmann (2017) by comparing the decision variables for both formulations.

Decision Variables NLIP:

$x_{ip}^k \in \{0, 1\}$ 1 if barge i is assigned to terminal k in the p th order; 0, otherwise.

Decision Variables MILP:

$y_i^k \in \{0, 1\}$ 1 if barge i is assigned to terminal k ; 0, otherwise, where $i \in B$ and $k \in K \cup D$

$x_{ij}^k \in \{0, 1\}$ 1 if barge i is serviced before barge j at terminal k ; 0, otherwise, where $(i, j) \in A$ and $k \in K \cup D$

T_i^k starting service time of barge i at terminal k , where $i \in V$ and $k \in K$

Constraint set (4.7) in the MILP model establishes the relation between the assignment, y_i^k , and the scheduling, x_{ij}^k , decision variables as follows: $\sum_{j \in B \cup \{d\} | (i,j) \in A} x_{ij}^k = y_i^k \quad \forall k \in K, i \in B$. We note that the NLIP decision variables x_{ip}^k can be expressed in terms of the MILP decision variables y_i^k in the same manner: $\sum_{p \in P} x_{ip}^k = y_i^k \quad \forall k \in K, i \in B$. Therefore, the equivalence between the MILP and NLIP decision variables is given by the following expression: $y_i^k = \sum_{j \in B \cup \{d\} | (i,j) \in A} x_{ij}^k = \sum_{p \in P} x_{ip}^k \quad \forall k \in K, i \in B$.

Next, we analyze the equivalence between the MILP and NLIP models in regards to the T_i^k MILP decision variables. We start by introducing the contributing time parameter used in the NLIP model. The NLIP requires a_{ip}^k , the actual contributing time of barge i that is

assigned to terminal k in the p th order, where

$$a_{ip}^k = \begin{cases} t_i^k + h_i^k & p = 1 & (4.17a) \\ h_i^k & p \neq 1 \text{ and } t_i^k \leq \sum_{m \in B} \sum_{p' \in P|p' < p} a_{mp'}^k & (4.17b) \\ \left(t_i^k - \sum_{m \in B} \sum_{p' \in P|p' < p} a_{mp'}^k \right) + h_i^k & p \neq 1 \text{ and } t_i^k > \sum_{m \in B} \sum_{p' \in P|p' < p} a_{mp'}^k & (4.17c) \end{cases}$$

The actual contributing time of a barge to a terminal consists of the terminal's idle time while waiting for the barge's arrival to be serviced plus the barge handling time at the terminal. There are three possible cases for the calculation of the actual contributing time (Equations 4.17a, 4.17b, 4.17c). The handling time is considered for all cases; however the terminal's idle time varies as follows. If a barge is serviced first ($p = 1$, Equation 4.17a), the terminal's idle time coincides with the barge's arrival time (water transportation time). On the other hand, when a barge is not serviced first ($p \neq 1$), if the barge arrives to the assigned terminal before the completion service time of its predecessor (Equation 4.17b), the terminal does not have idle time. Otherwise, if the barge arrives to the assigned terminal after the completion service time of its predecessor (Equation 4.17c), the terminal's idle time is the barge's arrival time minus the cumulative contributing time of the predecessor barges.

Regarding the MILP model, when $x_{ij}^k = 1$, from constraints sets (4.10) and (4.12) we have that $T_j^k = \max\{T_i^k + h_i^k, t_j^k\}$. We note that MILP and NLIP models are equivalent based on equation 4.18:

$$a_{ip}^k + \sum_{m \in B} \sum_{p' \in P|p' < p} a_{mp'}^k = T_i^k + h_i^k \quad \forall i \in B, k \in K, p \in P \quad (4.18)$$

Proof: We prove equation 4.18 by induction.

- When $p = 1$,

Based on equation 4.17a of the NLIP model, for $p = 1$, $a_{i1}^k = t_i^k + h_i^k$. Based on the relation $T_i^k = \max\{t_0^k + h_0^k, t_i^k\}$ from the MILP model and considering that $t_0^k = h_0^k = 0$ and $t_i^k > 0$, then $T_i^k = t_i^k$. Therefore, $a_{i1}^k = T_i^k + h_i^k$ and equation 4.18 holds.

- When $p = 2$,

1. If $t_{i+1}^k \leq a_{i1}^k$, and since $a_{i1}^k = T_i^k + h_i^k$, then $t_{i+1}^k \leq T_i^k + h_i^k$.

If $t_{i+1}^k \leq a_{i1}^k$, based on equation 4.17b of the NLIP model, $a_{(i+1)(2)}^k = h_{i+1}^k$

Based on $T_{i+1}^k = \max\{T_i^k + h_i^k, t_{i+1}^k\}$ from the MILP model and that $t_{i+1}^k \leq T_i^k + h_i^k$, we have that $T_{i+1}^k = T_i^k + h_i^k$.

Therefore, $a_{i1}^k + a_{(i+1)(2)}^k = T_i^k + h_i^k + h_{i+1}^k$, and since $T_{i+1}^k = T_i^k + h_i^k$, then $a_{i1}^k + a_{(i+1)(2)}^k = T_{i+1}^k + h_{i+1}^k$ and equation 4.18 holds.

2. If $t_{i+1}^k > a_{i1}^k$, and since $a_{i1}^k = T_i^k + h_i^k$, then $t_{i+1}^k > T_i^k + h_i^k$.

If $t_{i+1}^k > a_{i1}^k$, based on equation 4.17c of the NLIP model, $a_{(i+1)(2)}^k = t_{i+1}^k - [a_{i1}^k] + h_{i+1}^k = t_{i+1}^k - [T_i^k + h_i^k] + h_{i+1}^k$.

Based on $T_{i+1}^k = \max\{T_i^k + h_i^k, t_{i+1}^k\}$ from the MILP model and that $t_{i+1}^k > T_i^k + h_i^k$, we have that $T_{i+1}^k = t_{i+1}^k$.

Therefore, $a_{i1}^k + a_{(i+1)(2)}^k = T_i^k + h_i^k + t_{i+1}^k - [T_i^k + h_i^k] + h_{i+1}^k = t_{i+1}^k + h_{i+1}^k$, and since $T_{i+1}^k = t_{i+1}^k$, then $a_{i1}^k + a_{(i+1)(2)}^k = T_{i+1}^k + h_{i+1}^k$ and equation 4.18 holds.

- *Induction hypothesis:*

Let $p = n$, assume $a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k = T_{i+n-1}^k + h_{i+n-1}^k$.

- Now we show that when $p = n + 1$, $a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k + a_{(i+n)(n+1)}^k = T_{i+n}^k + h_{i+n}^k$ holds true.

1. If $t_{i+n}^k \leq a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k$, and since from induction hypothesis $a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k = T_{i+n-1}^k + h_{i+n-1}^k$, then $t_{i+n}^k \leq T_{i+n-1}^k + h_{i+n-1}^k$.

If $t_{i+n}^k \leq a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k$, based on equation 4.17b of the NLIP model $a_{(i+n)(n+1)}^k = h_{i+n}^k$.

Based on $T_{i+n}^k = \max\{T_{i+n-1}^k + h_{i+n-1}^k, t_{i+n}^k\}$ from the MILP model and that $t_{i+n}^k \leq T_{i+n-1}^k + h_{i+n-1}^k$, we have that $T_{i+n}^k = T_{i+n-1}^k + h_{i+n-1}^k$.

Therefore, $[a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k] + [a_{(i+n)(n+1)}^k] = [T_{i+n-1}^k + h_{i+n-1}^k] + [h_{i+n}^k]$, and since $T_{i+n}^k = T_{i+n-1}^k + h_{i+n-1}^k$, then $[a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k] + a_{(i+n)(n+1)}^k = T_{i+n}^k + h_{i+n}^k$ and equation 4.18 holds.

2. If $t_{i+n}^k > a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k$, and since from induction hypothesis $a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k = T_{i+n-1}^k + h_{i+n-1}^k$, then $t_{i+n}^k > T_{i+n-1}^k + h_{i+n-1}^k$.

If $t_{i+n}^k > a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k$, based on equation 4.17c of the NLIP model $a_{(i+n)(n+1)}^k = t_{i+n}^k - [T_{i+n-1}^k + h_{i+n-1}^k] + h_{i+n}^k$.

Based on $T_{i+n}^k = \max\{T_{i+n-1}^k + h_{i+n-1}^k, t_{i+n}^k\}$ from the MILP model and that $t_{i+n}^k > T_{i+n-1}^k + h_{i+n-1}^k$, we have that $T_{i+n}^k = t_{i+n}^k$.

Therefore, $[a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k] + [a_{(i+n)(n+1)}^k] = [T_{i+n-1}^k + h_{i+n-1}^k] + [t_{i+n}^k - [T_{i+n-1}^k + h_{i+n-1}^k] + h_{i+n}^k] = t_{i+n}^k + h_{i+n}^k$, and since $T_{i+n}^k = t_{i+n}^k$, then $[a_{i1}^k + a_{(i+1)(2)}^k + \dots + a_{(i+n-1)(n)}^k] + [a_{(i+n)(n+1)}^k] = T_{i+n}^k + h_{i+n}^k$ and equation 4.18 holds. \square

4.5 Computational Results

We validate and compare the solutions of the MILP and MILP' models in Section 4.5.1. To validate the models, we compare the optimal solutions with the lower bounds (LBs) of each model that are obtained when the relaxed version of each model is solved. We also compare the LBs of both models to show evidence that MILP' provides higher LBs and therefore is tighter than the MILP formulation. Then in Section 4.5.2, we validate and compare the solutions of the MILP' model and the NLIP model solved with the GA approach developed by Tong and Nachtmann (2017). We use the LBs of our improved MILP' model to validate the results obtained by Tong and Nachtmann (2017) with their NLIP solved with their GA approach. In addition, we compare the solutions of the GA and MILP' model twice. For the first comparison, we run the MILP' model for the same computational time that Tong and Nachtmann (2017) used to run their GA approach (less than 16 minutes). This allows us to make a fair initial comparison. For the second comparison, we run the MILP' model for seven hours to assess how much improvement the MILP' model provides when it is solved for longer computational time.

We use the instances proposed by Tong and Nachtmann (2017) to present our results. The authors

categorized fifty-five test instances into five cases depending on the size of the instances (number of terminals and number of barges). The instances that consider 5 terminals and between 5-9 barges, 10 terminals and 30 barges, and 15 terminals and 50 barges are classified as small, medium, and large size instances respectively. Table 4.4 presents the number of instances generated, number of terminals, and number of barges considered for each case.

Table 4.4. Instances general description (Tong & Nachtmann, 2017)

Case	No. Instances	No. Terminals	No. Barges
C1 (small size)	5	5	5
C2 (small size)	5	5	7
C3 (small size)	5	5	9
C4 (medium size)	10	10	30
C5 (large size)	30	15	50

The instances generated by Tong and Nachtmann (2017) are based on data collected from the Upper Mississippi River which we summarize in Tables 4.5 and 4.6. The water transportation time is calculated based on the terminal and barge locations and the assumed barge average speed as shown in Table 4.5. The probability density function for the barge draft is estimated from data provided by U.S. Army Corps of Engineers Navigation Data Center (USACE, 2012).

Table 4.5. Instance generation data (Tong & Nachtmann, 2017)

Parameter	Data / distribution function
Barge location	uniformly distributed across the study region
Cargo volume	1,000 tons per barge
Barge average speed	5 miles per hour
Handling time	uniformly distributed between 5-10 hours
Land transportation time	uniformly distributed between 18-96 hours
Barge draft	between 6 and 14 feet
Terminals water depth	between 8 and 15 feet
Safety level	1 foot
Terminals capacity	5,000 tons per each type of cargo

The cargo type carried by each barge is based on the probability density function estimated from the tonnage data presented in Table 4.6. Petroleum is considered hazardous cargo as well as fifty percent of the chemicals. The value decreasing rate per each type of cargo is calculated per 1,000 tons and per hour based on data provided in Table 4.6. The cargo value is calculated based on the market price shown in Table 4.6.

Table 4.6. Commodity type data. Updated from Tong and Nachtmann (2017)

Two digit	Cargo Commodity type	Tonnage data	Value decreasing rate (\$ per 1,000 tons per hour)	Market price (\$/ton)
10	Coal, lignite and coal coke	10,288.25	100	36.29
20	Petroleum and petroleum products	1,238.20	600	403.39
30	Chemicals and related product	18,331.33	Hazardous: 600 Non-hazardous: 400	399.88
40	Crude materials, inedible, except fuels	11,364.99	300	134.61
50	Primary manufactured goods	7,843.58	300	396.45
60	Food and farm products	58,670.63	400	164.52

Tong and Nachtmann (2017) solved their NLIP with the GA approach and obtained optimal solutions for small size instances. We implemented our model using CPLEX 12.6 and ran the model on a Dell Intel inside core i7 processor. We obtained optimal solutions for small size instances with our initial and our improved formulations.

4.5.1 MILP and MILP' Models Validation and Comparison

Initially, we use the fifteen instances associated with the three cases for which we obtained optimal solutions to validate the quality of our MILP and MILP' models. We show evidence that the MILP' model is a tighter formulation, since MILP' provides better LBs (higher values for minimization problems). We use Table 4.7 to present these results. The first three columns of Table 4.7 show the case, instance number (Ins), and the optimal solution (Opt) for each instance. The next columns present the solution of the relaxed MILP model (LB, under MILP heading), computational time to solve the MILP model (Time, under MILP heading), and the optimality gap of the MILP model (Gap, under MILP heading). In the same manner, the following columns present the solution of the relaxed MILP' model (LB, under MILP' heading), computational time to solve the MILP' model (Time, under MILP' heading), and the optimality gap of the MILP' model (Gap, under MILP' heading). The optimality gap is calculated as $(Opt - LB)/LB$. The last two columns of Table 4.7 show the gap between the lower bounds obtained with the solution of the relaxed MILP' and MILP models (LB, under Gap heading) and the gap between the computational time to solve MILP' and MILP models (Time, under Gap heading). These gaps are calculated as $(MILP' LB - MILP LB)/MILP LB$ and $(MILP' Time - MILP Time)/MILP Time$ respectively. All the computational times presented in the tables are given in seconds.

The MILP model optimality gap is on average 10.0% with a minimum gap of 3.5% for Instance 5 and a maximum gap of 17.2% for Instance 2. On the other hand, the MILP' model optimality gap is on average 4.7% with a minimum gap of 0.5% for Instance 3 and a maximum gap of 13.4% for Instance 2. These values show the quality of the results from both models. Moreover, the addition of valid inequalities increases the LB of MILP model by 5.0% on average and up to 8.1% (Instance 15). The MILP' model reduces the computational time by 84.0% on average and up to 93.0% (Instance 14). Due to the size of the problem, MILP' model is not able to obtain optimal solutions for medium and large size instances. If medium and large size instances are considered, the addition of valid inequalities increases the LB of MILP model by 6.5% on average and up

to 10%. These results show that the MILP' model is tighter than the MILP model, which is evidence of the improvement obtained when the valid inequalities are added to our initial formulation.

Table 4.7. MILP and MILP' validation and comparison

Ins.	Optimal (Opt)	MILP			MILP'			Gap		
		LB	Time	Gap	LB	Time	Gap	LB	Time	
C1	1	89,756	85,976	0.84	4.4%	88,622	0.19	1.3%	3.1%	-77.4%
	2	110,906	94,597	0.97	17.2%	97,799	0.30	13.4%	3.4%	-69.1%
	3	109,112	105,332	1.25	3.6%	108,584	0.25	0.5%	3.1%	-80.0%
	4	84,804	77,952	3.03	8.8%	80,592	0.44	5.2%	3.4%	-85.5%
	5	95,268	92,028	2.14	3.5%	93,813	0.42	1.6%	1.9%	-80.4%
C2	6	106,700	100,398	2.59	6.3%	103,430	0.27	3.2%	3.0%	-89.6%
	7	78,032	73,112	2.25	6.7%	75,590	0.50	3.2%	3.4%	-77.8%
	8	100,828	87,150	3.51	15.7%	94,246	0.58	7.0%	8.1%	-83.5%
	9	105,402	94,056	3.51	12.1%	101,369	0.64	4.0%	7.8%	-81.8%
	10	134,448	122,304	3.38	9.9%	130,667	0.61	2.9%	6.8%	-82.0%
C3	11	160,330	146,200	4.87	9.7%	154,223	0.56	4.0%	5.5%	-88.5%
	12	156,186	144,270	6.4	8.3%	150,464	0.53	3.8%	4.3%	-91.7%
	13	147,344	131,192	5.93	12.3%	141,224	0.64	4.3%	7.6%	-89.2%
	14	133,528	116,056	17.5	15.1%	123,135	1.23	8.4%	6.1%	-93.0%
	15	175,852	150,194	7.04	17.1%	162,388	0.66	8.3%	8.1%	-90.6%

4.5.2 NLIP and MILP' Validation and Comparison

The main complexity of the NLIP is calculating the actual contributing time for a given barge, since this time computation depends on the actual contributing time of all barges that have an earlier priority and have been served in the same terminal before the given barge. Note that this calculation resembles a nested structure, non-linear in nature and computationally expensive. To solve the NLIP, Tong and Nachtmann (2017) proposed a Genetic Algorithm (GA).

To evaluate the quality of a solution, researchers calculate the gap between the LB and the solution. Unlike a MILP formulation which provides a LB by means of the solution of its linear relaxation,

NLIP does not provide a LB directly. In order to evaluate the quality of their algorithm, Tong and Nachtmann (2017) proposed a strategy to obtain a LB. They replaced the actual contributing time with an “overestimated” value as $a_{ip}^k = t_i^k + h_i^k + l_i^k$ and solved their NLIP by using the solver Knitro for NLIP. However, due to the complexity of their model, the LB could be obtained only for the small size instances. Therefore, the quality of their NLIP model solved with the GA approach was evaluated only for small instances. We fill this gap by validating the GA solutions for all size instances proposed by Tong and Nachtmann (2017). We compare the GA solutions with the LB obtained with the solution of the linear relaxation of our MILP’ model.

Table 4.8. GA and MILP’ validation and comparison for small size instances

Ins.	Optimal (Opt)	LB	Opt Gap	Time			
				GA	MILP’	Gap	
C1	1	89,756	88,622	1.3%	8.8	0.2	-97.8%
	2	110,906	97,799	13.4%	8.6	0.3	-96.5%
	3	109,112	108,584	0.5%	8.6	0.3	-97.1%
	4	84,804	80,592	5.2%	8.6	0.4	-94.9%
	5	95,268	93,813	1.6%	8.6	0.4	-95.1%
mean	97,969	93,882	4.4%	8.6	0.3	-96.3%	
C2	6	106,700	103,430	3.2%	9.3	0.3	-97.1%
	7	78,032	75,590	3.2%	9.4	0.5	-94.7%
	8	100,828	94,246	7.0%	9.4	0.6	-93.8%
	9	105,402	101,369	4.0%	9.4	0.6	-93.2%
	10	134,448	130,667	2.9%	9.3	0.6	-93.4%
mean	105,082	101,060	4.0%	9.3	0.5	-94.4%	
C3	11	160,330	154,223	4.0%	10.5	0.6	-94.6%
	12	156,186	150,464	3.8%	14.1	0.5	-96.2%
	13	147,344	141,224	4.3%	12.8	0.6	-95.0%
	14	133,528	123,135	8.4%	10.6	1.2	-88.4%
	15	175,852	162,388	8.3%	10.0	0.7	-93.4%
mean	154,648	146,287	5.8%	11.6	0.7	-93.5%	

For small size instances, both GA and MILP’ obtain optimal solutions. Table 4.8 presents the case, instance number (Ins), optimal solution (Opt), lower bounds (LB), optimality gap (Opt Gap), computation time required to solve both approaches GA (GA, under Time heading) and MILP’

(MILP', under Time heading), and the gap between both computational times (Gap, under Time heading). Since both approaches obtain optimal solutions, the only difference in their performance for small size instances is the computational time. Table 4.8 shows that the MILP' outperforms the GA in terms of computational time to solve small size instances. The gaps between GA and MILP' computational time are 96.3%, 94.4%, and 93.5% on average for Cases 1, 2, and 3 respectively.

In Tables 4.9 and 4.10, we validate and compare the GA and MILP' approaches for medium and large size instances respectively. To make a fair initial comparison, in Tables 4.9 and 4.10 we record the solution of the MILP' model obtained when the model is run for the same computational time as Tong and Nachtmann (2017) used to solve their GA approach (less than 16 minutes). In Table 4.11, we summarize a second comparison between GA and MILP' approaches for medium and large size instances. For this second comparison, we run the MILP' model for up to seven hours on high performance computers of the Arkansas High Performance Computing Center at the University of Arkansas.

Table 4.9. GA and MILP' validation and comparison for medium size instances

Ins.	LB	GA		MILP'		Gap Solutions
		Solution	Gap LB	Solution	Gap LB	GA - MILP'
16	417,038	485,006	16.3%	472,966	13.4%	2.5%
17	443,969	501,560	13.0%	503,268	13.4%	-0.3%
18	447,428	505,892	13.1%	494,698	10.6%	2.3%
19	496,698	549,308	10.6%	543,292	9.4%	1.1%
20	364,230	424,098	16.4%	415,846	14.2%	2.0%
21	441,991	505,930	14.5%	493,290	11.6%	2.6%
22	425,868	480,822	12.9%	472,838	11.0%	1.7%
23	464,071	547,550	18.0%	537,792	15.9%	1.8%
24	473,122	524,986	11.0%	514,026	8.6%	2.1%
25	435,545	492,860	13.2%	488,894	12.2%	0.8%
mean	440,996	501,801	13.9%	493,691	12.03%	1.7%

Table 4.10. GA and MILP' validation and comparison for large size instances

Ins.	LB	GA		MILP'		Gap Solutions
		Solution	Gap LB	Solution	Gap LB	GA - MILP'
26	705,406	836,646	18.6%	804,050	14.0%	4.1%
27	677,274	819,302	21.0%	784,276	15.8%	4.5%
28	681,614	780,752	14.5%	751,028	10.2%	4.0%
29	711,708	838,204	17.8%	793,004	11.4%	5.7%
30	704,904	842,632	19.5%	815,338	15.7%	3.3%
31	658,505	749,468	13.8%	714,612	8.5%	4.9%
32	696,309	846,444	21.6%	787,732	13.1%	7.5%
33	689,265	837,048	21.4%	782,972	13.6%	6.9%
34	729,727	861,376	18.0%	827,790	13.4%	4.1%
35	626,957	747,068	19.2%	720,690	15.0%	3.7%
36	709,711	882,670	24.4%	851,550	20.0%	3.7%
37	699,993	821,966	17.4%	788,368	12.6%	4.3%
38	703,918	807,530	14.7%	770,766	9.5%	4.8%
39	645,291	742,138	15.0%	724,208	12.2%	2.5%
C5 40	745,841	868,730	16.5%	826,780	10.9%	5.1%
41	773,633	893,724	15.5%	863,938	11.7%	3.4%
42	680,933	812,968	19.4%	794,144	16.6%	2.4%
43	692,476	810,704	17.1%	763,490	10.3%	6.2%
44	703,960	841,086	19.5%	818,070	16.2%	2.8%
45	618,322	736,554	19.1%	700,402	13.3%	5.2%
46	636,661	750,782	17.9%	707,466	11.1%	6.1%
47	680,104	799,256	17.5%	754,232	10.9%	6.0%
48	755,512	861,198	14.0%	830,424	9.9%	3.7%
49	741,044	896,548	21.0%	870,034	17.4%	3.0%
50	667,810	783,578	17.3%	748,906	12.1%	4.6%
51	675,678	800,514	18.5%	737,970	9.2%	8.5%
52	755,993	888,756	17.6%	862,412	14.1%	3.1%
53	642,554	745,136	16.0%	713,746	11.1%	4.4%
54	701,603	791,820	12.9%	789,682	12.6%	0.3%
55	700,451	818,462	16.8%	762,860	8.9%	7.3%
mean	693,772	817,102	17.8%	782,031	12.7%	4.5%

Tables 4.9, 4.10, and 4.11 present the case, instance number (Ins), lower bound (LB), GA solution (Solution, under GA heading), gap between the GA solution and the LB (Gap LB, under GA heading), the MILP' solution (Solution, under MILP' heading), the gap between the MILP' solution and the LB (Gap LB, under MILP' heading), and the gap between the solutions for both approaches

(Gap solutions GA - MILP'). The gap between a solution and a LB is calculated as $(solution - LB)/LB$, and the Gap solutions GA - MILP' is calculated as $(GA\ solution - MILP'\ solution)/MILP'$ solution.

Table 4.9 shows that the average gap between the GA solutions and the LB is 13.9% for medium size instances. On the other hand, this gap is 12.03% for MILP' solutions. These results validate the quality of the solutions obtained with both approaches for medium size instances. In addition, the gap between the solutions obtained with both approaches shows that the MILP' outperforms GA for all but instance number 17. However, the gap between the solutions is only 1.7% on average.

Table 4.10 shows that the gap between the GA solutions and the LB is on average 17.8% for large size instances. On the other hand, this gap is 12.7% for MILP' solutions. These results validate the quality of the solutions obtained with both approaches for large size instances. In addition, the gap between the solutions obtained with both approaches shows that the MILP' outperforms GA for all large size instances. The gap between the solutions is 4.5% on average.

If the MILP' model is run for up to seven hours, the gap between the solution and the LB is improved on average to 10.5% for medium size instances and to 10.1% for large size instances (Table 4.11). The gap between the solutions obtained with GA and MILP' approaches is improved to 3.0% and to 7.0% for medium and large size instances respectively. However, the computer runs out of memory when solving seven out of thirty large size instances.

Table 4.11. GA and MILP' validation and comparison for medium and large size instances (7 hr)

		LB	GA		MILP'		Gap Solutions
			Solution	Gap LB	Solution	Gap LB	GA - MILP'
C4	mean	440,996	501,801	13.9%	486,978	10.5%	3.0%
C5	mean	693,772	817,102	17.8%	764,049	10.1%	7.0%

4.6 Conclusions

In this paper, we investigate how to improve inland waterway post-disaster outcomes by reducing the total cargo value loss during disruption response. We develop a new decision support technique to redirect disrupted barges and prioritize offloading at accessible terminals during disruption response. We target our work to benefit key inland waterway decision makers including the U.S. Coast Guard, U.S. Army Corps of Engineers, and U.S. Department of Transportation.

The problem studied in this research is known in previous literature as the cargo prioritization and terminal allocation problem (CPTAP). A previous study formulated the CPTAP as a non-linear integer programming (NLIP) model that was solved with a genetic algorithm (GA) approach. Due to the non-linearity of the model, the authors validated the quality of their solutions strictly for small size instances (5 terminals and less than 9 disrupted barges). In this paper, we propose a new CPTAP formulation as a mixed integer linear programming (MILP) model that is improved through the addition of valid inequalities. Our paper makes three major contributions: (1) we show how the addition of valid inequalities results in a tighter formulation that provides more accurate lower bounds and reduce the response time to solve the CPTAP, (2) we use the lower bounds obtained with the solution of the relaxed version of our improved model to fill the gap in the previous study by validating the quality of the NLIP and GA solutions for all size instances, and (3) we reduce the total cargo value loss during inland waterway disruption response in comparison to the previous approach.

Our results validated the quality of the NLIP model solved with the GA approach since the maximum gap between the GA solution and the lower bounds for all instances is 24.2%. However, the solutions obtained with our improved formulation (MILP') outperform the NLIP and GA solutions by reducing the cargo value loss during disruption response. Moreover, due to the non-linearity of the model, solving the NLIP required the development of a heuristic such as GA. In contrast, the linearity of the objective and constraints in the MILP' formulation facilitates the use of off-the-shelf

solvers such as CPLEX. Therefore, we conclude that our new CPTAP approach not only provides better results, it is easier to implement.

As a pure mathematical approach, our model is built to provide optimal solutions. However, due to the complexity of the CPTAP, MILP' is not capable of solving large sized realistic problems to optimality. To obtain a quality feasible solution, we set a time limit up to seven hours to solve the model before the computer runs out of memory. Future work includes: (1) exploring the structure of the model to propose a solution method that decomposes the problem into subproblems that are more tractable to solve, (2) examining additional solution approach to solve the CPTAP such as an exact method that exploits the effectiveness of the proposed model, while the decomposition method reduces the response time to solve the CPTAP, and (3) considering additional features in the model to represent more realistic problems, for instance stochastic barge arrival time and handling time.

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Appendix 1

Non-Linear Integer Programming Formulation (NLIP), excerpted from Tong and Nachtmann (2017)

The additional notation for the NLIP formulation is as follows:

P set of barge orders at a given terminal

r sinking threshold

a_{ip}^k actual contributing time of barge i that is assigned to terminal k in the p th order

Decision Variables

$x_{ip}^k \in \{0, 1\}$ 1 if barge i is assigned to terminal k in the p th order; 0, otherwise.

NLIP

$$\text{minimize } \sum_{k \in K} \sum_{i \in B} \sum_{p \in P} \left[\left(\sum_{m \in B} \sum_{p' \in P | p' < p} a_{mp'}^k x_{mp'}^k + a_{ip}^k + l_i^k \right) c_i \alpha_i x_{ip}^k \right] + \sum_{k \in D} \sum_{i \in NH} \sum_{p \in P} v_i x_{ip}^k \quad (4.19)$$

Subject to:

$$\sum_{k \in K \cup D} \sum_{p \in P} x_{ip}^k = 1 \quad \forall i \in NH \quad (4.20)$$

$$\sum_{k \in K} \sum_{p \in P} x_{ip}^k = 1 \quad \forall i \in H \quad (4.21)$$

$$\sum_{i \in B} x_{ip}^k \leq 1 \quad \forall k \in K, p \in P \quad (4.22)$$

$$\sum_{i \in B} x_{ip}^k \geq \sum_{i \in B} x_{i(p+1)}^k \quad \forall k \in K \cup D, p \in P/|P| \quad (4.23)$$

$$\sum_{i \in B} \sum_{p \in P} c_i e_{kn} x_{ip}^k \leq u_{kn} \quad \forall k \in K \cup D, n \in N \quad (4.24)$$

$$\sum_{k \in K} \sum_{p \in P} (w_k - d_i) x_{ip}^k \geq s \quad \forall i \in B \quad (4.25)$$

$$\sum_{k \in K} \sum_{p \in P} \left(\sum_{m \in B} \sum_{p' \in P | p' < p} a_{mp'}^k x_{mp'}^k + a_{ip}^k + l_i^k \right) c_i \alpha_i x_{ip}^k \leq v_i r \quad \forall i \in B \quad (4.26)$$

$$x_{ip}^k \in \{0, 1\} \quad \forall k \in K \cup D, p \in P, i \in B \quad (4.27)$$

We note that constraint set (4.26) resembles time windows constraints. Since the cargo value v_i is given in dollars and the sinking threshold r is a percentage, constraint set (4.26) is given in units of dollars. However, we can rewrite these constraints as follows:

$$\sum_{k \in K} \sum_{p \in P} \left(\sum_{m \in B} \sum_{p' \in P | p' < p} a_m^k x_{mp'}^k + a_i^k + l_i^k \right) x_{ip}^k \leq b_i \quad \forall i \in B \quad (4.28)$$

Where b_i is the upper bound of the time windows, such that:

$$b_i = \frac{v_i(\$) \times r(\%) }{c_i(\text{ton}) \times \alpha_i \left(\frac{\$}{s \times \text{ton}} \right)} \quad (4.29)$$

b_i represents the latest time at which a cargo must be delivered to its final customer because after that time the cargo value loss is not acceptable by the customer. Note that the sinking threshold constraint set (4.28) now is given in units of time, since all the terms in the left hand side are given in units of second (s) and the right hand side b_i results also in units of seconds (Equation 4.29).

Appendix 2



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This memorandum is to confirm that Liliana Delgado-Hidalgo is the first author of the following article and completed at least 51% of the work for the article.

“A Computational Comparison for Cargo Prioritization and Terminal Allocation Problem Models”

5 An Exact Algorithm for the Cargo Prioritization and Terminal Allocation Problem

Abstract

Inland waterways face natural and man-made disruptions that affect navigation and infrastructure operations and may lead to barge traffic disruptions and economic losses. We study inland waterway disruption response in order to redirect disrupted barges to available terminals and prioritize offloading to minimize total cargo value loss. This problem is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP) and was previously formulated as a non-linear integer programming (NLIP) model solved with a genetic algorithm (GA) approach. In this article, we present a new CPTAP formulation and a first known exact method to solve this problem. First, we present a mixed integer linear programming (MILP) model, which is then reformulated via Dantzig-Wolfe decomposition approach and solved with a branch-and-price technique. Earlier work obtained optimal solutions for small instances of CPTAP with up to five terminals and nine barges. The primary contribution of this work is obtaining optimal solutions of the CPTAP for instances consisting of up to ten terminals and thirty barges in a reasonable computational time.

Keywords: Disruption Response, Freight Transportation, Cargo Prioritization, Inland Waterways, Dantzig-Wolfe Decomposition, Branch-and-Price Approach.

5.1 Introduction

The freight transportation demand via land-based mode in United States is increasing faster than the land network capacity is growing, thus leading to roadway and rail congestion issues (Strocko et al., 2014). Shifting freight to the inland waterway transportation network can lessen roadway

and railway congestion since a single barge has the equivalent capacity to sixteen rail cars or seventy tractor trailers (Kruse, Protopapas, & Olson, 2012). In addition, the inland waterway transportation mode is cost-effective, safe, and environmentally-friendly (Kruse et al., 2017) and is becoming more relevant with the increasing demand for multi-modal network transportation (Lalla-Ruiz et al., 2016). However, the inland waterways face natural and man-made disruptions that may affect navigation and infrastructure operations, thus leading to barge traffic disruptions and economic losses as discussed in Delgado-Hidalgo and Nachtmann (2016).

We study inland waterway disruption response to redirect disrupted barges to available terminals and prioritize offloading to minimize total cargo value loss. The cargo value loss depends on the cargo's volume, the time it takes the cargo to reach its final destination, and the value decreasing rate defined as "the rate at which the cargo's economic and societal value diminishes as time elapses" (Tong & Nachtmann, 2017, p. 6). The problem studied in this article is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP) first studied by Tong and Nachtmann (2017).

The CPTAP assigns disrupted barges to available terminals and prioritizes cargo offloading to minimize total value loss during inland waterway disruption response. CPTAP assumes that each barge carries a single type of commodity that can be hazardous or non-hazardous. The prioritization component of the CPTAP is based on the cargo value decreasing rate, where cargo with a higher value decreasing rate is given a higher priority to be offloaded. CPTAP also assumes that only one barge at a time can be offloaded at one time into a terminal, terminals have limited offloading capacity, and some terminals are not able to handle certain types of cargo. The CPTAP considers barges' service time windows constraints and safety constraints with regards to the terminal's water depth and the barge's draft depth.

The CPTAP has similarity to the berth allocation problem (BAP) studied first by Imai et al. (1997). The BAP and the CPTAP study a maritime transportation planning problem which assigns and schedules vessels to berths. However, these two problems are different from each other since the

BAP focuses on ocean shipping and coastal port berths, whereas the CPTAP focuses on inland waterway navigation and inland terminals. Inland waterway navigation differs from ocean shipping in three key ways: (i) the inland waterway transportation contains lock and dam systems used to navigate waterways with varying water levels and maintain navigation pools, (ii) the vessels used in inland waterway transportation have shallow draft depths suitable for river navigation, and (iii) inland shipping routes are determined only by calling terminals in contrast to ocean shipping routes that require the description of port calling sequence as well (An et al., 2015).

The BAP for coastal ports has been extensively studied in the literature. See Bierwirth and Meisel (2010) and Bierwirth and Meisel (2015) for surveys on relevant BAP literature. On the other hand, research on the BAP for inland terminals (Arango et al., 2011; Grubišić et al., 2014; Lalla-Ruiz et al., 2018) and BAP in the context of disruptions (Umang et al., 2017; Zhang et al., 2016) have received little attention. The CPTAP extends the BAP by considering three additional components; cargo prioritization, disruption events, and inland waterway shipping. To the best of our knowledge, only Tong and Nachtmann (2017) and Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) have studied the CPTAP to date.

Tong and Nachtmann (2017) formulated the CPTAP as a non-linear integer programming (NLIP) model and obtained optimal solutions for small size instances involving up to five terminals and nine barges. In order to solve larger instances, Tong and Nachtmann (2017) developed a genetic algorithm (GA) approach and obtained solutions for instances considering up to fifteen terminals and fifty barges. However, due to the complexity of their model, the GA results were only validated for small size instances.

Later, Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) formulated the CPTAP as a mixed integer linear programming (MILP) model which was improved through the addition of valid inequalities. The authors obtained optimal solutions only for small size instances (five terminals and less than nine barges). For medium size instances (ten terminals and thirty barges) and large size instances (fifteen terminals and fifty barges), the authors obtained solutions with average gaps of

12.03% and 12.7% respectively in a computational time less than fifteen minutes. When the model was run for a limited time of seven hours, the average gaps were 10.5% and 10.1% for medium and large size instances respectively. Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) showed that the addition of valid inequalities improved the lower bounds (obtained at the root node) of the MILP model in 5.0% on average and up to 8.1% for the small size instances. However, even for the instances that they obtained optimal solutions, the optimality gap for fifteen small size instances was on average 4.73%, which shows that the linear relaxation of the MILP formulation yields weak lower bounds.

In order to improve the lower bounds and solve additional instances, in this research we reformulate Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.)'s MILP model via Dantzig-Wolfe decomposition approach to present a new and tighter CPTAP formulation. We develop the first known exact method based on a branch-and-price technique to solve the CPTAP. Our primary contribution is obtaining the optimal solutions to larger instances of the CPTAP consisting of up to ten terminals and thirty barges.

The remaining of this article is organized as follows. Section 5.2 presents a review of the relevant literature associated with our work. Section 5.3 presents a definition of the problem we are studying. We present the model formulation and the Dantzig-Wolfe reformulation in Section 5.4. Section 5.5 presents the branch-and-price approach consisting of the column generation approach and branching techniques to obtain integer solutions. We present our results in Section 5.6 and conclusions and future work in Section 5.7.

5.2 Literature Review

Due to the similarity between the CPTAP and the BAP, we discuss the relevant and recent literature for the BAP. The literature classifies the BAP into three aspects: (i) vessel arrival process, (ii) berth layout, and (iii) nature of the parameters. The vessel arrival process categorizes the BAP as static

or dynamic. The static BAP assumes the vessels are waiting at the port before the berth allocation plan starts (Imai et al., 1997; Qin et al., 2016), while the dynamic BAP assumes that vessels continue arriving at the port while the berth allocation plan is in progress (Arango et al., 2011; Boile et al., 2006; Buhrkal et al., 2011; Cordeau et al., 2005; Grubišić et al., 2014; Imai et al., 2001, 2003; Imai et al., 2005; Imai et al., 2007; Monaco & Sammarra, 2007; Qin et al., 2016; Simrin & Diabat, 2015; Umang et al., 2017; Yan et al., 2015).

The berth layout categorizes the BAP as discrete (DBAP), continuous (CBAP), or hybrid (HBAP). In the DBAP, the quay is partitioned into berths and only one vessel can be serviced at each berth (Arango et al., 2011; Boile et al., 2006; Buhrkal et al., 2011; Cordeau et al., 2005; Grubišić et al., 2014; Hu, 2015b; Imai et al., 1997; Imai et al., 2001, 2003; Imai et al., 2007; Kordić et al., 2016; Mauri et al., 2016; Monaco & Sammarra, 2007; Venturini et al., 2017). While in the CBAP, the quay is not partitioned and the vessels can berth in any position within the quay limits (CenkŞahin & Kuvvetli, 2016; Du et al., 2015; Ernst et al., 2017; Imai et al., 2005; Mauri et al., 2016; Xu & Lee, 2018). On the other hand, the HBAP is a combination of DBAP and the CBAP. Similar to the DBAP, the HBAP partitions the quay into berths, however vessels can use more than one berth as in the CBAP (Kordić et al., 2016; Umang et al., 2017; Umang et al., 2013).

The nature of the parameters classifies the BAP as deterministic (D-BAP) or stochastic (S-BAP). Most of the BAP papers study the D-BAP which does not consider uncertainty (Kordić et al., 2016), while the S-BAP research considers uncertainty primarily associated with vessel arrivals and handling times (Alsoufi et al., 2016; Budipriyanto et al., 2017; Golias et al., 2014; Umang et al., 2017; Ursavas, 2015; Ursavas & Zhu, 2016; Zhen, 2015; Zhen & Chang, 2012; Zhen et al., 2011).

Other authors have studied berthing allocation decisions as part of other integrated problems including the integrated berth allocation and crane assignment problem (BACAP) (Han et al., 2015; He, 2016; Hsu, 2016; Hu, 2015a; Iris et al., 2017; Iris et al., 2015; Li et al., 2017; Liu et al., 2016; Liu et al., 2018; Pratap et al., 2017; Shang et al., 2016; Song et al., 2018; Yuping et al., 2018; Zhang et al., 2018; Zhen et al., 2017), the integrated berth allocation and quay crane assignment

and scheduling problem (BACASP) (Agra & Oliveira, 2018; Expósito-Izquiero et al., 2016; Han et al., 2010; Karam & Eltawil, 2016; Türkoğulları et al., 2016; Zhang et al., 2016), and the integrated berth allocation and yard assignment problem (BYAP) (Al-Hammadi & Diabat, 2017).

The BAP has been solved with multiple heuristics and metaheuristics (Kovač et al., 2018) including tabu search (Cordeau et al., 2005; Emde et al., 2014), greedy randomized adaptive search procedure (Lee et al., 2010), adaptive large neighborhood search heuristic (Mauri et al., 2016; Ribeiro et al., 2016), squeaky wheel Optimization (Umang et al., 2013), variable neighborhood search (Hansen et al., 2008), simulated annealing (Kim & Moon, 2003), particle swarm optimization (Ting et al., 2014), bee colony optimization (Kovac, 2013), ant colony optimization (Cheong & Tan, 2008), evolutionary algorithms (CenkŞahin & Kuvvetli, 2016), genetic algorithms (Alsoufi et al., 2016; Hu, 2015b; Pratap et al., 2017; Simrin & Diabat, 2015; Tsai et al., 2017), memetic algorithms (Dulebenets et al., 2018), greedy algorithms (Umang et al., 2017), sedimentation algorithms (Kordić et al., 2016), and partial optimization metaheuristic under special intensification conditions (Lalla-Ruiz & Voß, 2016). Other authors have used simulation to study the BAP (Budipriyanto et al., 2017; Umang et al., 2017).

Bierwirth and Meisel (2015) stated that only a 24% of the papers they reviewed had solved the BAP with exact methods. In that percentage, Bierwirth and Meisel (2015) included papers that solve MILP and generalized set-partitioning (GSPM) (Buhrkal et al., 2011; Umang et al., 2013) models with CPLEX solver and papers that used an exact method to solve integrated problems that include the BAP (Chen et al., 2012; Robenek et al., 2014; Türkoğulları et al., 2016; Ursavas, 2014; Vacca et al., 2013). In addition, we found that Kordić et al. (2016) and Xu and Lee (2018) proposed exact methods to solve the BAP. Kordić et al. (2016) solved their model with an exact approach based on the model proposed by Rashidi and Tsang (2013). Xu and Lee (2018) developed an exact method based on a branch-and-bound approach, which incorporates a new lower bound with some heuristic and pruning techniques.

From our review, we note that some authors have studied the BAP considering vessels priority

(Imai et al., 2003; Lalla-Ruiz et al., 2016; Pratap et al., 2017; Qin et al., 2016; Umang et al., 2017; Ursavas & Zhu, 2016), others have studied the BAP under disruption (Liu et al., 2016; Umang et al., 2017; Zhen et al., 2011), and a few have studied the BAP for inland terminals (Arango et al., 2011; Grubišić et al., 2014; Lalla-Ruiz et al., 2018; Qin et al., 2016). However, only Tong and Nachtmann (2017) and Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) have considered berth allocation decisions in conjunction with cargo prioritization, disruptions, and inland waterway shipping.

Tong and Nachtmann (2017) studied the cargo prioritization and terminal allocation problem (CP-TAP) which is an extension of the BAP that considers cargo prioritization in the context of inland waterways disruptions. Tong and Nachtmann (2017) formulated their problem as a non-linear integer programming (NLIP) model that minimizes total cargo value loss. The authors were able to find optimal solutions with their NLIP model for small size instances considering up to five terminals and nine barges. Tong and Nachtmann (2017) developed a genetic algorithm (GA) approach to obtain solutions for larger size instances involving up to fifteen terminal and fifty barges. However, due to the difficulty of their NLIP, Tong and Nachtmann (2017) could validate the results for their GA only for small size instances.

Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) formulated the CPTAP as a MILP model that minimizes total cargo value loss. Their MILP model was improved through the addition of valid inequalities. Like Tong and Nachtmann (2017), Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) were able to find optimal solutions for small size instances. In addition, Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.)'s improved formulation outperformed the results obtained by Tong and Nachtmann (2017) for medium and large size instances considering up to fifteen terminals and fifty barges. Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) used the lower bounds of their improved MILP model to validate all the GA results. In this paper, we formulate a new CPTAP model based on Dantiz-Wolfe decomposition and develop the first known exact method to solve the CPTAP. Our methods contribute new optimal solutions of instances involving up to ten terminals and thirty barges in reasonable computational time. This enables more realistic problem size solutions to inland waterway disruption response.

5.3 Problem Definition

We use Figure 5.1 to introduce the problem we are studying. Figure 5.1 illustrates a real disruption occurred on the Arkansas River when a mechanical failure of the Arkansas and Missouri railroad bridge interrupted barge traffic (McGeeny & Magsam, 2014). Due to this failure, six barge tows (shaded in black), consisting of approximately 60 barges, were disrupted and could not continue navigating their original routes. Therefore, responsible parties need to implement a disruption response that assigns the obstructed barges to available terminals to transfer the cargo to a land-based transportation mode for delivering to the final destination. For the case shown in Figure 5.1, the disrupted barges located in the upper section of the river have to be assigned to a terminal among the three available terminals in that section (see Figure 5.1), while the other disrupted barges have to be assigned to a terminal among the seven available terminals in the lower section of the river. In addition, the disruption response needs to schedule the barge offloading sequence at each terminal. We study the barge assignment and cargo prioritization offloading to mitigate the negative impacts of inland waterways disruptions. As discussed earlier, Tong and Nachtmann (2017) denominated this problem as the cargo prioritization and terminal allocation problem (CPTAP). The CPTAP prioritizes the assignment and offloading of barges into available terminals to minimize total value loss during inland waterway disruption response.

The cargo losses value based on its value decreasing rate which is defined as the “rate at which the cargo’s economic and societal value diminishes as time elapses” (Tong et al., 2015). The total cargo value loss depends on the cargo’s value decreasing rate, the cargo’s value, its volume, and the time it takes the cargo to reach its final destination, i.e. water transportation time, waiting time, handling time, and land transportation time.

We assume barges carry a single type of cargo that could be hazardous or non-hazardous. If a barge carries hazardous cargo, it must be assigned and offloaded into a terminal during the disruption response. However, barges carrying non-hazardous cargo may remain on the waterways due to

limitations of the system or because the customer is not willing to accept the cargo after certain time.

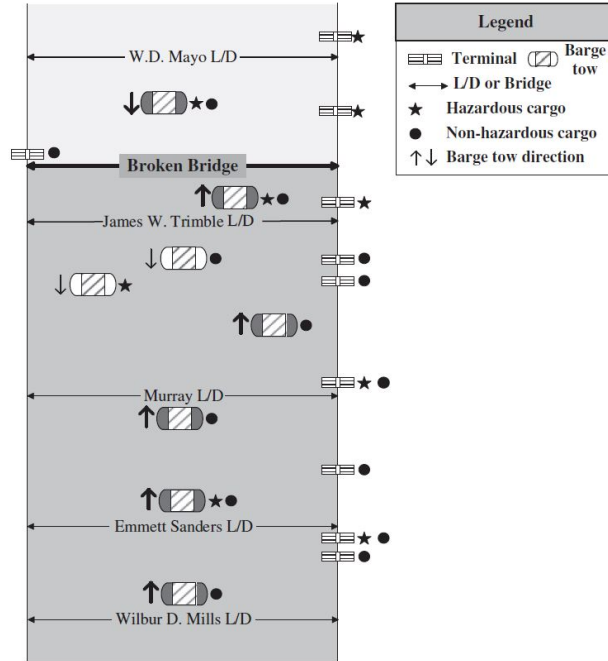


Figure 5.1. Arkansas river disruption (Tong & Nachtmann, 2017)

We assume that terminals have limited capacity to offload cargo and only one barge can be offloaded at a time. In addition, barges carrying certain commodities cannot be assigned to terminals that do not have the necessary handling equipment to offload that specific type of cargo. We consider terminals with various water depths and barges with various draft depths.

5.4 Model Formulation

The CPTAP was initially formulated by Tong and Nachtmann (2017) as a NLIP model. In this section, we present the CPTAP formulated as a MILP model as developed in previous work conducted by Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.). The problem is defined on a graph $G = (V, A)$, where V is the set of vertices and A is the set of arcs. The set of vertices V consists

of one vertex for each barge in the set of barges B and two dummy nodes $\{o\}$ and $\{d\}$ to represent the beginning and the end of a barge's offloading schedule in a terminal, $V = B \cup \{o\} \cup \{d\}$. The set A consists of arcs (i, j) for each $i \in B \cup \{o\}$, $j \in B \cup \{d\}$, and $i \neq j$. The notation used in the MILP model is as follows:

Sets

B	set of barges
NH	set of barges carrying non-hazardous cargo
H	set of barges carrying hazardous cargo
K	set of real terminals
D	set of dummy terminals (one)
N	set of commodity cargo types

Parameters

t_i^k	water transport time of barge $i \in B$ from its location at the time of disruption to terminal $k \in K$
l_i^k	land transportation time of barge $i \in B$ from terminal $k \in K$ to its final destination
h_i^k	handling time of barge $i \in B$ at terminal $k \in K$
c_i	cargo volume on barge $i \in B$
α_i	value decreasing rate per unit of volume and per unit of time of cargo carried by barge $i \in B$
v_i	total value of barge $i \in B$ cargo
e_{in}	1 if barge $i \in B$ carries cargo $n \in N$; 0 otherwise
u_{kn}	offload capacity for cargo $n \in N$ at terminal $k \in K$ during the disruption response
w_k	water depth at terminal $k \in K$
d_i	draft depth of barge $i \in B$

s safety level/clearance

b_i latest time at which a cargo $i \in B$ must be delivered to its final customer because after that time the cargo value loss is not acceptable by the customer.

M_{ij}^k defined as the $\max\{b_i + h_i^k - t_j^k, 0\}$ such that $(i, j) \in A$ and $k \in K$

Decision Variables

$y_i^k \in \{0, 1\}$ 1 if barge i is assigned to terminal k ; 0 otherwise. Where $i \in B$ and $k \in K \cup D$

$x_{ij}^k \in \{0, 1\}$ 1 if barge i is serviced before barge j at terminal k ; 0 otherwise. Where $(i, j) \in A$ and $k \in K \cup D$

T_i^k starting service time of barge i at terminal k . Where $i \in V$ and $k \in K$

$$\text{(MILP)} \quad \text{minimize} \quad \sum_{k \in K} \sum_{i \in B} \left[\left(T_i^k + \left(h_i^k + l_i^k \right) y_i^k \right) c_i \alpha_i \right] + \sum_{k \in D} \sum_{i \in NH} v_i y_i^k \quad (5.1)$$

Subject to:

$$\sum_{k \in K \cup D} y_i^k = 1 \quad \forall i \in B \quad (5.2)$$

$$\sum_{k \in K} y_i^k = 1 \quad \forall i \in H \quad (5.3)$$

$$\sum_{j \in B \cup \{d\} | (o,j) \in A} x_{oj}^k \leq 1 \quad \forall k \in K \quad (5.4)$$

$$\sum_{i \in B \cup \{o\} | (i,d) \in A} x_{id}^k \leq 1 \quad \forall k \in K \quad (5.5)$$

$$\sum_{j \in B \cup \{d\} | (i,j) \in A} x_{ij}^k - \sum_{j \in B \cup \{o\} | (j,i) \in A} x_{ji}^k = 0 \quad \forall k \in K, i \in B \quad (5.6)$$

$$\sum_{j \in B \cup \{d\} | (i,j) \in A} x_{ij}^k = y_i^k \quad \forall k \in K, i \in B \quad (5.7)$$

$$\sum_{i \in B} c_i e_{in} y_i^k \leq u_{kn} \quad \forall k \in K, n \in N \quad (5.8)$$

$$\sum_{k \in K} (w_k - d_i) y_i^k \geq s \left(1 - \sum_{k \in D} y_i^k \right) \quad \forall i \in B \quad (5.9)$$

$$T_i^k \geq t_i^k y_i^k \quad \forall k \in K, i \in B \quad (5.10)$$

$$T_i^k + (h_i^k + l_i^k) y_i^k \leq b_i \quad \forall k \in K, \forall i \in B \quad (5.11)$$

$$T_i^k + h_i^k - T_j^k \leq (1 - x_{ij}^k) M_{ij}^k \quad \forall k \in K, (i, j) \in A \quad (5.12)$$

$$T_i^k \geq 0 \quad \forall k \in K, i \in B \quad (5.13)$$

$$y_i^k \in \{0, 1\} \quad \forall k \in K \cup D, i \in B \quad (5.14)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall k \in K \cup D, (i, j) \in A \quad (5.15)$$

The objective (Equation 5.1) is to minimize the total cargo value loss. The first part of the objective function represents the assignment of barges carrying either hazardous or non-hazardous cargo to a real terminal. In this case, the value loss by the cargo depends on the cargo value decreasing rate, the volume of the cargo, and the time it takes the cargo to reach its final destination. The second part of the objective function represents the assignment of barges carrying non-hazardous cargo to a dummy terminal, D . We use the assignment of barges to the dummy terminal to represent the cases when barges are left on the waterways due to limitations of the system or because the time when the cargo reaches its final destination exceeds the maximum time the customer is willing to receive the cargo. For this case, the value loss by the cargo is its total value.

Constraints (5.2) assure that each barge is assigned to a terminal including the dummy terminal. Constraints (5.3) assure that barges carrying hazardous cargo are assigned to a real terminal. Constraints (5.4)-(5.6) are the flow balance constraints. Constraints (5.4) maintain that at most one barge is serviced first at each terminal. Constraints (5.5) establish that at most one barge is serviced last at each terminal. Constraints (5.6) establish that each barge has only one predecessor and only one successor including the dummy source and sink nodes $\{o\}$ and $\{d\}$ respectively. Constraints (5.7) represent the relation between the assignment decision variables y_i^k and the scheduling decision variables x_{ij}^k . Constraints (5.8) are the capacity constraints. Constraints (5.9) assure that the barge-terminal assignments allow a clearance between the barge's draft depth and the termi-

nal's water depth. Constraints (5.10)-(5.12) are associated with the scheduling component of the problem. Constraints (5.10) and (5.11) are the time windows constraints. Constraints (5.12) make certain that the starting service time of a successor barge is greater than the completion time of its predecessor barge. Finally, constraints (5.13), (5.14), and (5.15) correspond to the nature of the decision variables.

Dantzig-Wolfe Decomposition

Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) added a set of valid inequalities to the MILP model and used the improved model to solve the instances proposed by Tong and Nachtmann (2017). Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) obtained optimal solutions only for small size instances (five terminals and less than ten barges), and for medium size instances (ten terminals and thirty barges) and large size instances (fifteen terminals and fifty barges), the authors obtained solutions with average gaps of 12.03% and 12.7% respectively in a computational time less than fifteen minutes. When the model was run for a limited time of seven hours, the average gaps were 10.5% and 10.1% for medium and large size instances respectively. Delgado-Hidalgo, Rainwater, and Nachtmann (n.d.) showed that the addition of valid inequalities improved the lower bounds (obtained at the root node) of the MILP model in 5.0% on average and up to 8.1% for the small size instances. However, even for the instances that they obtained optimal solutions, the optimality gap for fifteen small size instances was on average 4.73%, which shows that the linear relaxation of the MILP formulation yields weak lower bounds.

In order to improve the lower bounds and solve more instances, in this section we propose a new CPTAP formulation which is based on Dantzig-Wolfe decomposition. Now we introduce the notation used in the new formulation. Let Ω^k be the set of feasible barges offloading sequences at terminal $k \in K \cup D$, i.e., the set of all possible barges offloading sequences at terminal $k \in K \cup D$ starting with the source node o and ending with the sink node d , servicing at most once each barge (feasible for constraints (5.4)-(5.7), (5.14)-(5.15)), satisfying capacity constraints (5.8), time

windows constraints (5.10)-(5.11), and sequencing constraints (5.12)-(5.13). Let $r_k \in \Omega^k$ be a sequence of barges scheduled at terminal $k \in K \cup D$. Let y_{ir_k} be a binary coefficient equal to 1 if barge i is assigned to terminal $k \in K \cup D$ in the sequence r_k . Let x_{ijr_k} be a binary coefficient equal to 1 if barge j follows barge i in sequence r_k . Let T_{ir_k} be a coefficient that represents the starting service time of barge i at terminal $k \in K \cup D$ in the sequence r_k . With each sequence r_k there is an associated value c_{r_k} that represents the cargo value loss when sequence r_k is used. The decision variables in the new formulation are λ_{r_k} associated with the selection of the sequence $r_k \in \Omega^k, \forall k \in K \cup D$. The new CPTAP model, problem P, is formulated as follows:

$$(P) \quad \text{minimize} \quad \sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} c_{r_k} \lambda_{r_k} \quad (5.16)$$

Subject to:

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} = 1 \quad \forall i \in B \quad (5.17)$$

$$\sum_{k \in K} \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} = 1 \quad \forall i \in H \quad (5.18)$$

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} g_{ki} y_{ir_k} \lambda_{r_k} \geq s \quad \forall i \in B \quad (5.19)$$

$$\sum_{r_k \in \Omega^k} \lambda_{r_k} \leq 1 \quad \forall k \in K \cup D \quad (5.20)$$

$$x_{ij}^k = \sum_{r_k \in \Omega^k} x_{ijr_k} \lambda_{r_k} \quad \forall (i, j) \in A, k \in K \cup D \quad (5.21)$$

$$y_i^k = \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} \quad \forall i \in B, k \in K \cup D \quad (5.22)$$

$$T_i^k = \sum_{r_k \in \Omega^k} T_{ir_k} \lambda_{r_k} \quad \forall i \in B, k \in K \cup D \quad (5.23)$$

$$y_i^k \in \{0, 1\} \quad \forall i \in B, \forall K \cup D \quad (5.24)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall (i, j) \in A, \forall K \cup D \quad (5.25)$$

$$\lambda_{r_k \in \Omega^k} \geq 0 \quad \forall k \in K \cup D \quad (5.26)$$

Where:

$$c_{r_k} = \begin{cases} \sum_{i \in B} [c_i \alpha_i (T_{ir_k} + (h_i^k + l_i^k) y_{ir_k})] & \forall r_k \in \Omega^k, k \in K \\ \sum_{i \in NH} v_i y_{ir_k} & \forall r_k \in \Omega^k, k \in D \end{cases} \quad (5.27a)$$

$$g_{ki} = \begin{cases} (w_k - d_i) & \forall r_k \in \Omega^k, k \in K \\ s & \forall r_k \in \Omega^k, k \in D \end{cases} \quad (5.28a)$$

$$(5.28b)$$

Objective (5.16) minimizes the total cargo value loss. Constraints (5.17) and (5.18) assure that there is only one feasible offloading schedule selected for each barge. Constraints (5.19) make certain that the offloading sequences selected in the optimal solution satisfy the clearance requirements between the barges' draft depth and the terminal's water depth. Constraints (5.20) guarantee that at most a single offloading sequence is selected for each terminal. Constraints (5.21)-(5.23) show the relationship between the original MILP decision variables y_i^k , x_{ij}^k , and T_i^k and the new decision variables λ_{r_k} for the Dantzig-Wolfe reformulated model. Constraints (5.24) - (5.26) impose the domain of the decision variables. Later in the results section, we will show that this formulation yields tighter lower bounds in comparison to the MILP formulation.

5.5 Branch-And-Price Algorithm

We develop a branch-and-price (B&P) algorithm to solve problem P. B&P is a combination of branch-and-bound algorithm and column generation procedure. We start this section describing the column generation procedure to solve the linear relaxation of problem P and then we introduce the branching techniques applied to obtain integer solutions of our problem.

5.5.1 Column Generation

If we relax the integrality requirements (5.24) - (5.25), constraints (5.21) - (5.23) become redundant resulting in the following master problem formulation:

Master Problem

$$(MP) \quad \text{minimize} \quad \sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} c_{r_k} \lambda_{r_k} \quad (5.29)$$

Subject to:

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} \geq 1 \quad \forall i \in B \quad (5.30)$$

$$\sum_{k \in K} \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} \geq 1 \quad \forall i \in H \quad (5.31)$$

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} g_{ki} y_{ir_k} \lambda_{r_k} \geq s \quad \forall i \in B \quad (5.32)$$

$$\sum_{r_k \in \Omega^k} \lambda_{r_k} \leq 1 \quad \forall k \in K \cup D \quad (5.33)$$

$$\lambda_{r_k} \geq 0 \quad \forall r_k \in \Omega^k, k \in K \cup D \quad (5.34)$$

Note that in the MP formulation, we change the equality constraints (5.17) and (5.18) to covering constraints (\geq) (5.30) and (5.31). This change does not impact the optimal solution because the value loss and the time coefficients satisfy the triangle inequality, and therefore there exists an optimal solution where each barge is offloaded exactly once. In addition, using covering constraints facilitates the convergence of the column generation procedure as explained later in the article.

MP involves a large number of decision variables (columns), λ_{r_k} , one for each possible barge's offloading sequence (assignment and scheduling) at each terminal. In an optimal solution, most of these columns will take the value of zero since at most one sequence is selected for each terminal.

Therefore, we solve the MP problem using a column generation approach which starts solving a restricted MP that contains only a subset of columns and iteratively adds columns with negative reduced cost because of their potential to improve the value of the MP objective function.

Calculating the reduced cost for each column that has not been considered in the restricted MP is computationally expensive. Therefore, we derive an optimization subproblem (SP) to find the column that has not been included in the restricted MP and has the minimum reduced cost. Now we introduce additional notation to present the SP formulation. Let $\pi_i \forall i \in B$, $\mu_i \forall i \in H$, $\beta_i \forall i \in B$, $\theta_k \forall k \in K \cup D$, $\eta_{r_k} \forall r_k \in \Omega^k, k \in K \cup D$ be the dual decision variables associated with constraint sets (5.30) - (5.34) respectively. Based on linear programming theory, we calculate the reduced cost of the nonbasic decision variables associated to a terminal as follows:

$$\eta_{r_k} = \begin{cases} c_{r_k} - \sum_{i \in B} \pi_i y_{ir_k} - \sum_{i \in H} \mu_i y_{ir_k} - \sum_{i \in B} \beta_i g_{ki} y_{ir_k} - \theta_k & \forall r_k \in \Omega^k, k \in K \quad (5.35a) \\ c_{r_k} - \sum_{i \in B} \pi_i y_{ir_k} - \sum_{i \in B} \beta_i g_{ki} y_{ir_k} - \theta_k & \forall r_k \in \Omega^k, k \in D \quad (5.35b) \end{cases}$$

Equation (5.35a) represents the reduced cost for each column associated to a real terminal, while Equation (5.35b) represents the reduced cost of the columns associated with the dummy terminal.

Note that the covering constraints (5.30) and (5.31) in the MP formulation lead to restricted π_i and μ_i dual decision variables (≥ 0), in contrast to free signed decision variables for the original equality constraints (5.17) and (5.18). This is why changing the partitioning constraints (5.17) and (5.18) to the covering constraints (5.30) and (5.31) facilitates the convergence of the column generation procedure. The subproblem formulation for the real terminals is the following.

Subproblem

$$(\text{SP}) \quad \text{minimize} \quad \sum_{k \in K} \sum_{i \in B} \left[c_i \alpha_i \left(T_i^k + (h_i^k + l_i^k) y_i^k \right) \right] - \sum_{i \in B} \pi_i y_i^k - \sum_{i \in H} \mu_i y_i^k - \sum_{i \in B} \beta_i (w_k - d_i) y_i^k - \theta_k \quad (5.36)$$

Subject to

$$\sum_{j \in BU\{d\} | (o,j) \in A} x_{oj}^k \leq 1 \quad \forall k \in K \quad (5.37)$$

$$\sum_{i \in BU\{o\} | (i,d) \in A} x_{id}^k \leq 1 \quad \forall k \in K \quad (5.38)$$

$$\sum_{j \in BU\{d\} | (i,j) \in A} x_{ij}^k - \sum_{j \in BU\{o\} | (j,i) \in A} x_{ji}^k = 0 \quad \forall k \in K, i \in B \quad (5.39)$$

$$\sum_{j \in BU\{d\} | (i,j) \in A} x_{ij}^k = y_i^k \quad \forall k \in K, i \in B \quad (5.40)$$

$$\sum_{i \in B} c_i e_{in} y_i^k \leq u_{kn} \quad \forall k \in K, n \in N \quad (5.41)$$

$$T_i^k \geq t_i^k y_i^k \quad \forall k \in K, i \in B \quad (5.42)$$

$$T_i^k + (h_i^k + l_i^k) y_i^k \leq b_i \quad \forall k \in K, \forall i \in B \quad (5.43)$$

$$T_i^k + h_i^k - T_j^k \leq (1 - x_{ij}^k) M_{ij}^k \quad \forall k \in K, (i,j) \in A \quad (5.44)$$

$$T_i^k \geq 0 \quad \forall k \in K, i \in B \quad (5.45)$$

$$y_i^k \in \{0, 1\} \quad \forall k \in K, i \in B \quad (5.46)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall k \in K, (i,j) \in A \quad (5.47)$$

The decision variables of the subproblem formulation (5.36)-(5.47) are the MILP original decision variables, y_i^k , x_{ij}^k , and T_i^k . The dual decision variables π_i , μ_i , β_i , and θ_k of the current solution of the restricted MP are passed to the subproblem as coefficients for identifying feasible assignments with negative reduced cost. We replace the definition of c_{rk} and g_{ki} in the objective (5.36).

The objective (5.36) minimizes the reduced cost of columns associated with the real terminals. Constraints (5.37)-(5.39) are the flow balance constraints. Constraints (5.40) link the assignment and scheduling decision variables. Constraints (5.41) impose the capacity constraints. Constraints (5.42)-(5.43) are the time windows constraints. Constraints (5.44) are the sequencing constraints, and Constraints (5.45)-(5.47) define the domain of the decision variables.

Formulation (5.36)-(5.47) consists of k independent subsystems. Therefore, we decompose the SP into k different subproblems and solve one subproblem for each terminal. We solve the SP for the dummy terminal only to calculate the reduced cost of the columns associated with that terminal. However, we do not check feasibility of constraints (5.37)-(5.45) since there is no need to schedule barges in the dummy terminal given its representation as barges that remain on the waterways for post-response salvage.

The SP structure represents the known elementary shortest path problem with resource constraints (ESPPRC). The objective of the ESPPRC is to generate a minimum cost elementary path from a source node to a sink node that satisfies all resource constraints. For the SP case of a real terminal, the nodes represent disrupted barges that can be offloaded in the terminal, a path represents a schedule or sequence to offload barges in the terminal starting with the dummy source barge $\{o\}$ and ending with the sink barge $\{d\}$. The resource constraints are the time windows constraints, capacity constraints, and elementary constraints that assure each barge is offloaded at most once. The SP as an ESPPRC aims to find the elementary barge offloading schedule with the minimum reduced cost that satisfies all the resource constraints.

We use the ESPPRC exact algorithm proposed by Feillet, Dejax, Gendreau, and Gueguen (2004) to solve the SP for each real terminal. Feillet et al. (2004)'s exact algorithm is based on the Ford-Bellman algorithm and its extension to the label correcting reaching algorithm proposed by Desrochers (1988). During the algorithm, each barge-node receives labels of the form $L_i = \{\tau, \eta, (q_1, q_2, \dots, q_n), e, v, (o, v_1, v_2, \dots, v_b, d)\}$ that represent terminal's partial schedules for barge offloading starting with the dummy source node $\{o\}$ and ending at the starting service time of barge-node i . For a terminal's partial schedule, a label indicates the turnaround time (τ), the reduced cost (η), the cargo offloaded for each type of commodity (q_1, q_2, \dots, q_n) , if the label has been examined ($e = 1$) or not ($e = 0$), the last barge included in the partial schedule (v), and the vector of unreachable barges $(o, v_1, v_2, \dots, v_b, d)$. A barge is said to be unreachable if it has already been assigned in the partial schedule for offloading (elementary condition) or if there are not enough resources to include that barge to the current partial schedule (resource constraints).

We set $v_i = -1$ to denote that barge i has not been offloaded and is a reachable barge. We set $v_i = -2$ to denote that barge i was the last barge included in the partial schedule and therefore is an unreachable barge. We set $v_i = j$, where j is the successor of barge i , to denote that barge i is an unreachable node and it is not the last barge serviced in the partial schedule. Note that the vector of unreachable nodes also keeps track of the barges included in the partial schedule and their offloading sequence.

We initialize the algorithm with the label $L_o = \{0, 0, (0, 0, \dots, 0), 0, 0, (-1, -1, \dots, -1, -1)\}$ for the dummy source barge $\{o\}$. Nodes are iteratively treated by extending their labels to every possible successor. When a label L_i for a node i is extended to a successor node j , the updated label L'_j for node j is obtained as follows:

$$\tau' = \begin{cases} \max\{(\tau + h_i), t_j\} & \text{if } j \neq d \\ \tau + h_i & \text{if } j = d \end{cases} \quad (5.48)$$

$$\eta' = \begin{cases} \eta + (\tau' + h_j + l_j) c_j \alpha_j - \pi_j - \mu_j - \beta_j(w - d_j) & \text{if } j \neq d \\ \eta + (\tau' + h_j + l_j) c_j \alpha_j - \pi_j - \mu_j - \beta_j(w - d_j) - \theta & \text{if } j = d \end{cases} \quad (5.49)$$

$$q'_n = q_n + (c_j e_{jn}) \quad \forall n \in N \quad \text{if } j \neq d \quad (5.50)$$

$$e' = \begin{cases} 0 & \text{if } j \neq d \\ 1 & j = d \end{cases} \quad (5.51)$$

$$v' = j \quad \text{if } j \neq d \quad (5.52)$$

$$v'_i = j, \quad v'_j = -2 \quad \text{if } j \neq d \quad (5.53)$$

For an extension of L_i to node j to be feasible, node j must be a reachable node before the extension ($v_j = -1$), the turnaround time for the partial schedule must not exceed the upper bound of the time windows for offloading the attached node j ($\tau' \leq UBTW_j$), and the total cargo offloaded for each type of commodity must not exceed the offloading cargo-terminal capacity ($q'_n \leq u_n \forall n \in N$). For efficiency, when the extension of label L_i to a successor node j is undertaken, the algorithm

evaluates the capacity and time windows constraints for the possible extension of the label L_j to a node k^* , where k^* is a successor of node j . If the potential extension to a node k^* does not satisfy the constraints, the vector of unreachable nodes in the label L_j is updated by setting $v_{k^*} = -2$ (Feillet et al., 2004).

In order to limit the proliferation of labels, we use the following dominance rules (Feillet et al., 2004). Let Z'_{oi} and Z^*_{oi} be two distinct partial schedules starting with the dummy barge $\{o\}$ and ending with the barge i with associated labels

$$L'_i = \{\tau', \eta', (q'_1, q'_2, \dots, q'_n), e', v', (o', v'_1, v'_2, \dots, v'_b, d')\} \text{ and}$$

$$L^*_i = \{\tau^*, \eta^*, (q^*_1, q^*_2, \dots, q^*_n), e^*, v^*, (o^*, v^*_1, v^*_2, \dots, v^*_b, d^*)\}$$

Z'_{oi} dominates Z^*_{oi} if and only if $\tau' \leq \tau^*$, $\eta' \leq \eta^*$, $q'_n \leq q^*_n \forall n \in N$, $v'_i \leq v^*_i \forall i \in B$, and $L'_i \neq L^*_i$.

For additional information about the exact algorithm to solve the ESPPRC, see Feillet et al. (2004).

The solution of the SP for each real terminal is part of the column generation procedure which works as follows. First, we solve the restricted master problem MP containing only a subset of columns $r_k \in \Omega_1^k$, where $\Omega_1^k \subset \Omega^k$, $\forall k \in K$. Then, we solve k subproblems, one for each terminal. If the reduced cost $\eta_{r_k^*} < 0$ for some column $r_k^* \in \Omega^k \setminus \Omega_1^k$, the MP dual feasibility is not satisfied and the current solution is not optimal. Hence, the column $\lambda_{r_k^*}$ with the negative reduced cost (obtained with the SP) and potential improvement in the MP objective function is added to the restricted master problem. The updated restricted MP is solved again, and the process is iterated until the minimum reduced cost $\eta_{r_k} \geq 0$, $\forall \eta_{r_k} \in \Omega^k \setminus \Omega_1^k, \forall k \in K$, which means an optimal solution for the MP has been found.

5.5.2 Branching Strategies

If the subproblems for the real terminals do not generate an offloading schedule with negative reduced cost, the simplex algorithm provides an optimal solution for the MP, which is the linear relaxation of problem P. If the MP solution is integer, this solution is the optimal solution of

problem P. However, if the MP solution is fractional, a branch-and-bound tree must be explored. We solve a restricted MP at each node of the search tree via column generation approach. If the solution is fractional, we implement branching strategies based on the standard rules for vehicle routing problems with time windows (VRPTW). Branching rules (i) and (ii) are based on the strategies proposed by Vacca et al. (2013) to solve the integrated planning of berth allocation and quay crane assignment. Branching rule (iii) is based on the one proposed by Feillet (2010) to solve the VRPTW. We apply the following branching rules in the order they are presented.

(i) Let \tilde{K} denote the number of terminals used in the MP solution, such that

$\tilde{K} = \sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} \lambda_{r_k}$. If \tilde{K} is fractional, we derive two branches one for each child node.

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} \lambda_{r_k} \leq \left\lceil \tilde{K} \right\rceil \quad \text{on the first child node} \quad (5.54)$$

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} \lambda_{r_k} \geq \left\lfloor \tilde{K} \right\rfloor \quad \text{on the second child node} \quad (5.55)$$

The addition of the constraint (5.54) or (5.55) to the MP formulation for a child node implies an additional dual decision variable that needs to be considered in the objective function of the SP. Let ρ be the dual decision variable associated to the constraint (5.54) for the first child node or (5.55) for the second child node. Note that ρ is a constant and the SP objective function is modified as follows:

Minimize

$$\sum_{k \in K} \sum_{i \in B} \left[c_i \alpha_i \left(T_i^k + (h_i^k + l_i^k) y_i^k \right) \right] - \sum_{i \in B} \pi_i y_i^k - \sum_{i \in H} \mu_i y_i^k - \sum_{i \in B} \beta_i (w_k - d_i) y_i^k - \theta_k - \rho \quad (5.56)$$

If the number of terminals, \tilde{K} , used in the current MP solution is integer, we explore branches type (ii).

(ii) Let \tilde{Y}_i^k represent the assignment of barge i to terminal k in the MP solution, such that

$\tilde{Y}_i^k = \sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k}$. If \tilde{Y}_i^k is fractional, we derive two branches one for each child node.

$$\sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} = 0 \quad \text{on the first child node} \quad (5.57)$$

$$\sum_{r_k \in \Omega^k} y_{ir_k} \lambda_{r_k} = 1 \quad \text{on the second child node} \quad (5.58)$$

Unlike the branches in (i), we do not add branches (5.57) and (5.58) directly as constraints of the MP, therefore they do not modify the SP objective function. Rather, we modify the set of columns in the MP and the network of the SP to represent the branches (5.57) and (5.58). For the branch (5.57) we remove the columns in the MP with a coefficient $y_{ir_k} = 1$. At the subproblem level, we remove node i from the network of terminal k .

For the branch (5.58), we remove the columns in the MP with a coefficient $y_{ir_{k^*}} = 1$ such that $r_{k^*} \in \Omega^{k^*}$ and $k^* \neq k$, i.e. we remove all the columns that consider the offloading of barge i in a terminal $k^* \neq k$. This modification in conjunction with constraints (5.30) and (5.31) in the MP guarantee that barge i is assigned to terminal k . At the subproblem level, we remove node i from the network of the SP for each terminal $k^* \neq k$ to keep the SP from generating columns where barge i is offloaded in a terminal $k^* \neq k$. If the assignments of barges to terminals, \tilde{Y}_i^k , in the current MP solution are integer, we explore branches of type (iii).

- (iii) Let \tilde{X}_{ij} represent the sequence of barge offloading where barge j is offloaded after barge i in the MP solution, such that

$\tilde{X}_{ij} = \sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} x_{ijr_k} \lambda_{r_k}$. If \tilde{X}_{ij} is fractional, we derive two branches one for each child node.

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} x_{ijr_k} \lambda_{r_k} = 0 \quad \text{on the first child node} \quad (5.59)$$

$$\sum_{k \in K \cup D} \sum_{r_k \in \Omega^k} x_{ijr_k} \lambda_{r_k} = 1 \quad \text{on the second child node} \quad (5.60)$$

Unlike the branches in (i), we do not add branches (5.59) and (5.60) directly as constraints of the MP, and therefore they do not modify the SP objective function. Rather, based on the

ideas proposed by Feillet (2010), we modify the set of columns in the MP and the network of the SP to represent the branches (5.59) and (5.60) in a similar way like we did with branches (ii). For the branch (5.59) we remove the columns in the MP with a coefficient $x_{ijr_k} = 1$. At the subproblem level, we remove the arc (i, j) from the network of terminal k .

For the branch (5.60), we remove the columns in the MP with a coefficient $x_{ibr_k} = 1$ such that $b \neq j$ and the columns with a coefficient $x_{bjr_k} = 1$ such that $b \neq i$. Note that constraints (5.30) and (5.31) in the MP guarantee that each barge is offloaded, and therefore the only way barge i and barge j are offloaded is if barge j is serviced after barge i and constraint (5.60) holds. At the subproblem level, we remove the arc (i, b) such that $b \neq j$ and arcs (b, j) such that $b \neq i$ from the network of each terminal k . If the sequences of barge offloading, \tilde{X}_{ij} , in the current MP solution are integer, we have found an optimal solution for the integer problem P.

5.6 Computational Results

We use the instances generated by Tong and Nachtmann (2017) based on data collected from the Upper Mississippi River to implement our B&P approach. Those authors solved five cases (from C1 to C5) that contain instances classified as small, medium, and large size instances depending on the number of terminals and the number of barges considered in each case as shown in Table 5.4.

Table 5.4. Instances general description (Tong & Nachtmann, 2017)

Case	No. Instances	No. Terminals	No. Barges
C1 (small size)	5	5	5
C2 (small size)	5	5	7
C3 (small size)	5	5	9
C4 (medium size)	10	10	30
C5 (large size)	30	15	50

Table 5.5 summarizes the data associated with barges, terminals, and transportation times. The

water transportation time is based on the barges initial location and assuming a barge average speed of five miles per hour. The barge draft probability density function is estimated based on data provided by U.S. Army Corps of Engineers Navigation Data Center (USACE, 2012).

Table 5.5. Instance generation data (Tong & Nachtmann, 2017)

Parameter	Data / distribution function
Barge location	uniformly distributed across the study region
Cargo volume	1,000 tons per barge
Barge average speed	5 miles per hour
Handling time	uniformly distributed between 5-10 hours
Land transportation time	uniformly distributed between 18-96 hours
Barge draft	between 6 and 14 feet
Terminals water depth	between 8 and 15 feet
Safety level	1 foot
Terminals capacity	5,000 tons per each type of cargo

Table 5.6 summarizes the data associated with the cargo. The probability density function for the cargo carried by each barge is based on the tonnage data. All petroleum cargo and fifty percent of the chemicals cargo are considered hazardous cargo. The cargo value decreasing rate is calculated per 1,000 tons and per hour, and the cargo value is calculated based on the market price. We solve our B&P approach using a 2x Intel E5-2670 computer with 32 GB of memory from the Arkansas High Performance Computing Center. The algorithm is implemented in C++, and the linear programs are solved with CPLEX 12.4.

To start the column generation at the root node, we use a feasible solution provided by CPLEX when we solve the MILP model for a limited time of fifteen seconds. At each node of the search tree, we initialize the MP with a restricted number of columns such that a feasible solution for the MP exists. To assure the MP feasibility at each node of the search tree, we add a dummy column to the MP with a very high cost and coefficient 1 for constraints (5.30), (5.31), and (5.33) and coefficient s for constraints (5.32).

Table 5.6. Commodity type data. Updated from Tong and Nachtmann (2017)

Two digit	Cargo Commodity type	Tonnage data	Value decreasing rate (\$ per 1,000 tons per hour)	Market price (\$/ton)
10	Coal, lignite and coal coke	10,288.25	100	36.29
20	Petroleum and petroleum products	1,238.20	600	403.39
30	Chemicals and related product	18,331.33	Hazardous: 600 Non-hazardous: 400	399.88
40	Crude materials, inedible, except fuels	11,364.99	300	134.61
50	Primary manufactured goods	7,843.58	300	396.45
60	Food and farm products	58,670.63	400	164.52

We present our results in Tables 5.7-5.10. Tables 5.7 and 5.8 summarize the results for small size instances, while Tables 5.9 and 5.10 summarize the results for medium size instances. Tables 5.7 and 5.9 show the case, instance number (Ins.), optimal solution (Optimal), number of iterations for the column generation (Iterations), number of columns generated for the column generation procedure (Columns), number of nodes in the search tree (MP, under Nodes heading), node number where the optimal solution was found (Opt, under Nodes heading), (Opt node/MP Nodes) percentage (% , under Nodes heading), computation time to solve the MP (MP, under CPU Time heading), computation time when the optimal solution was found (Opt, under CPU Time heading), and the (Opt CPU Time / MP CPU Time) percentage (% , under CPU Time heading).

Table 5.7 shows that the branching techniques were required to solve four out of fifteen small size instances. For Instance 2, the algorithm found the optimal solution at node 4 out of a total of 26 nodes (15%), for Instance 8, the algorithm found the optimal solution at node 2 out of a total of 4 nodes (50%), and for Instance 15, the algorithm found the optimal solution at node 6 out of a total of 10 nodes (60%).

Table 5.7. B&P results for small size instances

Ins.	Optimal	Iterations	Columns	Nodes			CPU Time (s)			
				MP	Opt	%	MP	Opt	%	
C1	1	89,756	2	174	1	1	100%	0.02	0.02	100%
	2	110,906	31	158	26	4	15%	0.13	0.03	23%
	3	109,112	3	85	1	1	100%	0.02	0.02	100%
	4	84,804	5	76	1	1	100%	0.02	0.02	100%
	5	95,268	4	97	1	1	100%	0.02	0.02	100%
C2	6	106,700	4	858	2	2	100%	0.14	0.14	100%
	7	78,032	4	368	1	1	100%	0.05	0.05	100%
	8	100,828	7	395	4	2	50%	0.07	0.07	100%
	9	105,402	4	432	1	1	100%	0.06	0.06	100%
	10	134,448	3	421	1	1	100%	0.05	0.05	100%
C3	11	160,330	3	4651	1	1	100%	5.00	5.00	100%
	12	156,186	5	1038	1	1	100%	0.30	0.30	100%
	13	147,344	5	2453	1	1	100%	1.34	1.34	100%
	14	133,528	4	3001	1	1	100%	2.29	2.29	100%
	15	175,852	12	1350	10	6	60%	0.51	0.50	98%

Table 5.8. MP and MILP results comparison for small size instances

Ins.	LB		Optimality Gap		CPU Time (s)			
	MP	MILP	MP	MILP	MP	MILP	Gap	
C1	1	89,756	88,622	0.00%	1.28%	0.02	0.19	-89.5%
	2	100,818	97,799	10.01%	13.40%	0.13	0.30	-56.7%
	3	109,112	108,584	0.00%	0.49%	0.02	0.25	-92.0%
	4	84,804	80,592	0.00%	5.23%	0.02	0.44	-95.5%
	5	95,268	93,813	0.00%	1.55%	0.02	0.42	-95.2%
C2	6	105,375	103,430	1.26%	3.16%	0.14	0.27	-48.1%
	7	78,032	75,590	0.00%	3.23%	0.05	0.50	-90.0%
	8	99,919	94,246	0.91%	6.98%	0.07	0.58	-87.9%
	9	105,402	101,369	0.00%	3.98%	0.06	0.64	-90.6%
	10	134,448	130,667	0.00%	2.89%	0.05	0.61	-91.8%
C3	11	160,330	154,223	0.00%	3.96%	5.00	0.56	792.9%
	12	156,186	150,464	0.00%	3.80%	0.30	0.53	-43.4%
	13	147,344	141,224	0.00%	4.33%	1.34	0.64	109.4%
	14	133,528	123,135	0.00%	8.44%	2.29	1.23	86.2%
	15	167,552	162,388	4.95%	8.29%	0.51	0.66	-22.7%

Tables 5.8 and 5.10 show a comparison between the MP solved with the B&P technique and the MILP model solved with CPLEX solver for small and medium size instances respectively. Table 5.8 shows the case, instance number (Ins.), MP lower bound (MP, under LB heading) obtained at the root node of the search tree, MILP lower bound (MILP, under LB heading) obtained by solving the linear relaxation of the MILP model, optimality gap for the MP (MP, under Optimality Gap heading) and the MILP model (MILP, under Optimality Gap heading), computation time required to solve the MP (MP, under CPU Time heading) and the MILP model (MILP, under CPU Time heading), and the gap between the MP and MILP computation time (Gap, under CPU Time heading).

The results in Table 5.8 indicate that the LB obtained with the MP formulation are higher than the LB obtained with the MILP model. The MP optimality gap is zero for eleven out of fifteen small size instances, while the MILP optimality gap is higher than zero for all instances. The MP average optimality gap is 1.14%, while the MILP average optimality gap is 4.73%. This computational evidence shows that the MP is a tighter formulation resulting in more accurate LB. Table 5.8 also shows that the MP outperforms the MILP model in twelve out of fifteen instances with regards to computation time.

Table 5.9. B&P results for medium size instances

Ins. C4	Optimal	Iterations	Columns	Nodes			CPU Time (s)		
				MP	Opt	%	MP	Opt	%
1	464,124	2,004	18,188	1,852	724	39%	1,034	598	58%
2	497,966	71,803	30,183	78,610	22,915	29%	46,175	16,059	35%
3	489,870	3,441	17,214	2,872	585	20%	1,523	496	33%
4	533,894	865	17,358	954	598	63%	776	770	99%
5	412,078	4,263	22,594	4,474	2,279	51%	3,585	2,653	74%
6	485,012	1,172	11,483	1,220	459	38%	527	323	61%
7	468,058	3,578	22,187	4,604	2,566	56%	2,118	1,996	94%
8	523,178	519	18,619	434	141	32%	642	440	69%
9	512,622	636	20,416	566	335	59%	606	581	96%
10	481,846	576	14,215	378	249	66%	494	433	88%

Table 5.9 shows that the branching techniques were required to solve all medium size instances. Instance 3 is the instance where the algorithm found the optimal solution higher in the search tree after exploring only 20% of the nodes and after 33% of the total computation time. On the other hand, Instance 4 required exploration of 63% of the nodes and 99% of the total computation time to find the optimal solution.

Table 5.10. MP and MILP results comparison for medium size instances

Ins.	LB		Gap		CPU Time (s)	
	MP	MILP	MP	MILP	MP	Improvement
1	454,213	417,038	2.18%	11.29%	1,034	-96.0%
2	487,167	443,969	2.22%	12.16%	46,175	79.0%
3	475,346	447,428	3.06%	9.49%	1,523	-94.1%
4	527,654	496,698	1.18%	7.49%	776	-97.0%
5	388,797	364,230	5.99%	13.14%	3,585	-86.1%
6	476,542	441,991	1.78%	9.73%	527	-98.0%
7	461,671	425,868	1.38%	9.91%	2,118	-91.8%
8	502,476	464,071	4.12%	12.74%	642	-97.5%
9	501,430	473,122	2.23%	8.35%	606	-97.6%
10	462,870	435,545	4.10%	10.63%	494	-98.1%

For medium size instances, Table 5.10 shows a comparison between the MP solved with the B&P technique and the MILP model solved with CPLEX solver for a limited time of seven hours. Table 5.10 shows the instance number (Ins.), MP lower bound (MP, under LB heading) obtained at the root node of the search tree, MILP lower bound (MILP, under LB heading) obtained by solving the linear relaxation of the MILP model, optimality gap for the MP (MP, under Gap heading) and the gap between the MILP solution and the LB (MILP, under Gap heading), computation time required to solve the MP (MP, under CPU Time heading), and the gap between the computation time to solve the MP and the seven hours time limit used to solve the MILP model with CPLEX (Improvement, under CPU Time heading). The LB for the MP are greater than the MILP LB. The MP average optimality gap is 2.82%, while the MILP average optimality gap is 10.49%. In addition, the CPU time to solve the MP outperforms the CPU time to solve the MILP model for all but Instance 2. The B&P algorithm was able to solve and find the optimal solution for one of

the large size instances. However, it took three days to obtain this solution.

5.7 Conclusions

In this paper, we investigated how to redirect disrupted barges to available terminals to minimize the total cargo value loss during inland waterway disruption response. The problem studied in this paper is known in the literature as the cargo prioritization and terminal allocation problem (CPTAP). A first study formulated the CPTAP as a non-linear integer programming (NLIP) model which was solved with a genetic algorithm (GA) approach (Tong & Nachtmann, 2017). Later, a second study formulated the CPTAP as a mixed integer linear programming (MILP) model improved with the addition of valid inequalities (Delgado-Hidalgo, Rainwater, & Nachtmann, n.d.). Both studies obtained optimal solutions only for small size instances involving five terminals and up to nine barges. The second study outperformed the results obtained with the GA proposed in the first study.

The main contributions of our research are: (1) a new mathematical model for the CPTAP based on Dantzig-Wolfe decomposition approach, where, in comparison to previous models, our model is tighter and yields better lower bounds, (2) a first known exact method to solve the CPTAP which provides optimal solutions for new instances of the CPTAP involving ten terminals and up to thirty disrupted barges in reasonable computational times, and (3) a new decision support technique to redirect disrupted barges and prioritize offloading at accessible terminals during disruption response. The methods proposed in this paper benefit inland waterway decision makers, namely the U.S. Army Corps of Engineers, U.S. Coast Guard, and U.S. Department of Transportation.

The B&P approach obtained new optimal solutions of the CPTAP. However, it was unable to solve large size problems involving fifteen terminals and fifty barges. We analyzed the computational time to solve each component of the B&P algorithm for a medium size instance and noticed that more than 90% of the time to solve an iteration of the column generation procedure is used to

solve the subproblems and each subproblem is solved in less than 22% of the total time to solve the iteration. Therefore, for future work, we plan to use parallel programming to solve all the SPs more efficiently. This may significantly reduce the computational time to solve each iteration of the column generation procedure. In addition, future work should focus on analyze other techniques to solve each SP including bidirectional labeling algorithm to solve the ESPPRC more efficiently.

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Appendix 1



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This memorandum is to confirm that Liliana Delgado-Hidalgo is the first author of the following article and completed at least 51% of the work for the article.

“An Exact Algorithm for the Cargo Prioritization and Terminal Allocation Problem”

6 Conclusions

This chapter summarizes the main conclusions of this dissertation research and highlights possible extensions for future work. This dissertation investigates how to improve inland waterway post-disaster outcomes by developing three new decision support techniques to redirect disrupted barges and prioritize offloading at accessible terminals during disruption response. The problem studied in this dissertation is known in previous literature as the cargo prioritization and terminal allocation problem (CPTAP). The CPTAP assigns disrupted barges and prioritizes barge offloading to minimize total cargo value loss during inland waterway disruptions response. The barge assignment and scheduling decisions are subject to limitations of the system including the capacity of the terminals and the required clearance between the water depth of the terminals and the draft depth of the barges.

The methods described in Chapter 3 reduce the time to provide a solution for CPTAP large size instances by developing a decomposition based sequential heuristic (DBSH) that decomposes the problem into three subproblems: cargo prioritization, assignment model, and scheduling model. The cargo prioritization is obtained from an Analytic Hierarchy Process (AHP) approach and a weighted geometric mean aggregation method. This subproblem determines the cargo priority index which is used to decompose the set of barges into subsets that consider barges carrying cargo with common priority index. The second subproblem assigns disrupted barges to available terminals in a sequential manner. First, an assignment model is solved considering only the subset of barges with the highest priority index. Then, the capacity of the terminals is updated and a second assignment model considering the subset of barges with the second highest priority is solved. This process continues until all the barges have been assigned to a terminal or there is not available capacity in the terminals. The assignment model is formulated as an integer linear programming (ILP) model that minimizes cargo value loss due to assignment decisions. The third subproblem schedules the offloading of barges assigned to a terminal. The scheduling model is formulated as a mixed integer linear programming (MILP) model that minimizes cargo value loss.

Chapter 3 finds that Petroleum cargo has the highest priority (0.386), while Coal cargo has the lowest priority (0.091). For scenarios considering fifteen terminals and fifty disrupted barges, although a previous approach obtains a slightly less cargo value loss than the DBSH, the gap between both approaches is minimal (0.36%) and the DBSH outperforms on the computational time required to solve the previous approach with an average gap of 92.3%, which supports solving large sized decision problems. For larger scenarios considering twenty terminals and seventy disrupted barges, the DBSH is able to solve all instances, while the previous approach solves only five out of twenty instances. Furthermore, for the instances solved by both approaches, the DBSH slightly outperforms the cargo value loss obtained with the previous approach (0.5%) and significantly improves the computational time (95.7%).

The methods described in Chapter 4 reduce cargo value loss during inland waterway disruption response by developing a pure mathematical approach that integrates barge-terminal assignment and scheduling decisions. Unlike the DBSH, the methods presented in Chapter 4 integrate the assignment and scheduling of barges to terminals in a single model and present a new CPTAP formulation as a MILP model which results in an average optimality gap of 10%. In addition, when valid inequalities are added to this model, the lower bounds are increased by 5% on average, and the computational time is reduced by 84% on average. This improved formulation (MILP') results in an average optimality gap of 4.7%.

A previous study formulated the CPTAP as a non-linear integer programming (NLIP) model that was solved with a genetic algorithm (GA) approach. Due to the non-linearity of the model, the authors validated the quality of their solutions only for small size instances (five terminals and less than nine disrupted barges). Chapter 4 fills this research gap by using the lower bounds of the MILP' model to validate the GA results. The maximum gap between the GA solutions and the lower bounds is found to be 24.2% for all size instances. In addition, the results in Chapter 4 show that the MILP' outperforms the GA computational time for small size instances with an average gap of 94.75%, outperforms the GA solutions for medium size instances with an average gap of 1.7%, and outperforms the GA solutions for large size instances with an average gap of 4.5%.

The methods described in Chapter 5 reduce cargo value loss during inland waterway disruption response by developing an exact method to optimally solve new instances of the CPTAP. Chapter 5 presents the reformulation of the MILP model via Dantzig-Wolfe decomposition method which decomposes the problem into an upper level master problem (MP) and lower level subproblems (SPs) that are more tractable to solve. The reformulated model is solved with a branch-and-price (B&P) algorithm. The B&P algorithm explores a branch-and-bound tree and solves a linear relaxation of a restricted MP at each node of the search tree via column generation.

The findings of Chapter 5 show that, for small size instances, the MP outperforms the MILP model optimality gap. The MP average optimality gap is 1.14%, while the MILP average optimality gap is 4.73%. The MP optimality gap is 0.0% for eleven out of fifteen instances, while the MILP optimality gap is greater than 0.0% for all instances. In addition, the MP outperforms the MILP model computational time in twelve out of fifteen small size instances. However, the MILP model outperforms the MP computational time with an average gap of 5.7%. For medium size instances, the MP finds optimal solutions with an average gap of 2.82%, while the MILP average gap between the MILP solutions and the lower bounds is 10.49%. Furthermore, the MP outperforms the MILP model average computational time with a gap of 77.7%.

In conclusion, based on the findings of this dissertation, the MILP model is recommended to obtain optimal solutions of small size instances of the CPTAP, the MP is recommended to obtain optimal solutions of medium size instances of the CPTAP, and the GA, DBSH, or MILP approaches are recommended to obtain good solutions of large size instances of the CPTAP. The DBSH is the preferred approach when fast decision support is critical as its computation time is less. The exact method described in Chapter 5 obtained new optimal solutions of the CPTAP involving ten terminals and thirty disrupted barges; however, the method was not able to solve large size problems involving fifteen terminals and fifty barges. An analysis of the computational time to solve the B&P shows that more than 90% of the time to solve an iteration of the column generation procedure is used to solve the subproblems. Each subproblem is solved in less than 22% of the total time to solve an iteration. Therefore, for future work, we plan to use parallel programming to solve

all the subproblems more efficiently. Solving the subproblems in parallel would significantly reduce the computational time to solve each iteration of the column generation procedure embedded in the B&P approach. In addition, future work should focus on analyzing other techniques including bidirectional labeling algorithm to solve each subproblem more efficiently. In order to reduce the computational time to get a solution, we could solve the SPs heuristically. The SPs would be solved to optimality only when the heuristic does not provide a new attractive column in order to prove optimality of the current master problem solution. Another extension to this research is associated to the nature of the parameters. We want to consider additional features in the model to represent more realistic problems including stochastic barge arrival and handling time.