Transportation Research Part E 62 (2014) 55–67

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Importance measures for inland waterway network resilience

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ARTICLE INFO

Article history:
Received 9 April 2013
Received in revised form 17 September 2013
Accepted 26 November 2013

Keywords:
Inland waterways
Network resilience
Importance measures

ABSTRACT

This work demonstrates a time-dependent paradigm for resilience and associated stochastic metrics in a waterway transportation context. We deploy two stochastic resilience-based component importance measures that highlight the critical waterway links that contribute to waterway network resilience and develop an optimization approach that determines the order in which disrupted links should be recovered for improved resilience. A data-driven case study illustrates these metrics to describe commodity flows along the various links of the US Mississippi River Navigation System.

1. Introduction and motivation

> "The current system of inland waterways lacks resilience. Waterway usage is increasing, but facilities are aging and many are well past their design life of 50 years. Recovery from any event of significance would be negatively impacted by the age and deteriorating condition of the system, posing a direct threat to the American economy." 2009 Report Card for America's Infrastructure, American Society for Civil Engineers (ASCE) (2009).

Infrastructure systems are critical for performing the functions of everyday life. Such criticality is due to their interdependence among other infrastructure networks, as well as industries and labor forces that rely upon their function. Among these critical infrastructure networks are electric power, telecommunications, and transportation, among others (DHS, 2009). Disruptive events, whether they be malevolent attacks, natural disasters, human-made accidents, or common failures, can have significant widespread impacts when they lead to the failure of network components. For example, Hurricane Sandy left areas of the highly populated east coast without electric power, communication, and mass transit systems for several days.

Hurricane Sandy highlights the need to better understand resilience, or the ability to "bounce back" from a disruptive event. The use of the term "resilience" has increased substantially in the literature in recent years (Park et al., 2013), with several different qualitative and quantitative frameworks resulting (e.g., Bruneau et al., 2003; McDaniels et al., 2008; Zobel, 2011). Domain-specific discussions of resilience range from ecological systems (Holling, 1973; Carpenter et al., 2001), to economic systems (Rose, 2009; Pant and Barker, 2012), to organizational systems (Jackson, 2007). Specifically for critical infrastructure systems and key resources (CIKR), the Infrastructure Security Partnership (2011) noted that a resilient infrastructure sector would "prepare for, prevent, protect against, respond or mitigate any anticipated or unexpected

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http://dx.doi.org/10.1016/j.tre.2013.11.010

significant threat or event" and "rapidly recover and reconstitute critical assets, operations, and services with minimum damage and disruption."

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. As a result of their critical role, the effects of large-scale disruptive events could result in the closure of key transportation links and nodes. These critical components in a transportation network (e.g., inland waterways) are particularly susceptible to disruptions in commodity flows (Lee et al., 2003; Sacone and Siri, 2009; Lee and Kim, 2010). The recovery of transportation networks from disruptions has been given some recent attention (Cadarso et al., 2013; Chen and Miller-Hooks, 2012; Zeng et al., 2012; Zeng and Peeta, 2011).

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; Pant et al., 2011; MacKenzie et al., 2012). Some studies have focused on forecasting commodity flows in inland waterway networks (Babcock and Lu, 2002; Beuthe et al., 2011), however, such models do not capture the effect of uncertain disruptive events and their impacts on the commodity flows. Vital to commodity flows in the US, almost 80% of all US international trade is transported through coastal ports, with 40% of these shipments moving inside the US through inland ports before reaching their final destination (Haveman and Howard, 2006). During recent ASCE testimony to the US Senate, it was stated that the costs attributed to delays in US inland waterways were $33 billion in 2010 (rising to $49 billion by 2020), with interdependent impacts cascading to economic sectors that require inland waterway transport (e.g., petroleum, coal) (ASCE, 2013). As such, the study of the resilience of inland waterway networks is an important area of focus.

When planning for transportation networks such as inland waterways, it is important to understand which components (e.g., locks, dams, waterway links) are most influential on the performance of the entire network and are most influenced by other components in the networks. This is a well-studied topic in reliability engineering, with component importance measures (CIMs) quantifying the influence of particular components on the overall structural performance or reliability of the system (Leemis, 2009; Kuo and Zhu, 2012). Other explorations of CIMs in a network context include those by: Murray-Tuite and Mahmassani (2004), who determine transportation link importance based on the disruption of an optimal traffic assignment network; Jenelius et al. (2006), who provide several vulnerability-based importance measures for transportation networks; and Nagurney and Qiang (2007, 2008), who develop a more general flow efficiency metric with which to rank the importance of transportation network components. Natvig et al. (2011) suggest that importance measures are helpful in (i) determining which components merit resources to improve overall system performance, and (ii) preparing an efficient component repair checklist in the event of system failure. This work addresses these two items in the context of waterway transportation resilience.

The contributions of this paper lie in (i) the deployment and validation of resilience-based importance measures (Barker et al., 2013) to study the important links of inland waterway networks and (ii) the development of a recovery optimization approach to strengthen resilience in the network. The importance measures, extended from stochastic measures of the time required for a network to achieve full resilience after a disruption (Pant et al., submitted for publication; Baroud et al., 2013a), along with the cost of recovery activities, are aimed at determining the best recovery set aimed at restoring the service in the disrupted links. Section 2 provides the methodological background of the resilience metrics applied here. Section 3 provides an optimization approach using the metrics reviewed in Section 2. Section 4 provides some background on the data-driven case study, namely commodity flows along the various links of the US Mississippi River Navigation System, and applies the resilience metrics to this network. Section 5 provides concluding remarks.

2. Methodological background

Whitson and Ramirez-Marquez (2009) and Henry and Ramirez-Marquez (2012) propose a paradigm for describing and quantifying the resilience of a system. They broadly define system resilience following a disruptive event e^j as the time dependent ratio of recovery over loss, or $Я(t) = \text{Recovery}(t)/\text{Loss}(t_d), t_d < t$. Note the notation for resilience, Я (Whitson and Ramirez-Marquez, 2009), as R is historically reserved for quantifying reliability.

That is, $Я(t)$ quantifies resilience at time t, $t_d < t < t_f$, as illustrated in Figs. 1 and 2, extended from previous work (Henry and Ramirez-Marquez, 2012), showing the transition among three distinct states in which the network can operate: (i) S_0, the original, or as-planned, state of the network, (ii) S_d, the disrupted state resulting from an event e^j disrupting the network, and (iii) S_f, the recovered state that results from a recovery effort. Note from the horizontal axis of Fig. 1 (and Fig. 2) that the network operates in S_0 until disruptive event e^j occurs at time t_e. The effect of e^j decreases network performance until time t_d, when the network reaches its maximum disrupted state S_d. Recovery from the disruption commences at time t_s, and state S_f is attained at time t_f and maintained thereafter. Note that S_f need not to be the same as S_0: it could be at a new (lower) equilibrium state, or the network could find an improved equilibrium (e.g., the state of infrastructure following the 2010 earthquake in Haiti may be improved over pre-disruption levels). Figs. 1 and 2 are similar in appearance to the subsequently published graphical depiction of system performance by Ouyang et al. (2012).

However, to model $Я(t)$ at a given point in time t, $t_s < t < t_f$, the network service function, $\varphi(t)$, is introduced to quantify the behavior or performance of the network. The general behavior of $\varphi(t)$ is shown in Fig. 1, where increasing values of $\varphi(t)$