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A framework for travel time variability analysis using urban traffic incident data

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ABSTRACT

This study aims to develop a framework to estimate travel time variability caused by traffic incidents using integrated traffic, road geometry, incident, and weather data. We develop a series of robust regression models based on the data from a stretch in California's highway system during a two-year period. The models estimate highway clearance time and percent changes in speed for both downstream and upstream sections of the incident bottleneck. The results indicate that highway shoulder and lane width factor adversely impact downstream highway clearance time. Next, travel time variability is estimated based on the proposed speed change models. The results of the split-sample validation show the effectiveness of the proposed models in estimating the travel time variability. Application of the model is examined using a micro-simulation, which demonstrates that equipping travelers with the estimated travel time variability in case of an incident can improve the total travel time by almost 60%. The contribution of this research is to bring several datasets together, which can be advantageous to Traffic Incident Management.

1. Introduction

A number of factors affect travel time and its variability. Higher than average travel time and travel time variability are two immediate consequences of congestion. Such congestion can be classified as either recurrent or non-recurrent [1]. Recurrent congestion is caused by everyday peak-hours delays which occur when the demand exceeds the capacity of a highway, while non-recurrent is due to atypical causes, such as incidents [2,3], disabled vehicles, work and construction zones, adverse weather events [4,5], and special events [6]. Both types of congestion impose travel time variability and uncertainty for drivers since they do not know exactly when they will arrive at the destination. In the United States non-recurring congestion caused by incidents constitutes approximately 25% of the total congestion [7]. The two major causes accounting for non-recurrent congestion are traffic incidents and weather. Short-term traffic forecasting plays an important role in traffic management [8] in cases of incidents and adverse weather.

The vital role of highway transportation system in daily life makes it the key to achieving long-term planning [9–11]. One of the planning process in case of incidents on highways is the Traffic Incident Management (TIM), which is composed of four different phases as depicted in Fig. 1 [12]. Each of these phases has been the subject of several research studies aiming at managing incidents [13,14]. The incident clearance time is the period between reporting an incident and removing all vehicles from the scene [12], as seen in phase 1 to 3 in Fig. 1. In most cases, however, the traffic stream remains affected by the incident even after it is cleared. *Highway clearance time* is the time between the incident detection and the resuming of normal traffic operations; this total time period in seen in Fig. 1. Incident clearance time can be estimated based largely on incident responders. Highway clearance time, however, is more complicated to calculate due in part to the difficulty of defining the time when the traffic recovers its pre-incident condition. While many studies have investigated the incident clearance time, few, if any, have focused on modeling *highway clearance time*.

Apart from the type and severity of incidents, several exogenous variables affect highway clearance time, including weather conditions, geometric features of highway, and topography. Adverse weather affects post-incident traffic flow in different ways. Highway systems of course vary in length, number of lanes, and traffic volume. Consequently, it is difficult to shape a generalized model for estimating the incident clearance time.

As the first step in addressing the existing challenge, this paper will integrate weather, geometric, and incident data. The objective of this research is to combine these sources for the purpose of estimating highway clearance time through real-time data sharing. In addition, the methodology is configured to run with real-time data in order to provide operators with travel time variations under the current incident.

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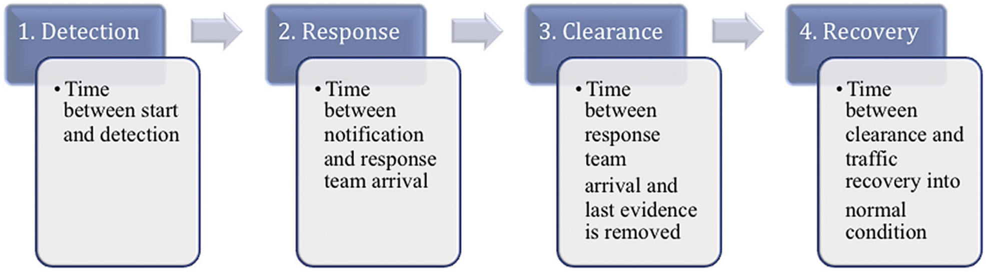

Fig. 1. Traffic incident phases and timeline.

While travel time is more tangible to drivers compared to delay, density, speed, and flow [15,16], existing models cannot simply deliver the online travel time variability to travelers, which is the purpose of this framework. The lack of a model that uses integrated incident and weather data, together with the importance of providing drivers with real-time changes in travel time variability in case of an incident, motivated this research.

This study utilizes a robust regulator model capable of integrating the influence of outliers to improve the prediction. The model is developed using roadway geometry information, detailed weather data, 5-minute traffic speed data, and an extensive incident inventory database collected from a stretch of highways in California. The two main data sources for this research are the PeMS software solution by the California Department of Transportation and the National Oceanic and Atmospheric Administration (NOAA).

The amount of available traffic and non-traffic data is growing, which increase the need to integrate the data sources in order to obtain better results [17]. A fundamental contribution of this research is to bring several datasets together and identify interactions that may occur to improve TIM. The current framework can effectively deliver the travel time variability to travelers using an extensible model. This study can thereby contribute importantly to Intelligent Transportation Systems (ITS) through Vehicle-to-Vehicle (V2 V) and Vehicle-to-Infrastructure (V2I) programs including in-vehicle navigation systems, variable message signs, highway advisory radio, and smart phones.

This section is followed by a literature review, succeeded by data description, and research methodology. Estimation results and travel time variability are presented in subsequent sections. Finally, application of the model and conclusions are addressed in the final section.

2. Literature review

Existing literature on the subject matter falls into two major categories: assessment and estimation. Various methods in the first category have been used to address incident-induced congestion and travel time reliability. As an example, Skabardonis et al. [18] assessed recurrent and non-recurrent delays on urban highways using loop detector data in which the probability distribution of delays for two real highway corridors in Los Angeles and the Bay Area, were calculated. Kim et al. [19] laid out an integer-programming model to minimize the total incident delays using Maryland incident data. While these methodologies benefit planners, they cannot quantify incident impacts for travelers. Wright et al. [20] analyzed the impacts of different accident types on travel time reliability using the incident data collected on two Interstates in the Seattle, Washington, and found incidents can significantly reduce travel time reliability.

In the second category, researchers from a wide range of disciplines have quantified and estimated incident delays. A comprehensive research study by Chunkg and Recker [21] quantified both temporal and spatial aspects of incident-induced delay using Binary Integer Programming (BIP). Pan et al. [22] modeled spatiotemporal impact of incidents in terms of delay by analyzing the archived traffic data in Los Angeles. In another recent effort Yu et al. [23] estimated incident-induced delay by using a combination of modified queuing diagram and short-term traffic flow forecasting techniques.

Besides using different modeling approaches to estimate incident-induced delay in the second category, other studies focused on estimating the duration of the different phases of an incident. Ozbay and Noyan [24] used Bayesian Networks to estimate duration of incidents for which data might be partially available in Northern Virginia. Qi et al. [25] investigated the factors impacting the time required to clear incidents using hazard-based models by considering Exponential, Weibull, Log-logistic, and Lognormal distributions for incident duration. Hou et al. [13] proposed a mechanism-based approach to model the incident response process. Response time involves both preparation delay and travel time to the incident site. Several factors regarding incident and spatiotemporal variables were considered. The model had the potential to be used for optimal incident response time. Additionally, research by Ghosh et al. [12] explored the factors contributing to incident clearance time in the southeastern Michigan freeway network, using a series of parametric hazard duration models. Li et al. [26] used a hazard-based competing risks mixture model to analyze the influence of clearance methods on incident clearance time. Xie et al. [27] showed that incidents during and post hurricane Sandy are expected to have 116.3% and 79.8% longer durations respectively than those that occurred at any regular time. Ding et al. [28] used the endogenous switching model to explore the influential factors in incident clearance time, considering the effect of self-selection bias by incident response process in Washington State. Zou et al. investigated the impact of different explanatory variables on incident clearance time and found the finite mixture model can better estimate the survival and hazard probability of incident clearance time [29]. Although these studies contribute significantly to the science of incident management, most of them ignore highway clearance time.

To bridge this gap, a few studies attempted to address highway clearance time and estimate the time to traffic recovery. Maestre and Munford [30] researched the recovery time and claimed that no mathematical model exists that can accurately predict the recovery time in real-time since highway clearance time is difficult to model. Zhou and Tian [31] concluded that incident clearance time and highway clearance time had been studied separately but the relationship between these two has not yet been examined. To explore this, Zhou and Tian generated 300 incidents in VISSIM based on different blocked lanes and incident clearance times and traffic volumes. The scenario simulation results demonstrated the high correlation between recovery time and incident clearance time. Unfortunately, this study did not use real-world data, rendering their simulation-based analyses quite questionable. In another recent study Tavassoli Hojati et al. [32] applied a hazard-based approach to model incident duration as a function of a variety of influencing variables on freeways in Australia. This method used historical data to investigate potential independent variables, including incident details, traffic characteristics, infrastructure, and temporal effects. This method, however, cannot be used for online prediction and the results remain unvalidated.

All these studies are useful in enhancing the performance of incident management and transportation planning systems. As the output of

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