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Supporting Secure and Resilient Inland Waterways

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Heather Nachtmann, Ph.D.
Liliana Delgado Hidalgo, Ph.D.
Justin Chimka, Ph.D.
University of Arkansas

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University of Arkansas
4190 Bell Engineering Center
Fayetteville, AR 72701
479-575-6021

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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 mitigate negative time and value loss impacts 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. We solve thirty-five scenarios based on real-world Upper Mississippi River barge traffic data and find that our DBSH has similar performance compared to a previous approach with drastically improved computational time.

Project Description

Inland waterways are an important transportation mode to alleviate landside congestion and have proven to be economic, fuel-efficient, reliable, and environmentally-friendly (J. 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 transportation 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 sys- tem has 239 lock chambers operated at 193 sites and 1,930 cargo handling docks (USACE, 2016). In 2014, there were 5,476 tugboats, towboats, and push boats and 31,043 barges operating on the U.S. waterways (The American Waterways Operators and the U.S. Maritime Administration, 2017).

The tugboat, towboat, and barge industry in the U.S. supports international trade by providing tugboat services to large containerships and other oceangoing vessels entering U.S. ports. The industry contributes to domestic Commerce moving an average of 763 million tons of cargo on the U.S. waterways each year. In 2012, the U.S. inland navigation system moved 565 million tons of freight valued at $214 billion (Grossardt, Bray, & Burton, 2014). 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 2014, the tugboat, towboat, and barge industry contributed $9.0 billion to the U.S. gross domestic product (GDP), invested nearly $2.2 billion (property, plant, and equipment), generated $15.9 billion of revenues, employed 50,480 direct workers, and paid out $4.7 billion in compensation (The American Waterways Operators and the U.S. Maritime Administration, 2017).

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 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 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 (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.

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 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 support 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 2 summarizes the model and objectives from the reviewed papers in this area.

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 capacity 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).

Table 1. Inland waterway disruptions

Disruption	Year	Consequences	Reference
Drought on Missis-sippi 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, Johnson, and Cooper (2012)
Barges crashed into Belleville Lock in Reedsville	2005	Shutdown cost $4.5 million a day. General Electric closed its plant	Güler, Johnson, and Cooper (2012)
Flooding in the Mis-sissippi River	2011	River barge traffic, transporting billions in crops, were delayed. River- boat 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 water- way, 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.	Captain (2017)
Barge collided with Smothers Park	2017	Estimated half a million dollars to re-pair	O'Rourke (2017)

Table 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, Baroud, and Barker (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, Barker, Ramirez-Marquez, and Rocco (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 in-operability	Pant, Barker, And Landers (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 Nacht-mann (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)

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 (Lalla-Ruiz et al., 2018; Tong & Nachtmann, 2017) that study a similar problem on inland waterways. Arango et al. (2011) developed an integrated simulation and optimization model based on 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 trans- shipment 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 (CP- TAP). 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.

The reviewed inland waterway disruption response literature motives 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; S. Zhang, Lee, & Holmer, 2017), cargo price and economic surplus (Yu, English, & Menard, 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), and 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 terminal 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 contribution 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 contribution time of a barge depends on the actual contribution 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 project 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, whereas the CPTAP non-linear model requires developing specialized heuristic solution procedures. Our approach can be more widely adopted by planners in the maritime transportation community.

Methodological Approach

Problem Definition

We define our problem using an inland waterway disruption occurred on January 20, 2014. A disruption occurred when the Arkansas and Missouri railroad bridge became stuck due to a malfunction, impeding barge tows to pass beneath the bridge. Figure 1 depicts the disrupted section of the Arkansas River. This section contains five lock and dam (L/D) systems that allow barges to navigate through varying water levels. The upper waterway section includes three terminals and one barge tow which commonly carries between nine to fifteen barges each. 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 impacted by the disruption.

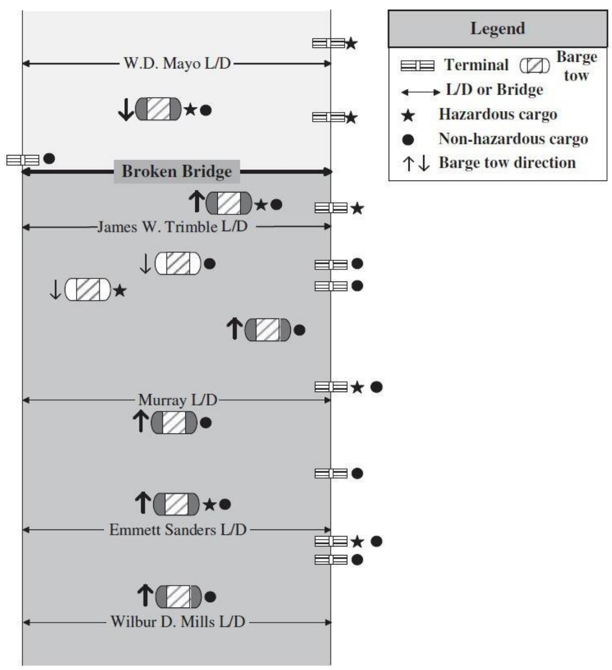

Figure 1. Arkansas River disruption (Tong & Nachtmann, 2017)

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 terminals have limited capacity to offload a single barge at a time. The assignment of barges to terminals considers the 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. Due to the terminal limitations, some disrupted barges may not be assigned to a terminal if there is not available offload capacity. However, barges transporting hazardous cargoes must be assigned to a terminal and offloaded. Barges carrying non-hazardous cargo that are not assigned to a terminal are assumed to remain on the waterway to be salvaged at a later date which results in a total value loss of the cargo. 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.

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).

Flow Diagram for the Decomposition Based Sequential Heuristic

Figure 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 2). The Cargo Prioritization Model (Model 1 in Figure 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 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.

A sequential use of the Assignment Model (Step 3 in Figure 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 2) and knowing which terminals receive cargo of the highest priority, we update the capacity of those terminals (Step 4 in Figure 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 2) have been considered or there is no remaining capacity at the terminals available. 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 2) at each terminal (Step 6 in Figure 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 2). Next, we present an explanation of the three components of our approach.

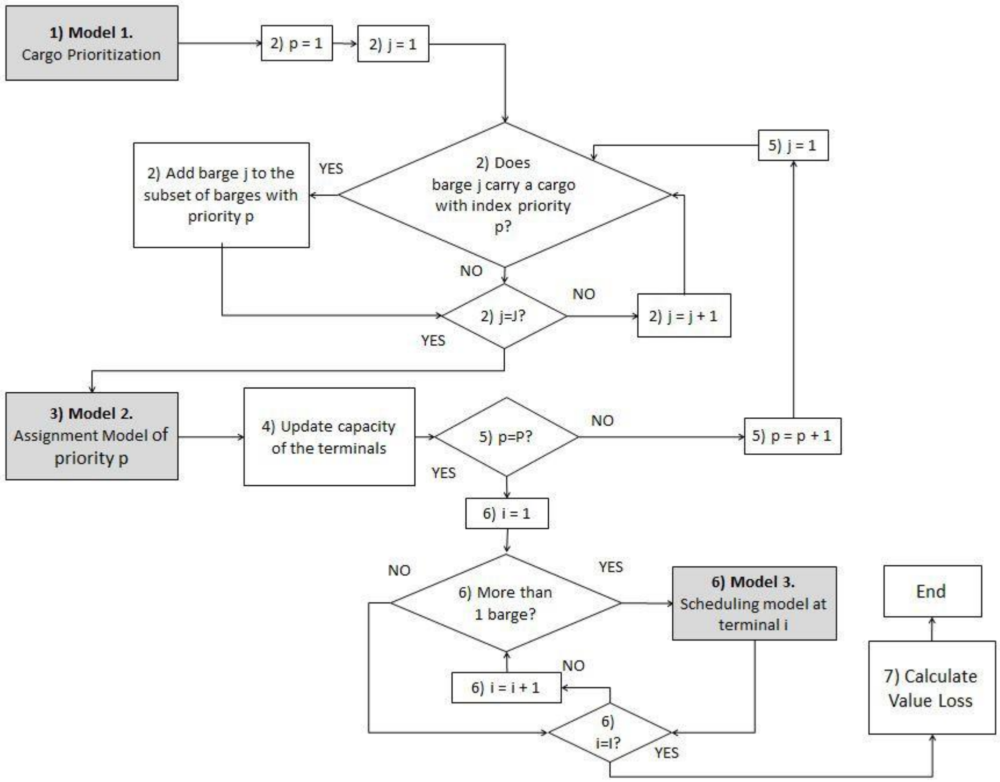

Figure 2. Flow diagram DBSH

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, 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 aggregation method 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).

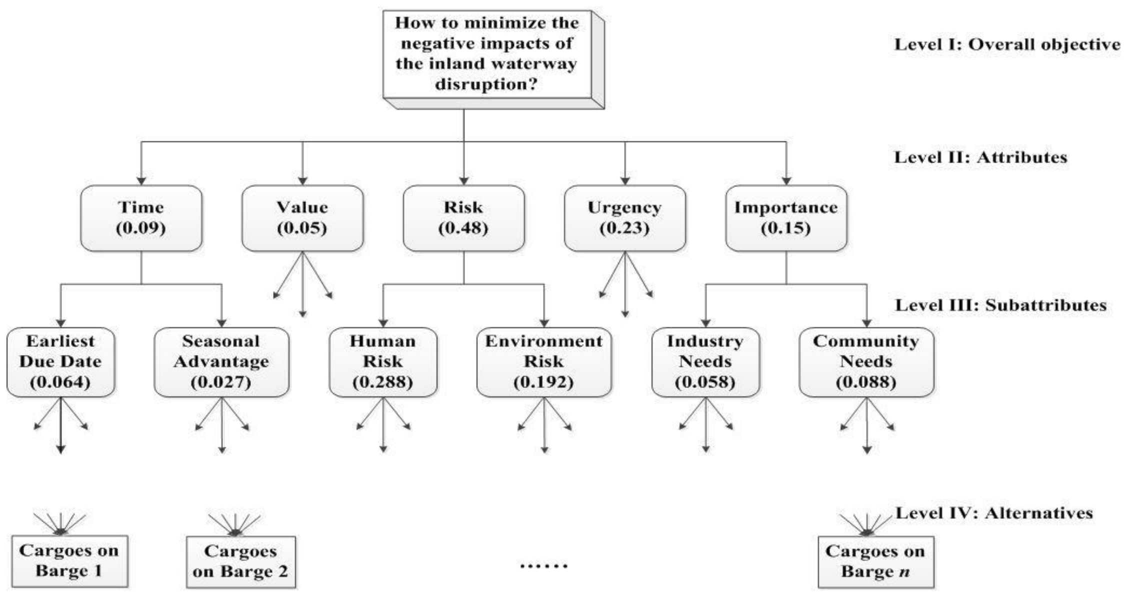

Figure 3. AHP decision hierarchy for cargo prioritization within inland waterway transportation (Tong & Nachtmann, 2013)

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. 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. 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

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_i is the capacity 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

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.

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

Subject to

$$\sum_{i \in I \cup D} y_{ij} = 1 \qquad \forall j \in J \tag{3.2}$$

$$\sum_{i \in I} y_{ij} = 1 \qquad \forall j \in H \tag{3.3}$$

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

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

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

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

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 1 in Figure 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. Finally, constraint set (3.6) corresponds to the binary nature of the decision variables.

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 3.11 for the cases when barge $j \in J \cup H$ is not serviced before barge k ($x_{jk} = 0$)

Equation (3.7) 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.

Constraint set (3.8) assures that there is only one barge serviced first. Constraint set (3.9) assures that there is only one barge serviced last. Constraint set (3.10) 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 (3.11) represents the sequence of the barges.

Constraint set (3.12) assures that each barge has arrived to the terminal before start being serviced. Constraint sets (3.13) and (3.14) correspond to the nature of the decision variables.

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

Subject to

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

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

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

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

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

$$s_j \geq t_j \qquad \forall j \in B \tag{3.14}$$

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

$$s_j \geq 0 \qquad \forall j \in V \tag{3.16}$$

Results/Findings

First, we solve a case study taken from Tong and Nachtmann (2017) which is illustrated in Figure 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 sub- sections (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.

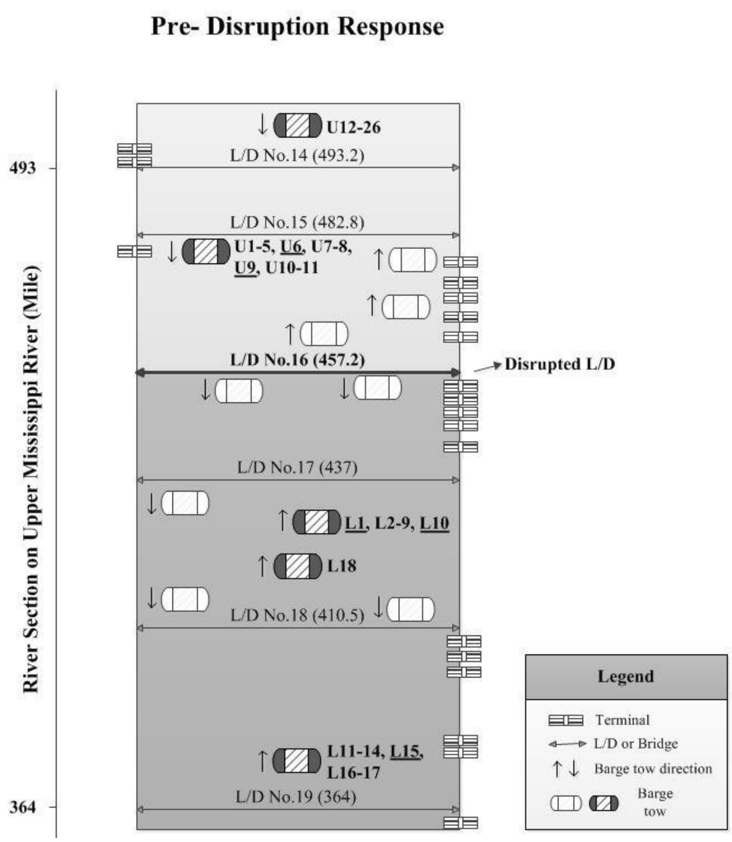

Figure 4. River disruption case study (Tong & Nachtmann, 2017)

For the disrupted barge tows, Figure 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 4. 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 4. 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 5. 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 5. The cargo value is calculated based on the estimated market price given in Table 5 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 are 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.

Table 5. 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 3.15 (Tong & Nachtmann, 2017).

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

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. 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 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 5. 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.

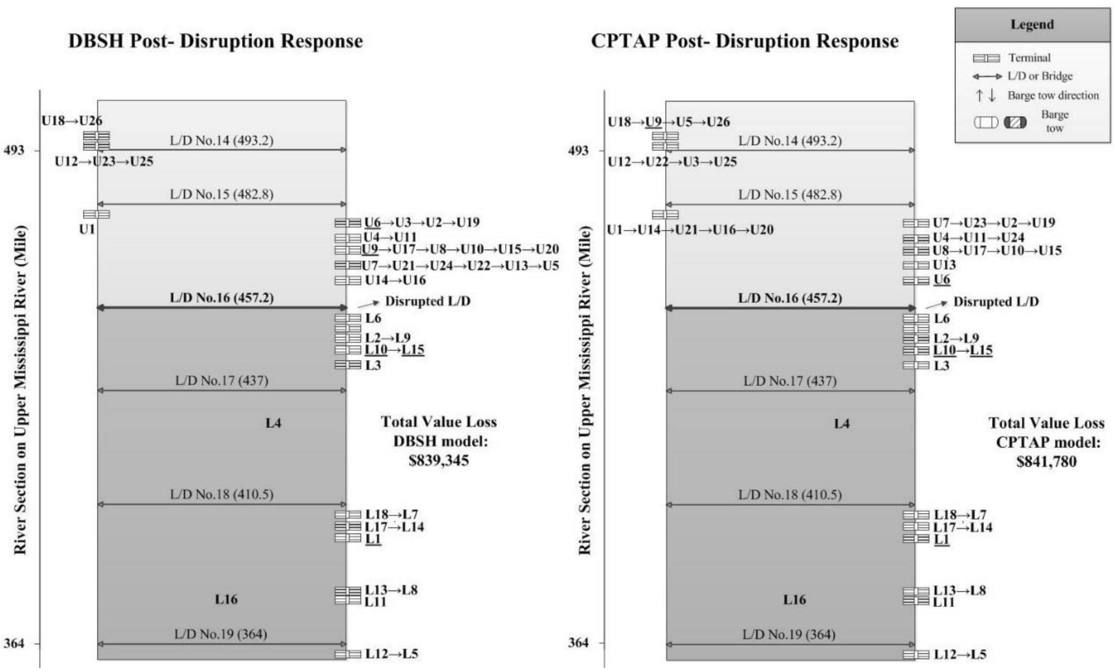

Figure 5. DBSH and CPTAP comparison results. Updated from Tong and Nachtmann (2017)

We present our results in Table 6, 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 contribution time of every barge for all possible combinations of terminal assignments, which is a non-linear calculation and computationally expensive.

In this paper, 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.

Table 6. Results for thirty-five large size instances

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	758266	-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	811894	-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	763284	-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	777700	-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	744050	-0.94%	115.7	1.3	-98.8%
Mean	812,403	815,553	0.36%	201.2	8.3	-92.30%

The CPTAP modeling effort is therefore more computationally complex than that of the proposed DBSH, and the implementation of the DBSH is more user friendly than the CPTAP approach. The capabilities of off-the-shelf solvers are better suited to solve linear models over non-linear models, which typically require development of specialized and specific solution procedures such as the GA developed by (Tong & Nachtmann, 2017). Considering the results and ease of implementation, the use of the less complex DBSH approach is recommended.

4 Impacts/Benefits of Implementation

In this section, we highlight the benefits of this study. Transportation engineers and planners 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 costs 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 1. In these situations, it is necessary for transportation engineers and planners 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 paper, we contribute a decision support tool that engineering managers can use to support their inland waterway disruption response efforts.

5 Recommendations and Conclusions

This paper 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 an 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.

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, and the proposed DBSH is easier to implement as compared to the CPTAP approach. 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 similar results from the CPTAP approach while less complexity in the implementation 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 as stochastic handling or transport time.

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