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Estimation of road network reliability on resiliency: An uncertain based model

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ABSTRACT

Past research shows that a better understanding of reliability and identification of ways to improve it can help a system's response to a disaster, leading to increased transportation system resilience. This study focuses on the quantification of improved reliability, which reduces the time of annealing and recovery post uncertain disruption. A reliability model is presented by using three performance functions that estimate the total travel time, flow, and consumer surplus. Network reliability is estimated by considering uncertainties in link-capacity and demand sensitivity with respect to travel time, following a disaster. Sensitivity and uncertainty analyses are conducted to identify the most crucial links in the transportation network, for which resistance should be increased to mitigate disaster risk. The simulation results show that the model provides accurate predictions of the system performance, and that a reliability model that accounts for uncertainty yields better results than a deterministic (no uncertainty) model. With higher accuracy models, planners are able to make informed decisions in disaster mitigation planning.

1. Introduction

An effective and resilient transportation infrastructure is vital for the functioning of any society. Disruptions can have substantial negative effects, which are uncertain and unpredictable, on both infrastructure (supply) and demand. Ignoring these uncertainties results in inaccurate estimation of disruption outcomes. For this reason, assessing infrastructure resiliency while considering uncertainties in supply and demand is of great value to transportation professionals.

In this paper, resiliency is defined as the ability of the transportation network to accommodate perturbations/disasters and return to normal function within a "reasonable" time frame. Resiliency can be construed as a four-part cycle of normalcy, breakdown, annealing, and recovery [15]. Annealing refers to the immediate system response to the breakdown in finding a new equilibrium for the degraded network without recovery intervention. Recovery refers to the improvements to the network in response to the disaster, such as the reopening of links necessary to return to a new normal state.

Reliability is defined as the probability that the transportation network will meet an acceptable level of service given an unusual event. Therefore, reliability is a subset of resiliency, one that can effectively predict the efficacy of the annealing phase. Knowing the system reliability can greatly help improve the network resiliency, before and after the disrupting event. With such knowledge, professionals can identify ways to improve network resistance prior to the disrupting event to reduce the effects after the disturbance. This information can also help identify the links that will be most critical after a disaster, thus indicating where to focus the first efforts of the recovery phase. To develop the reliability functions, the network is assumed to be in equilibrium.

An effective method is devised to predict the reliability of a system following a perturbation that reduces the capacity of one or more network links. Demand and capacity uncertainties are also considered. Previous work has mainly focused on only a single type of perturbation. The authors present a methodology to evaluate network reliability due to a wide range of disturbances, from very small (such as a single lane closure) to very large (such as a massive earthquake). In this methodology, potential disturbances are considered to have a variable effect on link-capacity, rather than a binary effect of either fully-functioning or closed (only 100% or 0% of ideal capacity).

The primary focus of this paper is to estimate network reliability using a demand function with link capacity and people

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willingness to pay (demand sensitivity) as two uncertain parameters. Uncertainty should be considered in any reliability model. In real-world situations prima facie imply uncertainty in the response/reaction to a disturbance. Under equilibrium conditions prior to an event, the general parameters that guide the system function, such as sensitivity of the demand with respect to travel time (user willingness to pay) and the link-capacity, can be reasonably well known. However, the system and user responses to a disturbance are uncertain. Rather than having fixed deterministic values, the user and system responses are better represented by distributions. Though many types of uncertainties are possible, a constrained numerical example with uncertainty in link-capacity and demand sensitivity to travel time is considered in this paper. The effects of such uncertainties are evaluated in comparison with the deterministic state. Simulation results showed that the inclusion of uncertainties provides a far more reasonable model that better reflects real-world scenarios.

Consumer surplus, total network travel time, and network flow are used as performance measures. Their respective functions are presented in the "Reliability Modeling" Section of this paper. Also, the effects of supply and demand uncertainty on different performance measures are investigated to capture demand elasticity and capacity changes. Sensitivity and uncertainty analyses are then performed to identify the critical link(s) in the network. The propagation of uncertainties throughout the performance functions is assessed using uncertainty analysis. Finally, a numerical example with a simulation application is modeled to contrast network reliability under uncertain and deterministic scenarios.

2. Literature review

Numerous studies have discussed the resilience of transportation networks. Mattsson and Jenelius [21] conducted an overview of such studies on vulnerability and resilience of transportation systems. They discussed definitions, concepts, and formulations of vulnerability and resilience using extensive literature. D'Lima and Medda [10] proposed a new measure to quantify resilience, and applied it to the case of the London Underground. They used a mean-reverting stochastic model based on the Pimm's [25] viewpoint that "*a system is more or less resilient depending on the rate at which it returns to equilibrium after a disturbance away from equilibrium*". Reggiani et al. [26] addressed the conceptual relevance of resilience and vulnerability in transportation networks. They provided various interpretations and measures given of the existing literature. In another study, Murray-Tuite [23] described resilience as a characteristic that indicates system performance under unusual conditions, recovery speeds, and amount of outside assistance required for the restoration to its original functional state.

Many studies evaluating road network resiliency and reliability have been conducted assuming various sources of disruption. Some studies only considered traffic congestion resulting from large increases in demand, such as during holiday weekends [7]. Others examined exceptional events (i.e. major natural and man-made disasters) and/or regular events (i.e. vehicle crashes) [2]. To improve the treatment of such uncertainty, researchers have considered the effects of various disruptions on transportation network performance on both the design (Asakura et al., 2001) and economic appraisal [11] of transport policy measures. Previous reliability analyses have been limited to connectivity reliability, travel time reliability, capacity reliability, behavioral reliability and potential reliability.

Connectivity reliability is defined as the probability that the nodes of the network remain connected. Iida and Wakabayashi [17] define connectivity by first assigning each link a binary statement of 0 or 1, corresponding to a failed or operating condition. Each origin–destination (*OD*) pair is deemed reliable if at least one path linking the two is operational. Due to it binary function, such reliability analysis cannot consider any changes in capacity. A link represented by 1 is assumed to operate at full capacity while a link represented by 0 at zero capacity (failed). This reliability analysis is suitable for extreme situations such as an earthquake or another destabilizing event, where the binary assumption of link capacity applies. However, such an assumption proves inaccurate for application to everyday traffic situations.

Travel time reliability relies on estimating the distribution of *OD* travel times given the variations in link travel times. Such reliability is defined as the probability that the ratio between the travel time before and after an event exceeds an acceptable level. This reliability model is suitable for daily traffic disruption. Asakura [1] calculated network reliability as a function of *OD* travel time before and after a disturbance. He considered two states for all components of the network; failed or not failed, and used Li's approximate method for estimating reliability [18].

An example of flow reliability can be found in [11]. They used a user equilibrium model with elastic demand to obtain *OD* pair flows and compared the flow of a normal network to a degraded one. A sensitivity analysis of the system surplus is performed to identify the most important links of the network.

Capacity reliability is estimated by comparing network capacity before and after an event. But first, the range of *OD* demands that allow the network to function within its capacity needs to be determined. This range is used to estimate the probability with which the network can accommodate a given traffic demand at a required service level [8]. The capacity reliability can be defined as the probability that the network capacity after an event will still exceed some pre-defined level.

Behavioral reliability is concerned with the effect of the modified mean behavior of drivers on the mean network performance, as a result of their attitude to the unpredictable variation and/or the "risks" perceived. Some researchers consider the impact on the typical route choice pattern [19,20,34] while others consider other responses such as departure time choice [24,30].

Potential reliability of a network aims to identify potential weak problems and their effects. Berdica [4] and Berdica (2002) proposed various network vulnerability tests to examine the effect of different network parameters on output performance measures. D'Este and Taylor [9] defined node vulnerability as a node that significantly lost its accessibility due to the loss of a small number of links.

Existing models are useful for evaluating network reliability, but many have limitations in addressing the nature and effects of the perturbations on the trip making decision. This study is more focused on behavioral reliability by considering the uncertainty in people's trip making decisions after a disaster. The effects of perturbations on link capacity are considered along with their effects on driver trip-making behavior, including potential changes in the demand function.

3. Transportation network resilience

Concepts of resilience cycle was introduced by Bruneau et al. [6] and elaborated by Heaslip et al. [15]. A resilience cycle comprises four stages: Normality, Breakdown, Self-annealing, and Recovery. The first stage, *normality*, is defined as the condition when the network is functioning under normal or standard conditions without the effect of any disturbances or disruptions. A system operates with maximum efficiency in the latter stage. When a disruption or disturbance occurs, the network experiences reduction in performance, leading to the second stage, the