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# Reprint of: Modelling the impact of traffic incidents on travel time reliability $\stackrel{\scriptscriptstyle \,\triangleleft}{\scriptstyle}$

Ahmad Tavassoli Hojati<sup>a,\*</sup>, Luis Ferreira<sup>a</sup>, Simon Washington<sup>b</sup>, Phil Charles<sup>a</sup>, Ameneh Shobeirinejad<sup>c</sup>

<sup>a</sup> School of Civil Engineering, The University of Queensland, Australia
<sup>b</sup> Faculty of Built Environment and Engineering, Queensland University of Technology, Australia
<sup>c</sup> School of ICT, Griffith University, Brisbane, QLD 4111, Australia

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#### ABSTRACT

Traffic incidents are recognised as one of the key sources of non-recurrent congestion that often leads to reduction in travel time reliability (TTR), a key metric of roadway performance. A method is proposed here to quantify the impacts of traffic incidents on TTR on freeways. The method uses historical data to establish recurrent speed profiles and identifies non-recurrent congestion based on their negative impacts on speeds. The locations and times of incidents are used to identify incidents among non-recurrent congestion events. Buffer time is employed to measure TTR. Extra buffer time is defined as the extra delay caused by traffic incidents. This reliability measure indicates how much extra travel time is required by travellers to arrive at their destination on time with 95% certainty in the case of an incident, over and above the travel time that would have been required under recurrent conditions. An extra buffer time index (EBTI) is defined as the ratio of extra buffer time to recurrent travel time, with zero being the best case (no delay). A Tobit model is used to identify and quantify factors that affect EBTI using a selected freeway segment in the Southeast Queensland, Australia network. Both fixed and random parameter Tobit specifications are tested. The estimation results reveal that models with random parameters offer a superior statistical fit for all types of incidents, suggesting the presence of unobserved heterogeneity across segments. What factors influence EBTI depends on the type of incident. In addition, changes in TTR as a result of traffic incidents are related to the characteristics of the incidents (multiple vehicles involved, incident duration, major incidents, etc.) and traffic characteristics.

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#### 1. Introduction

Travel time is an effective factor for measuring transport network performance. It reflects the efficiency of the road network and is easily understood by most travellers. Travel time on a given road link varies over time, and is influenced by a variety of factors that lead to congestion. Recurrent congestion relates to predictable peak period traffic when demand

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<sup>\*</sup> Corresponding author at: School of Civil Engineering, Faculty of Engineering, Architecture and Information Technology, The University of Queensland, Brisbane St Lucia, QLD 4072, Australia. Tel.: +61 7 334 61349; fax: +61 7 336 54599.

E-mail address: a.tavassoli@uq.edu.au (A. Tavassoli Hojati).

exceeds road capacity. Non-recurrent congestion arises from unsteady and unpredictable changes from time to time or day to day; and also to the unexpected events such as incidents, accidents, work zones and adverse weather (Lomax et al., 2003).

Acknowledging the effects of congestion on travel time variability, many studies have attempted to measure travel time reliability (TTR) in order to present average conditions and indications of how often and/or how much travel time varies over time.

Traffic incidents are the key sources of non-recurrent congestion, and account for 25–60% of total congestion on highways (Hall, 1993; Skabardonis et al., 2003; CamSys/TTI, 2005). In this regard, the importance and impacts of traffic incidents vary from place to place as a function of local conditions. Identifying and quantifying the effects of factors that influence TTR is vitally important for improving the management of traffic incidents, as it allows appropriate strategies to be implemented to alleviate the congestion impacts of incidents through efficient allocations of equipment and personnel.

The collection of comprehensive and reliable data of traffic incidents and related contributory factors is challenging in many ways. Data collection is often inadequate, incomplete, imprecise and expensive. In this regard, an effective and efficient procedure for collecting and gathering incident data is essential to perform an accurate assessment and analysis of traffic incidents and its components (Gregoriades and Mouskos, 2013). As shown in the study by Shi and Abdel-Aty (2015), the benefits of Big Data technologies such as loop detectors include direct and indirect applications to analyse the interrelation of congestion and traffic safety. On this basis, this study put forward an innovative approach dealing with comprehensive incident data mining and analysis from different sources of data including the application of big data.

The aim of this paper is to understand and predict the impacts of traffic incident features and characteristics on TTR on freeways. A methodology is proposed to achieve this aim.

The paper begins with a review of previous research on models focused on quantifying the effects of traffic incidents on TTR. This review is followed by details of the model development. Attention is then directed towards describing the methodology to extract traffic incident impacts. Australian incident data and traffic measures are examined in this study. The subsequent section describes the modelling results including estimation of model parameters, and identifying significant model variables. The final section concludes with a summary of the analysis findings and identifies areas for future research.

#### 2. Literature review

A number of studies have been aimed at estimating and predicting travel times, and have incorporated reliability measures to compare and analyse TTR measures (Emam and Al-Deek, 2006; Taylor, 2013). However, very few studies have focused on TTR modelling.

Elefteriadou and Cui (2007) proposed a set of linear regression travel time estimating models under 24 series of scenarios based on four main factors, namely congestion, weather, work zones, and incidents Using traffic data on a 15 km freeway in Philadelphia. These models produced expected travel times for each scenario and the travel time distribution was obtained based on the frequency of occurrence of each scenario. By applying a reliability measure, namely the buffer time index, the percentage of "reliable trips" has been proposed as a function of various on-time performance approaches. The model used dummy variables for incidents, work zones, and weather. The main disadvantage of the model is that it did not cover all the effects of unexpected events, particularly incidents.

Saberi and Bertini (2010) prioritised freeway segments based on TTR measures using archived loop detector data from five freeways in Portland and Oregon in the USA. They found that the buffer time index and the coefficient of variance were the most consistent among the measures of TTR. Although TTR measures were analysed, the factors contributing to the unreliability of travel times were not identified.

Tu (2008) estimated a travel time unreliability model defined as a function of inflow, travel time unreliability in free flow, and critical travel time unreliability. This model was calibrated and validated using traffic data from urban freeways in the Netherlands. The results indicate that travel time unreliability following traffic accidents was 7.8% higher than without traffic accidents. In addition, traffic accidents were not identified to be the main factor affecting travel time unreliability. Interestingly, an assumption of a 3-h duration for all accidents was applied to distinguish between accident-related and accident-free traffic data.

Guo et al. (2010) and Park et al. (2010) demonstrated the application of multistate model to assess travel time distributions on freeways on the basis that travel time is dominated by the underlying traffic conditions. Using multistate models in a recent study by Park et al. (2011), the impact of traffic incidents on TTR were investigated based on microscopic simulation models of a 16-mile section of I-66 in Washington, DC, USA. The study obtained travel time under typical traffic and incident conditions. Three traffic incident scenarios were designed by varying the number of lanes blocked from one lane to three lanes. TTR dropped significantly after the occurrence of traffic incidents. In addition, incident impact on TTR was found to be more critical during congested conditions. However, there were a couple of limitations in this study. First, incident duration was assumed fixed at 40 min for all incidents, perhaps an unrealistic assumption. Second, incident severity was defined in terms of number of blocked lanes by traffic incidents. However, even for incidents blocking the same number of lanes, the congestion impact will differ based on severity of the crash itself, mitigation strategies, in place, etc. Third, an even greater source of concern is the use of simulation models for incident analysis. The calibration process needs to make use of actual incident situations in order to obtain realistic results. Download English Version:

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