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Factors Influencing Freeway Traffic Upstream of an Incident

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ABSTRACT

We examine the effects of incident occurrence on freeway traffic. Although the true influence of a freeway incident may not be directly observed, it may be identified using the maximum spatial extent of the disturbance induced to upstream traffic. Spatial and temporal extent is susceptible to various traffic, weather, geometry and incident specific factors. The above framework is implemented using a Multiple Indicators-Multiple Causes (MIMIC) latent variable model. Results using data from Athens, Greece indicate that the MIMIC model is able to accurately determine the influence of an incident on upstream traffic with 72% probability of producing mean square errors less than 0.05. Speed, lane volume, alignment, rainfall intensity, clearance time and whether the incident is a secondary or a primary one are among the most influential factors for assessing the anticipatory effect of incidents to traffic.

Keywords: incidents, freeway operations, spatial and temporal traffic evolution, structural equation modeling.

INTRODUCTION

Identifying and proactively managing the effects of incidents is the cornerstone of modern freeway traffic and safety management systems (Vlahogianni et al., 2012; Ahmed and Abdel-Aty, 2013). Overall, incidents are critical, as they form a region upstream of their occurrence with degraded traffic characteristics and reduced roadway capacity; this region may entail increased risk of secondary accident occurrence (Khattak et al., 2011; Vlahogianni et al., 2012). There are several interesting topics related to freeway incident management that have attracted significant research over the years. These include automatic incident detection (Jeong et al. 2011), modelling of incident duration (Ozbay and Nayan, 2006; Vlahogianni et al., 2010; Khattak et al., 2011; Vlahogianni and Karlaftis, 2013), estimating the delays induced due to incidents (Garib et al., 1997; Kwon et al., 2006) and detecting secondary accidents (Raub et al. 1997, Moore et al. 2004, Zhang and Khattak, 2010; Vlahogianni et al., 2010; Imprialou et al., 2013).

In incident management strategies, the influence of an incident on freeway traffic has been mainly considered as static. Researchers have defined several spatiotemporal criteria to account for the effect of an incident on upstream traffic (e.g. km upstream and 15 minutes after the incident occurrence) (Raub et al. 1997, Karlaftis et al. 1999). Recently, a series of papers have focused on dynamically assessing the spatio-temporal propagation of the influence of an incident to upstream locations of the road network from visually observing the progression of the queue formulated upstream of a primary incident (Sun and Chilukuri, 2010), to queue based analytical estimations (Zhang and Khattak, 2010), cumulative arrival and departure plots (Zhan et al., 2009), and other analytical estimation methods stemming from loop detector data (Orfanou et al., 2011, Imprialou et al. 2012). These methods have been almost exclusively dedicated to identifying the duration of the incident or detecting secondary accidents as those occurring within or at the boundaries of the formed queue (Moore et al., 2004; Zhang and Khattak, 2010; Vlahogianni et al., 2012).

The above studies usually define the influence based on the duration of the queue (most times taken to coincide with the incident clearance time), formed upstream of an incident. At the same time, they disregard the spatial influence of the incident to upstream traffic given, for example, by the spatial extent of the formed queue. The duration of the queue is usually related to aggregate traffic and weather information and rarely related to the disaggregate traffic and weather conditions at the occurrence of the incident. Interestingly, this approach is not inclusive enough as there are cases where the effect of an incident to the upstream traffic is not translated to queue formation and stop and go conditions, but to a disturbance (e.g. a moving jam or an area with reduced traffic characteristics) upstream of the incident's location. Moreover, no attempt to develop explanatory relationships between the spatio-temporal extent of the incident's influence to traffic and other, geometry and incident related factors has been made in the literature. Relating the effects of an incident on upstream traffic and connecting it to observable factors may have significant management and policy making implications.

In this paper, we research the influence of incident occurrence on freeway traffic by jointly considering the maximum spatial extent and total duration of a disturbance formed upstream of an incident. The methodological approach is based on structural equation modeling, a generalized multivariate statistical technique commonly used in social sciences that may incorporate constructs that cannot be directly observed (latent variables) (Washington et al. 2010). The paper is structured as follows: the nest section provides a presentation of the problem statement and the basic notions of structural equations modeling. Following the area of implementation and the dataset is presented, along with the results. The paper ends with some concluding remarks.

ASSESSING THE INFLUENCE OF INCIDENTS ON TRAFFIC

Problem Formulation

Every incident may create a disturbance on traffic flow that is propagated upstream of the incident's location. We assume that the true influence of a freeway incident may not be directly observed but may be identified using the maximum length $L_{\max}$ and the duration T of a disturbance formed upstream of an incident as indicators. Moreover, we assume that these indicators are susceptible to various traffic, weather, geometry and incident specific factors, such as speed and hourly volume at the occurrence of the incident, rainfall intensity, upstream geometry or alignment, number of vehicles involved in the accidents, number of blocked lanes and so on. The above framework is implemented using a Multiple Indicators-Multiple Causes (MIMIC) latent variable model.

Model and Estimation

The MIMIC model is a case of Structural Equation Modeling (SEM), also known as latent variable modeling, a thorough technique for testing hypotheses for the relations between observed and unobserved (latent) variables (Washington et al., 2010). The model consists of two components: a measurement model which defines the relations between a latent variable and its indicators and a structural model which specifies the casual relationships among latent variables and explains the casual effects. MIMIC model considers the latent variable η to be scalar and relates the vector of indicators $\mathbf{y}$ and the observed exogenous variables $\mathbf{x}$ that cause η by the following system of equations:

$$\begin{aligned} \boldsymbol{\eta} &= \boldsymbol{\Gamma}\mathbf{x} + \boldsymbol{\varepsilon} \\ \mathbf{y} &= \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\zeta} \end{aligned} \tag{1}$$

where $\boldsymbol{\Gamma}$ and $\boldsymbol{\Lambda}$ are matrices of unknown parameters to be estimated and ε and $\boldsymbol{\zeta}$ are the error terms. Path analysis may be implemented to identify a MIMIC model (Figure 1). The unobserved endogenous latent variables are usually represented with ellipses, whereas the observed variables - either being causal variables or indicators - may be represented by boxes. Simple associations between variables are depicted with two-way arrows (paths), whereas causal associations are depicted by unidirectional paths, the direction of which is from the independent to the dependent variable. Regression coefficients show the strength of the paths.

SEM has been previously applied to many fields of transportation including transit system quality of service analysis (Karlaftis et al.; 2001), travel behavior modeling (Golob, 2003), mode choice modeling (Johansson et al., 2006), driver's behavior modeling (Hassan and Abdel-Aty, 2011) and public acceptability analysis of new technologies for traffic management (Chung et al., 2012). SEM models may be viewed as a generalized case of multivariate classical statistical models and suffer from similar constraints as classical statistical models, but outperform other techniques due to their ability to treat auto-correlated errors, non-normal data and latent variables (Karlaftis et al., 2001).

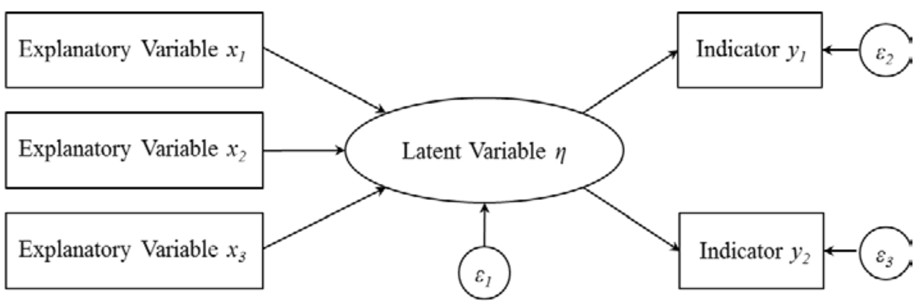

Figure 1: The structure of the MIMIC model.

IMPLEMENTATION AREA AND DATA

Data come from Attica Tollway, a 65km tollway located at the boundaries of the metropolitan area of Athens (Greece). The dataset consists of 1287 detailed accident records and have been analyzed to detect and assess the occurrence of secondary accidents using both dynamic analytical and empirical based approaches (Vlahogianni et al., 2010; Vlahogianni et al., 2012; Imprialou et al., 2013). Moreover, the accident dataset has been enriched with traffic information in the form of volume and speed at the occurrence of the accidents, for the location of the accident, as well as the adjacent upstream location (up to 10 km upstream to reference point). Further, synchronized information on precipitation intensity was available by the Hydrological Observatory of Athens, operated by the National Technical University of Athens. All available variables – either measured or estimated – may be found in Table 1. These variables will be considered in structural equation modelling.

Table 1: Description of variables.

Variable	Description
Continuous	
Clearance Time	The incident duration in minutes
Travel Speed	Travel speed (km/h) at the occurrence of the incident
Hourly volume	Hourly volume (veh/h/lane) at the occurrence of the incident
Rainfall Intensity	Rainfall at the occurrence of the incident in mm/1min
Categorical	
Type of Accident	0 for primary and 1 for secondary
Severity	0 for only damages and 1 for injuries/fatalities and damages
Nr. Lanes	1 to 3, 1:1 lane, 2: two, 3: more than 2
Nr. Vehicles	1 to 3, 1:one, 2: two, 3: more than 2 vehicles involved
Heavy Vehicle	0 to 1(Heavy Vehicle involved)
Alignment	0 to 1(curve)
Downstream Toll	0 for no toll 1 if adjacent to toll
Downstream Entrance/Exit Ramp	0 for no toll 1 if adjacent to entrance/exit
Downstream Tunnel	0 for no toll 1 if adjacent to tunnel
Downstream Complex	0 for no complex geometry 1 if complex geometry
Upstream Toll	0 for no toll 1 if adjacent to toll
Upstream Entrance/Exit Ramp	0 for no toll 1 if adjacent to entrance/exit
Upstream Tunnel	0 for no toll 1 if adjacent to tunnel
Upstream Complex	0 for no complex geometry 1 if complex geometry
Indicators	
T	Duration of the disturbance propagated upstream of the incident (minutes)
L_{max}	Maximum spatial extend of influence (km)

Apart for the variables collected by the traffic management centre of Attica Tollway and the Hydrological Observatory of Athens, indicators are estimated based on a methodology for moving bottleneck tracking implemented by Imprialou et al. (2013). This method is based on both an analytical approach introduced by Kerner et al. (2004) and an empirical approach introduced by Chen et al. (2004). Moreover, this methodology will be further used to tag accidents as secondary or primary.

Estimation of the temporal and spatial extend of incident's influence to traffic

Maximum length $L_{\max}$ and Duration T of the disturbance propagated upstream of an incident is calculated based on both analytical and empirical approaches. We implement the methodology introduced in Imprialou et al. (2013), based on a combined analytical and empirical approach to estimate the maximum length $L_{\max}$ and the duration T formed due to an incident on freeways. The analytical part of the methodology is based on the ASDA algorithms that tracks a moving jam at all times using data from consecutive loop detectors (Kerner et al., 2004).

For two consecutive loop detectors (Q_o, Q_n) on a freeway road section that are L meters apart, at the occurrence of a moving jam at the detector Q_n at time t_o, the ASDA model starts to calculate continuously the positions of the upstream front, $x_{up}^{(jam)}(t)$. After the downstream front of the moving jam is registered at the detector Q_n at the later time t_1, the ASDA model starts to calculate continuously the positions of the downstream front, $x_{down}^{(jam)}(t)$. The positions of both the fronts of the formulated wide moving jam caused by the primary incident may be calculated by using the following two equations (Kerner et al., 2004):

$$x_{up}^{(jam)}(t) = L_{i+1} - \int_{t_o^{(i+1)}}^{t} \frac{q_0^{(i)}(t) - q_{min}}{\rho_{max} - \left(q_0^{(i)}(t) / w_0^{(i)}(t)\right)} dt$$

$$x_{down}^{(jam)}(t) = L_j - \int_{t_1^{(j)}}^{t} \frac{q_{out}^{(j)(jam)}(t) - q_{min}}{\rho_{max} - \left(q_{out}^{(j)(jam)}(t) / w_{max}^{(j)}(t)\right)} dt \tag{2}$$

where index i and j represent detectors, whose time values at time t have to be used, L_{i+1}, L_j are the coordinates of the corresponding detectors; $t_0^{(i+1)}$ indicates the time when the upsteram front of the moving jam has been observed at the detector $i+1$; $t_1^{(j)}$ indicates the time when the downstream front of the jam has been observed at the detector j; $q_0^{(i)}(t)$ and $w_0^{(i)}(t)$ are the measured flow rate and the average vehicle speed at the detectors i upstream of a wide moving jam; $q_{out}^{(j)(jam)}$ and $w_{max}^{(j)}$ are the measured flow rate and the average vehicle speed at the detector j downstream of the wide moving jam (Kerner et al., 2004).

Moreover, a modified Chen's et al. (2004) speed threshold algorithm is implemented in order to detect when the upstream and the downsteram front are observed at each detector. The upstream front of the moving jam is considered to have reached one detector - at some time - if the three following criteria are fullfilled:

1. The speed at the detector is below the maximum speed threshold,
2. The speed drop at the detector is greater than a certain threshold (estimated from real time data),
3. The difference between the speeds at the detector and the next downstream detector is greater than the speed differential.

In the case where the analytical manner is difficult to apply, influence areas are defined by the modified speed threshold algorithm that is sequentially applied to all detectors upstream of the incident: an adjacent upstream location controlled by a loop detector is considered to be congested by the time it fulfill the above three criteria. Congestion persists until these criteria are no longer fulfilled. By combining all these information about the duration of the congestion at each position in a time-space diagram, it is possible to "track" the actual boundaries of an influence area and also the exact manner of its formation and dissipation.

Using the above approach the influence evolution of each incident to the upstream traffic may be identified. Figure 2 shows the upstream evolution of the incident influence for the available data. Evidently, the relationship between the L_s and T is quite complex and affected by various factors, such as the characteristics of the incident (accident type, severity, number of blocked lanes or vehicles involved etc), the weather (rain or not) and traffic conditions (speed and volume). Figure 2 shows a complex relationship between L_s and duration T that should be further researched and related t factors to be explained.

The above approach to track the influence of an incident may be used to detect secondary incidents. Every incident that occurs within this spatiotemporal area can be characterized as secondary with a good level of certainty to the extent that the quality of loop detector data permits. It is important to note that the secondary incident detection resulting from this method depend almost entirely on loop detectors performance.

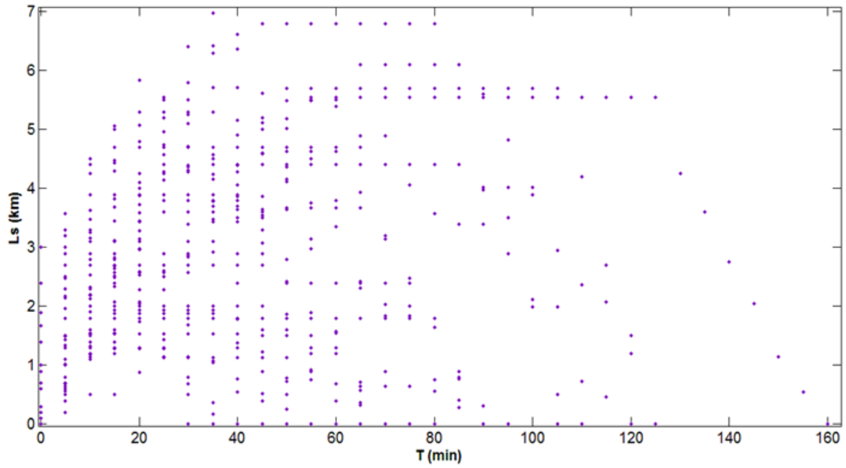

Figure 2: Influence evolution for a sample of accidents.

We implement the above approach which results in identifying three different patterns of traffic disturbance propagation induced by an incident (seen in Figure 3).

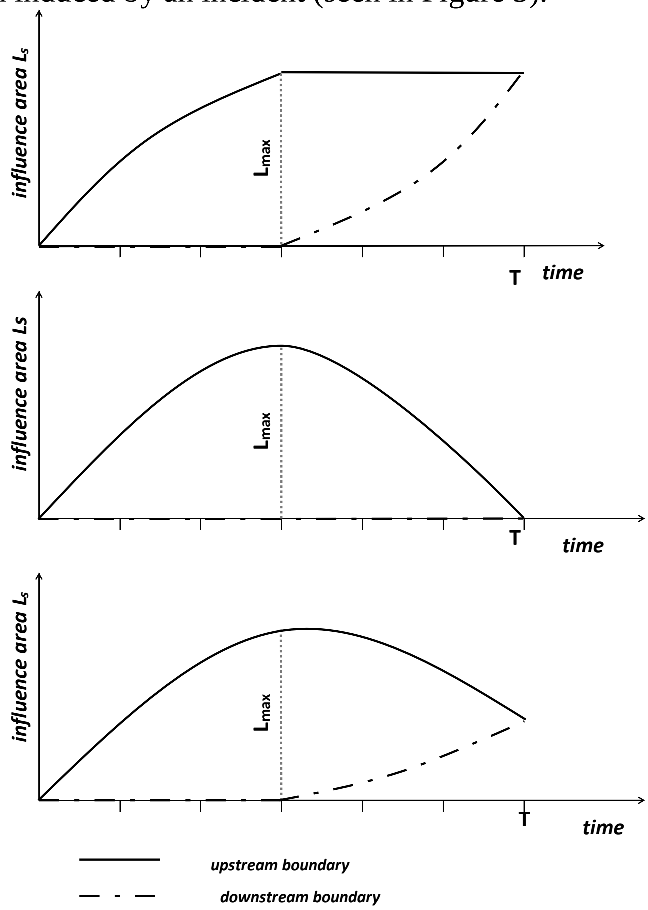

Figure 3: Patterns of traffic disturbance propagation induced by an incident.

These patterns describe different formation and dissipation types that are probably related to the changing demand pattern that may be observed in real-time. Interestingly, a fourth category including 9% of the total patterns that did not follow any of the above patterns was discovered. This inhomogeneity in disturbance evolution upstream of an incident reveals complexities probably attributed to factors including geometry, volume, speed, the presence of tunnels or interchanges, weather conditions (Imprialou et al. 2013).

Based on these patterns, a set of accidents that may be tagged as secondary were detected. Overall, it was found that 1.79% of the total number of accidents may be tagged as secondary. Although this percentage may be characterized as low, it is in line with the rest of the literature; according to Raub (1997) only 1.6% of the total incidents observed may be considered as secondary, whereas Moore (2004) has found that 3.27% of the available total set of incidents may be tagged as secondary.

Factors Affecting the Influence of an Incident of Freeways

A MIMIC model is constructed to account for the complex interrelationships between the different traffic, weather, geometry and accident related factors and the spatial and temporal influence of the incident. As the influence is not measured, the maximum length L_{max} and the duration of the disturbance induced by the incident to the upstream traffic are used as indicators. The different modelling structures defined by the various possible interconnections between the available variables are evaluated based on the Akaike's Information Criterion (AIC). This is given by $AIC = N\ln(MSE) + 2k$, and the Bayesian information criterion (BIC) defined as $AIC = -2\ln l + k\ln N$, where k is the number of network weights, N the number of training paradigms (sample size), MSE the mean square error and l is the maximized value of the likelihood function for the estimated model. The selection of the optimum structure among a set of candidate models is done by choosing the model producing the smallest value of AIC and BIC. Figure 4 depicts the resulted SEM model. Numbers on the connections indicate the values of the coefficients, and the numbers in parentheses are the standard error and the *p* value.

Due to the complexities involved in structural equation modeling, we followed a tedious evaluation procedure to assess the goodness of fit of the model developed. This approach include likelihood ratio tests for comparing the proposed model to the saturated one (the model that fits the covariances perfectly) and baseline models (model that includes the means and variances of all observed variables plus the covariances of all observed exogenous variables). It also compares the root mean squared error of approximation (RMSEA) along with the probability of RMSEA being below 0.05, the standardized root mean squared residual SRMR and the coefficient of determination or the various models

Table 2 shows the goodness of fit statistics for the proposed SEM. A fit is close to the real data if the lower bound of the 90% CI is below 0.05 and is poor if the upper bound is above 0.10 (Browne and Cudeck, 1993). A good fit provides SRMR less than 0.08 (Schermelleh-Engel et al., 2003). CD is similar to R^2 for the entire model. Finally, a CFI above 0.95 demonstrates a good fit (Schermelleh-Engel et al., 2003). Based on the above values, Table 2 results are indicative of a SEM that provides a good fit.

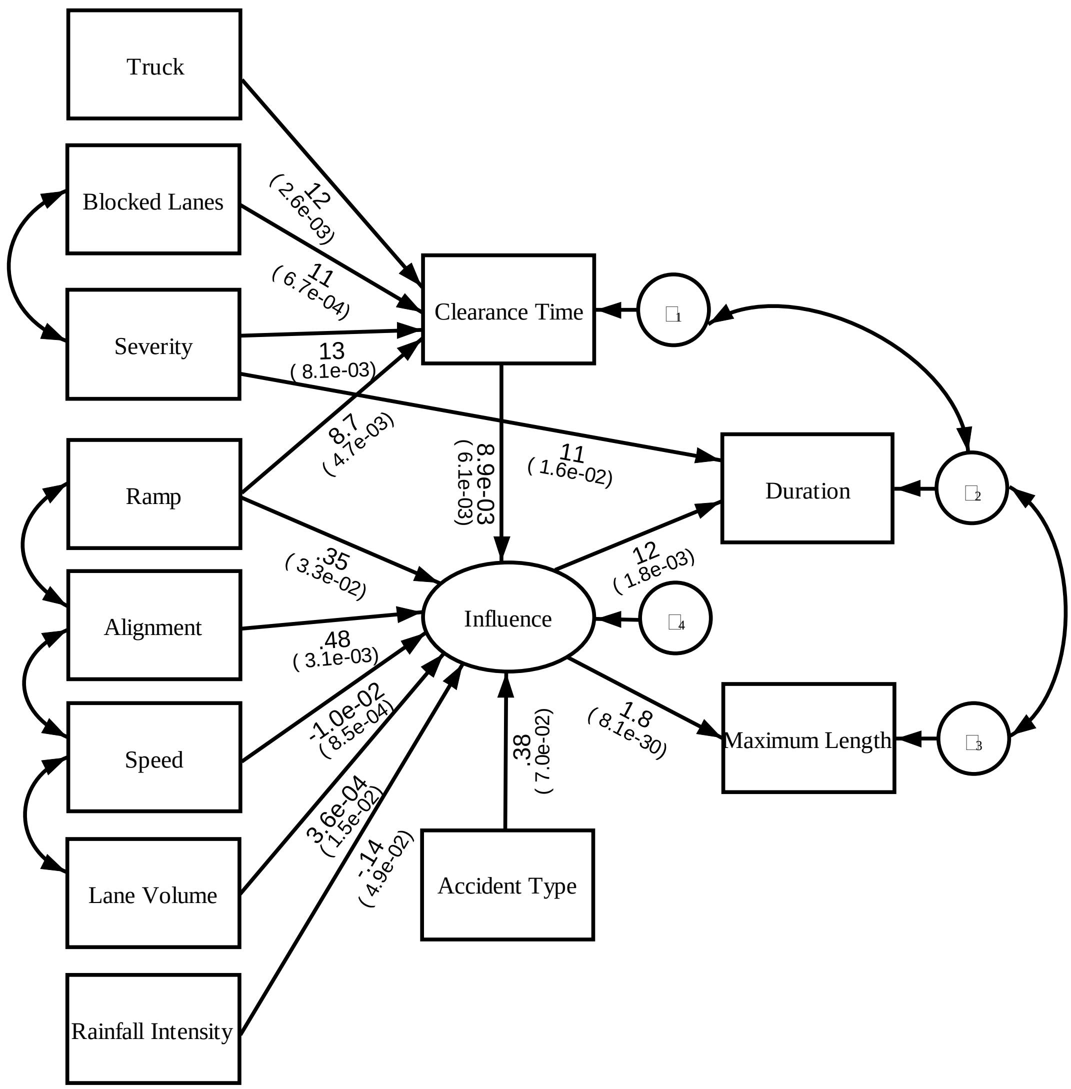

Figure 4: Final SEM for describing the factors influencing the disturbance in traffic induced by an accident.

As can be observed from the coefficients and p-values shown in Figure 4, for the measurement model, both indicator coefficients are positive and significant and may contribute to defining the influence of an incident to upstream traffic. Nevertheless, the disturbance duration T is a stronger indicator of the influence than maximum moving spatial extend of the disturbance L_{max}.

Apart from the indicator variables (L_{max} and T), a strong positive relationship between the latent influence of the accident with the type of the accident (secondary or not), as well as the alignment (whether the accident occur on a curve or not) and the existence of entrance/exit ramps upstream of the accident location are detected. Weaker positive relations are observed between the latent variable and the traffic volume and the clearance time of and accident. Moreover, speed increases negatively influence upstream traffic. Interestingly, rainfall intensity is negatively related to the upstream traffic conditions just after the accident occurs. Although this - at first - contradicts the understanding that adverse weather may create risky driving conditions, it may be intuitively explained by the tendency of the drivers to drive cautiously during rain. This may also be due to the effect of information provided to drivers - for example via VMS - during the course of driving or by reduced demand during adverse weather conditions. Nevertheless, it seems that the effect of weather - as introduced to the specific model - may not be adequately addressed.

Table 2: Goodness of Fit statistics for model evaluation.

Fit statistic	Value
Likelihood ratio	
χ^2 (p > χ^2) – Saturated	12.774 (0.689)
χ^2 (p > χ^2) - Baseline	192.172 (0.00)
Population error	
RMSEA	0.000
90% CI, lower bound	0
90% CI,upper bound	0.025
Probability RMSEA <= 0.05	0.924
Baseline comparison	
CFI	1.00
TLI	1.037
Size of residuals	
SRMR	0.026
CD	0.408

Further, a significant result is that accident related characteristics (such as the number of blocked lanes, the severity of the accident or the traffic compositions) are introduced as predictors to the clearance time and not directly to the latent variable. Findings show that only three characteristics - the involvement of trucks in the accident, the number of blocked lanes as well as the existence of tolls adjacent to the area of the accident - are adequate to describe clearance time. These three variables may positively affect the clearance time and - by extension - the manner the disturbance is propagated upstream.

CONCLUSIONS

This paper proposed a SEM approach to develop explanatory relationships between traffic, geometry, accident and weather related factors and the manner an incident may influence upstream traffic conditions in both space and time. We considered the influence of an incident to be a latent variable, and we introduced two indicators to measure it: the duration and the maximum spatial extent of the disturbance induced by an incident and propagated backwards. Findings showed that the duration of the disturbance is a more powerful indicator than its maximum spatial extent. The accident type, the existence of tolls and the alignment upstream of the incident, as well as rainfall are the most influential predictors of accidents spatiotemporal influence. Moreover, speed, volume and the incident’s clearance time significantly contribute to the determination of the spatiotemporal influence to upstream traffic. Interestingly, the accident specific data (the number of lanes that were blocked by the incident, the severity of the incident and the truck involvement) are only related to the clearance time and do not directly affect the spatiotemporal influence.

Overall, the proposed modeling approach may reveal complex interrelations between traffic, geometry, accident and weather specific factors with far reaching implications to incident management and policy making. Apart from improving freeway operations at the occurrence of an incident, by applying for example traffic specific measures for filtering traffic and affecting short-term demand, the efficient representation of the influence propagation upstream of an incident may significantly improve the definition and detection of secondary accidents. Moreover, the quantification of the influence of an incident to upstream traffic may significantly improve the knowledge on the impact of incidents from various angles, including safety, environmental, financial and productivity perspectives.

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