Crash Event Modeling Approach for Dynamic Traffic Assignment

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INTRODUCTION

Given limited crash data availability, commonly used safety modeling approaches typically consider the steady-state representation of traffic conditions, and predict long-term crash rates based on annual traffic volume, or using a combination of traffic volume and average link speed at peak or non-peak hours. These figures are then used to plan safety improvement projects, selecting project locations and choosing relevant mitigation strategies. While tools and techniques are currently available to estimate the safety improvement from these projects, many of these techniques ignore the more complicated relationships between traffic flow and safety. For example, improving safety on a road segment may result in fewer crashes, which will impact the travel time experienced by drivers on that segment and potentially alter the traffic volumes as a result. This change in traffic volume could then also change our expected safety (in terms of expected crashes) at that location and change the estimated effectiveness of that strategy. Alternatively, operational strategies and/or traffic flow improvement projects could influence safety at a location too. In order to capture these effects, we propose a dynamic traffic assignment methodology which integrates safety modeling techniques.

The proposed model, shown in Figure 1, attempts to both forward the current practice and provide a model that addresses the main obstacles associated with using a dynamic traffic assignment approach to modeling safety. Using an incident calendar, the vehicles are assigned to an OD pair based on the shortest path. Multi-day simulations are run which will output the average link travel times across different days. The link with the least expected travel time path can be identified and a path assigned shift can be done to move vehicles to the shortest path. The model is then checked for convergence using a gap function. When the model converges, a crash probability model is introduced which can consider the effects of highway design characteristics and safety improvement strategies. A new incident calendar is developed, which includes stochastic and time-dependent capacity for all links by day, and the model is reiterated. Additionally, link travel times are determined using a hybrid analytical/simulation approach to improve simulation run times. This model represents a significant enhancement compared to previous related studies, where static safety estimates and deterministic queue analysis techniques limited analytical capabilities.
4. Find descent direction: Least expected travel time path

5. Path Assignment: Shift a fraction of demand flow to the least expected travel time path

6. Check traffic assignment convergence using gap functions

Stop

CRASH PREDICTION AND INCIDENT CALENDAR

The crash prediction approach implemented in this model is adapted from AASHTO’s Highway Safety Manual [1] for urban and suburban arterial road segments and intersections, as well as work on freeway crash prediction by Porter and Le [2]. The HSM describes general predictive models, called safety performance functions, which consider traffic volume, facility classification/type, segment length, and cross section characteristics (i.e. number of lanes, divided vs. undivided, number of driveways, etc.), producing long-term estimates of safety (in expected number of crashes per year). Predicted crashes can be further disaggregated by crash type and severity.
Porter and Le [2] use a number of link characteristics, including distance between cross-streets, ramp and mainline volumes, and the presence of auxiliary lanes, to describe the expected crash frequency for freeway segments.

After the expected annual crash frequencies are predicted for each road segment, this prediction must be broken down into a predicted crash frequency for each modeling period, such as the crash frequency per peak period. This could be accomplished using national statistics to estimate crash frequency distributions by day of the week and time of day, but local crash data would be preferred to improve distribution estimates for implementation. Since the number of crashes per peak period is often very small, and sometimes even approaches zero, a duration model is used to predict the stochastic time between crashes, resulting in crash occurrence times. This information is combined for all links to create an incident calendar, a large table indicating when incident conditions occur on each link in the network over the entire modeling horizon, which is often at least several months in length in order to reasonably produce/replicate the expected crash rate on the links in the network.

Capacity reduction and incident duration can be generated from probability distributions for each crash in the incident calendar based on event characteristics, or deterministic values can be used. Relatively few studies exist to describe capacity reduction. The Highway Capacity Manual offers deterministic estimates for capacity reduction based on the number of lanes blocked by an incident, which are commonly used for these applications, but several studies have described methods to estimate stochastic capacity reduction factors, including Qin and Smith [3] and Hadi et al. [4]. Incident duration has been heavily studied using freeway incident databases, and multiple studies suggest using the lognormal distribution to describe the duration as a stochastic variable. Ignoring stochastic incident characteristics has been shown to underestimate delay [5], so deterministic or average values are less preferred.

HYBRID APPROACH TO QUANTIFY THE IMPACT OF PROBABILISTIC CRASH EVENTS

Various procedures are available to quantify the impact of crashes in a dynamic traffic simulation model. A review of the basic procedures, including their associated limitations, is provided below:

(1) The first model type can consider average capacity reduction due to all crashes. Only a single simulation needs to be performed, but the traffic results are simplistic and fail to capture the within-day traffic impact of different types of incidents.

(2) A Monte Carlo simulation approach can consider a multi-month incident calendar, where discrete crash events and the resulting crash occurrence times, capacity reduction and incident duration are pre-specified based on a crash prediction model. This method allows the dynamic traffic simulation models to fully capture the impacts of different event types over multiple days, but simulating crash events over an extended period of time is numerically intensive and subject to large sampling errors.

(3) A set of analytical point-queue-based formulas can be developed or adapted to utilize a probabilistic capacity reduction distribution to calculate average delay. While these models can generate reliable statistics thanks to the use of analytical formulas, the point-queue-based models are unable to capture the effects of queue spillback and induced delays along a congested corridor.

(4) To reach the right balance between computational efficiency and representation details, a hybrid analytical and simulation approach will be used to quantify the impact of probabilistic crash events. Given capacity reduction records over multiple days in an incident calendar, we first use a spatial-queue-based formula to detect queue spillback at the incident occurrence location to the upstream link. With significant queue spillback (typically due to severe crashes with large capacity reduction), the full scale simulation runs are executed to describe the
impact of crashes. Without queue spillbacks, the **analytical point-queue-based formulas** will be used to rapidly calculate the additional delay due to incidents. The computed delay measures, using both approaches but on different days, will be aggregated to generate average delay over the modeling horizon. The potential benefit of this hybrid approach is that, if the crash probability or the probability of dramatic capacity reduction is sufficiently small, most days do not have queue spillbacks at the incident occurrence locations, so the computationally efficient analytical models should provide reasonable queueing delay estimates. On the other hand, the simulation-based approach still serves as the last resort to systematically capture the corridor-wide and network-wide traffic congestion propagation and traffic impacts from severe crashes.

**UNDERLYING MODELING COMPONENT 1: ANALYTICAL MODELS FOR QUANTIFYING IMPACT OF PROBABILISTIC CRASH EVENTS**

One approach for systematically estimating average travel time delay in a traffic network is to use a day-to-day dynamic traffic assignment module, where the travel time patterns evolve depending on a number of variability sources, e.g. stochastic capacity and random route choice behavior. Although this approach provides a fully dynamic and stochastic modeling environment for studying multiple variability sources and assessing the benefits of traffic management strategies, performing realistic day-by-day simulation runs still requires considerable computational effort.

To meet the above mentioned modeling challenges, this research aims to develop analytical formulas for transforming stochastic distributions directly from an incident event calendar and the related capacity input data (as a result of crash prediction modeling) to the travel time output measure consistently. By using an analytical point queue model, we are interested in estimating the time-dependent travel time delay for a traffic bottleneck. To this end, we will derive and construct an analytical relationship between the capacity change and the waiting time change on a bottleneck by extending theoretical results from the sensitivity analysis for traffic queuing systems.

Without loss of generality, we now consider a typical incident event with partial lane closure shown in Figure 2 (top).

![Figure 2: Queue profile after an incident with reduced capacity Q^R and incident duration h occurring from time t1 to t3 (top). Additional waiting time for a vehicle leaving from the queue at time t (bottom).](image)

The recurring congestion is assumed to occur from time s to e, with a constant queue discharging rate Q. The incident under consideration begins at time t1 and ends at time t3 with a reduced capacity Q^R, and the capacity is restored back to Q after time t3. Our focus here is on how to estimate the additional waiting time ΔW(t) for a vehicle leaving from the queue at time t. Using the detailed plot from Figure 1 (bottom), ΔW(t) = t - t2, where t2 is the original leaving time from the queue under recurring congestion for the same vehicle. ΔN is denoted as the number of vehicles that can be discharged under recurring congestion from t1 to t2, which can be derived as...
\[ \Delta N = Q \times (t_2 - t_1) = Q^k \times (t - t_1) \quad (1) \]

Because \( t_2 - t_1 = -\frac{\Delta N}{Q} = -\frac{Q^k}{Q}(t - t_1) \),

we can calculate the additional waiting time as:

\[ \Delta W(t) = (t - t_1) - (t_2 - t_1) = (t - t_1) \times (1 - \frac{Q^k}{Q}) \quad (3) \]

**UNDERLYING MODELING COMPONENT 2: SIMPLIFIED KINEMATIC WAVE MODEL FOR MODELING QUEUE SPILLBACK**

The above point queue-based analytical formulas provide a reasonable approximation for computing additional delay when there is no queue spillback. It is critical to recognize the need for using dynamic simulation models to capture the evolution of traffic congestion building and dissipation along a corridor, resulting from variations in queue discharge flow and limited link/capacity spatial capacities.

Newell’s simplified kinematic wave (KW) model [6] is built upon an assumption of a triangular flow-density relationship. The following proposed methodology aims to incorporate Newell’s KW model to describe traffic congestion propagation realistically, such as phenomena of queue build-up, spillback, and dissipation, in a road traffic network.

In the following, we adopt Hurdle and Son’s framework [7] to explain how Newell’s model is able to model forward and backward waves using the cumulative vehicle counts, as well as capturing queue spillbacks. Let \( x \) be the location along the corridor, and \( N(x,t) \) the cumulative flow count at location \( x \) and time \( t \) of a link. For the triangular shaped flow-density relation with constant forward and backward wave speeds, it is easy to verify that, when the speed of forward wave is \( v_f \), the general cumulative flow count formula is

\[ -k + \frac{a}{v_f} = -k + k = 0. \quad (4) \]

Under congested traffic conditions with a constant backward wave speed \( w_b \), we have

\[ -k + \frac{a}{w_b} = -k_{jam}, \quad (5) \]

and the equation to describe a backward wave through the link becomes

\[ dN = \left( -k + \frac{a}{w_b} \right) dx = -k_{jam}(a) \times length(a) \times nlanes(a) \quad (6) \]

where \( nlanes(a) \) and \( length(a) \) is the number of lanes and the length for link \( a \), respectively.

When a queue spills back from the downstream to the upstream, the arrival and departure cumulative flow counts at the two ends of a link (at timestamps \( t \) and time \( t - BWTT(a) \), where \( BWTT \) is the backward wave travel time) need to ensure a constant difference of \( dN = k_{jam}(a) \times length(a) \times nlanes(a) \), and the capacity restriction is propagated throughout the link using a time duration of \( BWTT(a) = length(a) / w_b(a) \).

**EXPECTED TRAVEL COST (ETC) KNOWLEDGE-BASED USER EQUILIBRIUM**

As there are different realized capacity values due to incidents on different days, the travel times on different links can be viewed as a set of stochastic variables. In reality, most travelers rely on their expected travel times and their knowledge and experience on incident occurrence probability over different days to make route choices. This long term travel time average is obtained from the queue analysis.

To check the traffic assignments made earlier in the model, the corresponding Karush-Kuhn-Tucker optimality conditions can be written and used as

\[ gap^{ETC} = f_1^{ETC} \times (\overline{T}_1 - \pi) + f_2^{ETC} \times (\overline{T}_2 - \pi) = 0 \quad (7) \]

where \( f_1^{ETC} \) is the flow rate and \( \overline{T}_i \) is the expected travel time (both on path \( i \)), and \( \pi \) is the least
expected travel time between the given OD pair over a multi-day horizon which satisfies the condition

\[ \bar{\tau} = \min(\bar{T}_1, \bar{T}_2) \]  

(8)

When \( \text{gap}^{ETC} = 0 \), it can be shown that if \( f_a^{ETC} > 0 \), then \( \bar{T}_a = \bar{\tau} \). That is, the routes selected by expected travel time information users between an OD pair have equal and minimum costs. On the other hand, if \( f_a^{ETC} = 0 \), then \( \bar{T}_a \geq \bar{\tau} \), which indicates that all unused routes by ETC users have greater or equal costs (compared to the used path costs). These two conditions further imply that no individual trip maker with expected travel time information can reduce his/her expected path costs by switching routes on any given day, under a user equilibrium condition.

**CONCLUSIONS**

This paper has presented a new methodology to further the current state of practice for modeling safety. Existing methodologies suggest there is an interest in incorporating safety into the transportation planning process, but its effectiveness is limited by ignoring the relationship between traffic flow and safety. The proposed model uses an incident calendar to predict the crash rate on a link. Vehicles are then assigned to an OD pair based on the shortest path. Multi-day simulations, which include the ability to model queue spillback and network wide traffic flow, are performed. The link with the least expected travel time path can be identified, and a path assigned shift can be used to move vehicles to the shortest path. The model is then checked for convergence using a gap function.

When the model converges, a new incident calendar can be developed with consideration for proposed safety improvements for each link. The model is reiterated, and the resulting traffic flow distribution and travel times can be compared to the base case. This model represents a significant enhancement compared to previous related studies, where static safety estimates and deterministic queue analysis techniques limited analytical capabilities.

**REFERENCES**


