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Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports

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ABSTRACT

Infrastructure systems, including transportation, telecommunications, water supply, and electric power networks, are faced with growing number of disruptions such as natural disasters, malevolent attacks, human-made accidents, and common failures, due to their age, condition, and interdependence with other infrastructures. Risk planners, previously concerned with protection and prevention, are now more interested in the ability of such infrastructures to withstand and recover from disruptions in the form of resilience building strategies. This paper offers a means to quantify resilience as a function of absorptive, adaptive, and restorative capacities with Bayesian networks. A popular tool to structure relationships among several variables, the Bayesian network model allows for the analysis of different resilience building strategies through forward and backward propagation. The use of Bayesian networks to quantify resilience is demonstrated with the example of an inland waterway port, an important component in the intermodal transportation network.

1. Introduction

Infrastructure systems are faced with growing number of disruptions due to their age, condition, and interdependence with other infrastructures. These systems are subject to common cause failure, but also natural disasters that are becoming more frequent and more impactful (e.g., Hurricane Sandy in 2012, the Japanese earthquake and tsunami of 2011, the Haiti earthquake in 2010, Hurricane Katrina in 2005).

The resilience of infrastructure systems in the face of the variety of disruptive events and resulting consequence has become an increasingly important topic among planners. Infrastructure systems must be designed in a way so that they are resistant enough to withstand and recover quickly from disruptions. Previously, the emphasis of preparedness planning dealt with protection and prevention of disruptive events. Such strategies may not be sufficient to withstand disruptive events, particularly for uncharacteristically devastating events, because it is almost impossible in practice to harden infrastructure systems against all types of disruptive events. Accordingly, the concept of resilience emerged to supplement a mitigation-focused philosophy, recognizing the significance and need for timely response and recovery from disruptions. Activities that account for response and recovery are commonly referred to as post-disruption or contingency strategies. A suitable resilience strategy for a critical infrastructure might be different from one to another. For example, rerouting alternative is a suitable resilience strategy for transportation and communication networks when the connectivity and redundancy degree of networks are high, however having a high degree of connectivity is not suitable for power grid systems where the cascading failures are common.

In this paper, we propose the novel quantification of resilience with Bayesian networks, a technique that has found popularity in such fields as reliability engineering but with little application in resilience modeling. Bayesian networks can model the causal relationships among various aspects of resilience and are especially useful when varying levels of data describing those relationships are known (e.g., data sets describing commodity flows through a port, expert elicitation of the effects of a natural hazard on the condition of dock-specific equipment). Different disruptive scenarios, as well as different resilience building strategies, can be simulated, and a sensitivity analysis of parameters can be performed for a robust analysis.

To illustrate the proposed quantification approach, we use an inland waterway port case study. Inland ports play a vital role in intermodal transportation networks by maintaining the flow of commodities among industries and regions. The disruption of ports can have significant adverse impacts on supply and demand, ultimately affecting productivity. U.S. inland waterway infrastructure

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was recently given the grade of D- (American Society of Civil Engineers, 2013), with locks and dams increasingly vulnerable to common cause failure and natural disasters that could exploit their state of repair. Port closures could result in cargo congestion at the gates, vessel queuing, backlogs at warehousing transloading facilities, and manufacturing production stoppages (National Cooperative Freight Research Program (NCFRP), 2014). For example, the impact of a 10-day shutdown of West Coast port could be approximately $2.1 billion per day on the overall economy (West coast port congestion could cost retailers $ 36.9 billion in the next 24 months, 2015). Closures to inland waterway ports can have significant regional impacts (Pant, Barker, & Landers, 2015; Pant, Barker, Ramirez-Marquez, & Rocco, 2014).

The remainder of the paper is as follows. Section 2 provides background literature on resilience modeling and on the construction of Bayesian networks. Section 3 describes the contributors of port resilience used in this paper, and Section 4 provides the development and analysis of the Bayesian network for port resilience. Concluding remarks are given in Section 5.

2. Literature review

This section offers some background on the study of resilience, as well as the use of Bayesian networks, which will be used to quantify resilience in this paper.

2.1. Quantifying resilience

Despite the extensive research recently on the subject of resilience, most work in infrastructure systems deal with system vulnerability (withstanding a disruption) rather than system resilience (withstanding then recovering) (Eusgeld, Kroger, Sansavini, Schlapfer, & Zio, 2009; Johansson & Hassel, 2010; Johansson, Hassel, & Zio, 2013; Wang, Hong, & Chen, 2010). Various general metrics have been defined to measure the resilience that is applicable to the infrastructure systems (Carvalho, Barroso, Machado, Azevedo, & Cruz-Machado, 2012; Chang & Shinozuka, 2004; Hashimoto, 1982; Jain & Bhunya, 2010; Losada, Scaparra, & O'Hanley, 2012; Muller, 2012; Vugrin, Baca, Mitchell, & Stamber, 2014). Hosseini, Barker, and Ramirez-Marquez (2016) classified the literature related to the resilience measurement approaches into two groups: qualitative based approaches and quantitative based approaches. Qualitative approaches were further divided into conceptual frameworks and semi-qualitative indices, while quantitative approaches were further divided into general probabilistic and deterministic measures and structural-based models (e.g., optimization, simulation, fuzzy logic models).

Several works have focused on transportation and logistics systems, in particular. Omer, Mostashari, and Lindemann (2014) introduced a metric for infrastructure system resilience, measuring the closeness centrality of network before and after a disruptive event. Soni, Jain, and Kumar (2014) proposed a deterministic modeling approach based on graph theory to measure supply chain resilience. Their proposed approach is able to capture dynamic nature of environment for handling disruptive events in supply chains. Carvalho et al. (2012) applied discrete event simulation technique to assess alternative supply chain scenarios for improving supply chain resilience. The authors considered two performance measures including lead time ration and total cost for comparing the merit of alternatives. Rajesh and Ravi (2015) addressed the enablers of supply chain risk mitigation and then proposed Grey theory and DEMATEL approaches to explore cause/effect among the enablers of supply chain risk mitigation. Faturechi, Levenberg, and Miller-Hooks (2014) proposed a mathematical model to evaluate and optimize airport resilience, focusing on the quick restoration of post-event take-off and landing capacities to the level of pre-disruption capacities. Vugrin, Turnquist, and Brown (2014) proposed a multi-objective optimization model for transportation network recovery, designed as a lower-level problem that involves solving a regular network flow problem and an upper-level problem that explores the optimal recovery sequences and modes. The objective of the optimization model presented by Vugrin et al. (2014) is to maximize the resilience of disrupted transportation networks. Their proposed model was applied to two networks: a maximum flow network and a complex congested traffic flow network for recovery task sequencing. Khaled, Jin, Clarke, and Hoque (2015) proposed a mixed integer nonlinear programming problem and heuristic solution approach for evaluating critical railroad infrastructures to maximize rail network resilience. Youn, Hu, and Wang (2011) proposed a metric for measuring the resilience of engineered systems, calculating the degree of passive survival rate (i.e., reliability) plus proactive survival rate (i.e., restoration), as represented by Eq. (1)

$$\text{Resilience}\ (\Psi) \triangleq \text{Reliability}\ (R) + \text{Restoration}\ (\rho) \tag{1}$$

Restoration in Eq. (1) is defined as the ability of an engineered system to restore by detecting, predicting, and mitigating the effects of disruptive events. Restoration is modeled as the joint probability $(1-R)$ of system failure, the probability (Λ_D) of correctly diagnosing the failure event, probability (Λ_P) of correctly predicting the failure event, and the probability (k) of successfully mitigating the event. By considering restoration elements, the resilience formula in Eq. (1) can be rewritten with Eq. (2).

$$\text{Resilience}\ (\Psi) \triangleq R + k \times \Lambda_P \times \Lambda_D \times (1-R) \tag{2}$$

Youn et al. Youn et al. (2011) also proposed an optimization model to minimize system lifecycle cost, subject to system's resilience constraint. Both lifecycle cost and system resilience are modeled as functions of target component reliability, target component redundancy, and target component prognostics and health management (PHM) efficiency.

Hosseini, Yodo, and Wang, (2014) proposed a generic Bayesian network approach for quantifying the resilience of an electric motor supply chain, where the resilience of supply chain is measured by the metric proposed by Youn et al. (2011). Reyes Levalle and Nof (2015a), Reyes Levalle and Nof (2015b) proposed an approach based on fault tolerance by teaming principle of collaborative control theory for design and operation of resilient supply networks. Their proposed approach is capable of achieving higher fault tolerance with fewer resources in the case of disruptions.

Note that many of the previous approaches to quantifying resilience focus solely on modeling system reliability, whereas more recent methods also account for system recovery. Such a trend aligns with the comprehensive definition of infrastructure resilience presented by the National Infrastructure Advisory Council (NIAC), (2009), which defines the resilience as the ability to predict, adapt and/or quickly recover from a disruptive event. Given this definition, we are primarily motivated by the time-dependent resilience measure proposed by Henry and Ramirez-Marquez (2012) which represents resilience metric at time t, Я(t), as ratio of recovery to loss at time t. The performance of a system over time, $\varphi(t)$, is generally represented in Fig. 1. Three transition states have been defined in which a system can operate: (i) S_0, the baseline or steady state when system operates under normal conditions until disruptive event e^j occurs at time t_e, (ii) S_d, the disrupted state at time t_d due to disruptive event e^j disrupting the performance of system, and (iii) S_f, the recovered state at time t_f, resulting from recovery activities triggered at time t_s.

Depicted in Fig. 1, the system operates normally with service function of $\varphi(t_0)$ (e.g., inventory rate, capacity level) within time