2-2015

Travel Time Reliability Versus Safety: A Stochastic Hazard-Based Modeling Approach

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Keywords
Car-following, lane-changing, hazard functions, prospect theory, Monte Carlo simulation, safety, travel time reliability

Disciplines
Civil Engineering | Transportation Engineering

Comments
This is a manuscript of an article published as Hamdar, Samer H., Alireza Talebpour, and Jing Dong. "Travel time reliability versus safety: A stochastic hazard-based modeling approach." *IEEE Transactions on Intelligent Transportation Systems* 16, no. 1 (2015): 264-273. DOI: 10.1109/TITS.2014.2331561. Posted with permission.

Travel Time Reliability versus Safety: A Stochastic Hazard-Based Modeling Approach

Samer H. Hamdar, Alireza Talebpour and Jing Dong, *member, IEEE*

***Abstract*—This paper presents a modeling approach to linking stochastic acceleration and lane changing behavior to travel time reliability on congested freeways. Individual driving behavior is represented by a prospect theory based model that takes into account uncertainty and risk evaluation in terms of gains and losses while following a lead vehicle. Given a set of stimuli (i.e. headways, relative speeds, etc.), the stochastic acceleration model generates acceleration probability distribution functions rather than deterministic acceleration values. Such distribution functions may be associated with travel time reliability through the construction of travel time distributions. In addition, lane changing decision is represented by a stochastic hazard-based duration model that accounts for the surrounding traffic conditions (i.e. traffic density, distance to ramp, etc.). Numerical results from Monte Carlo simulations demonstrate that the proposed microscopic stochastic modeling approach produces realistic macroscopic traffic flow patterns and can be used to generate travel time distributions. With proper experimental set-up and sensitivity analysis, the travel time distributions may be estimated and linked to safety-based parameters.**

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I. Introduction

Capturing and predicting congestion dynamics using different macroscopic and microscopic traffic models have been a major area of interest in the traffic flow theory research community (e.g. Chandler et al., 1958, Treiber et al., 2000). Lately, the efforts have further shifted to understanding the safety and the reliability of vehicular traffic networks (Dong and Mahmassani, 2006; Li et al., 2006, Hamdar and Mahmassani, 2008). Although significant progress has been made in understanding safety and reliability of traffic flow, further studies are needed to link these two aspects especially when dealing with nonrecurrent traffic disruptions such as accidents, work-zones, adverse weather and special events. To quantify network-wide reliability and safety impacts of various intelligent transportation systems (ITS) strategies, traffic simulation models needs to account for the stochastic nature of traffic flow and capture drivers' risk-taking attitudes when faced by a given stimuli.

Unreliable travel times tend to create unsafe maneuvers. Among many sources that contribute to travel time variability, flow breakdown is one of the causes that is mainly caused by the interactions among individual drivers. Flow breakdown may occur when demand exceeds capacity on specific highway segments, due to merging, weaving, lane closure and so on. To model the breakdown phenomena as probabilistic collective effects in the context of microscopic simulation, Dong and Mahmassani (2012) proposed an integrated modeling approach that combines a stochastic macroscopic model of flow breakdown with a microscopic model of driver behavior. Focusing on freeway traffic, car-following and lane-changing decisions result in different congestion dynamics (e.g. shockwaves, congestion clusters) (Treiber et al. 2000), and thus leading to different probabilities of flow breakdown and breakdown event durations (Elefteriadou et al., 1995; Brilon, 2005). Even though multiple microscopic traffic models were able to generate realistic traffic patterns, few of them took into consideration drivers' cognitive decision-making processes. By modeling drivers' perception and judgment, stochastic acceleration distribution functions rather than deterministic acceleration values can be generated, when faced by a given surrounding traffic environment. Therefore, as suggested by Hamdar and Mahmassani (2008), most of the existing microscopic traffic simulation models are unable to capture traffic behavior endogenously in extreme situations. Hamdar et al. (2008) generated such distributions by using parameters associated directly with traffic safety (crash weights, relative weight of losses compared to gains in travel time, uncertainty related to velocity of leading vehicle etc.). Building on these research findings, the objective of this paper is to produce random flow breakdowns by changing specific safety-related parameters, capture the subsequent wave propagation among drivers, and thus generate travel time distributions. Data collected from multiple sources, at individual and aggregated levels are used to calibrate the proposed model.

The rest of this paper is organized as follows: in the next section, a literature review on basic travel time reliability and traffic safety studies is presented. Section III introduces the stochastic acceleration and lane-changing modeling approach with special focus on the resulting acceleration distribution function, hazard function, and their linkage to travel time reliability. Section IV presents the experimental setup and the

This work of S. H. Hamdar was supported by the National Science Foundation under Grant No. 0927138. Any opinions, findings, conclusions or recommendations expressed in this paper are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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Monte Carlo simulation. Based on the numerical analysis presented in Section V, conclusions and remarks on possible directions for future investigation are discussed in Section VI.

II. LITERATURE REVIEW

Travel time reliability has been recognized as a key factor in travelers' route and departure time choices, in addition to the travel time itself (Jackson et al., 1981; Noland and Polak, 2002; Brownstone and Small, 2005; Fosgerau and Karlström, 2010). One way to examine travel time variation is to look at the distribution of travel times. Based on travel time distributions, various travel time reliability measures could be derived, including the standard deviation of the travel time, buffer time, the difference between the 90th and 10th percentiles of the travel time distribution, and the probability that a trip can be successfully completed within a specified time interval (Dong et al., 2006; Tu et al., 2007; Higatani et al. 2009). Empirical studies had shown that the travel time distribution was not symmetrical, indicating that the mean and median values would not be the same. The distribution is highly skewed with a long right tail. Under free-flow conditions the distribution of travel times has shorter right tail. Li et al. (2006) suggested that a lognormal distribution best characterized the distribution of travel time when a large (in excess of 1 hour) time window was under consideration, especially in the presence of congestion. However, when the focus is on a small departure time window (e.g., on the order of minutes) a normal distribution appears more appropriate. Considering the limited value range of travel times in practice, Wang et al. (2012) suggested truncated normal and lognormal distributions. Based on measurements of traffic flow aggregated at 5-minute time intervals, Dong and Mahmassani (2009) observed that travel time distributions vary greatly at different flow levels and are better captured using bimodal distributions under certain scenarios.

On the other hand, traffic safety has always been a subject of interest when dealing with driver behavior and the human errors leading to vehicular crashes. In the traffic flow theory community, the challenge lies in the fact that existing microscopic traffic models are built in an accident-free environment that may not produce realistic distribution of crashes across transportation networks (Hamdar and Mahmassani, 2008). The majority of these models aimed initially at reproducing realistic congestion dynamics rather than predicting incident formation (Newell, 1961). Some of the models were event built using a safety constraint forcing the driver to adopt safe acceleration values with the assumption of the lead vehicle applying, at any moment, a maximum deceleration rate (Gipps, 1981). These models could reproduce some surrogate measures (including Time To Collision, TTC) but these safety measures always needed to be validated against collision data (Minderhoud and Bovy, 2001). Lately, further focus shifted towards understanding driver's psychology but such understanding did not fully translate into easily implementable efficient microscopic traffic models with special focus on safety (Ranney, 1999). This gap in the research is problematic especially that traffic safety is best observed and quantified using accidents related measurements such as accident type, accidents distribution across space and time (i.e. frequency, fatalities, injuries etc.) while most microscopic models do not produce such performance measures (NHTSA, 2007). Instead, other indirect safety performance measures have been adopted. In addition to the gaps between a lead vehicle and a subject vehicle that reflects a "herding" behavior, the main standard safety indicator is referred to as time to collision (TTC). TTC is the time difference between the leading vehicle and the following vehicle that may lead to collision if these vehicles would keep their current speeds without performing evasive maneuvers. It is calculated by having the space gap between two successive vehicles divided by the corresponding relative velocity. Even without observing any crash, with the availability of trajectory data, this measure proves to be easy to compute in a dynamic traffic environment for traffic safety assessment. Other safety measurements are developed including the rear-end crash index (CPI) (Oh and Kim, 2010). This index expands the TTC concept incorporating a lane-change decision model and a probabilistic crash potential estimation model. In addition to TTC and the CPI, some efforts have been made lately to incorporate safety parameters as a property inherent to acceleration and lane-changing models. Such properties can reflect drivers' risk-taking tendencies and gain versus loss evaluation processes (Hamdar et al., 2008). The corresponding parameters can be also calibrated using accident-free trajectory data.

III. METHODOLOGY

Given that a limited amount of highly-accurate vehicle trajectory data is present and that such data are collected during a short period of time, a Monte-Carlo simulation is adopted to generate travel time distributions. An explicit acceleration and lane changing modeling approach is needed to predict drivers' behavior. Such modeling approach requires a formulation that incorporates safety related parameters as shown in the next section.

The two main elements in freeway traffic modeling are the acceleration and the lane-changing models. Such models capture the operational and the tactical driving decision-making processes, respectively. Since the model of interest needs to incorporate safety related parameters while generating real world congestion dynamics, the simulation model of Hamdar (2009) is adopted in this paper. A utility-based acceleration framework and a duration based lane-changing framework are introduced in the next two subsections. Details of these frameworks can be found in Hamdar et al. (2008) and Hamdar and Mahmassani (2009). These modeling frameworks were never used to explore travel time distributions. The motivation behind such exploratory analysis is the premise that the acceleration probability distribution functions and the hazard functions generated from the corresponding models may be related to travel time reliability.

A. Acceleration Model

Drivers evaluate their acceleration choice options based on the resulting potential gains and losses. Prospect theory

(Kahneman and Tversky, 1979) was used to model this decision making process. First, the drivers frame the stimulus where different utilities are assigned to different acceleration choices considering different weights for gains and losses. Then, the drivers "edit" the choices based on a prospect index calculated in the same way as expected utility are calculated. For a faster judgment process, subjective decision weights are used to calculate such index instead of the respective probabilities of each outcome. The prospect theory value function is formulated as:

$$U_{PT}(a_n) = \frac{\left[w_m + (1-w_m)\left(\tanh\left(\frac{a_n}{a_0}\right)+1\right)\right]}{2} \frac{\left(\frac{a_n}{a_0}\right)}{\left[1+\left(\frac{a_n}{a_0}\right)^2\right]^{\frac{(1-\gamma)}{2}}} \quad (1)$$

where U_{PT} is the acceleration value function, a_0 is the normalization parameter, $\gamma > 0$ is a sensitivity exponent indicating how sensitive a driver is towards gains or losses in travel times (i.e. speeds), and w_m is the relative weight of losses compared to the gains. A sample value function produced by (1) is presented in Figure 1.

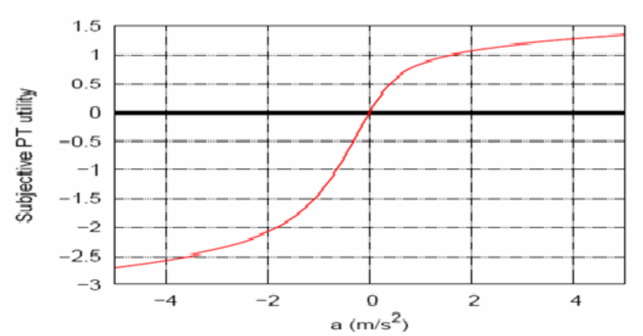


Fig. 1. Value function possibly used to evaluate different acceleration alternatives (Hamdar, 2009).

A driver choosing a_n as his/her desired acceleration will gain U_{PT} unless he/she is involved in a rear-end collision. A crash seriousness term $k(v, \Delta v)$ is used to calculate the disutility resulting from a crash as follows:

$$U(a_n) = (1 - p_{n,i})U_{PT}(a_n) - p_{n,i} w_c k(v, \Delta v) \quad (2)$$

where $p_{n,i}$ is the subjective probability of being involved in a crash at the end of a car-following duration. $p_{n,i}$ is approximated by a normal distribution given that drivers are assumed to estimate the future speed $v_{n-1}(t+\Delta t)$ of vehicle *n-1* to be normally distributed with a mean equal to the current speed $v_{n-1}(t)$ and a standard deviation of $\alpha * v_{n-1}(t)$ (α is a velocity uncertainty parameter); $U_{PT}(a_n)$ is defined by equation 1 and w_c is a crash weighting function which is lower for drivers willing to take a higher risk.

A logistic functional form is used to reflect the stochastic nature of acceleration choice:

$$f(a_n) = \begin{cases} \dfrac{e^{(\beta_{PT} \times U(a_n))}}{\int_{a_{min}}^{a_{max}} e^{(\beta_{PT} \times U(a'))} da'}, & a_{min} \le a_n \le a_{max} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where $1/\beta_{PT}$ is random utility component. $f(a_n)$ is the probability density function.

With a seriousness term $k(v, \Delta v)$ assumed to be 1 at this stage, five remaining safety related parameters may be observed in the acceleration model and will be adopted in the numerical analysis section: $\alpha, \gamma, w_m, , w_c$ and β_{PT}.

B. *Duration Framework*

At the tactical level, the driving experience is considered as sequence of driving episodes that ends based on a risk taking hazard-based process. Accordingly, each episode is characterized by a termination probability depending on the driver's experience. Episodes can be divided into car-following and free-flow episodes and the duration of each episode is defined as the time lapses before the driver enter another episode. A free-flow episode ends when either the corresponding vehicle changes lanes (exit strategy q = 1) or the distance between the corresponding vehicle and its leader is close enough to be considered as car-following episode (exit strategy q = 2). A car-following episode ends when either the corresponding vehicle changes lanes (exit strategy q = 3) or the distance between the corresponding vehicle and its leader is large enough to be considered as free-flow episode (exit strategy q = 4).

The hazard at time u is defined as the termination probability of the current episode at small time period δ after u (Hamdar, 2009),

$$\lambda_{iq} = \lim_{\delta \to 0^+} \frac{P\left(u \le T_{iq} < u + \delta \middle| T_{iq} \ge u\right)}{\delta} = \lambda_{0q} \phi\left(x_{iq}, \beta_q\right) \quad (4)$$

where i is the driver indicator, q defines the candidate exit strategy of an episode, and T_{iq} is a non-negative random variable representing the duration of an episode for driver i and the exit strategy q. λ_{0q} is the base line hazard value at time u, x_{iq} is the vector of explanatory variables for driver i at time u, and β_q is the corresponding parameters to be estimated. Hamdar and Mahmassani (2009) assumed that the function of exogenous covariates has the exponential form,

$$\phi\left(x_{iq}, \beta_q\right) = e^{(-\beta_q x_{iq} + w_{iq})} \quad (5)$$

where w_{iq} is the error term to capture random heterogeneity. In this study, the baseline hazard function is represented by two types of parametric hazard functions, constant hazard function and two-parameter hazard function. The constant hazard function is used for the free-flow episodes where hazard function is not duration dependent ($\lambda_0 = \sigma$). The two-parametric hazard function captures the duration dependent behavior in the car-following episodes, as follows,

$$\lambda_0 = \sigma_h \, \alpha_h (\sigma_h \, u)^{\alpha_h - 1} \quad (6)$$

where σ_h and α_h are model parameters and u represents the duration length. Note that the duration framework is stochastic in nature and involves safety related concepts (hazard or risk of terminating an episode and the corresponding relation to surrounding traffic parameters) which were discussed in detail by Talebpour et al. (2012). Their findings indicated that hazard values increase as flow rate increases at low density (high flow rate) situations, whereas, lower hazard values are more likely to observe in high density situations. Therefore, this paper focuses on the two parameters of the hazard function (σ_h and α_h) as well as the five explicit safety parameters introduced in the acceleration framework (crash weight w_c, relative weight of losses to gains in speeds w_m, sensitivity to gains and losses γ, velocity uncertainty parameter α and sensitivity to utility changes β_{PT}).

C. *Acceleration Distribution Functions and Travel Time Distribution*

To bridge individual driving behavior and the macroscopic traffic flow properties, Kharoufeh and Gautam (2004) derived an analytical expression for the cumulative distribution function of travel time for an individual vehicle traversing a stochastic, time-varying freeway link. In their paper, a continuous-time Markov chain process (CTMC) was assumed to govern vehicle's speed at a given point in time and space. In the present paper, the CTMC assumption was relaxed; instead, the stochastic acceleration and lane-changing model, introduced in the previous section, is adopted to describe individual driving behavior.

Given that the drivers' acceleration choices are the governing factor impacting speed dynamics, a sensitivity analysis is performed using the stochastic acceleration distribution function introduced in (3). The main objective is to form a hypothesis on the impact of the five safety parameters (i.e. w_c, w_m, γ , α and β_{PT}) on the acceleration distribution characteristics, and then translate the stochastic acceleration choice process into travel time distribution patterns. A simulation based sensitivity analysis is performed to answer this research question.

D. *Hazard Function and Travel Time Distribution*

Patire and Cassidy (2011) identified lane changing as one of the main triggering factors in shockwave formation. Based on their findings, lane changing in a congested traffic regime can initiate disruptions in the traffic stream which may result in shockwave formation and negatively impact the travel time reliability. Therefore, the most intuitive assumption would be the positive relationship between the lane changing frequency and shockwave occurrence which itself is negatively correlated with travel time reliability.

In the presented model, the hazard function is used to model drivers' lane changing decisions. This study investigates the impact of two baseline hazard function parameters (i.e. σ_h and α_h) on the lane changing frequency and travel time distribution. The above assumption is then evaluated through a simulation based sensitivity analysis with regard to hazard model parameters.

IV. SIMULATION EXPERIMENT

A. *Data Description*

To link the presented framework to a real-life scenario and to analyze the corresponding travel time distribution functions, NGSIM trajectory data, collected on the 13th of April, 2005, were used (FHWA, 2005). The data were collected on Interstate I-80 northbound segment in Emeryville, California, USA through 6 cameras mounted on a high-rise building in the city of Emeryville. The corresponding freeway segment consists of 6 lanes and an on-ramp lane located between Powell-Street interchange (south-end) and Ashby Street Interchange (north-end) (Figure 2). The total segment length is 1650 ft. In addition, speed and volume data, collected from loop detector on the same day and aggregated over 5-minute time interval, were obtained from California Freeway Performance Measurements System (PeMS) (CalTran, 2013) (Figure 2).

This mix of microscopic and macroscopic traffic data is required to calibrate the proposed model (duration and Prospect Theory based models) and analyze travel time distributions. In particular, the acceleration and lane-changing models were calibrated for each vehicle with the corresponding 30 minutes trajectory recordings (5 pm - 5:15 pm, FHWA, 2005a; and 5:15 pm – 5:30 pm, FHWA, 2005b). The calibrated parameters resulted in distributions with clear peaks and substantial heterogeneity. The peak values corresponding to the safety-related acceleration parameters are shown in Table 1 (Hamdar, 2009).

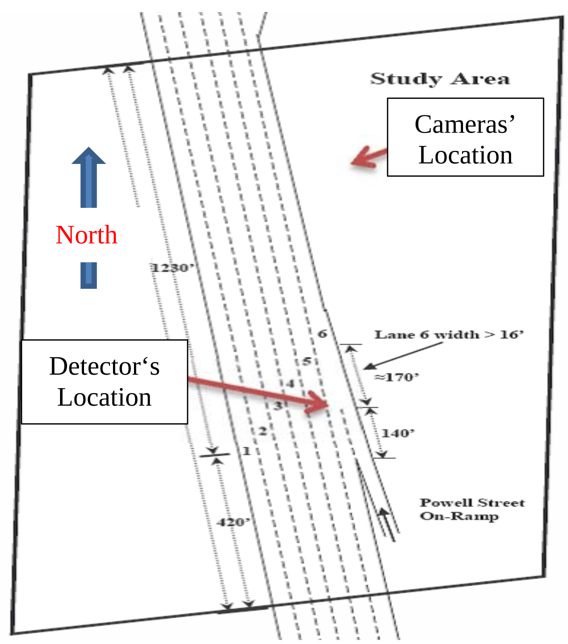


Fig. 2. Schematic illustration of the study area (FHWA, 2005) along with the cameras and detector locations.

B. *Experimental Setup*

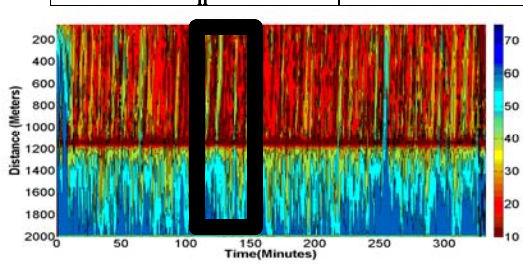
Since no proper travel time distributions can be generated using 30 minutes time interval data, Monte-Carlo simulation of the car-following and lane-changing models is used. The loop detector data obtained from the right side lane (Lane 6, Figure 2) detector allowed generating realistic traffic flow patterns as observed on the NGSIM trajectory data collection day (13th of April, 2005). Out of the 24 hours recordings, 6 hours of 5-minutes aggregate flows and speeds are adopted (between 8 am and 2 pm) given the breakdown condition observed from the speeds at the corresponding time period. Since no loop-detector data was available on the Powell Street on-ramp, on-ramp flow was varied in the simulation so that speeds on the right-side through lane follow the same trends as the speeds collected by the loop detector. In other words, when needed, the ramp flow is increased to 20% of the main stream flow to create congestion and speed/flow breakdown conditions. With a simulation segment of 2 km length and the merging length equal to 130 m starting from the middle of the segment, the following speed distribution is observed for all the main inflow-traffic (Figure 3-a). Notice the traffic breakdown occurrence at the merger (red-palette indicating lower speeds) and the congestion propagation upstream (location 1130 m to location 0 m on the y-axis). The resulting travel time distribution is presented in Figure 3-c. This base case simulation scenario shows that the calibrated model produced realistic traffic flow patterns (i.e. those observed at the through right-most lane) while generating a realistic travel time distribution similar to the one observed during the breakdown conditions in Dong and Mahmassani (2012). It should be noted that inter-driver heterogeneity is allowed for specific parameter values, the normally distributed parameters are generated using 20 random seeds with the means equal to the calibrated peak parameters values (Table 1 and Table 2) and the standard deviations equal to 5% of the mean. Note that the average travel time distribution remains statistically indifferent for any replication number above 20.

Table 1: Peak values of the acceleration model parameters

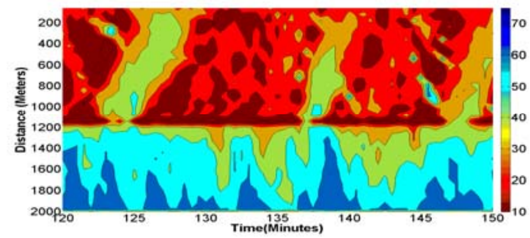
Parameter	Calibrated Value
Sensitivity to gains and losses	$\gamma = 0.49$
Relative weight of losses to gains	$w_m = 3.69$
Velocity uncertainty parameter	$\alpha = 0.09$
Crash weight	$w_c = 91600$
Sensitivity to utility changes	$\beta_{PT} = 6.20$

Table 2: Peak values of the hazard model parameters

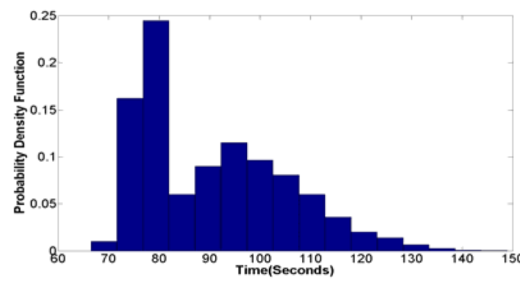
Parameter	Calibrated Value
$\boldsymbol{\sigma_h}$	0.066
$\boldsymbol{\alpha_h}$	1.604



a) Speed pattern



b) A zoomed view of breakdown propagation

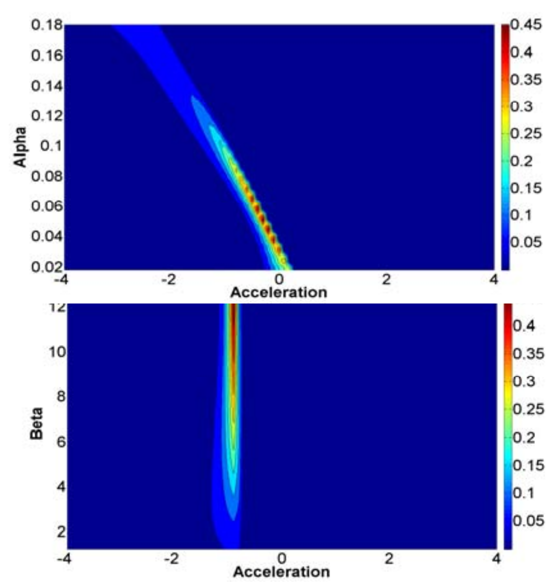


c) Travel time distribution

Fig. 3. Speed pattern and travel time distribution observed in the simulation base case scenario.

C. Acceleration Distribution Functions

After setting the base-case scenario, the mean of each of the five safety parameters is changed as follows: 20%, 40%, 60%, 80% and 100%, 120%, 140%, 160%, 180% and 200% of each mean value is adopted while keeping all other simulation variables constant (except for Gamma where 80%, 90%, 100%, 110%, 120%, 130%, 140% and 150% of each mean value is adopted because of the extreme braking actions, presented in Figure 4, which result in unrealistic behaviors). In other words, for each parameter, 10 sensitivity scenarios are simulated and the corresponding travel time index is recorded. Travel time index is defined as the ratio of the travel time to the free flow travel time.



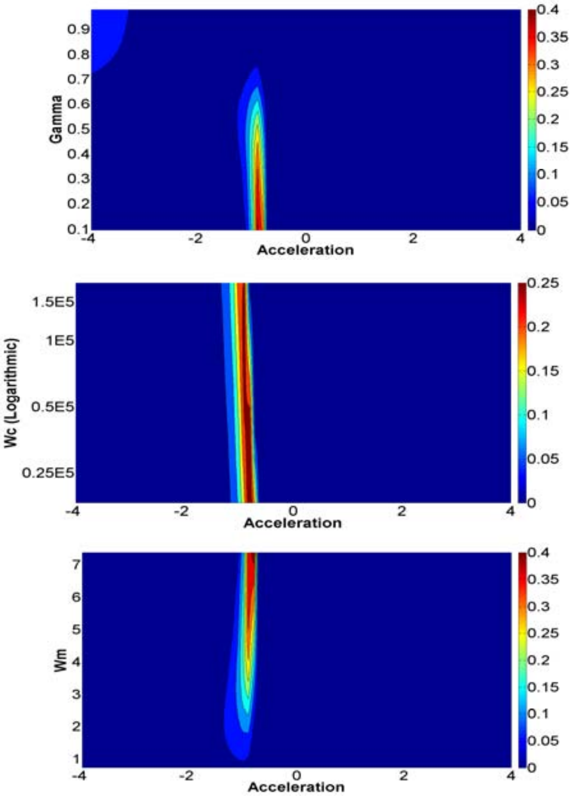


Fig. 4. Acceleration distribution functions when changing the 5-safety acceleration model parameters

Based on the surrounding traffic conditions mentioned above and to form some hypothesis linking safety to travel time reliability the acceleration probability density functions are plotted when changing the 5 safety related parameters individually (w_c, w_m, γ , α and β_{PT}). A basic scenario is assumed where a vehicle is following a leader with a relative speed Δv_0 = 0 m/s (positive Δv indicates that the speed of the leader is greater than the speed of the follower) and a spacing s_0 = 20 m. The vehicle of interest has an initial velocity v_0 = 10 m/s. The results are presented in Figure 4. As a first remark, an increasing α (Alpha) parameter will cause a wider distribution function leading to more uncertainty in the choice of the corresponding acceleration value. Such increase also leads to higher deceleration values suggesting drivers' risk-averseness when faced with unstable leaders' behavior/velocities. Second, a decreasing β_{PT} (Beta) parameter is associated with a wider distribution function but no significant change in the acceleration peak value is observed. Third, when the γ (Gamma) parameter increases, only the standard deviation associated with the acceleration distribution function also increases. As for the peak acceleration value (brighter color), it almost remains the same until hitting the 0.7 threshold value. Afterwards, a driver's behavior tends to be represented by extreme braking (bright blue in the top left corner of the corresponding graph). On the other hand, interestingly enough, the crash weight parameter w_c (Wc) does not seem to have an impact on the corresponding acceleration probability distribution function. This is possibly due to the fact that w_c only plays a major role when in near crash situations without being incorporated in the process of evaluating gains and losses in travel times (i.e. speeds) (equations 1 and 2). Accordingly, drivers may be "insensitive" in correctly estimating the crash weight in "normal" commute conditions. The Wc may be then perceived logarithmically. Finally, a decrease in w_m (Wm) leads to greater variation in the acceleration choice process as reflected in the wider acceleration distribution function.

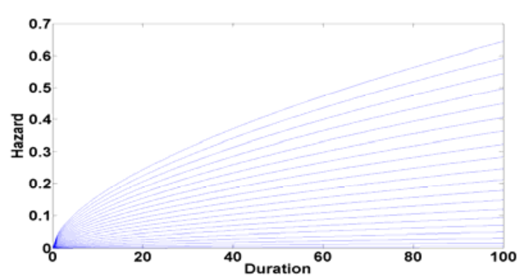
D. Hazard Function

After setting the base case scenario, similar to the acceleration distribution functions, the mean of each of the two main hazard function parameters is changed as follows: 20%, 40%, 60%, 80% and 100%, 120%, 140%, 160%, and 180% of each mean value is adopted while keeping all other simulation variables constant (including the calibrated $\beta_q's$) . The travel time index is then recorded for each scenario.

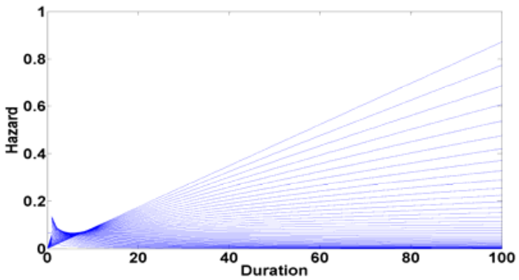
In addition, the hazard function is plotted when changing these two hazard parameters individually in order to form a hypothesis to link the lane changing behavior to the travel time reliability. The results are presented in Figure 5. As a first remark, when α_h (Hazard Alpha) is set to its calibrated value, the hazard value becomes an increasing function of duration length (for a fixed σ_h (Hazard Sigma)) and σ_h (for a fixed duration length). In other words, higher hazard values correspond to higher σ_h values at a specific duration length (see Figure 5-a) and hazard values increase as the duration length increases for all values of σ_h. It should be noted that the presented calibration results correspond to an episode exit strategy q = 3 (Section III*B*) as we are dealing with congested conditions. On the other hand, the relationship between the hazard value and α_h is non-monotonic for a fixed σ_h. This non-monotonicity is more evident considering both Figures 5-b and c. Based on these figures, once duration length passes a certain threshold (i.e. this threshold depends on the value of σ_h), the hazard value becomes an increasing function of duration length (at a fixed α_h) and α_h (at a fixed duration length). Below that threshold, however, for a fixed duration length, hazard values increase as α_h increases to a certain value and then hazard values start decreasing.

E. Travel Time Distribution

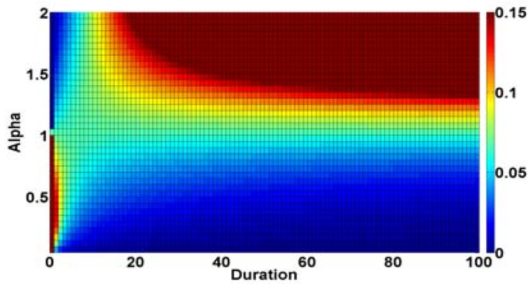
The travel time distributions are plotted in Figures 6 (acceleration) and 7 (hazard). In these figures, the travel time distribution is presented using travel time index.



a) Hazard function values when changing σ_h at a fixed α_h

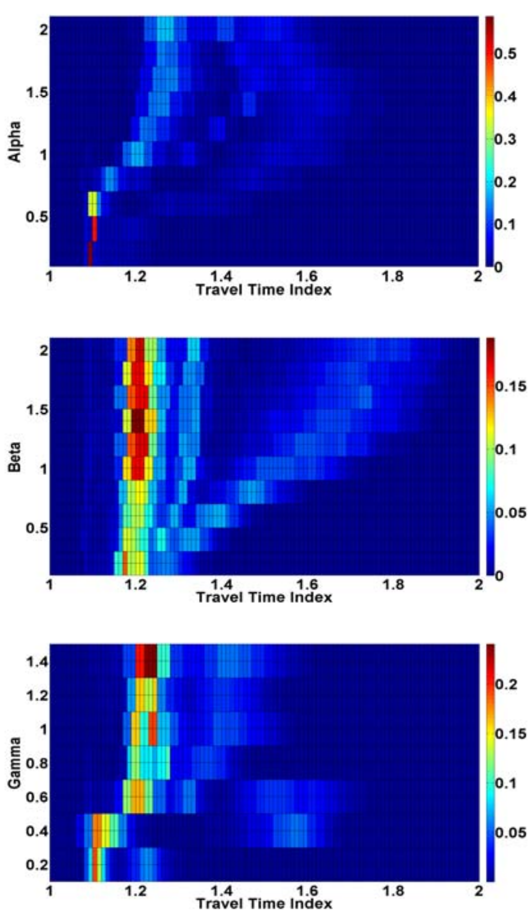


b) Hazard function values when changing α_h at a fixed σ_h



c) Hazard function values when changing α_h at a fixed σ_h

Fig. 5. Hazard function values when changing a) σ_h at a fixed α_h and b, c) α_h at a fixed σ_h



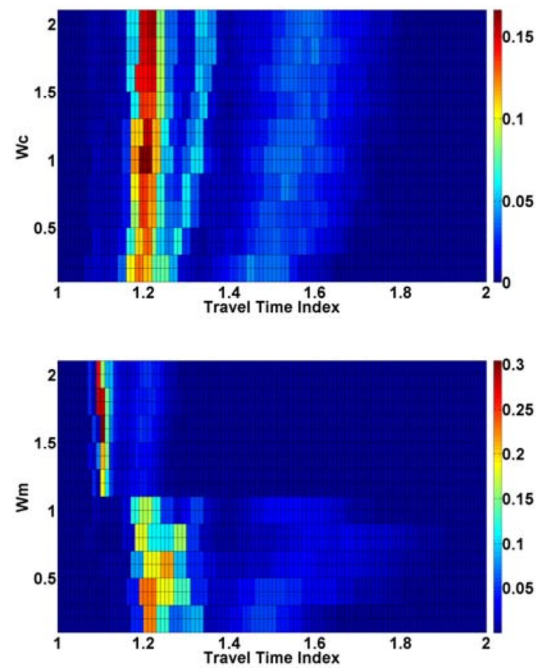


Fig. 6. The travel time index distribution as a function of the 5 safety-related acceleration parameters

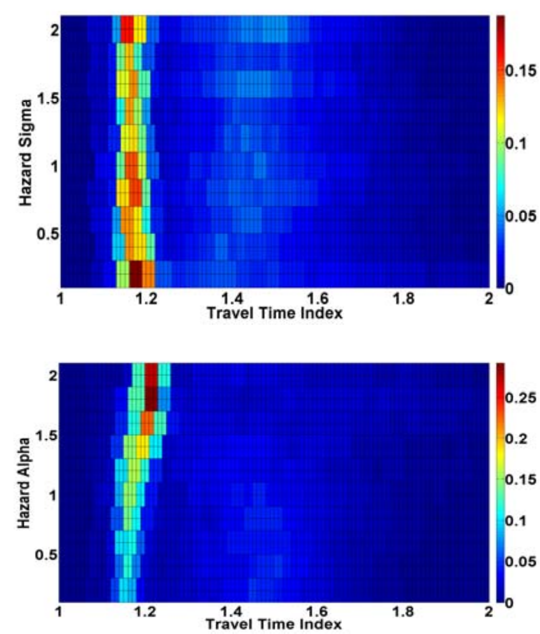


Fig. 7. The travel time index distribution as a function of the hazard function parameters

V. RESULTS AND EXPLORATORY ANALYSIS

Generally speaking, there are two possible changing trends in the travel time reliability: a) the conditions on the freeway link may become more reliable and the travel time distribution becomes narrower (one peak); b) otherwise, the conditions become less reliable and the travel time distribution becomes wider (multiple peaks possibly representing more unstable traffic flow dynamics). In this section, the authors first focus on the meaning of the safety related parameters of Section III and the corresponding impact on travel time distributions. An association between such impact and the characteristics of the acceleration distribution functions shown in Figure 4 is established. Then, the effects of hazard function parameters of Section III on travel time distributions are investigated.

A. Acceleration Distribution Functions

In terms of uncertainty about future leaders' speed, an increase in α indicates that the followers are less certain about such speed and tend to have a wider range of acceleration values to respond to such uncertainty. This behavioral trend representing a less safe driving environment is translated into more braking (higher braking rates, and wider range of deceleration choice) (see Figure 4) and a move from one peak-travel time distribution when α is equal to 0.018, to a two-peak distribution (shift to the right) when α is equal to 0.036. After attempting different distributions (including exponential and log-logistic distributions) to model travel time distributions, the Generalized Extreme Value (GEV) distribution resulted in the best statistical fit and thus is used in this paper. As the distribution fitting results in Table 3 show, at low values of α, the distribution has positive shape parameter and very low scale parameter which corresponds to a narrow distribution. The shape parameter has a huge jump after this point due to the existence of two peaks in the distribution. As α increases after this jump, the shape parameter decreases while the scale parameter remains almost constant. This observation indicates that the travel time distribution is wider for larger values of α.

The change in uncertainty leads to more travel time variability and traffic flow disturbances (resulting from sudden braking with high braking rates). Such disturbances cause shockwave creation and congestion indicated by the longer travel times experienced (skew to the right). On the other hand, a greater β_{PT} indicates a higher sensitivity to changes in utility possibly reflecting drivers' learning process. In other words, a driver with greater β_{PT} may be more experienced and tuned to the changes in the surrounding conditions. Therefore, lower braking rates and less braking events may be observed. From a safety perspective, increasing β_{PT} may smoothen the traffic patterns with a clearer peak observed. However, it may result in a longer tail as drivers are less likely to use high acceleration and deceleration rates and some of them may experience longer travel times. Looking at the travel time distribution, it can be seen that an increase in β_{PT} translates to a clearer peak when β_{PT} = 12.40 and indicates a more reliable traffic regime. This is partly caused by an increase in the braking tendency, at lower values of β_{PT}, as observed in the skewed acceleration probability distribution function in Figure 4 (widening tilted to the left). Table 4 shows the distribution fitting results. The Shape parameter increases as β_{PT} increase which indicates the travel time distribution has longer tail and clearer peak for larger values of β_{PT}.

Regarding the w_c, interestingly enough, the crash weight does not seem to have significant impact on both the acceleration distribution function (see figure 4) and the travel time distribution function (see Figure 6). A slight difference in travel time distribution, however, can be observed between very high and very low values of w_c where wider distribution is observed for higher values of w_c. As indicated in Section III, it seems that drivers do not tend to evaluate or consider the losses due to a crash unless he/she is in a near-crash situation. Accordingly, safety may be represented by two set of parameters: "high-risk safety parameters" and "low-risk safety parameters". High-risk safety parameters such as w_c does not have significant impact on travel time distribution unless in rear-crash or extreme conditions (emergency evacuation). Moreover, distribution fitting results in Table 5 confirms this observation. The shape parameter slightly increase as w_c increases. As for low-risk safety parameters (such as w_m), the impact on travel time reliability is perceived even if no near-crash conditions exist (i.e. every day commute traffic conditions). For further illustration, when increasing w_m, drivers put more weight on the losses in speed if compared to the weight on the gains in speed (i.e. w_m= 4 indicates that a driver puts 4 times the weight on a loss in speed if compared to weight on the same gain in speed). Accordingly, as drivers become more risk averse, the corresponding w_m increases. Based on the travel time distribution, risk-averseness may be beneficial to improve travel time reliability and reduce congestion: as w_m decreases, the distribution shifts to the right with the low-travel time peak dissipating and higher travel times generated. In this case, risk-averse "safe" drivers may lead to an increase in travel time disturbances and thus, less reliable conditions. In other words, extreme risk-aversion behavior can improve the performance of the system as less variation is observed in drivers' choice of acceleration. Less variation creates a safe driving environment and decrease the travel time as drivers use the road efficiently. Table 6 shows the distribution fitting results for w_m. The scale parameter is dramatically higher for lower values of w_m which shows a wider distribution.

Finally, when γ increases drivers put more weight on both gains and losses. Therefore, it can magnify the risk-aversion at low values of w_m, and vice versa. Consequently, at low γ values, drivers tend to choose their acceleration from a limited range; thus, a narrow travel time distribution can be achieved. At higher γ values, drivers tend to choose their acceleration from a wider range which causes more chaos in the driving environment and results in a wider travel time distribution. Table 7 shows the distribution fitting results for different values of γ. The lowest scale parameter value (narrowest distribution) is observed when γ = 0.39.

In summary, the numerical results analyzed in this section suggest that the adopted approach allows linking quantifiable traffic safety related parameters to travel time reliability. The produced distributions are realistic and have the same characteristics as empirically observed distributions (Dong and Mahmassani, 2012). Due to the nature of the suggested acceleration model, it is difficult to relate the model parameters (i.e. Figure 6) to physical drivers' characteristics. Generally, with varying parameters related to the perception limitation of the drivers (i.e. β_{PT}), the risk-taking attitudes or the weighing of gains and losses (i.e. w_m, w_c and γ) and uncertainty (i.e. α), specific travel time trends are observed moving from "narrow" uni-modal travel time distributions to bi-modal "wider" travel time distributions. With the approach presented in this paper, further insights are gained on the type of behavior that may improve safety versus the type of behavior that may improve reliability.

Table 3: GEV distribution fitting results for $\boldsymbol{\alpha}$.

	0.2	0.6	1.0	1.4	1.8
Shape	0.0910	0.3759	0.2216	0.0708	-0.0485
Scale	0.0277	0.0596	0.1129	0.1371	0.1200
Location	1.0991	1.1227	1.2476	1.3245	1.3286

Table 4: GEV distribution fitting results for $\boldsymbol{\beta}$.

	0.2	0.6	1.0	1.4	1.8
Shape	-0.0972	-0.1202	0.2216	0.3315	0.3712
Scale	0.0498	0.083	0.1129	0.1265	0.1333
Location	1.1867	1.2353	1.2476	1.2549	1.2591

Table 5: GEV distribution fitting results for $\boldsymbol{w_c}$.

	0.2	0.6	1.0	1.4	1.8
Shape	0.1486	0.2087	0.2216	0.2492	0.2469
Scale	0.0999	0.1105	0.1129	0.1171	0.1186
Location	1.2269	1.2415	1.2476	1.2541	1.2572

Table 6: GEV distribution fitting results for $\boldsymbol{w_m}$.

	0.2	0.6	1.0	1.4	1.8
Shape	0.1248	0.2554	0.2216	0.1019	0.1323
Scale	0.0944	0.1122	0.1129	0.0354	0.0374
Location	1.2635	1.2649	1.2476	1.1138	1.1133

Table 7: GEV distribution fitting results for $\boldsymbol{\gamma}$.

	0.8	1.0	1.2	1.4
Shape	0.1558	0.2216	0.0412	0.0747
Scale	0.043	0.1129	0.0791	0.079
Location	1.121	1.2476	1.2436	1.2441

B. Hazard Function

In general, shockwave occurrence and lane changing frequency are positively correlated. In addition, shockwave formation and propagation results in a decrease in travel time reliability. The presented model employs a hazard-based duration framework to capture lane changing frequency. Therefore, a correlation between the hazard function and travel time reliability is expected.

The relationship between σ_h and hazard value was established in Section IV. Based on this relationship, as σ increases, the hazard value increases. As a result, the lane changing frequency increases which results in more unstable flow patterns. This phenomenon is illustrated in Figure 7 where the travel time distribution has one peak in low values of σ_h and two peaks in high values of σ_h. However, the impact of σ_h on travel time distribution is found to be minimal. Regarding the α_h, , the travel time distribution is wider at low values of α_h compare to high values of this parameter. At high values of α_h, the hazard function is an increasing function of duration (see Figure 5). Therefore, drivers tend to improve their driving situation more often. However, frequent lane changing can be observed in this situation which triggers more shockwaves, creates unstable flow, and increases average travel time. On the other hand, at low values of α_h, the hazard function is a decreasing function of duration (see Figure 5). Thus, less frequent lane changing can be observed which can have negative effects on the traffic flow in congested regimes. Appropriate lane changing in a traffic stream has positive effect on congestion relief as drivers can avoid shockwaves and other disturbances in the traffic stream. Once the number of appropriate lane changings reduces, more disturbances in the traffic stream can be converted into shockwaves. This phenomenon can lead to less travel time reliability and wider travel time distribution.

VI. Conclusion

This paper has presented a methodology for quantifying traffic safety via a stochastic acceleration process while linking the safety-related parameters to travel time reliability. The proposed modeling framework has been tested via a case study using both microscopic and macroscopic traffic data. Monte Carlo simulation has been adopted, in conjunction with the stochastic traffic modeling methods, to produce travel time distributions. Such approach may also be used to (1) predict traffic safety and travel time reliability, (2) design and assess ITS strategies to improve both safety and reliability, such as connected vehicle technologies, variable speed limits, coordinated ramp metering, and dynamic pricing, and (3) produce and evaluate different safety and reliability performance measures of the traffic network. A novel feature of this approach is linking both safety and reliability through a stochastic risk-based acceleration and lane changing modeling approach. Sensitivity analysis results revealed the effectiveness of this model in capturing the safety related behavior. The results showed that the existence of conservative drivers, higher uncertainty in driving environment, and higher sensitivity to losses have negative impact on travel time reliability. The results also indicated that drivers do not tend to consider the losses due to crash in their acceleration choice unless they are in a near crash situation.

Future work includes additional statistical analysis of the link between the adopted safety-related parameters and the travel time distributions. Moreover, further investigation on the impact of driver heterogeneity may help better understand behavioral trends and the corresponding collective flow characteristics. On the other hand, further calibration and validation of the proposed methodology is needed using data collected in different segments with different infrastructure and control characteristics.

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