Spatiotemporal Analysis of Traffic Congestion Caused by Rubbernecking at Freeway Accidents

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***Abstract*—In this paper, we present a well-specified analytical methodology for estimating capacity reduction that is attributable to accidents in the opposite direction of accident—the condition whereby drivers in the opposite direction of an accident, by virtue of their curiosity, tend to be distracted by the accident. The methodology is based on a binary integer programming formulation that is used to identify the spatiotemporal region that is affected by the influence of the accident. Thresholds measured against control sample readings from inductance loop detectors are used to determine the patterns and magnitudes of the delay. A key feature of the methodology is its ability to separate nonrecurrent delay from any recurrent delay that is present on the road at the time and place of a reported accident, to estimate the contribution of nonrecurrent delay caused by the specific accident. A case study that is based on historical inductance loop detector data from six major freeways in Orange County, California, is presented. Potential factors contributing to delay, including accident characteristics, geometric characteristics, environmental condition, traffic characteristics, and congestion characteristics, are analyzed for their effects by using the semiparametric Cox proportional-hazards model.**

***Index Terms*—Binary integer programming (BIP), censored data, Cox's proportional-hazards (PH) model, freeway accident, inductive loop detector (ILD), rubbernecking, traffic congestion.**

I. Introduction

ALTHOUGH there is no direct capacity reduction by lane blockage in the opposite direction of accident, drivers in the opposite direction of an accident, by virtue of their curiosity, tend to be distracted by the accident—this is commonly called the "rubbernecking" or "gawking" phenomenon. Basically, rubbernecking/gawking refers to the tendency of drivers of vehicles in adjacent lanes or the opposite direction to slow down as they pass by an incident to see what is happening [1]–[10]. Since such behavior invites sudden slowdowns in traffic, it may result in additional congestion in the opposite direction. Moreover, during rubbernecking, the eyes of drivers may be focused more on the accident scene than on the direction of their driving. This, in itself, can lead to another vehicular accident. According to a study by the Transportation Safety Training Center, Virginia Commonwealth University, Richmond, VA, USA [11], the leading cause of vehicular accidents is, in fact, rubbernecking. Additionally, rubbernecking caused by vehicular accidents and other incidents accounted for 16% of all vehicular accidents, whereas the total number of outside-the-car distractions accounted for 35% [11].

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Although secondary problems caused by rubbernecking are critical, virtually most research regarding delay by incidents has been focused on quantifying congestion that is occurring in the direction of the incident [12]–[19]. On the other hand, few basic studies have tried to identify the negative impact of rubbernecking. For instance, they include the determination of capacity reduction due to the incident [9], [20], [21], the explanation of traffic oscillations due to rubbernecking using a behavioral car-following model [22], and the identification of secondary incidents due to rubbernecking [2].

However, for the purpose of the successful operation of accident management systems, knowing the basic factors affecting total delay caused by rubbernecking is also crucial. Thus, the objective of this paper is to develop the methodology for spatial and temporal estimation of the congested region caused by rubbernecking at a traffic accident and to identify its major causal factors. The congested region is identified by binary integer programming (BIP) and is based on basic accident information and empirical statistics from traffic variables obtained from inductive loop detectors (ILDs). Since a number of estimated results were censored by time and/or space boundary conditions, general statistical approaches were not available. An approach based on survival analysis was applied to analyze estimated rubbernecking delay. Specifically, a statistical model based on the Cox-type proportional-hazard (PH) analysis is estimated, which describes rubbernecking delay as a function of day of week, time of day, weather, and observable (e.g., from emergency calls and/or aerial or on-scene observation) characteristics of the accident.

Consequently, the results of this paper will be useful for the efficient operation of accident management systems and the evaluation of its performance by quantifying accident congestion in terms of total delay to evaluate the benefit of accident management systems accrued from efficient traffic operations. In addition, they will provide a basis for simulation modeling of the rubbernecking phenomenon.

II. Preliminary Analysis

A. Section Definition

A freeway section in this study corresponds to a portion of the freeway whose boundaries are defined by the midpoints

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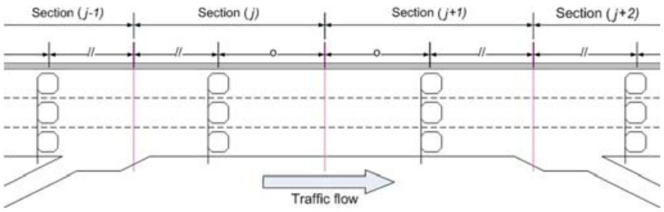

Fig. 1. Section definition and the corresponding detector location.

TABLE I
BASE CASE OF DISTRIBUTIONAL PROPERTIES FOR FREEWAY SECTION SPEEDS

Time	Freeway section (traffic flow direction ←)				
	i	$i-1$	$\cdots$	2	1
t_1	$\Omega_{i,1}=\Omega\left(\bar{s}_i(t_1),\sigma_{s_i(t_1)}\right)$	$\cdots$	$\cdots$	$\cdots$	$\Omega_{1,1}=\Omega\left(\bar{s}_1(t_1),\sigma_{s_1(t_1)}\right)$
t_2	$\Omega_{i,2}=\Omega\left(\bar{s}_i(t_2),\sigma_{s_i(t_2)}\right)$	$\cdots$	$\cdots$	$\cdots$	$\Omega_{1,2}=\Omega\left(\bar{s}_1(t_2),\sigma_{s_1(t_2)}\right)$
t_3	$\Omega_{i,3}=\Omega\left(\bar{s}_i(t_3),\sigma_{s_i(t_3)}\right)$	$\cdots$	$\cdots$	$\cdots$	$\Omega_{1,3}=\Omega\left(\bar{s}_1(t_3),\sigma_{s_1(t_3)}\right)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
t_{M-1}	$\Omega_{i,M-1}=\Omega\left(\bar{s}_i(t_{M-1}),\sigma_{s_i(t_{M-1})}\right)$	$\cdots$	$\cdots$	$\cdots$	$\Omega_{1,M-1}=\Omega\left(\bar{s}_1(t_{M-1}),\sigma_{s_1(t_{M-1})}\right)$
t_M	$\Omega_{i,M}=\Omega\left(\bar{s}_i(t_M),\sigma_{s_i(t_M)}\right)$	$\cdots$	$\cdots$	$\cdots$	$\Omega_{1,M}=\Omega\left(\bar{s}_1(t_M),\sigma_{s_1(t_M)}\right)$

of two consecutive detector stations, as shown in Fig. 1. It is assumed that the estimated speed at the ILD station is representative of the speed for the corresponding section. Based on the sections and their corresponding detector stations, estimated speeds for each section are calculated for each 5-min interval during the one-year analysis period.

B. Speed Distribution

For each section, for each day, for one year, and for t_m in 5-min increments, speed $s_j(t_m)$ has been established; that is, for every j and t, nominally 52 observations have been constructed. For example, section j on Monday from $t_m = 08{:}10$ to 08:15 for 52 weeks is composed of 52 samples. Thus, the nth speed for any particular day of the week/time interval/section combination can be represented as $s_{jn}(t_m)$.

Let $\Omega_{jm} = \Omega(\bar{s}_j(t_m), \sigma_{s_j(t_m)})$ denote the set of parameters defining the distribution of speeds $s_{jn}(t_m)$ corresponding to the accident-free case. Then, for $t_m > t_o$, $m = 1, 2, \ldots$ (i.e., time intervals after the accident that occurs in the opposite direction of section i at t_o), for all upstream sections that could have been possibly affected by the accident, we can compose a matrix of accident-free-case conditions (i.e., conditions in which there is no accident) that can be expected to prevail, as described in Table I.

Similarly, the speed distribution in the opposite direction under each traffic accident can be described as in Table II. For example, suppose that an accident occurred in the opposite direction of freeway section i at time $t = t_o$. Then, we can observe the corresponding measurements for the rubbernecking conditions, $\hat{s}_j(t_m)$; $j = i, i-1, i-2, \ldots$; $m = 1, 2, \ldots$. We can then compose a matrix of rubbernecking conditions as in Table II.

TABLE II
OBSERVED RUBBERNECKING SPEEDS

Time	Freeway section (traffic flow direction ←)					
	i	i-1	$i-2$	$\cdots$	2	1
t_1	$\hat{s}_i(t_1)$	$\hat{s}_{i-1}(t_1)$	$\cdots$	$\cdots$	$\cdots$	$\hat{s}_1(t_1)$
t_2	$\hat{s}_i(t_2)$	$\hat{s}_{i-1}(t_2)$	$\cdots$	$\cdots$	$\cdots$	$\hat{s}_1(t_2)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
t_m	$\hat{s}_i(t_m)$	$\hat{s}_{i-1}(t_m)$	$\cdots$	$\cdots$	$\cdots$	$\hat{s}_1(t_m)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
t_{M-1}	$\hat{s}_i(t_{M-1})$	$\hat{s}_{i-1}(t_{M-1})$	$\cdots$	$\cdots$	$\cdots$	$\hat{s}_1(t_{M-1})$
t_M	$\hat{s}_i(t_M)$	$\hat{s}_{i-1}(t_M)$	$\cdots$	$\cdots$	$\cdots$	$\hat{s}_1(t_M)$

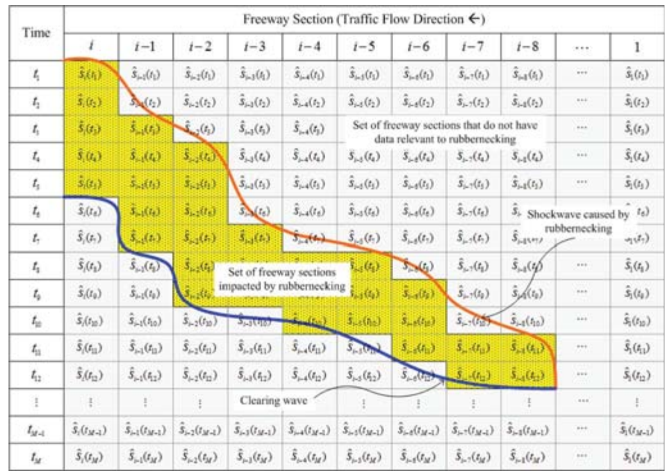

Fig. 2. Schematic congestion effect by rubbernecking at an accident.

Relative to the display of information in Table II, we can describe the negative effects (i.e., speed reduction) of rubbernecking schematically, as shown in Fig. 2. The negative effect of rubbernecking will be propagated from the opposite section of the accident to its upstream sections (i.e., to downstream sections on the basis of the accident section). Such distinct discontinuity between noncongested and congested flow is known as a shockwave [23]. If the dot-shaded area that is affected by the shockwave in Fig. 2 is identified, then the temporal and spatial impacts of rubbernecking will be also determined. The following section describes the method for distinguishing the regions between noncongested and congested areas due to rubbernecking at traffic accidents.

C. Quantifying Total Delay Caused by Rubbernecking

To identify the spatiotemporal congested area caused by rubbernecking, the methodology developed by Chung and Recker [12] was applied. A key feature of their methodology is the development of a method to separate nonrecurrent delay from any recurrent delay that is present on the road at the time and place of a reported accident, to estimate the contribution of nonrecurrent delay caused by the specific accident [12]. While the proposed methodology has been shown to work for estimating the spatiotemporally congested region on freeway sections on which an accident has occurred (i.e., traffic flow is in the same direction as the accident), this is not the case for the

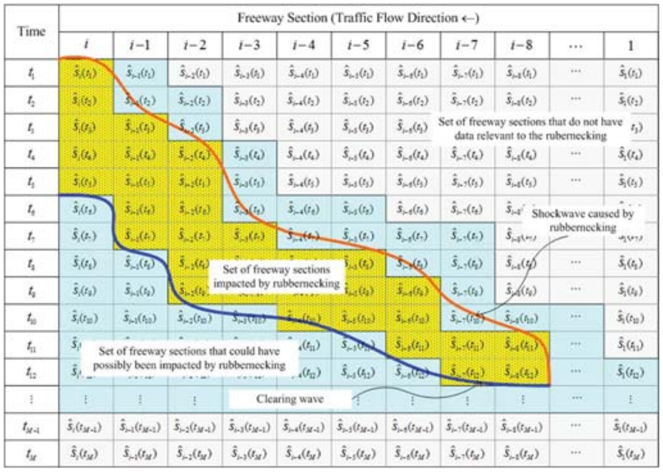

Fig. 3. Maximum set of freeway sections impacted by rubbernecking.

opposite direction. The objective of this study is to apply the methodology proposed by Chung and Recker [12] to the opposite direction of accident occurrence and, in turn, establish if the spatiotemporally congested region caused by rubbernecking can be determined. The following steps highlight the procedure.

1) Step 1—Determining the Maximum Extent of Rubbernecking Influence: The first step to identify the congested region due to rubbernecking is to estimate the maximum possible extent of the shockwave by assuming the worst possible conditions—total blockage for some prespecified time period. Thus, for any given accident occurring in the opposite direction of section i at time t_1, we compute the maximum number of upstream sections that could be affected by the assumed persistent total blockage at section i at time t_1. Using this spatiotemporal information, the "maximum area of interest" for any accident occurring at the opposite section of section i at time t_1 can be schematically constructed. Based on this interpretation, the only data relevant to a rubbernecking phenomenon occurring at section i at time t_1 are restricted to cells in the shaded (blue) area in Fig. 3. In Fig. 3, the cells in the dot-shaded (yellow) area represent speeds, i.e., $\hat{s}_j(t_m)$, that have been reduced due to rubbernecking at the accident. Other shaded ("blue") cells represent speeds that are not significantly different from nonrubbernecking conditions.

2) Step 2—Determining the Congested Region: The second step is to distinguish between the shaded (blue) area and the dot-shaded (yellow) area in Fig. 3. Since the speed of traffic in sections that are adversely affected by rubbernecking will be reduced, the basic idea behind distinguishing between these two regions is to compare the rubbernecking speed, i.e., $\hat{s}_j(t_m)$, with the distribution of nonrubbernecking speeds, i.e., $s_{jn}(t_m)$; $n = 1, 2, \ldots, n_{\text{obs}}$; $n_{\text{obs}} \leq T$, and assign some level of confidence that any particular $\hat{s}_j(t_m)$ was not drawn from the distribution of $s_{jn}(t_m)$. Based on this idea, Chung and Recker [12] used the discriminant variable P_{jm} to identify affected versus nonaffected speed by rubbernecking as follows:

$$P_{jm} = \begin{cases} 0, & \hat{s}_j(t_m) \leq \bar{s}_j(t_m) - \alpha \cdot \sigma_{s_j(t_m)}; \quad n_{\text{obs}} \geq n_{\text{min obs}} \\ 1, & \hat{s}_j(t_m) > \bar{s}_j(t_m) - \alpha \cdot \sigma_{s_j(t_m)}; \quad n_{\text{obs}} \geq n_{\text{min obs}} \\ 0.5, & n_{\text{obs}} < n_{\text{min obs}} \end{cases} \tag{1}$$

where $\hat{s}_j(t_m)$ is any particular speed not drawn from the distribution of $s_{jn}(t_m)$, $\bar{s}_j(t_m)$ and $\sigma_{s_j(t_m)}$ are the mean speed and the standard deviation speed drawn from the distribution of $s_{jn}(t_m)$, and α is a positive value. Additionally, $n_{\text{min obs}}$ represents to set a threshold regarding the minimum number of observations to have some confidence in the statistical calculations for mean and standard deviation. Since 30 is commonly used as the minimum number of observations required for the law of large numbers to apply, it was determined that $n_{\text{min obs}} = 30$.

Using this procedure, the problem of determining the "best" set of dot-shaded (or yellow) cells can be formulated by using BIP as follows:

$$\begin{aligned} &\min_{\delta_{jm}} Z = \sum_{\forall j,m} \left[P_{jm} \cdot \delta_{jm} + (1 - P_{jm}) \cdot (1 - \delta_{jm})\right] \\ &\quad \text{s.t.} \\ &\delta_{j+k,m} \leq [1 - (\delta_{j,m} - \delta_{j+1,m})] \cdot R, \ \forall j, m; \ \forall k \leq J - j \\ &\delta_{j,m+r} \leq [1 - (\delta_{j,m} - \delta_{j,m+1})] \cdot R, \ \forall j, m; \ \forall r \leq M - m \\ &\delta_{j,m+k} \leq [1 + (\delta_{j,m} - \delta_{j+1,m})] \cdot R, \ \forall j, m; \forall k \ \leq M - m \\ &\delta_{jm} = \begin{cases} 0 \\ 1 \end{cases} \end{aligned} \tag{2}$$

where δ is the binary variable, R is a large number, J is the maximum number of upstream sections, and M is the maximum number of subinterval time periods that define the maximum duration assumed for congestion caused by the accident (e.g., for 5-min subintervals and a maximum analysis time period of 4 h, $M = 48$).

III. Case Study

A. Data Description

1) Traffic Flow Data: This research uses one year (from March 2001 to February 2002) of historical ILD data from six major freeways in Orange County, California, i.e., Interstate 405 (I-405), Interstate 5 (I-5), State Route 22 (SR-22), State Route 55 (SR-55), State Route 57 (SR-57), and State Route 91 (SR-91). The study area includes 499 mainline loop detector stations, and the average space between two consecutive detector stations is about 0.8 mi. Since the size of the database aggregated into 5-min intervals is over 52 000 000 records, a database management system is employed to efficiently manage the data set, and its application program interface programs with C and C++ were employed in most analyses.

B. Accident Data

Accident data were obtained from the Traffic Accident Surveillance and Analysis System (TASAS) maintained by the California Department of Transportation (Caltrans) for the six major Orange County freeways in 2001. Approximately 6200 accidents were included for the study period. The accident data include basic information related to accident time and location in terms of freeway milepost. In addition, data for each accident include three primary accident characteristics: 1) accident type, which is based on the type of collision (rear end, sideswipe, or hit object), the number of vehicles involved, and the movement of these vehicles prior to the accident; 2) accident location, which is based on the location of the primary collision (e.g., left lane, interior lanes, right lane, right-shoulder area, off-road beyond the right-shoulder area); and 3) accident severity, in terms of injuries and fatalities per vehicle.

C. Estimation of Total Delay Due to Rubbernecking

If each loop detector in the affected region is correctly working and reporting without error, the pattern of congestion resulting from an accident should be represented, as shown in Fig. 3. However, in practice, it is often the case that some loop detectors may temporarily be not providing valid data, which is usually due to a variety of reasons, including broken cables, interference from other electronic devices, communication failure, and software error [24]. On the Orange County freeway system, there are many such cases of missing data traced to these reasons, leading to the delay of only 2394 of the 6182 total accidents being successfully estimated.

However, certain results were censored by temporal constraints (or time boundary conditions). As suggested by Chung and Recker [12], an upper limit of 4 h after accident occurrence was applied in the determination of the spatiotemporal extent of the congestion region. However, in some cases, congestion was observed to remain after the maximum number of time period M. Similarly, calculations for some of the rubbernecking delays were cut off in terms of a spatial boundary condition, which is due either to county lines or to an end of roadway (e.g., freeway interchange). Another spatial cutoff result is due to detector problems (or missing data). Most of such results are caused by accidents related to fatalities, hazardous materials, secondary accidents that occurred either before the first accident was cleared or while rubbernecking, etc., and they are called censored observations. In such cases, since the congestion caused by rubbernecking is not cleared, the causal factor analysis for total delay would lead to an erroneous conclusion if censored delays are ignored.

Having completed the given steps, which determine the region (in time and space) that is negatively affected in the opposite direction by any particular accident, we can calculate the total delay (TD) caused by rubbernecking as

$$TD = \sum_{\forall m,j \in \text{dot-shaded cells}} \times \max\left\{ L_j \cdot \left[\frac{1}{\hat{s}_j(t_m)} - \frac{1}{\bar{s}_j(t_m)} \right] \cdot V_{jm}, 0 \right\} \quad (3)$$

where

- L_j Length of freeway segment j.
- V_{jm} Volume (count) of vehicles in segment j during time m.
- $\hat{s}_j(t_m)$ Speed affected by rubbernecking in segment j at time m.
- $\bar{s}_j(t_m)$ Annual average speed in segment j at time m.

There are many cases of missing data on the Orange County freeway system. Thus, the total delay caused by rubbernecking was successfully estimated for only 2394 (38.73%) of the 6182 total accidents. Moreover, 432 (18.05%) of 2394 accidents resulted in censoring due to the space and time boundary conditions and/or temporarily not providing valid data issues, as previously described. From the estimated results, the median total delay for 2394 accidents (including censored results) was 2.87 vehicle hours, with the minimum total delay and the maximum total delay being 0 and 1445.44 vehicle hours, respectively.

IV. Critical Factors to Total Delay Caused by Rubbernecking

A. Definition of Candidate Variables

Candidate variables are classified into five groups based on TASAS, traffic data, and estimated congestion regions: 1) accident characteristics, including accident type, accident causal factor, truck accident, accident location, accident severity, number of vehicles involved, number of persons killed, number of persons injured, and accident time; 2) geometric characteristics referring to the opposite direction of the corresponding accident in terms of the number of lanes; 3) environmental condition (i.e., whether or not the road surface was wet); 4) traffic characteristics referring to the opposite direction of the corresponding accident, such as annual average daily traffic (AADT), truck AADT, and occupancy[1]; and 5) congestion characteristics referring to the duration time, maximum congested time, and maximum congested length based on the estimated congestion region in the accident direction. The value of occupancy employed is referenced to the accident section and its opposite section during the 5-min period prior to the accident occurrence time; this variable represents the mean value for the 5-min interval.

Some of the nominal variables that can affect the total delay caused by an accident are classified into binary variables. Specifically, the accident time variable (in terms of time of day) is divided into four time intervals, i.e., 06:01–09:00, 09:01–15:30, 15:31–18:00, and 18:01–06:00. The accident time variables, including time of day and week, reflect the general traffic pattern that is present. Table III shows the candidate variables.

B. Multivariate Analysis Using Cox's PH Model

1) Estimation of Multivariate Cox Model: Since the result that the majority (26.9%) of 2394 observations for rubbernecking have zero values for delay leads to the rubbernecking delay observations not nicely fitting such formal distributions as exponential, Weibull, gamma, lognormal, log-logistic, and Gompertz, multivariate effects on rubbernecking delay are analyzed by using the semiparametric model (Cox's PH model) rather than fully parametric survival models. The Cox model, which assumes that the covariates multiplicatively shift the baseline hazard function, is by far the most popular choice, due to its elegance and computational feasibility [26]. It has a considerable advantage compared with the parametric approaches in that it does not need an assumption about the baseline hazard function.

[1] Initially, traffic volume was considered as a candidate variable. However, due to its property of having the same value under two different traffic situations (i.e., uncongested and congested conditions), using this variable may result in a biased model. Thus, this variable was ignored.

TABLE III
CANDIDATE VARIABLES

Category	Variable		Accidents	Unit (0=no, 1=yes)
Accident characteristics	Collision type	1 veh hit obj./overturn	258	Dummy
		2+ veh hit obj./overturn	116	Dummy
		2 veh weaving	456	Dummy
		3+ veh weaving	139	Dummy
		2 veh rear end	873	Dummy
		3+ veh rear end	552	Dummy
	Causal factor	Alcohol	63	Dummy
		Improper turn	205	Dummy
		Speeding	1459	Dummy
		Other violations	577	Dummy
		Other than driver	69	Dummy
		Unknown	21	Dummy
	Truck accident	Truck involved	238	Dummy
		Truck not involved	2156	Dummy
	Collision location	Off-road left	235	Dummy
		Left lane	665	Dummy
		Interior lane(s)	862	Dummy
		Right lane	495	Dummy
		Off-road right	137	Dummy
	Severity	Property damage only	1829	Dummy
		Injury and/or fatality	565	Dummy
	Number injured		2394	Number
	Number vehicles involved (1, 2, 3, 4+)		2394	Number
	Number killed*	0	2389	n/a
		1	4	
		2	1	
	Time of day	Night (18:01~06:00)	519	Dummy
		AM peak (06:01~09:00)	474	Dummy
		Midday (09:01~15:30)	785	Dummy
		PM peak (15:31~18:00)	616	Dummy
	Day of week	Monday	424	Dummy
		Tuesday	492	Dummy
		Wednesday	436	Dummy
		Thursday	496	Dummy
		Friday	546	Dummy
Geometric characteristics	Number lanes in opposite direction	3 or less lanes	407	Dummy
		4 lanes	1223	Dummy
		5 lanes	700	Dummy
		6 lanes	64	Dummy
Environmental characteristics	Road surface	Wet	127	Dummy
		Dry	2267	Dummy
Traffic characteristics	5-minute occupancy (%) in accident direction		2394	Number
	5-minute occupancy (%) in accident direction		2394	Number
	AADT (scaled in 100,000 vehicles)		2394	Number
	Truck AADT (scaled in 1000 vehicles)		2394	Number
Estimated congestion characteristics	Duration of accident[2]		2394	Number
	Maximum congested time in accident direction		2394	Number
	Maximum congested length in accident direction		2394	Number

* The variable Number killed is not analyzed because the number of samples is not enough for analysis.

Despite the semiparametric nature, methods for assessment of the fitted Cox model are essentially the same as for other regression models, i.e., similar to diagnostic assessments in the ordinary least squares model that check for model misspecification, outliers, influential point, etc. Thus, three types of assessments are applied for the Cox model: 1) testing the assumption of PH; 2) identifying outliers/leverage points; and 3) assessing the overall model fit. Table IV shows the fitted Cox model for rubbernecking delay, including seven variables identified as being significant at 95% confidence level.

TABLE IV
FITTED COX MODEL FOR RUBBERNECKING DELAY

Variable	Estimated coefficient	Hazard ratio	Wald statistics
5-minute occupancy (%) in opposite direction	-0.043	0.958	-14.62
Duration of accident (min)	-0.003	0.997	-4.07
Maximum congested time in accident direction (min)	-0.009	0.991	-14.44
Maximum congested length in accident direction (mile)	-0.469	0.626	-21.53
Number injured	-0.073	0.929	-2.51
Truck AADT (scaled in 1000 vehicles)	-0.026	0.974	-4.81
Accident time of day (1 if night period, 0 otherwise)	0.254	1.289	4.35
Initial log likelihood	-13,709.906		
Log likelihood at convergence	-12,406.746		
Number of accident	2394		

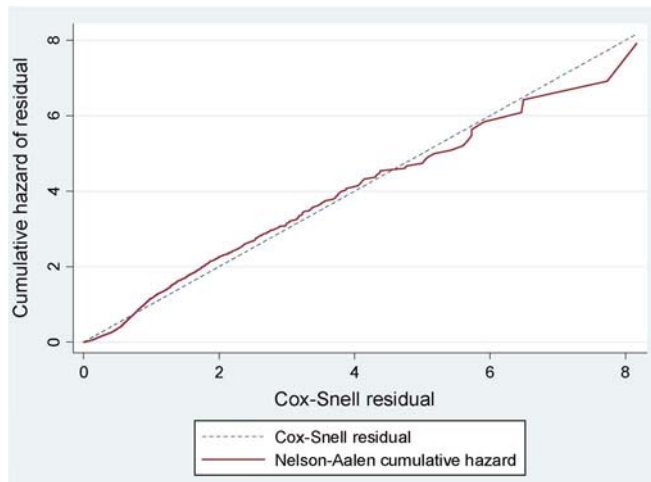

Fig. 4. Graph on cumulative hazard of Cox–Snell residuals.

2) Assessment of Model Adequacy: The Cox–Snell residual plot was used for assessing the overall goodness-of-fit of the model [27]. If the Cox model fits the data well, then the Cox–Snell residuals should have a standard exponential distribution with a hazard function that is equal to 1, and thus, the cumulative hazard of the Cox–Snell residuals should be a straight 45° line [26]. Since the plot in Fig. 4 is comparatively close to the 45° line, it was concluded that the Cox model for the total delay caused by rubbernecking at a traffic accident fits the data fairly well.

C. Interpretation of the Cox Model

When interpreting a Cox model for each variable, a positive coefficient (or a hazard ratio of > 1.0) for a variable means that the hazard is higher. Conversely, a negative coefficient (or a hazard ratio of < 1.0) implies a lower hazard for subjects with higher values of that variable. In this paper, we should note that the subject is rubbernecking delay, unlike the life of a patient or machine. Thus, if the estimated hazard ratio is increased in comparison to another case, it implies that the rate of the rubbernecking delay is decreased.

TABLE V
PERCENTAGE CHANGE IN RUBBERNECKING DELAY FOR FITTED COX MODEL

Variable	Percentage change
5-minute occupancy (%) in opposite direction	4.2%
Duration of accident (min)	0.3%
Maximum congested time in accident direction (min)	0.9%
Maximum congested length in accident direction (mile)	37.4%
Number injured	7.1%
Truck AADT (scaled in 1000 vehicles)	2.6%
Accident time of day (1 if night period, 0 otherwise)	-28.9%

For example, the hazard ratio of 5-min occupancy in the opposite direction of the accident location is estimated as 0.958. This would indicate that for every 1% increase in the 5-min occupancy in the opposite direction of the accident location, the rate of rubbernecking delay would increase by 4.2%. Conversely, the hazard ratio for accidents during night time periods is estimated as 1.289, which would indicate that the rubbernecking delay for accidents during night time periods is about 28.9% less than for those during other time periods. Table V shows the percentage change in rubbernecking delay due to one unit change (change from 0 to 1 in the case of the dummy variable) of each variable for the model in Table V.

From the percentage changes in Table V, all of the results were consistent with intuitive expectation. Particularly, an increase in percent in the 5-min occupancy in the opposite direction of accident, in the number of persons injured, and in 1000 truck AADT resulted in greater rubbernecking delay. In addition, accidents that are related to longer duration exhibited greater rubbernecking delay. Moreover, rubbernecking delay was found to be greater with increasing maximum congested time or length in the accident direction. Finally, accidents that occurred during the night time period tended to have less rubbernecking delay than those during the other time periods. This result could be due to the fact that there is low traffic volume during the night time period.

V. CONCLUSION AND FUTURE STUDIES

Although congestion due both to the direct effect of accidents and to its secondary problems caused by rubbernecking is critical, virtually all research regarding delay caused by incidents has been focused on quantifying congestion that is only attributable to the direct effect in the lanes in the accident direction. In this paper, nonrecurrent total delay caused by rubbernecking and its causal factors were statistically analyzed by Cox's PH approach. Based on the results, seven factors were found to be statistically significant in contributing to the delay encountered due to the principle of rubbernecking. These factors include the level of 5-min occupancy in the opposite direction of accident, accident duration time, maximum congested time and length in the accident direction, number of persons injured due to the accident, and an accident time effect for the night period. In addition, the results were consistent with intuitive expectation.

Overall, it is anticipated that the results of this paper will be useful for the efficient operation of accident management systems and the evaluation of its performance by quantifying accident congestion in terms of total delay to evaluate the benefit of accident management systems accrued from efficient traffic operations. In particular, nonrecurrent congestion has been estimated for the same direction of accident occurrence. However, nonrecurrent congestion occurs not only in the accident direction but also in the opposite direction. Thus, traffic congestion costs will be estimated within a reasonable value. In addition, most studies on secondary accident identification were conducted based on spatiotemporally predefined thresholds for the negative impact on accidents. In addition, studies on secondary accidents due to rubbernecking were very limited. Since this study provides spatiotemporally congested regions with respect to each accident, the proposed method and its result can be used in the identification of secondary accidents caused by rubbernecking. Finally, most microscopic traffic simulators (e.g., CORSIM) use capacity reduction rates to capture the rubbernecking phenomenon due to traffic incidents; however, the reduction rates vary with incident types, occurrence time, and so on. Thus, the results from this study will provide a basis for simulation modeling of the rubbernecking phenomenon. For instance, they can be used for the calibration of the capacity reduction rate in traffic simulation models.

Finally, although accident data used in this study did not include accident duration time information and with the intuitive sense that accident duration has a high impact on congestion caused by accidents and subsequent rubbernecking, this study applied the estimated duration time rather than the observed time for the multivariate statistical analysis. However, based on duration times observed in the field, a new model is recommended for testing the significance of the variable of duration time, although it seems to be statistically significant to delay caused by rubbernecking.

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