Assessing the System Resilience Trade-Off Space: Empirical Model of the Port of Houston Waterway Recovery Process

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Abstract: When they are disrupted, complex, technical-social systems, such as maritime ports, require operators to negotiate a resilient solution that satisfies a broad range of individual business and societal needs without compromising the long-term integrity of the system. In order to achieve this, port operators must make complex tradeoffs among various objectives. For example, during operational disruptions, port operators in some systems may create formal and informal procedures (i.e., protocols) to shift from decentralized to centralized decision-making temporarily. In this context, the term *port operator* refers to any entity private or public operating within the port. Within this shift from decentralized to centralized decision-making, we found two high-level heuristics, which can be categorized as feasibility and prioritization. Feasibility assessments are generally safety-based and tend to be very risk-averse, whereas prioritization rules allow more flexibility. This paper explores—within an empirical context—how varying these prioritization rules define the trade-off space for vessel-move sequencing decisions. This trade-off space describes the qualitative impact of the heuristic across different industry segments. This article demonstrates that prioritization rules can alter the recovery dynamic without compromising existing safety protocols. **DOI: 10.1061/(ASCE)IS.1943-555X.0000606.**

Introduction

The global economy is largely dependent upon maritime infrastructure to support the large volume of goods transported between continents. The US receives 45.7% by value and 67.02% by ton of its imports by vessel (Bureau of Transportation Statistics 2018). Ports are vulnerable to a number of threats, from malicious actors to climate-induced challenges. In order for a port to remain a competitive business entity, it must be equipped both organizationally and physically to cope with these challenges. If the recovery of a disrupted port is poorly managed, the effects can ripple throughout the economy, causing increased gas prices, increased food processes, shortages of consumer goods on store shelves, and potentially serious environmental hazards resulting from stressed chemical and energy production facilities. The ability to cope effectively and broadly defines resilience.

An important part of coping in complex social-technical infrastructure systems is the ability to identify and manage trade-offs by collectively processing information and directing the application of limited resources. Systems characterized by complexity and decentralized governance rely heavily on well-established strategic heuristics for collaborating rather than the optimization for effectively navigating disruptions wrought with uncertainty and sophisticated impacts (Amodeo and Francis 2019). Andersson and Ostrom (2008) described such governance systems as responses to collective action problem-solving. Transportation systems, such as ports and inland waterways, rely heavily on common use resources that must be collectively managed through these governance systems. In a related work, Dietz et al. (2003) laid out five characteristics for effective governance: an ability to monitor the resources, gradual variation in consumption dynamics over time, personal engagement of stakeholders, ability to easily prevent new users, and a willingness to enforce rules. Simon (1981) characterizes intelligent systems as ones that are goal-oriented, adaptive, and capable of learning—language strikingly similar to that used by resilience scholars. However, Simon also expresses concerns about the use of optimization in complex systems centered on how one defines *optimal* and how problems are formulated. This tension is clearly at play in the Hurricane Harvey Port of Houston case study presented in this article. While optimization and simulation are widely applied in the resilience research literature, there exists an opportunity to study this problem from the perspective of how real-world empirical heuristic variants impact the quality of a response within a particular governance framework as systems shift from decentralized to centralized governance when disrupted (Amodeo and Francis 2019).

Semiempirical research efforts into the resilience of inland waterways exist but tend to focus on optimization (e.g., Baroud et al. 2014; Nair et al. 2010). These examples tend to assume high degrees of centralization as a prerequisite for solution search and selection. The research reported in this article is part of a larger mixed-methods case study in which we conducted semistructured interviews and an empirical simulation to explore these governance dynamics (Amodeo and Francis 2019). The objective of the current article is to contribute to the field of resilience—specifically, the resilience of inland waterways—by exploring the contribution of empirically identified and modeled decision heuristics used during a recovery effort. These heuristics are the mechanisms by which a system flexes in the face of disruption.

This article makes three specific contributions:

- First, the model of the system and heuristics is a significant contribution. Previous attempts to model the recovery efforts in the

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Port of Houston never took off due to a perception of insurmountable complexity. While intuition remains a factor, the model presented is capable of expanding to meet additional requirements.

- Second, we have empirically and quantifiably explored the contribution of the decision and safety protocols themselves as opposed to generic high-level strategies. The decision space is constrained by the level of risk-averse rules applied. However, modifying priorities within these safety rules produces a different recovery quality. This contribution can help operators reassess their prioritization process based on localized and current needs while fixing safety protocols.
- Third, we have demonstrated a method for assessing the trade-off space defined by variations in protocols in an environment defined by common user resources. While this article does not explicitly measure resilience, the dynamics explored in this study are crucial in capturing the dynamics of macrocognitive system behaviors in future investigations in resilience science.

The remainder of this paper proceeds as follows. In the next section, a theoretical background positions the current research in the current infrastructure resilience space. The "Method" section provides methodological discussions. The subsequent two sections present the model validation and numerical experiments, respectively, and a discussion follows.

Theoretical Background

The concept of rebound or recovery is a popular method of defining resilience in the infrastructure field. The faster a system can recover, the more resilient it is considered. Previous work emphasized the optimization of recovery times or budgets (Baroud et al. 2014, 2015; Nair et al. 2010). These works made an important contribution to demonstrating the trade-offs associated with various decisions. The optimization formulations assume a high level of control, centralized data collection, and centralized knowledge management that can quickly be implemented during disruption characterized by uncertainty. The current article does not contradict this earlier work but explores a different dynamic of the problem. In the current context, the physical component recovery occurs external to the model, and the recovery decisions in question pertain to the decision-makers operating within the constrained space defined by the physical state of the system. The question at hand is not how or when to fix assets but how operational decisions are made once the state defined by the asset recovery decisions is made. For example, our work might assume that the state of the waterway is the function of recovery sequencing decisions, such as those described by Baroud et al. (2015). Insight from the data collection process involved with the current article indicates that the sequencing of recovery activities is influenced by demand for services, as well as resource constraints required to quantify a required action and position the required assets. If this is true, the recovery decisions modeled by earlier authors and the processes modeled in this study are interdependent and possibly nested processes.

The notion of robustness, as described by Woods (2015), describes how much damage a system can sustain. Our interviews indicated that decision-makers consider the broader impacts of their decisions but were not assessing their alternatives based solely on economic impact as much as aiming to make the most effective use of the waterway while treating local stakeholders fairly and avoiding worse case scenarios that seemed plausible and likely. While economic analysis is attractive, the issue of fairness and avoiding worst-case scenarios (i.e., environmental) simply cannot be overlooked as central to decision-making. Each disruption is unique, and resilience can only be measured in the context of a specific disruption (Haimes 2009). Therefore, it is important to understand how the systems' decision-making protocols interact with the physical state of the system in order to understand how and where to implement planning and response strategies.

In a study of the vessel traffic service in the Port of Rotterdam, van Westrenen makes the point that resilience is designed in system property arising from a system's ability to make an on-the-spot system redesign to cope (van Westrenen 2014). Van Westrenen highlights that reorganization to manage scarce resources is a characteristic of resilient control and advocates for more centralized control of vessel management. The current article focuses on what van Westrenen refers to as soft constraints within the abstract function. The tension between centralized and decentralized control is referred to as the concentrated-deliberate action trade (Hoffman and Woods 2011). However, the trade-off occurs across the spectrum of decentralized-centralized control. A 2014 National Academy of Science port resilience report provides an in-depth discussion on the factors driving port operations during a recovery, descriptions of doctrinal response frameworks, attributes of past disruptions, and findings from stakeholder interviews covering information flow, physical infrastructure, and regulatory considerations (Southworth et al. 2014). The Port of Houston transitions from decentralized to centralized governance when the system is disrupted (Amodeo and Francis 2019). When governance structures shift, the decision-making framework is modified appropriately. The heuristics explored in this work represent the framework for the Port of Houston under a decentralized governance structure.

Aven (2018) argues that resilience management requires broad qualitative assessments. This article provides an empirical demonstration of these broad qualitative assessments in support of resilience analysis and management. When complex systems respond to a disruption, their responses often involve the use of resources and assets in hazardous and vulnerable situations. Therefore, the decisions made during these responses must mitigate the risks of these hazards so as to avoid further disrupting the system at its most vulnerable. This study demonstrates that resilient systems implicitly integrate risk mitigation into their resilience management strategies. These risk mitigation decisions can define the short term ceiling on service restoration. Van Asselt and Renn (2011) make a similar point, arguing that risk governance "pertains to the various ways in which many actors, individuals, and institutions, public and private, deal with risk surrounded by uncertainty, complexity, and/or ambiguity." They propose three principles required to manage risk: communication and conclusion, integration, and reflection. The current research provides an empirical investigation into how a system self-organizes and employs qualitative heuristics that encode broad qualitative assessments response to apply these principles and achieve a resilient response while avoiding further disruption to the system.

Resilient systems learn from prior events and create structures, heuristics, and formal and informal means to deal with unforeseen challenges. This learning is part of *sustained adaptability*, which Woods (2015) describes as the ability to manage/regulate the adaptive capacities of systems that are layered networks and are also part of larger layered networks. This ability is manifested over longer time frames, years, or generations. Simon (1981) presented similar ideas, arguing that intelligent systems exhibit a type of evolution by passing down knowledge through social systems and continuously refining their heuristic. In a sense, the categories proposed by Woods (2015) are not independent skillsets but part of an iterative resilience management process with both near and

Table 1. Summary of the four concepts of resilience proposed by Woods (2015)

Component of resilience	Description	Example
Rebound	The ability of a system to recover from a surprise or unexpected disturbance.	A hurricane disrupts a coastal port; stakeholders must make smart decisions to restore capability.
Robustness	Ability to withstand a blow to the system.	A city imposes strict building codes requiring new infrastructure to employ earthquake-resistant technology.
Graceful extensibility	Ability of a system to flex capabilities to meet surprise or unexpected disturbances.	A regional community stands up an emergency response center with additional personnel to respond to the additional management and information management requirements.
Sustained adaptability	Ability of a system to continue to adapt over the long term effectively.	City planners are able to improve their ability to internalize the city's collective historical experience and new insights for improved city planning.

long-term subprocesses. Table 1 summarizes the four concepts posed by Woods (2015).

The present authors hold that sustained adaptability is a process of managing the resilience value chain. System managers and policymakers assess uncertainty and invest in physical, informational, and organizational architecture prior to a disruption. For example, Baroud et al. (2014) explored the stochastic relationship among the amount invested in preparedness prior to a disruptive event, the scale of the disruptions, and the subsequent recovery. These investments in preparedness are part of sustained adaptability because they require both insights from past experiences while anticipating potentially different challenges in the future (i.e., previously unexperienced climate change impacts). Allocating funds to a response is driven by the particular characteristics of an event as well as the approach the system stakeholders have adopted in managing the recovery. However, recovery funds are limited, and recovery strategies are interdependent. Once a disruption occurs, the system must navigate the challenges determined by long-term predisruption investments and near-term preparations. However, once the immediate challenges have passed, or a new norm is established, the system must modify its architecture or protocols based on an updated understanding of uncertainty or a new priority among trade-offs. Sustained adaptability is the management of this cyclic process. Fig. 1 presents a process concept map depicting the

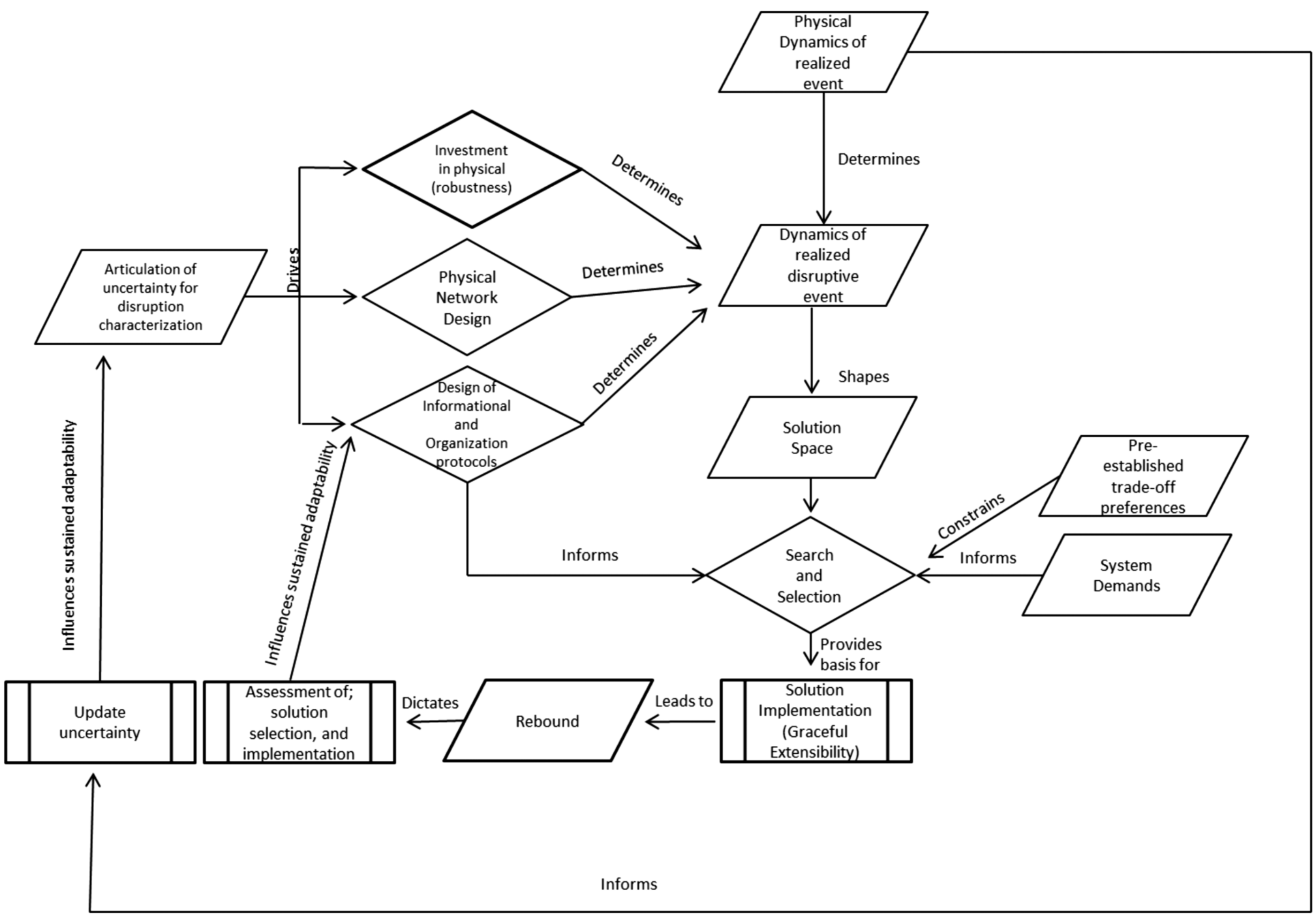

Fig. 1. Process concept map describing the resilience value chain where initial uncertainty impacts decisions in the physical, organizational, and informational architecture and protocols of a system. These, in turn, serve as the framework for a response. The assessment after the response includes updating the understanding of the dynamics, the uncertainty, and the trade-off priorities. This triggers a process of system self-reflection and sense-making. A system exhibiting sustained adaptability will consciously conclude this process by taking explicit steps to evolve.

relationship between design decisions, human responses, and uncertainty within the resilience value chain. Fig. 1 combines elements of the concept map developed by Novak (1990) with process mapping. This process map format is not entirely new. McDaniels et al. (2008) depicted the disaster management process as an influence diagram that mapped sources of uncertainty to decisions before and after the event, referred to as *ex-ante* and *post-ante*, respectively. The conceptual difference between the resilience value chain presented in Fig. 1 and the model presented by McDaniels et al. (2008) is the framing of the value chain around the four concepts of robustness, graceful extensibility, rebound, and sustained adaptability.

This article addresses how a system searches for, selects, and implements a solution. This segment of the resilience value chain is where a system flexes its adaptive capacity in the near term during a recovery effort. In the context presented in this study, a flexible process for collective management of a disrupted system has evolved as the result of repeated exposures and rounds of collaboration. This process not only affects the evolution of protocols but also provides input to physical system improvements.

A key stakeholder in the Port of Houston is the vessel traffic service (VTS) operated by the United States Coast Guard (USCG). Praetorius and Hollnagel (2014) conducted a study of the VTS model from the perspective of a joint cognitive system (JCS) (Hollnagel and Woods 2005). This interview and focus group-based research analyzed these systems across modes of control and the following four cornerstones: monitor, respond, anticipate, and learn. The concept of modes of control is an important lens to assess as systems resilience. In the context of this article, the control mode most applicable is tactical, characterized by a small number of competing goals, with sufficient time, a thorough assessment of outcomes, and an action plan based on well-established protocols. These strategic control efforts are part of the resilience value chain, with each short-term tactical control period updating the strategic control process.

Method

The current article is an in-depth case of the Port of Houston, which applies a high-level self-organizing approach defined as *core-centric* by Amodeo and Francis (2019). Davis et al. (2007) laid out the appropriate conditions for the use of simulation in theory building; the theory developed is simple, and the research in question involves a fundamental trade-off or tension. The theory proposed in this study is simple; given a fixed set of feasibility and safety rules, how does varying the prioritization rule impact the nature of the recovery. The trade-off or tension derives from the exact nature of the prioritization rules. One set of rules may lead to a more favorable outcome for one set of stakeholders over another. Davis et al. (2007) require experimentation for theory building; this is achieved by modifying prioritization rules and comparing the recovery outcomes across several different performance metrics to study the trade-offs.

Alderson et al. (2015) argue that a more *operational* approach toward investigating and planning for resilience is required. The current article agrees with Alderson et al. that resilience research should rely on quantitative measures that are meaningful to operators while employing models that capture domain-specific details. The current article meets both criteria of an operational model. First, it measures performance quantitatively. Second, the model is built around a decision. A slight point of deviation with Alderson et al. is the degree of prescriptiveness in the current model. The model in the current paper assumes that the upper bound on the resilience of the particular system is defined by the feasibility rule sets. Altering the priority rule sets explore the broad nature of the recovery by studying several metrics for a diverse set of interests. Complex systems are characterized as such not only because of the physical complexity but because of the complex trade-offs among the interested operators.

System operators have a well-established process, from which they are unlikely to deviate for experimental purposes. Therefore, simulation allows us to explore the what-if scenarios without operational risk while experimentally exploring the trade-off space. In this paper, the authors explore the trade-off space through a simulation of responses in the Port of Houston, US, to Hurricane Harvey in August 2017. The simulation focused on the scheduling of deep-draft vessels into the Port of Houston along the Houston Shipping Channel. Deep-draft ocean-going vessels require detailed coordination for pilots and channel access, for which data was available. This data was not available for the less coordinated barge lanes. Therefore, this model focused only on pilot coordinated moves. While the experimental outcomes cannot be empirically validated, they provide insights to system operators regarding the impact of the prioritization rule set on the trade-offs made within the system. The simulation relies on the elicitation of decision-making heuristics from a few key decision gatekeepers and detailed modeling of the event from historical data sources. The remainder of this section describes the case study narrative and data sources, while the following section describes the simulation model.

Port of Houston

The Port of Houston is an industrial hub for both the energy and general cargo industries (Port of Houston Authority 2018). It consists of a large variety of stakeholders and is both physically complex and diverse in the wide range of disruptions it faces. Disruptions range from routine fog to less occasional allisions, collisions, and hurricanes. The port community has developed a guiding set of principles for collaborating and making transparent decisions during disruptions. Hurricane Harvey is one noteworthy occurrence of these principles in practice. Fig. 2 provides a geographic overview of the Port of Houston.

Hurricane Harvey Narrative

Hurricane Harvey bore down on the Houston Area on August 25, 2017, bringing a large volume of rain and halting commerce through the Port of Houston waterway for over a week. Although Houston is accustomed to hurricanes and has procedures for operating under these conditions, Hurricane Harvey presented novel challenges, including a high degree of uncertainty over the duration and magnitude of high-velocity currents. The duration and volume of rainfall inland resulted in dynamic shoaling conditions due to the high-volume run-off. Shoaling is the accumulation of sediment deposits of sufficient quantity to alter a channel's navigable depth. Just prior to the arrival of Hurricane Harvey, most vessels headed to the open ocean as a safety precaution. The main poststorm objectives were to allocate resources to validate the safety of the channel, recover navigability where required, and minimize the impact on commerce.

In Houston, the USCG operates a vessel traffic service and is authorized under provisions of 33 USC § 161. The VTS is employed across the globe (van Westrenen and Praetorius 2014). In the US, the VTS is primarily an information-sharing body with some traffic management authority commanded by the USCG Captain of the Port. In the Port of Houston, the VTS has evolved a unique role. It forms the nucleus of the Port Coordination Team (PCT).

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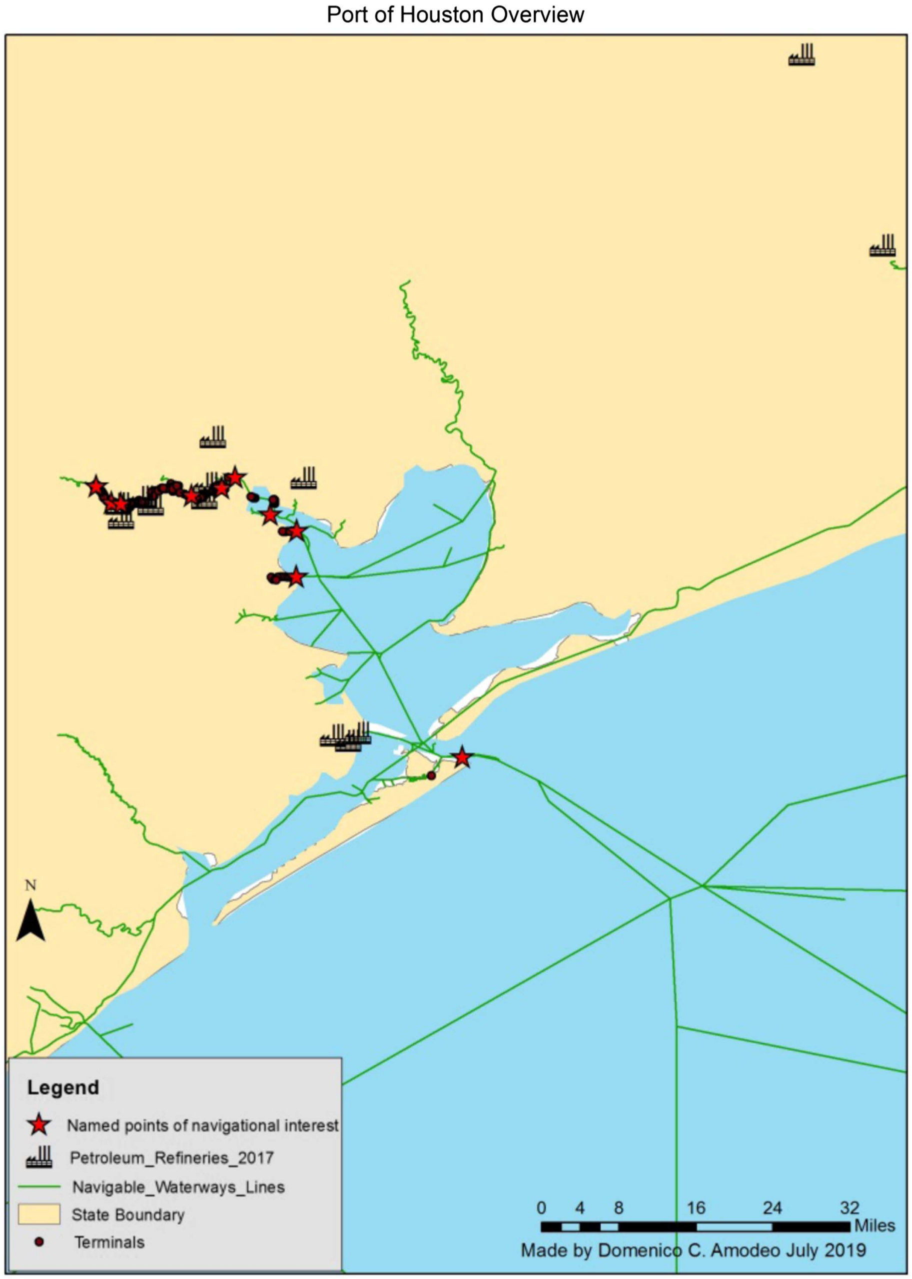

Fig. 2. Overview of the Houston shipping channel showing refineries, terminals, and points of interest identified during industry collaboration meetings held during the disruption period.

The PCT is a roundtable of industries and agencies involved in the safety, operation, and commerce within the Port of Houston. Each industry-sector sends a delegate from the constituent firms to represent its interests. At this round table, information is exchanged in structured ways, and recovery approaches are developed based on the needs expressed and trade-offs identified through negotiation and compromise. The PCT can be seen as a method for managing the revelation-reflection on perspective trade-off (Hoffman and Woods 2011). Aside from information sharing, the PCT serves as a forum, sharing concerns and providing new perspectives across industries.

Data Sources

The data come from four general categories: semistructured interviews, Houston pilot historical logs, port coordination team meeting summaries, and USACE post–Hurricane Harvey channel surveys.

Interviews

The Houston Port Coordination Team Standard Operating Procedure states that there are 19 nonfederal members drawn from those industries most impacted by a navigational halt in the waterway. Federal members include USCG, USACE, and NOAA. In this research, we conducted interviews with 12 managerial level representatives intimately involved with the PCT process from the relevant port sector. The interview participants are summarized in Table 2.

Historical Logs

The Port of Houston Pilots Association provided all vessel movement logs for the year 2017 in an excel spreadsheet of over

Table 2. Summary of port operator interviews conducted within the Port of Houston

Industry sector	Role
Petroleum terminals	Terminal manager that stores and transships petroleum and chemical products for multiple factories.
Container shipping lines	Manager responsible for coordinating vessel arrival and loading/unloading.
Pilots association	Gatekeepers responsible for driving vessels within the port and keeping the port safe.
Chemical shipping lines	Manager responsible for coordinating vessel arrival and loading/unloading.
Chemical terminals	Represents explicitly chemical terminals and shipping interests.
USACE	Manages the efforts to sound and dredge the channel.
United States Coast Guard	Manages the vessel traffic service.
Texas general land office	Provides spill response and environmental assessment.
Harbor tug	Coordinates with pilots and vessel agents to maneuver vessels in and out of berths.
Petroleum maritime manager	Coordinates the arrival and shore side support for petroleum vessels.
General cargo terminals	Port of Houston (publicly-owned) container terminals.
Refinery economics manager	Makes decisions impacting the production and operations state of the refinery that inform internal vessel priority assessments.

18,000 entries. Our period of interest was September 1, 2017, to September 11, 2017, during which period there were roughly 270 vessel moves: 60% supported the chemical and petroleum industry, and 40% carried containerized or break-bulk cargo. Each entry contains 66 characteristics per vessel move. These logs were analyzed and used to develop the following model parameters:

- Vessel arrival times in the Port of Houston and the prestorm queue sequence;
- Vessel commodities;
- Transit times from the sea buoy to the terminal;
- Turnaround time at the terminal;
- Poststorm inbound sequence;
- Vessel draft; and
- Indication of whether the vessel arrived empty.

Port Coordination Team Meeting Summaries, Pilot Association Website, and Survey Data

The PCT published the minutes of each daily meeting from September 1, 2017, to September 11, 2017, providing rich insights into system dynamics throughout the period. Information elicited from these notes includes the following:

- Named vessel priorities by industry and refinery where indicated;
- A timeline for channel sounding and dredges;
- Detailed channel disruption information for named segments of the waterway;
- Day-by-day channel depths along each segment; and
- Day-by-day listing of daylight movement restrictions along the channel.

Complementing these notes were a set of yet more detailed notes published by the West Gulf Maritime Association (WGMA). These two sources allowed us to construct a network topology. These reports were coded as followed:

- Identified named segments of the waterway; and
- Identified conditions along the segment for each day, allowing draft, daylight restrictions, underwater obstructions, and surveys completed or underway.

Additionally, USACE channel soundings were available online. The soundings are publicly posted on the USACE website. In order to create a uniform description of the surveys, the named locations were plotted with the terminals and USACE surveys. The coordinates for the terminals in the Port of Houston were extracted from the Houston Pilot Association website. The result was a mapping of named segments to terminals to survey areas and named segments expressed as a topology in matrix form. Combining the surveys with the terminals and named areas, the authors developed a day-by-day depiction of the state of the waterway that captured depths and daylight restrictions. Segments of the channels were combined into 14 unique paths. Each path was identified by the path's terminal segment.

Simulation Model Design and Implementation

There are two main components to the simulation modeling effort: the physical model and the decision-making heuristics.

Physical Model

The physical component entails modeling the topology of the network, which describes the movement constraints each day. The physical model is composed of a series of matrices. Because vessel movement decisions were made on roughly an hourly basis for 11 days, there are 264 decision periods. This is described as a 24×11 matrix in which each entry represents a decision period. This matrix was populated with empirical data, using the actual number of vessels moved within each hour from the historical pilot logs. These hourly moves are a function of channel feasibility and the time involved with transiting and boarding a queued vessel. The number of vessels moved in a particular hour is dependent upon a large number of factors and could not be modeled as a variable in the context of the current study. Therefore, the constraint for feasible vessel moves per hour was parameterized with the observed data, which is a known feasible and reasonable realization of the dynamic. The next input matrix mapped individual segments of the waterway to recovery days in which the values represented the channel depth on a given day. A binary matrix was created to describe daylight restrictions for a segment on a given day.

The interviews revealed one important part of the system's physical structure that could not be modeled effectively due to the lack of detailed information. Harbor tugs play a critical role in maneuvering vessels into a berth. Under normal circumstances, tugs are a constraint due to their limited number and specialized requirements. Prior to Hurricane Harvey's landfall, the harbor tugs were dispersed through the port to spread the risk of their poststorm unavailability. The availability of the tugs factored into the feasibility of individual vessel moves. In the absence of reliable information on tug locations, we assumed sufficient tugs to support a selected move. This underlines the challenges of modeling decisions in these systems. In reality, these decisions are part of an interdependent set of decisions, such as vessel sequencing, dredger location and dredge sequencing, tug location decisions, and sounding sequence decisions. As shown by the

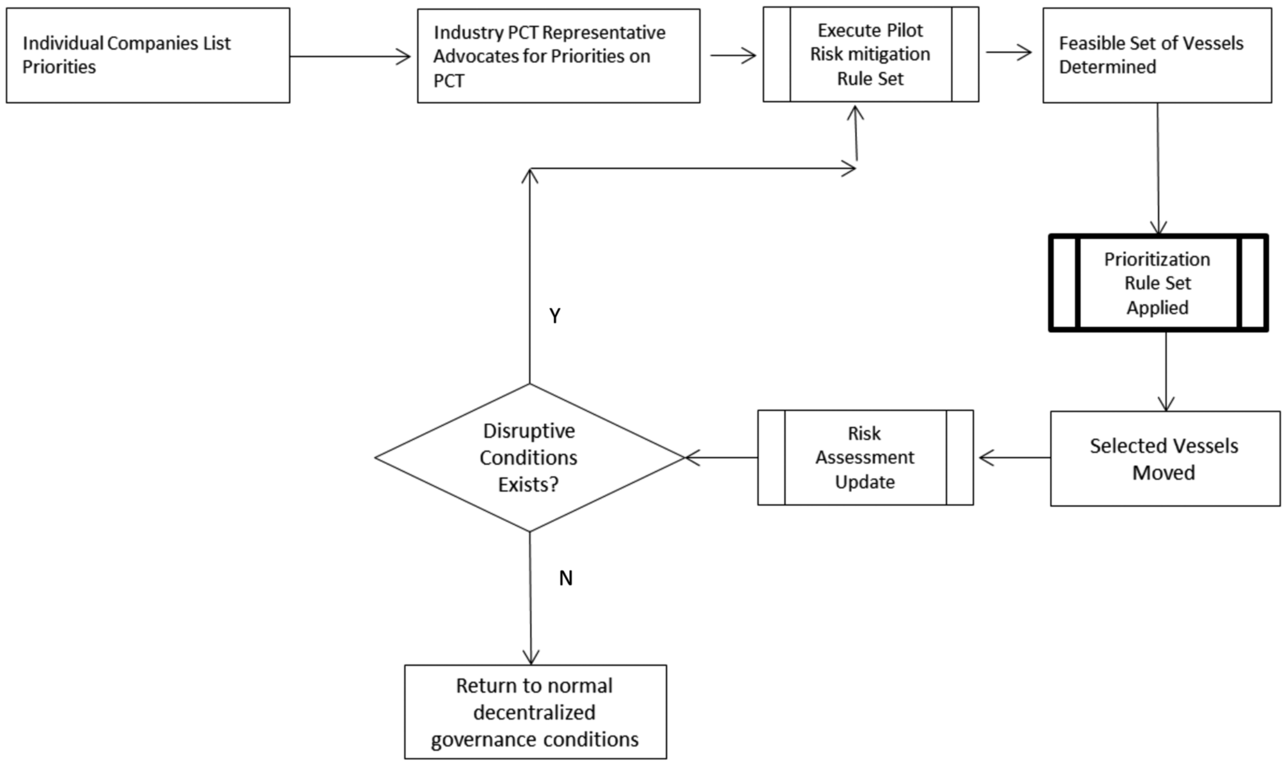

Fig. 3. High-level process description for determining vessel moves. The subprocesses are an in-depth set of rules that can be modified. The prioritization subprocess emphasized is the focus of this article.

decision to disperse the tugs in Hurricane Harvey, the uncertainty surrounding the final characteristics of a disruption makes detailed planning a real challenge. For this reason, the model only focuses on the vessel sequencing decision but recognizes that a feasibility rule for tug availability is possible given sufficient information.

Across all the interviews, there was a general agreement that refineries typically rank as a high priority to avoid risky shutdowns, known as thermal cycling. Refineries keep operational data closely held, so it is difficult to ascertain from publicly available data the degree to which refineries curtailed operations. The Energy Information Agency's Division of Energy Infrastructure Security and Energy Restoration published daily event reports for the duration of Hurricane Harvey and its subsequent recovery. While a detailed understanding of refinery operational status could not be developed, news reports combined with vessel movement data and the meeting minutes indicate that refineries in Houston were receiving maritime support as early as September 1st and ramping up around September 4th.

Decision Model

Port Coordination Team

The Port Coordination Team is an open stakeholder body that convenes for information sharing and coordination across industry and agency boundaries during disruptions. Interviews revealed the PCT often discusses vessel movement priorities, and an interesting dynamic was repeatedly and consistently described. From interviews, it was revealed that industry stakeholders are willing to accommodate a competitor's immediate requirement to avoid a refinery shut down or similar emergency at the expense of their own fewer pressing needs. This is achieved through a process of communal vetting, enabled by trust and information sharing. However, all vessel movements are constrained by safety rules imposed by the USCG and the Houston Pilot Association. As one interviewee stated, these organizations represent regulatory control and operational control, respectively. Fig. 3 shows the basic pilot safety protocol, with a generic prioritization subprocess. There are three parts to this process. In the first part, individual firms feed their priorities to their industry representative/advocate on the PCT. According to the pilots, the most critical reasons for requesting priority are a crew member health emergency, a refinery in danger of shutting down, low fuel levels on a vessel, and the risk of perishable cargo spoilage. Next, the pilots determine the feasibility of a vessel based on safety protocols and professional judgment. Finally, the pilots prioritize vessel moves while attempting to accommodate stakeholder identified and vetted priorities. The pilot's goal is to maximize waterway usage while maintaining fair and transparent decisions.

The PCT convenes after representatives from each industry sector have collected the requirements of their constituency and vetted the request as viable and valid. The system can be viewed as a series of gatekeepers: the industry gatekeepers responsible for collecting and advocating individual firm demands, the system gatekeepers responsible for regulating and determining the physical constraints on the system, and the final arbitrators of the decision. Under this framework, firms share sensitive operational information that they otherwise would not share. A baseline heuristic was constructed from these interviews.

As we can see from the general process detailed previously, the risk analysis mitigation protocols constrain the vessel sequencing decision problem. The uncertain state of the channel and the hazards associated with vessel characteristics informs the recovery process and resilience management.

1) Take the vessel list in the original arrive time sequence.
2) Assign each vessel to a path based on the terminal destination
3) Initiate the risk allowable on each path to 0
   a) 0 indicates low risk (non-chemical, non-petroleum) Petroleum vessels with lower inbound than outbound draft (empty) is considered low risk.
   b) 1 Indicates all non-energy/chemical vessels empty or not
   c) 2 Indicates all energy/chemical non-empty inbound vessels
4) Initiate period to first day of movement
5) Initiate decision period to 1 of 24 (based on hourly decision periods)
6) **Feasibility Routine** : Starting at the top of the list and check each vessel for **feasibility** based on following conditions:
   a) Has vessel arrived and requested pilot services before current time?
   b) Is the vessel traveling along a daylight only restricted path, and is the entire transit time during daylight hours?
   c) Does the required path have sufficient depth given the vessel draft?
   d) Is the path cleared for the risk level associated with the vessel?
   e) Will the destination terminal be open when the vessel arrives?
7) **Sequence Routine** Categorize and rank the feasible vessels as follows:
   a) First: Petroleum and Chemical vessels that are a named priority.
   b) Second: General cargo vessels that are a named priority.
   c) Third: Vessels that are not a named priority.
8) **Selection Routine**: Select vessels based on decision period quota, ensuring no vessel is sent to the same terminal in the current period.
   a) Move vessels to and from the 'in-transit table' based on time in route.
   b) Move vessels to and from the 'on-station table' to the 'departure table' based on time at terminal.
   c) Update risk level for utilized path by one, unless risk level is currently 2.
9) If the decision period is 24, update the day, else update the decision period by 1.
10) Repeat above until there are no more vessels to move or until the last period.
11) If at the end of the last period, vessels remain unmoved, they are ordered in sequence starting with the last simulated move.

Fig. 4. Baseline decision heuristic.

Baseline Nonrandom Decision Heuristic (BNR)

Based on the 13 interviews and study of the various primary sources, a baseline heuristic was extracted. The heuristic was then modeled as a simulation implemented in MATLAB version R2019a that ran for 264 decision periods. Fig. 4 describes the heuristic elicited from the experts within the system.

Model Validation

Model validation determines how close the baseline heuristic replicates the observed sequence of vessels. Because this is a model of a one-time event, it was not possible to test the heuristic repeatedly on numerous real-world events. Therefore, an alternate method was required. The sequence of vessel moves represents a vector in n-dimensional space, where n is the number of vessels requiring inbound movement (in this case, 255 vessels). The coordinate along each dimension is the order of each vessel in the sequence. In order to measure the proximity of the simulation to the observed sequence, the $\ell 1$-norm shown in Eq. (1) was used at the distance measure, which is similar to the hamming distance in this case

$$\text{Distance} = \sum_i |x_i| \tag{1}$$

The $\ell 1$-norm is used as the distance measure because it is the least sensitive measure to extreme deviations from the observed value.

This norm is the sum of the absolute value of deviations between each vessel observed and the simulated rank. The distance is scaled by the maximum possible distance between the observed vector and some theoretical maximum distance vector. The configuration of this maximum distance was determined using the following optimization problem. The maximum possible distance between the observed sequence and some theoretical furthest point in the 255-dimensional spaces is 32,512. All distances are divided by the maximum possible distance to create a relative distance value.

Maximize

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{i,j}(|p_j - v_i|)$$

Subject to

- $x_{i,j}$ Binary
- $\sum_i (|p_j - v_i|) = 1 \quad \forall\ j \in J$
- $\sum_j (|p_j - v_i|) = 1 \quad \forall\ i \in I$

where $x_{i,j}$ = decision variable indicating whether vessel i occupies position j of the theoretical vector; v_i = parameter indicating the observed position of a vessel i; and p_j = parameter indicating a potential position a vessel could occupy in a theoretical vector.

The calculated distance is divided by the maximum distance that results in a relative distance value between 0 and 1. For example, a value of 0.2 means that a simulated vector has a distance from the A.

The linear integer program was used to find the coordinates in a 255-dimensional space that maximized the distance from the observed vector. The distribution of the distances from the observed vector is bound between 0 and the solution objective value of this program. Dividing all distances by the maximum distance creates a relative distance bound between 0 and 1, therefore allowing for distribution with lower and upper support to be fit.

The baseline model includes no randomness. However, two alternate versions of the baseline are developed that introduce random elements. The validation method determines whether the baseline model with the expert elicited prioritization rules outperforms a random prioritization. The two comparative models are described subsequently. The choice of the modifications is designed to test two important aspects of the baseline: sequencing by arrival time and sequencing by cargo category.

- *Random Feasible First (RFF):* The RFF maintains all the feasibility rules as the baseline model but randomly selects one vessel at a time for movement in the current period from the feasible set. Each selection redefines the feasibility space for subsequent selections in that decision period by prohibiting multiple selections to the same terminal within a period. Unlike the baseline heuristic, this heuristic does not prioritize system identified priorities based on the following commodity categories.
- *Baseline randomized within cargo (BRC):* This heuristic is nearly identical with the baseline heuristic; however, rather than selecting identified priorities by the arrival date within the hierarchy of commodities, it maintains the cargo prioritization and hierarchy but randomizes vessel selection within each category.

These two heuristics allow us to validate two aspects of the model. The RFF heuristics provide insight into whether the commodity prioritization in the baseline model is meaningful. The BRC heuristic provides insight into whether the arrival time component of the prioritization is captured. Each random heuristic was run for 100 replications. To compare the random processes, the Wilcoxon Rank Sum test of the empirical cumulative distribution functions was conducted, and a visual comparison of the nonrandom baseline process to the random processes was made. The results shown in Fig. 5 indicates the nonrandom baseline model deviates least from the observed sequence and, therefore, adequately captures the real-world dynamics.

Throughout the interviews, there was a prevailing sentiment that certain industries received priority consideration. Vessels are broadly

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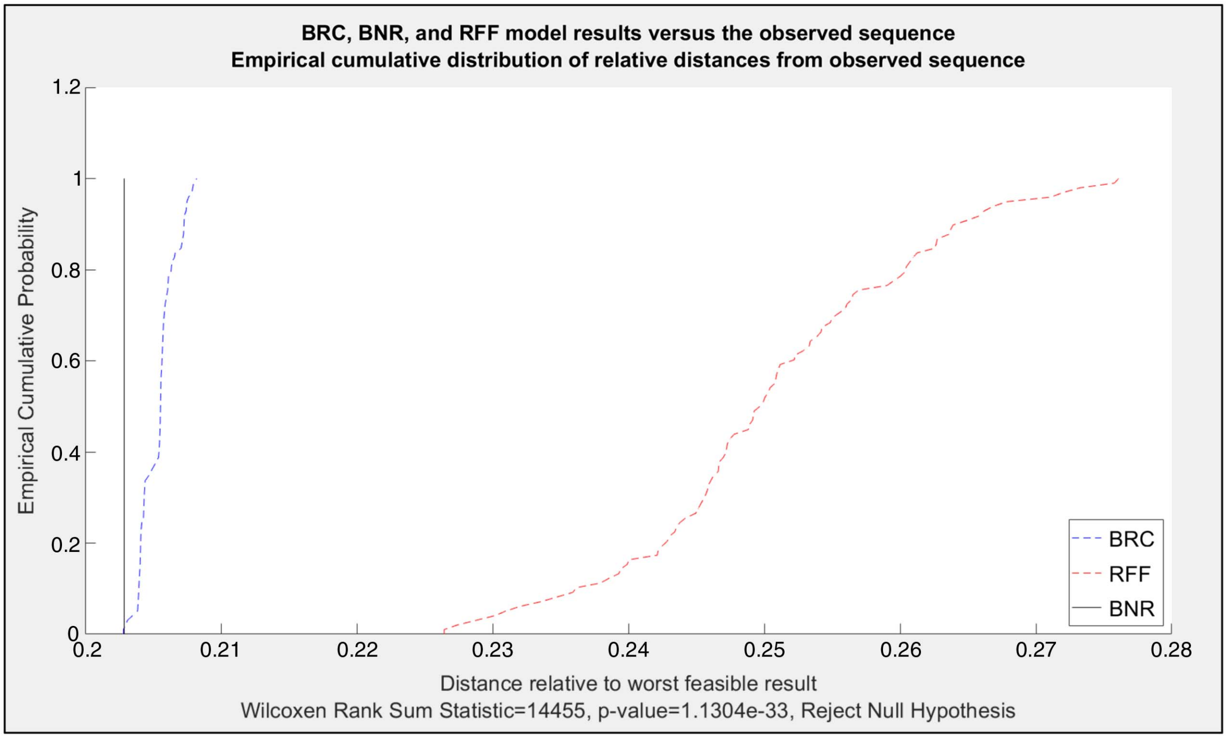

Fig. 5. Comparison of the empirical cumulative distributions of the relative distances for the two randomized validation heuristics and the single run of the baseline nonrandom. The Wilcoxon-Rank Sum test indicates that the two random processes have different medians. The baseline randomized model outperforms the random feasible first model in terms of its relative deviation from the observed. The nonrandom baseline outperforms the vast majority of the randomized process, indicating that both commodity prioritization and arrival time prioritization are important dynamics captured by the baseline model.

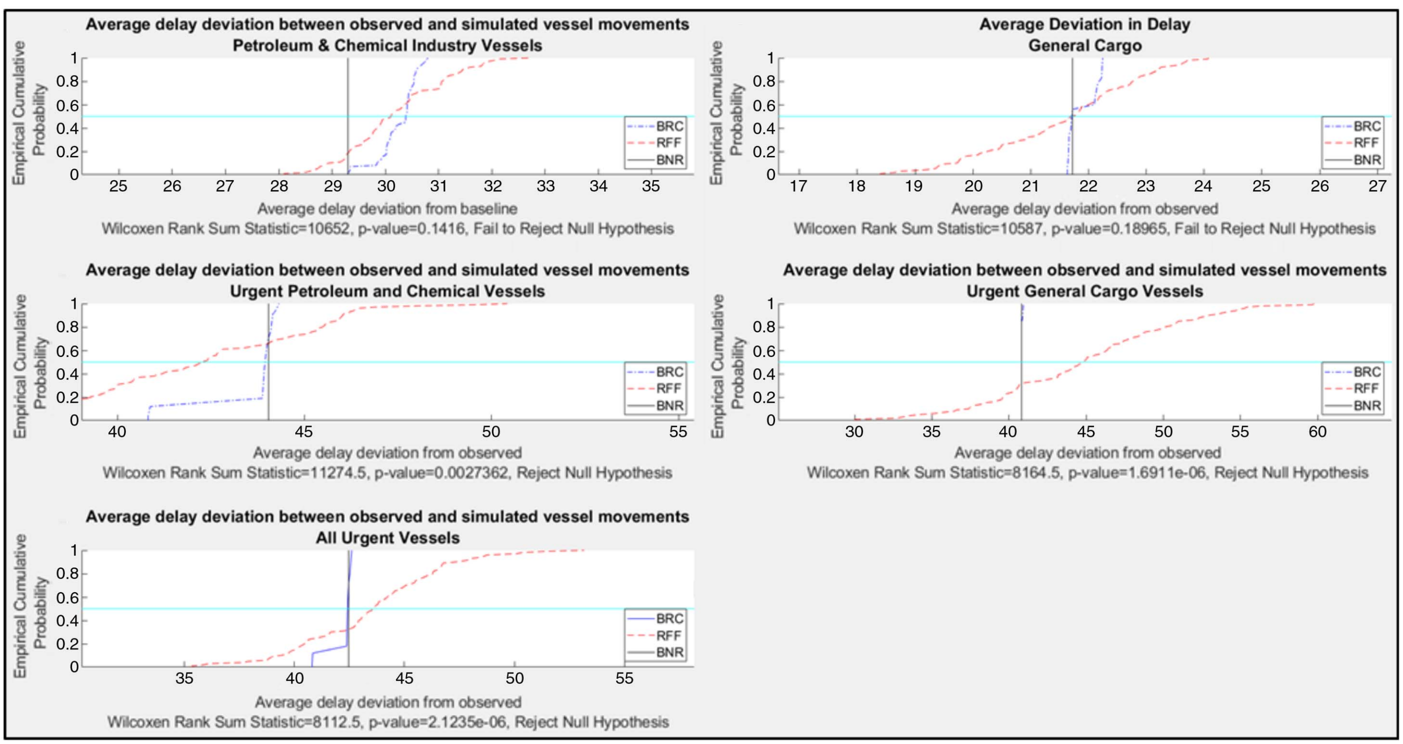

Fig. 6. Cumulative distribution functions that show the average deviation in the delay for each replication and each of the designated categories. The deviation is the elapsed time in hours between the arrival and the time a pilot arrives on board. Each empirical cumulative distribution function is shifted by the observed average delay observed.

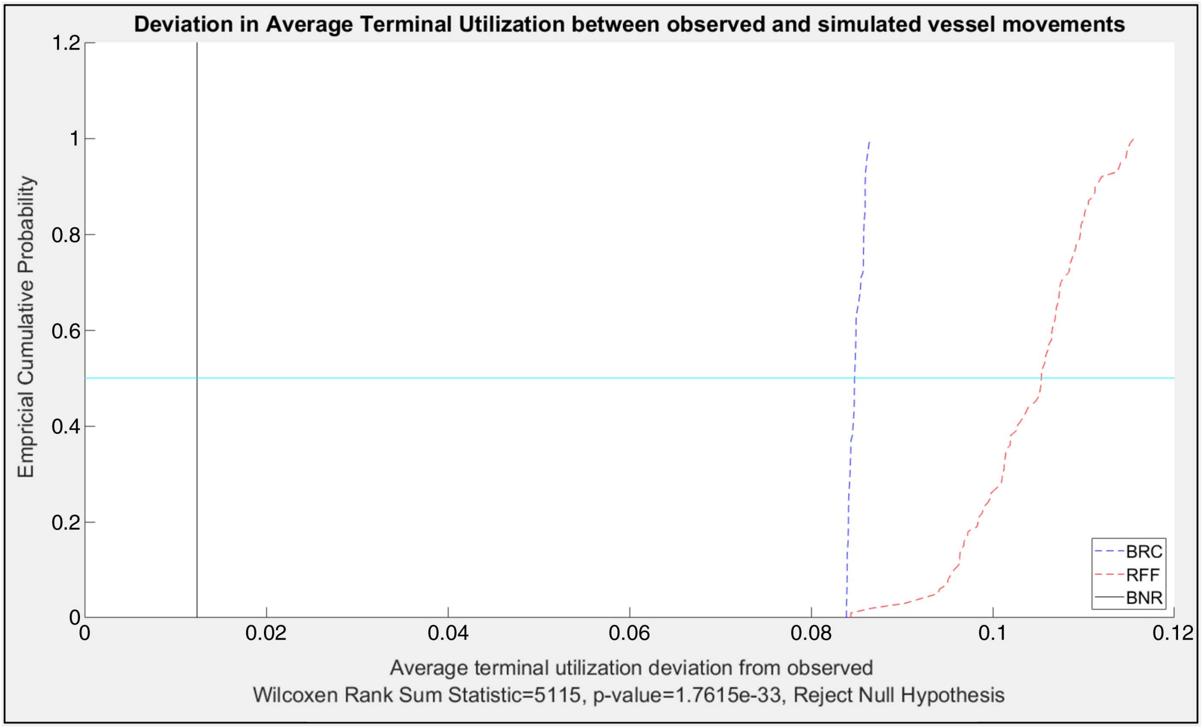

Fig. 7. Empirical cumulative distribution of the average terminal utilization deviation between the observed and simulated processes over 100 iterations. The RFF deviates the greatest from the observed utilization.

categorized into those carrying energy and chemical products and those carrying general cargo. The energy and chemical industries are closely interrelated; they use many of the same terminals, and many of the products are derived from related refining processes. General cargo includes both breakbulk cargo and containerized cargo. Based on these general categories, we assessed the average delay time for each category for each replication. Additionally, we assessed the delay for each category for those vessels identified as urgent priorities. Fig. 6 demonstrates how each process varies in the delay time as a deviation from the observed delay time. A failure to reject the null hypothesis in the Wilcoxon-Rank Sum test is an indication that the heuristics perform at approximately the same level.

The aim of the validation is to demonstrate that the baseline model captures the behavior and dynamics exhibited by the system during the real event. There are some operational factors impacting the decision that were not captured at the time of the event, and there is a significant amount of professional judgment that goes into these decisions. However, the previous analysis shows that the baseline model deviates significantly less than the random feasible first model and slightly less than the baseline randomized model, which randomizes only within the commodity category. This indicates that the priority given to the arrival time and commodity is important and captured by the model. The assessment of the model, based on the deviation between simulated and observed delays, also indicates that regardless of urgency and commodity, most vessels are moved within 1–2 days of the observed movement date. The combination of sequence and simulated timing supports model validation.

One of the interviewees asserted that sequencing decisions were made to optimize the use of the waterway. While the idea of best or optimal was not strictly defined, terminal utilization did arise as an important concept in several interviews. Therefore, terminal utilization was calculated based on both observed and simulated results. The utilization rate is defined as follows:

$$U_h = \frac{T_h}{T_h + S_h} \tag{2}$$

where U_h = utilization rate of terminal h; T_h = total time a terminal was occupied; and S_h = total time terminal h was unoccupied while there was a vessel waiting for or transiting to that terminal.

This method of calculating terminal utilization mitigates the risk of penalizing terminals that have low demand or did not receive demand until the later periods because a terminal only accrues unutilized time when it is unoccupied and has a vessel waiting to arrive. The baseline and randomized validation variants all showed deviation from the observed terminal utilization. However, the baseline model and BRC model performed similarly to each other and significantly better than the RFF model, as shown in Fig. 7.

In navigating a solution to the vessel sequencing problem, the stakeholders and final decision-makers work through a commonly understood framework. Across the interviews, there was a common, albeit informally, articulated understanding of the process for sharing information and making decisions. In the next section, we will demonstrate how the trade-off space across industries can be assessed and defined by studying alternate decision-making heuristics.

Numerical Experiments

Decisions to move vessels are made on a very short time horizon. The pilots take into account explicitly stated priority demands, the state of the waterway, tug availability, other factors (such as professional judgment), and the physical location of a vessel awaiting inbound movement. Once these inputs are on hand, they create an updated sequence, which is shared through a digital portal accessible by paying port customers. The feasibility guidelines, which are largely safety derived, are nonnegotiable for the purpose of this study. These serve to constrain the decision space. These safety protocols that define the feasibility are an example of *acute-chronic responsibility trade-off* (Hoffman and Woods 2011). The system creates highly restrictive safety protocols and rarely deviates from them, trading off short-term opportunities for the improved use of the waterway in order to avoid the opportunity for a catastrophic amplification of the existing disruption. The prioritization guidelines are the main source of flexibility. However, the system participants place a high value on transparency in the process. Therefore, it is important that the prioritization protocols are not arbitrary, are widely understood, and are generally adhered to. However, the choice of prioritization protocol may drive the trade-offs made within the system.

Different prioritization protocols other than the one elicited are possible, and these variations can result in different trade-offs across industries. Several alternate prioritization heuristics were simulated in the Hurricane Harvey context. Each disruption is different both quantitatively and qualitatively. Because of this, it is difficult to make statistical inferences about the impact of a heuristic on a particular industry sector. However, if the prioritization protocols define the trade-off space in this instance, one can postulate that it will have similar impacts of varying scales under similar circumstances. This insight can assist decision-makers in mitigating risk in operations (i.e., refining curtailment rates) or rerouting (perishable cargo). The insight might also help decision-makers realize that they have transitioned from a *routine* event to a *novel* event and adjust their protocols accordingly (Kayes 2015). The experimental heuristics are as follows:

- *First Come First Feasible First (FCFFF):* In this heuristic, the feasibility assessment is conducted in the same way as the baseline model; however, feasible vessels are selected in order of their arrival date in the system. A representative from the general cargo shipping industry expressed this as a possible alternative that would be most fair.
- *Empty Feasible Petroleum Vessels First (EFPVF):* Feasibility assessments are the same as the baseline model; however, from the feasible vessels, all empty petroleum tankers are given top priority, and no other vessels are treated as a priority. In the baseline, a petroleum vessel is given priority to avoid containment issues. However, this modification recognizes that empty petroleum vessels are most likely to create additional onpremise storage and prevent dangerous overflows. Empty petroleum vessels are also considered low risk.
- *All Priorities Equal (APE):* Feasibility assessments are the same as the baseline model; however, in this alternative, all identified priorities are treated as equally important and ranked in order of their arrival date into the system. All vessels not identified as named priorities are ranked after all named priorities. The logic behind this alternative is that a vessel identified and elevated by a priority must be sufficiently important to its sector, and no sector can be considered intrinsically more important than another.
- *General Cargo First (GCF):* This alternative explores the opposite end of the priority spectrum by prioritizing all named general cargo vessels before petroleum and chemical cargo vessels.
- *Daylight Path Preference (DPP):* It came up in some conversations that pilots in applying their judgment will at times give preference to a vessel that is traveling along a daylight restricted path or that is restricted to daylight hours for some other reason. While we could not identify vessels restricted to daylight hours based on construction and cargo, we could identify daylight-restricted paths. This alternative gives preference to vessels traveling along these paths during daylight hours.

Model Comparisons

The experimental heuristics were run deterministically: a single replication with no random elements based on observed and modeled system data. The goal is to determine how varying the prioritization heuristic, without altering the safety protocols, defines the trade-off space in the system. Any decision naturally includes a trade-off that can ultimately be mapped to specific vessels, terminals, and factories. However, this level of detail is not achievable with the currently available data. Therefore, the trade-off space is defined broadly as the aggregate impact on a specific industry and is measured by the mean and median of the average delay time for the vessels within an industry. Delay time is the time lapse between when a vessel contacts the pilot dispatcher and the time that a pilot arrives on board the vessel. Terminals make their money by managing a physical location for multimodal clients to transship cargo across modes. To terminal operators, the ability to keep a terminal operating and quickly transition between customers is one of their top priorities. Therefore, a terminal utilization rate was also evaluated.

Results

A common feature of resilience research is to ascertain the speed of recovery. As discussed previously, the system can continue to operate and maintain core functionality or "the persistence of relationships, rather than stability in quantitative measures of state variables," as stated by Park et al. (2013). Under normal operating circumstances, decentralized coordination occurs through a network of agents, vessels, terminals, and pilots. During a disruption, these normal relationships still exist, but part of the coordination takes place in full view of the public and with the added constraint imposed by the temporary controls imposed by the regulatory and operational control functions manifest in the Coast Guard and pilots, respectively. It is this temporary modification of component interactions that allow for long term persistence. Under this governance scheme, the increased level of control asserted on otherwise independent operators affect the outcome.

Based on our numerical experiments, there are two primary takeaways. First, the choice of heuristic used under the core-centric self-organized system has the potential to noticeably impact the quality of port services to be expected by industry participants. *Core-centric* self-organizing is a strategy by which a sociotechnical decentralized, under normal conditions, coalesces around a predesignated but generally inactive node for coordination and collaboration during a disruption (Amodeo and Francis 2019). Second, the fact that there are marginal changes across the trade-off space in several recovery dimensions indicates that the safety control measures significantly limit the options available to a given heuristic. This is a high-level trade-off to carefully preserve the core functionality during a period of increased brittleness.

The aim of the research presented in this article is not to make prescriptions but to demonstrate that decision-making heuristics within the context of ongoing physical recovery impact resilience and that these heuristics impose trade-offs that should be considered beforehand. Based on the median values of the five metrics, trade-offs pertaining to the delay time for vessels identified as urgent priority presents the most variation across heuristics. This is true regardless of commodity. Based on Fig. 8, it seems that there is relatively little trade-off opportunity across the heuristics. The one notable exception seems to be the DPP heuristic, a dynamic worthy of further exploration.

The DPP heuristic gives preference to vessels traveling along a daylight path but preserves the baseline heuristic's hierarchy within this: petroleum, chemical, and general cargo vessels

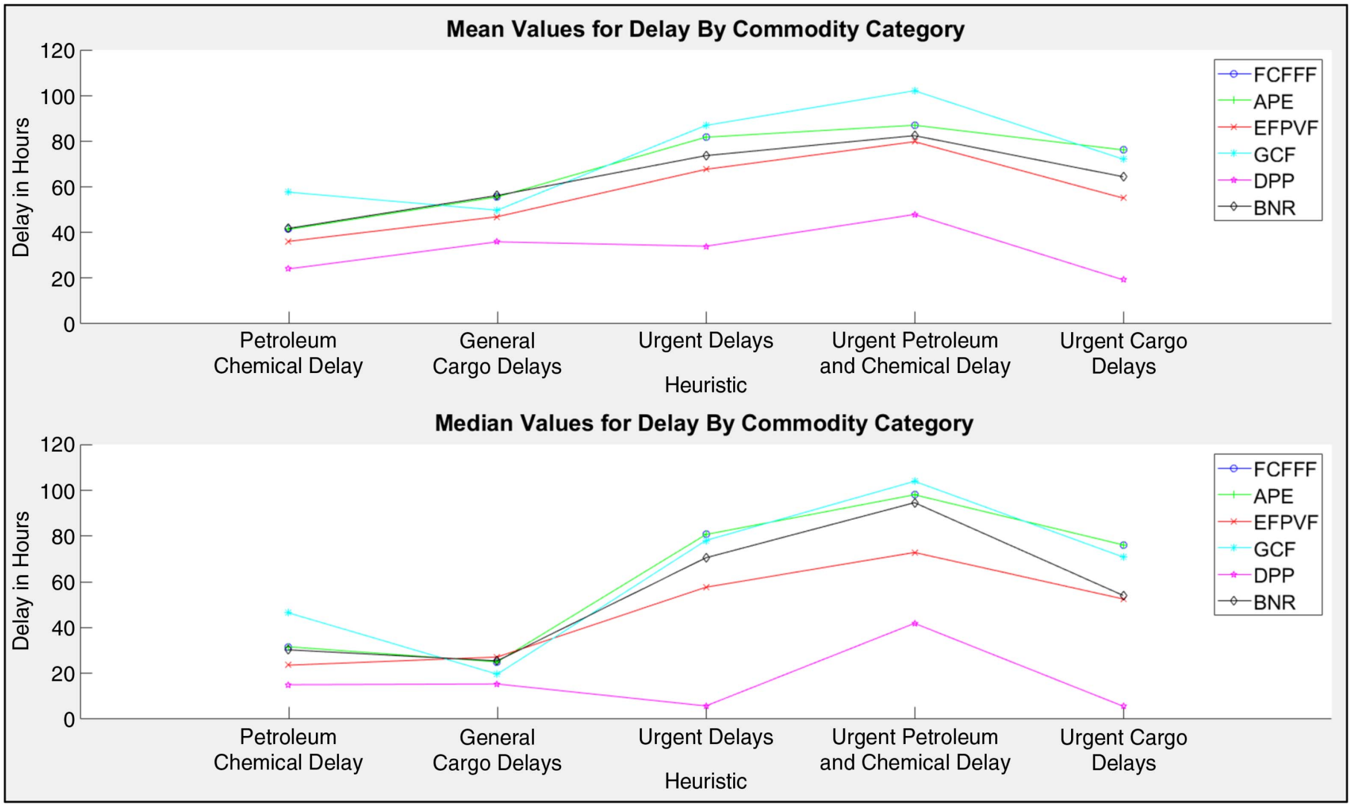

Fig. 8. Industry and commodity impact by the heuristic. Notice that the DPP heuristic outperforms on all measures and that the FCFFF and APE heuristics have identical performances.

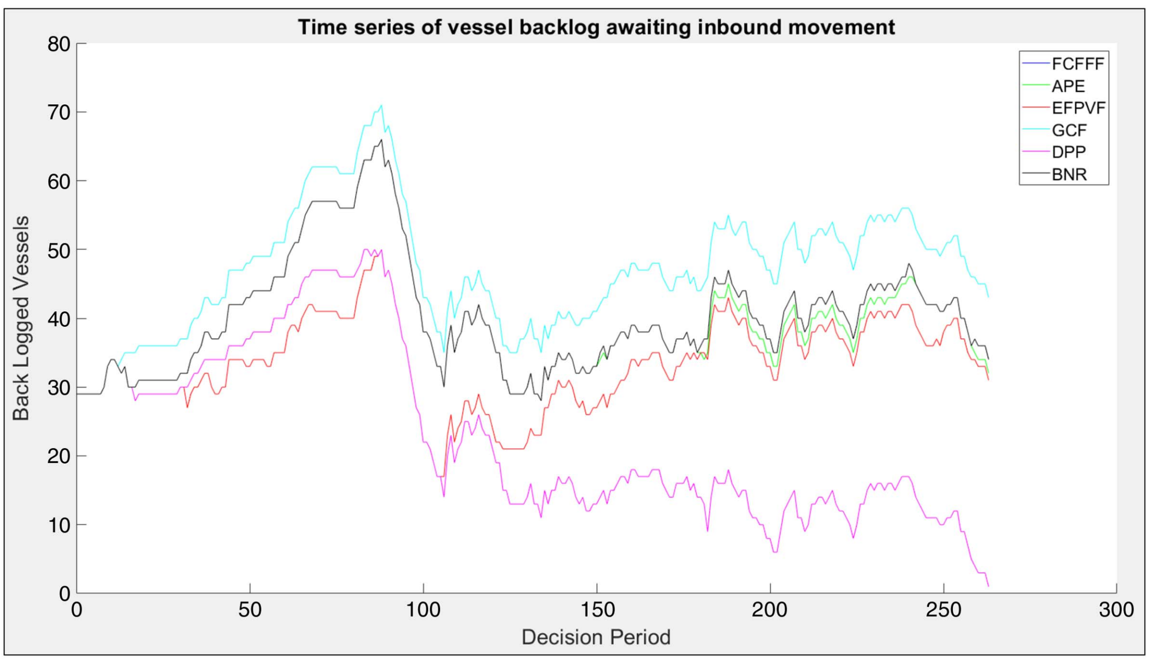

Fig. 9. Time-series plot of the backlog over 264 decision periods. The heuristic that prioritizes vessels traveling along a daylight-only restricted path appears to have a stronger downward trend in reducing the backlog of queued vessels.

identified as a priority. Preserving priorities—but adding a control measure to prioritize by path constraints—increases flow through the waterway earlier on in the recovery while also increasing the number of feasible solutions during the night hours. Fig. 9 gives support to this postulate because the initial drop in the backlog about 4 days into the recovery remains consistently lower than other heuristics.

A further explanation for the increased performance of the DPP can be seen in Fig. 10. In this figure, we can see that the DPP heuristic resulted in a moderate number of terminals experiencing an

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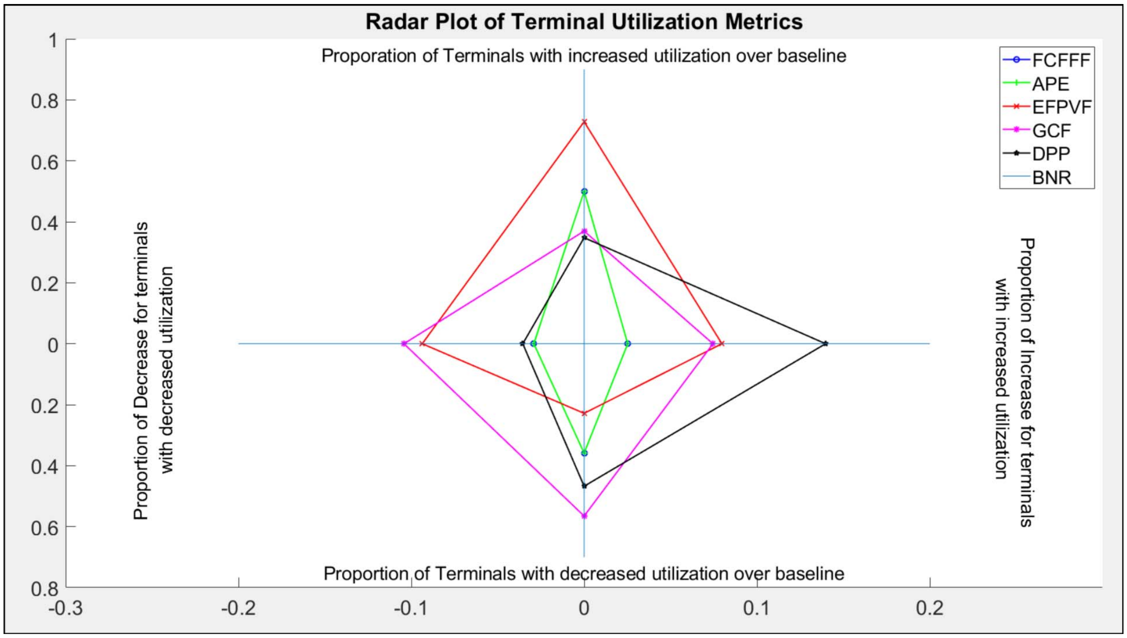

Fig. 10. Radar plot comparing the percent of terminals showing increased utilization and the average rate of increased or decreased utilization over the baseline model.

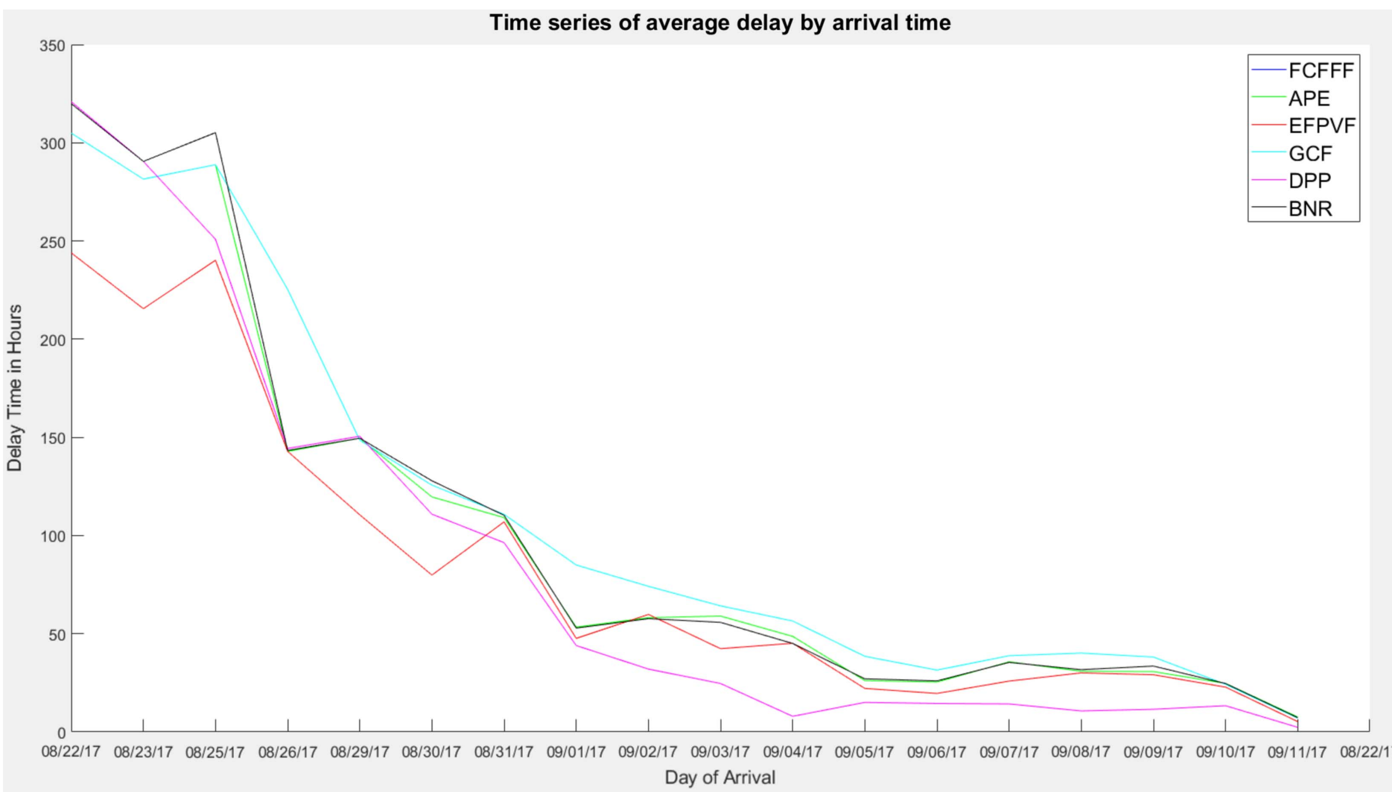

Fig. 11. Comparison of how each heuristic compared with regards to reducing the time between the time a vessel contacted the pilot dispatcher and the time the pilot boarded the vessel. The metric of interest is the average delay for all vessels arriving on a given day.

increase in utilization; however, it is important to notice that those showing a decrease in utilization experienced a small average decrease relative to the nearly 15% average increase in utilization for those that did experience an increase. In the DPP, more than any other, the increased gain in utilization dominates over those cases with decreased utilization.

Fig. 11 reenforces this story. Starting on September 1, 2017, the first day of vessel movements following Hurricane Harvey, the DPP heuristics shows the steepest decline in average delay. The DPP heuristic is unique among the other heuristics in that it has a forward-looking element. Unlike the others, which place little weight on future feasibility space, the DPP heuristic deliberately makes present decisions in a way that increases the size of the future feasibility space. In the scenario currently modeled, this results in increased efficiency of terminal utilization.

The current study demonstrated that even if the rules that define a feasible solution set are rigid and tightly constrain the decision set, there are high-level operational trade-offs that can be defined, measured, and managed. The current study proved this case by creating a detailed model of a particular disruptive event and overlaying two interacting subproblems: feasibility determination and a heuristic search and selection of the feasibility space. Based on this analysis, there are five recommendations:

- First, prioritizing purely on arrival time, as suggested by at least one interviewee, is likely to produce a poorer solution for all segments and urgency categories.
- Second, incorporating some form of forward-looking rules, such as daylight path restrictions, into the prioritization hierarchy may improve terminal utilization and rapid reduction in backlog.
- Third, primary prioritization of a relatively low-density commodity category may result in poorer recovery performance across the board.
- Fourth, systems of this scale should maintain centralized decision-making processes for these scenarios. Furthermore, these centralized processes should apply hybrid heuristics that consider stated vessel priorities while leveraging information gathering and an analytical framework to incorporate forward-looking system states into the decision.
- Fifth, ports should adopt similar tools to the one presented in this study to test heuristics in advance.

Discussion

The main research question this article addresses is whether or not policies that enforce risk-averse behavior and subsystem prioritization impact the recovery trade-off from the perspective of multiple stakeholders. More specifically, the article studies how the trade-off space is defined by the prioritization rules but constrained by the risk mitigation rule set. In this in-depth empirical case study, the empirical response of a real system to a real event was modeled. Hypothetical alternate prioritization methods for sequencing vessels within the already safety constrained feasibility space were developed and tested through simulation. While previous works have focused on decision-making to improve and prepare the system, this current article explores the impact of decisions nested within the prescriptive context emphasized by other studies. This article acknowledges that there are frontline decision-makers who are aware of and constrained by broader recovery activities but who contribute to recovery by continuing operations while taking the ongoing broader recovery efforts as inputs to the short term struggle to persist. At this level, there are trade-offs—whether they are explicitly identified, measured, and discussed remains unclear.

The first contribution of this research is the model itself. The modeling effort contained two parts. First, the physical model of the system as the foundational context for decision-making is important. There are no known computational models that attempt to model the complex port system of the Texas Gulf Coast. Certainly, gaps remain. However, filling these gaps is feasible from a model perspective if broad industry and in-depth industry interest become available, along with more detailed data collection apparatuses. However, this model serves as a baseline and proof of concept. It is our hope that this model serves as the foundation for future decision support tools. Second, the modeling of the decision heuristics is a novel contribution. One interviewee felt that a single heuristic could not be developed because the process primarily consisted of senior stakeholders sitting around a table exchanging ideas and developing a solution based on context specifics. However, after interviewing multiple stakeholders, we hold that the truth lies between a rigid heuristic and the dynamic position held by the aforementioned interviewee. The current model has limitations, as previously discussed, but it demonstrates that key tensions and dynamics can be captured. Furthermore, it demonstrates that such a model may be useful as a decision support tool to assist decision-makers in becoming more transparent about the trade-offs that are currently and implicitly accepted.

The second contribution is the impact of the near-term decision-making heuristic on resilience. There are two broad levels of decision-making that impact resilience. The highest level is the strategic decisions regarding physical network recovery. The second level consists of the immediate operational decisions taking place in the constrained environment. Our findings demonstrate that the heuristic applied to carry out the second level does involve trade-offs that result in various degrees of resilience from the perspective of an individual sector perspective. The method presented in this study would allow the system to understand the trade-off involved with a particular heuristic on these goals. The demonstration of these trade-offs is the third theoretical contribution and can provide insights for future prescriptive exploration.

It is our hope that resilience studies continue the efforts presented in this study by collecting data and modeling complex systems responding to real-world disruptions.

Data Availability Statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g., anonymized semistructured interview data): (1) vessel movement data is proprietary and cannot be made publicly available per an agreement with the party that provided it; (2) meeting notes and daily summaries are proprietary and cannot be made publicly available per an agreement with the party that provided it; and (3) simulation code can be made available upon request.

Acknowledgments

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