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Stochastic measures of resilience and their application to container terminals

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ABSTRACT

While early research efforts were devoted to the protection of systems against disruptive events, be they malevolent attacks, man-made accidents, or natural disasters, recent attention has been given to the resilience, or the ability of systems to "bounce back," of these events. Discussed here is a modeling paradigm for quantifying system resilience, primarily as a function of vulnerability (the adverse initial system impact of the disruption) and recoverability (the speed of system recovery). To account for uncertainty, stochastic measures of resilience are introduced, including Time to Total System Restoration, Time to Full System Service Resilience, and Time to α%-Resilience. These metrics are applied to quantify the resilience of inland waterway ports, important hubs in the flow of commodities, and the port resilience approach is deployed in a data-driven case study for the inland Port of Catoosa in Oklahoma. The contributions herein demonstrate a starting point in the development of a resilience decision making framework.

1. Introduction and motivation

While early research efforts have been devoted to the protection (or hardening) of systems against disruptive events, be they malevolent attacks, man-made accidents, or natural disasters, recent attention has been placed on preparedness, response, and recovery (PR^2) from these events. This is particularly true for the nation's critical infrastructure and key resources (CIKR), as DHS (2009) recently stated that "CIKR resilience may be more important than CIKR hardening."

Resilience research has been an emerging research area for the last decade, though no standard definition or quantitative technique for the paradigm of system resilience has emerged. One approach, illustrated in Fig. 1 as described in Henry and Ramirez-Marquez (2012), describes resilience as the ability to restore a system from disrupted state, S_d, to a stable recovered state, S_f. Resilience is thus defined as the time dependent ratio of recovery over maximum loss in Eq. (1).

$$я(t) = \text{Recovery}(t)/\text{Maximum Loss}(t_d) \quad (1)$$

For multi-modal transportation, as with any other CIKR, system resilience planning is important (DHS, 2009). The multi-modal transportation system plays a vital role in maintaining commodity flows across multiple industries and multiple regions. Examples of actual disruptive events that befall the transportation system include the collapse of the I-40 bridge spanning the Arkansas River in Oklahoma resulting in the daily detour of 22,000 vehicles for nearly 2 months (Federal Highway Administration, 2008) and the I-35W bridge collapse over the Mississippi River in Minnesota, which required daily rerouting of 140,000 vehicles (Zhu, Levison, Liu, & Harder, 2009).

As a result of their critical role, the effects of large-scale disruptive events could result in the closure of key transportation facilities such as rail yards, cargo terminals, airports, seaports, and inland ports. Critical nodes in a transportation network (e.g., inland waterway ports) are particularly susceptible to disruptions in commodity flows (Lee, Park, & Lee, 2003; Lee & Kim, 2010; Sacone & Siri, 2009; Simao & Powell, 1992). Although inland ports face many of the same risks as coastal ports, relatively few studies have developed risk assessments of inland ports (Folga et al., 2009; MacKenzie, Barker, & Grant, 2012). Inland waterways are common in North America and prominent in the economies of Europe (Rodrigue, Debrie, Fremont, & Gouvernal, 2010) and Asia (Xu & Zeng, 2008). The importance of the 25,000 miles of commercially

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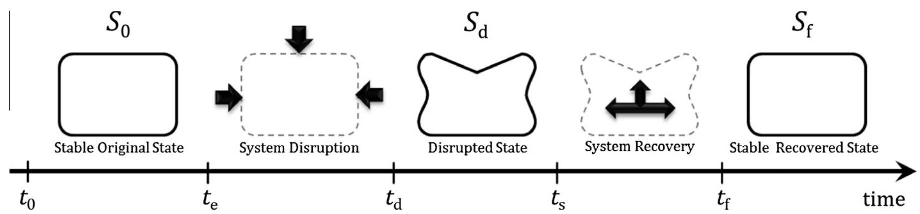

Fig. 1. System state transition with time.

navigable US waterways for transporting goods may grow in the future as barge transportation represents a cheaper and environmentally friendlier alternative to already highly-congested truck and train transportation. Further, an expansion of inland waterways to deal with larger shipments (i.e., containers) has been proposed, leading to an increased need in addressing container security and the malevolent man-made attacks that could go along with unsecured containers (GAO, 2009). Container security will become even more important when the planned Panama Canal expansion project opens in 2014, enabling bigger ships, and more containers, from Asian to Atlantic and Gulf coastal ports and their associated inland waterways. And as the most recent Report Card for America's Infrastructure gave inland waterway infrastructure a D-(ASCE, 2009), inland ports are particularly susceptible to natural cause and accidental failures.

Recent explorations of resilience in transportation systems include (i) a conceptual discussion of resilience with several qualitative definitions of resilience-related terms in a transportation context by Ta, Goodchild and Pitera (2009) and (ii) a graph theoretic optimization framework for resilience by Ip and Wang (2011) that does not include an accounting for recovery time. Work described here proposes stochastic and time dependent metrics of system resilience, as applied to waterway container terminals. The contributions of the paper are twofold: (i) the deterministic metrics described in Henry and Ramirez-Marquez (2012) are extended to the stochastic case (Time to Total System Restoration, Time to Full System Service Resilience, and Time to α%-Resilience), and (ii) these metrics are used to develop a port resilience approach that is deployed in a data-driven case study for the inland Port of Catoosa in Oklahoma. These contributions serve as a starting point in the development of a resilience decision making framework.

The remainder of this manuscript is as follows: Section 2 provides the quantitative background for the resilience framework, and Section 3 integrates the work of Henry and Ramirez-Marquez (2012) and Pant, Barker, Grant, and Landers (2011) to provide stochastic measures of port operations. Section 4 develops the port resilience framework, and Section 5 illustrates with a data-driven illustration from the inland Port of Catoosa in Oklahoma. Concluding remarks are provided in Section 6.

2. Resilience background and methodological development

This section describes some of the modeling ideas that comprise our methodological approach, including previous work in measuring resilience and in simulating the operations at a container terminal.

2.1. General representation of resilience

Several approaches to describe resilience have been proposed across several application domains. Qualitative discussions of the "resilience triangle," whose area is produced by *robustness* (the amount of initial impact to the system) and *rapidity* (the speed with which recovery takes place), is a well-studied concept in civil infrastructure applications (Bruneau et al., 2003; Bruneau & Reinhorn, 2007; Cimellaro, Reinhorn, & Bruneau, 2010; McDaniels, Chang, Cole, Mikawoz, & Longstaff, 2008). Zobel (2011) discusses a more quantitative decision making framework based on the resilience triangle, highlighting tradeoffs between robustness and rapidity for the same level of disaster resilience. MacKenzie and Barker (2012) integrate an interdependency model with regression to quantify the resilience of electric power infrastructure disruptions. The quantitative measures of resilience developed in this section are adapted from Henry and Ramirez-Marquez (2012).

Let $\Omega = (A)$ represent a system, where $A = \{i|1 \leqslant i \leqslant m\}$ is the set components comprising the system. For component i at time t, $x_i(t)$ is the state variable (real number) describing the performance of the component, possibly valuating an entity such as capacity, delay, or length, among others. The system state vector at time t, $\mathbf{x}(t) = (x_1(t), x_2(t), \ldots, x_m(t))$, denotes the state of all the system components at time t. The entire system performance can be quantified with respect to an overall system performance/service measure. The service function, $\varphi(\mathbf{x}(t)) = \varphi(t)$, which can be analyzed for any possible realization of $\mathbf{x}(t)$, maps the system state vector into a real number system state at time t.

As described in Fig. 1, a system can operate in three distinct states: (i) its original, as-planned state, S_0, (ii) its disrupted state, S_d, that results from a disruption to the system, and (iii) its recovered state, S_f, that results from a recovery effort. State S_f need not be the same as S_0, as the new state may reach an alternative (lower, or perhaps higher) equilibrium level (e.g., for economic systems (Rose & Liao, 2005)). Transitions between these states include (i) system disruption, taking the system from S_0 to S_d, and (ii) system recovery, taking the system from S_d to S_f. While Fig. 1 provides a broad description of the process of resilience, it does not include key entities related to resilience that are provided in the detailed representation in Fig. 2. According to Henry and Ramirez-Marquez (2012), resilience of a system at time t, is exhibited if and only if there is an external disruptive event, e^j, that affects the original system state (depicted in Fig. 2 as S_0) at time t_e. Set $\mathcal{D} = \{e^j|1 \leqslant j \leqslant J\}$ describes the set of possible external disruptive events that could affect the system at time t_e.

Let $x_i(t_0)$ represent the as-planned state of the ith component prior to the onset of disruptive event e^j. Assume that the effect of e^j is a proportional reduction in the performance of the ith component by $V_i^j(e^j) = V_i^j$ where $V_i^j \in [0, 1]$. V_i^j essentially refers to a component's vulnerability, or its lack of ability to maintain performance after e^j. As such, the effect of e^j on the state variable of component i is provided in Eq. (2). The decreasing system performance due to the disruptive event is seen in its response until time t_d when the new system state is measured. Note that a complete reduction in the functionality of the link occurs when $V_i^j = 1$. The vector quantifying the disruptive effects of e^j for all components is $\mathbf{V}^j = (V_1^j, \ldots, V_i^j, \ldots, V_m^j)$.

$$x_i(t_d) = \left(1 - V_i^j\right)x_i(t_0) \tag{2}$$

Note that in this work we do not focus on the trajectory of the decrease in system performance (i.e., linearly or non-linearly over t_d–t_e), but in the final decreased state until the maximum effects