TOPIC C2
SAFETY ANALYSIS
AND POLICY

QUANTITATIVE ANALYSIS ON ANGLE-ACCIDENT RISK AT SIGNALIZED INTERSECTIONS

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Quantitative Analysis on Angle-Accident Risk at Signalized Intersections

Abstract:

This paper demonstrates how a new modeling methodology can be applied to intersection angle-accident risk evaluation with data collected from 81 signalized intersections in the Tokyo Metropolitan area.

Angle collisions between through traffic flow and opposite right-turn (please note that vehicles travel along the left side of the road in Japan) traffic flow are the second most common type at signalized intersections in Tokyo, accounting for 25.6% of total vehicle-to-vehicle accidents. A risk model for such angle accidents was developed with the occurrence mechanism considered in this study. Unlike most existing accident models, human factors, which caused about 95% of all the traffic accidents, can be considered quantitatively in this model. Very specific flow data, regulation data, geometric data and accident observations of each approach were applied for calibrating the model using a modified negative binomial regression. Nineteen explanatory variables were found significantly affecting angle-accident risk at signalized intersections. Such estimation results may help to improve traffic safety at signalized intersections in metropolitan areas.

INTRODUCTION

While traffic fatalities have been fluctuating around 10,000 per year, injury accidents have been increasing since 1990. The record high number of injury accidents, 720,880 in 1969, was reset by 761,789 in 1995, and has been reset yearly since then ("IATSS", 1997). In 2000, it reached a new high of 930,277. Correspondingly, the number of injuries, 1,153,841 also reached a record high in 2000 ("ITARDA" 2001).

Approximately 58.7% of all accidents, or 44.7% of all fatal accidents occurred at intersection areas in 1995 ("ITARDA", 1996). This indicates that intersections are accident-prone areas, and to reduce intersection accidents is an urgent task in Japan. Statistics show that AG accidents (angle accidents between through vehicles and opposite right-turn vehicles) are the second most common accident type, next to rear-end accidents, at intersections. AG accidents account for 25.6% of total intersection vehicle-to-vehicle accidents. Quantitative study of the relationship between AG accidents and their causal factors is a very significant step toward improving traffic safety at signalized intersections.

In this paper, we begin with a brief review of previous work on traffic accident modeling. Then, we describe our microscopic methodology for modeling AG accidents considering the mechanism of their occurrence. This is followed by the presentation of a modified negative binomial approach used for model calibration and the data collected for this study. Finally, model estimation results are discussed and study findings are summarized.

PREVIOUS WORK

Although many researchers have addressed intersection accidents, very few studies have modeled AG accidents specifically. Most previous work has dealt with modeling relationships between total accidents at an intersection and the geometric/road-environment elements. Methods often adopted have been linear regression, Poisson regression and negative binomial regression. For example: Resende *et al* (1997) used traffic flow, median width and surface rating to predict accident numbers on rural interstate highways with a linear equation. Hyodo *et al* (1993) studied effects of landuse, and highway geometric factors on aggregated accident numbers of a region by Poisson regression based on GIS oriented data. Shankar *et al* (1995) developed a negative binomial regression model for evaluating the impacts of road geometric and environment-related factors on rural freeway accident frequencies.

Several studies have addressed the issue of fitness of various models (e.g. Jovanis *et al*, 1986, Miaou *et al*, 1993, and Poch and Mannering 1996). The researchers concluded that despite of the lack of random features and the existence of negative predictions, linear models are very easy to construct and are suitable for long interval and large sample data. Poisson models possess most of the desirable features in describing vehicle accident events - discrete, nonnegative and random. The problem with Poisson models is that the requirement that the mean equals the variance is not met by most collected accident data. If data are over-dispersed (i.e. the variance of accident frequency data is greater than the mean), Poisson models will result in biased coefficients and erroneous standard errors. Although the negative binomial distribution models can deal with over-dispersed data, the fact that a constant variance to mean ratio is imposed across samples violates the reality that the variance-to-mean ratio varies with the actual mean value. However, Lawless (1987) concluded that such a violation would not lead to biased estimations. Some researchers, such as Shankar *et al* (1995), Poch and Mannering (1996), and Wang *et al* (1999) have already successfully applied negative binomial regression models to prediction of traffic accidents on rural freeways and intersections.

Although most of the previous studies did not directly focus on modeling intersection AG accident risks, they provided methodological insights on dealing with this issue. Hauer *et al* (1988) clearly classified intersection vehicle-to-vehicle accidents into 15 types according to the vehicle movements prior to collisions. Also, the frequencies of each accident type were attributed to the relevant traffic flows. This classification provided a microscopic perspective to the analysis of intersection vehicle-to-vehicle accident frequencies. In addition to the impacts of related traffic flows on accident frequencies, Poch and Mannering (1996) further studied the effects of intersection approach conditions on accident frequencies as well. Negative binomial regression models were developed for calculating the frequencies of various types of accidents. Their work advanced a reasonable method for modeling intersection AG accident risks.

A common criticism of many previous studies is that they did not include considerations of human factors (Poch *et al*, 1996). Since more than 95% of traffic accidents are caused by human factors, either alone or in combination with other factors (Rumar, 1985), the absence of human factors in accident models may produce inappropriate results. Consequently, further effort is required to take human factors into consideration in accident modeling. In a recent study, Wang (1998) developed a microscopic approach for intersection accident modeling that clearly takes human factors into account. Following this approach, Wang *et al* (2002) developed a risk model for intersection rear-end accidents; Karim (2000) used the approach for estimating lane-change accident risks; and Siddique (2000) applied the approach for vehicle-to-bicycle and vehicle-to-pedestrian accident risk evaluation. In this study, we apply the approach to the modeling of AG accident risk at signalized intersections.

METHODOLOGY

The Occurrence Mechanism of AG Accidents

The occurrence of intersection AG accidents is normally a combined result of the hazardous right-turn movement of a vehicle from the opposite approach and the ineffective reaction of the arriving through-vehicle driver. Hence, from the perspective of the through-vehicle driver, the probability of having an AG accident is determined by the probability of encountering an obstacle vehicle and the probability of the driver's reaction failure. There might be various reasons for a right-turn vehicle to become an obstacle vehicle for the through-vehicle driver, but the most important ones are the misjudgment of the right-turning vehicle driver and suddenly dashed-out disturbances, such as legally crossing pedestrians or bicyclists.

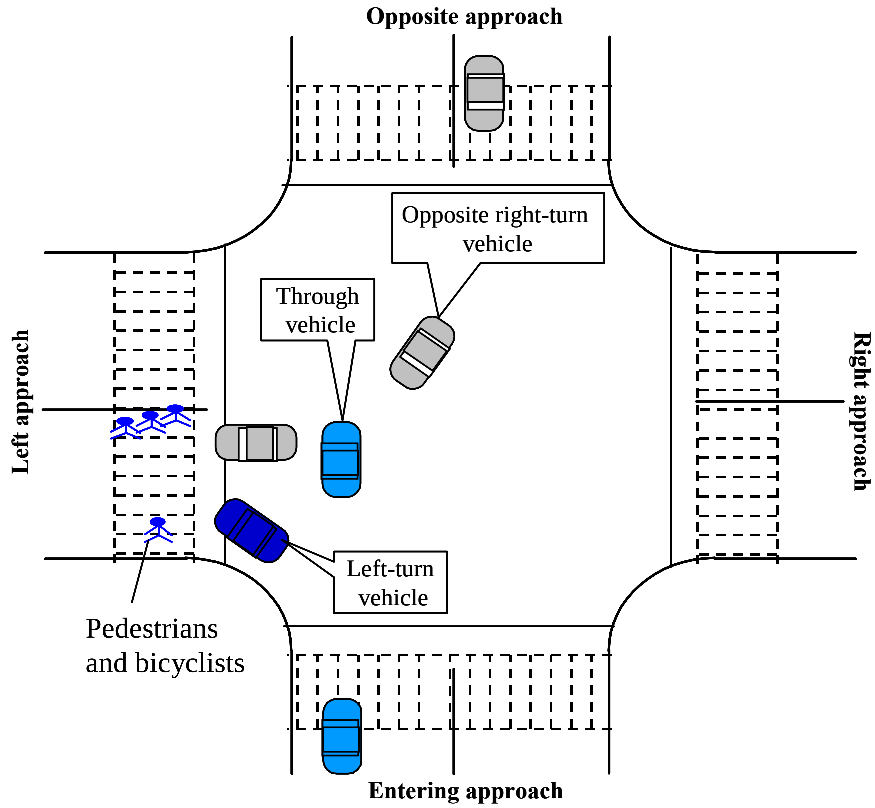

Figure 1 Conflicts between opposite right-turn flow and through, left-turn, and pedestrian/bicyclist flows at two-phase controlled intersections

As an example, consider the case shown in Figure 1. If the intersection is under two-phase signal control, the conflicts between a) through flow and opposite right-turn flow, b) opposite right-turn flow and pedestrian/bicycle flow, and c) opposite right-turn flow and left-turn flow may be inevitable. If a right-turning vehicle driver accepts a gap but a suddenly appearing pedestrian/bicyclist stops the driver from completing the intended movement, then the right-turning vehicle may become an obstacle vehicle to the through vehicles. If the arriving through-vehicle driver fails to avoid a collision, an AG accident will occur.

When passing through an intersection, a through vehicle driver's performance consists of three successive procedures: first, perceiving the changes in the traffic environment; second, making a decision to deal with the changes, if any; and, third, carrying out the decision by action. Factors affecting a driver's abilities to perceive, think and act will definitely affect his/her reaction effectiveness to the obstacle vehicles, and hence affect the driver's AG accident risk. On the other hand, the possibility of encountering obstacle vehicles depends on the frequency of disturbances generated in the intersection. Thus, causal factors of disturbances will also affect AG accident risk indirectly. We need to reflect the effects of all these factors in the AG accident risk model.

Modeling AG Accident Risk

As mentioned previously, an AG accident is caused by both the hazardous movement of a right-turning vehicle from the opposite approach and the ineffective response of the arriving through-vehicle driver. Thus, the probability of a randomly selected through vehicle having an AG accident at a certain place is determined by both the probability of encountering an obstacle vehicle, denoted by P_o, and the probability of its driver's failure to avoid the collision, denoted by P_f. As P_o and P_f are normally independent, the AG accident risk of the vehicle (P_{AG}) can be expressed as the product of P_o and P_f, as shown in Equation (1).

$$P_{AG} = P_o \cdot P_f \tag{1}$$

Since P_o and P_f are not directly observable, we need to further formulate P_o and P_f respectively as follows.

Formulating Drivers' Failure Rate P_f

Driving is a process of perceiving changes of traffic situation, and adjusting vehicle operation to adapt the changed situation. Time needed for a driver to detect emerging disturbances and the quality of his/her response within the available time are quite important for avoiding potential collisions. As noted by Johansson *et al* (1971), one of the main factors determining whether or not an accident can be avoided is the driver's PRT (perception and response time). Drivers' PRT can be regarded as a comprehensive reflection of human related factors.

The PRT has a wide range of values depending on the complexity of the problem, the complexity of the solution, and the driver's expectancy of the hazard (Bates, 1995). In this study, our discussion will be based on the following two concepts concerning PRT, one is the available PRT (APRT), and the other is the necessary PRT (NPRT). The APRT refers to the amount of time a driver can get for completing his perception and response under certain traffic situations. The NPRT is the ability-oriented minimum possible PRT and may vary from person to person. It is assumed that a driver cannot avoid a collision if his/her NPRT is longer than the APRT. Both the APRT and the NPRT are random variables. If the distributions of the two variables are known, it is straightforward to calculate the probability of the arriving vehicle driver's failure (P_f), which is equivalent to the probability of his/her NPRT being larger than the APRT.

Researchers began to measure drivers' NPRT several decades ago. Silva (1936) made a brake reaction time test with 2,000 subjects in a laboratory. He found that for drivers from 15 to 23 years old, PRT decreases with age, but increases with age for drivers older than 23. Other researchers also conducted various experiments to understand how drivers' NPRT changes with age and environmental factors (e.g. Liebermann *et al*, 1995 and Welford *et al*, 1977). These researchers obtained both consistent and inconsistent results. For example, Welford (1977) concluded that reaction time increases with age, while Olson *et al* (1986) got opposite results, i.e. old drivers and young drivers have almost the same PRT under surprise and alerted situations. In this study, the difference in NPRT across age is neglected by assuming that all drivers' NPRT follows the same Weibull (α, λ) distribution. The density function of the Weibull distribution is shown in Equation (2),

$$f(t) = \alpha\lambda\, t^{\alpha-1} e^{-\lambda t^{\alpha}} \quad \text{for } t>0 \tag{2}$$

where α and λ are the shape and scale parameters, respectively. Figure 2 shows the density function curves with different λ values and a fixed α. We choose α=3.25 because it has been empirically verified that, when shape parameter equals 3.25, the Weibull distribution is a very good approximation to the normal distribution (Kao, 1960 and Plait, 1962). If the APRT is known as t_{av}, then the shadowed area in Figure 3 represents the failure probability – P_f.

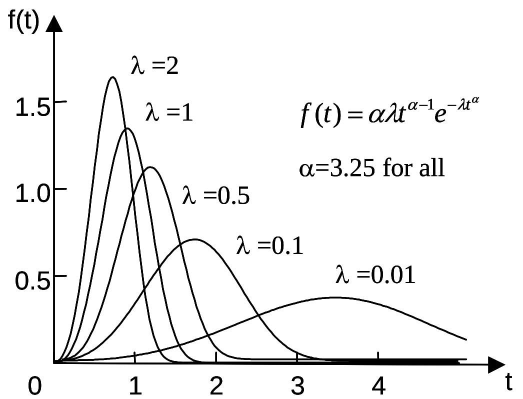

Figure 2 Weibull distribution's density functions

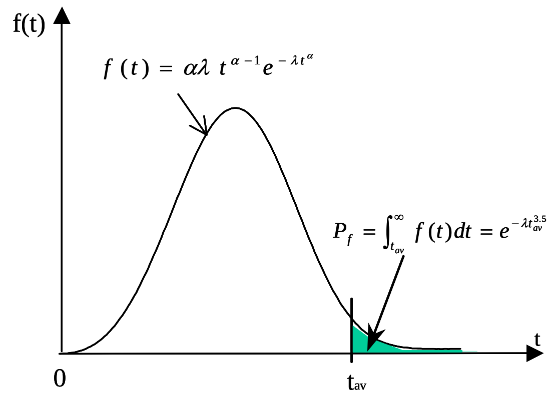

Figure 3 Illustration of drivers' failure probability

The APRT, t_{av}, is indeed a random variable relating to many dynamically changing variables, such as headway, speed, slope, surface condition and etc. Although in the practice of highway design, a constant value of APRT (e.g. 2.5s) is adopted with the consideration of compensating for poor driver behavior ("AASHTO", 1973), it is unsuitable to omit the random feature of the APRT when studying the occurrence of traffic accidents, since the randomness itself is one of the most determinant features of accidents. In this study, we also assume that the APRT is a Weibull (α, γ) distributed variable. The density functions of the APRT can be written as

$$f(t_{av}) = \alpha\gamma t_{av}^{\alpha-1} e^{-\gamma t_{av}^{\alpha}} \quad \text{for } t_{av}>0 \tag{3}$$

where α and γ are the Weibull distribution's shape and scale parameters respectively. Please note that the shape parameter, α, has been assumed to be the same for both the NPRT and the APRT. Then P_f can be calculated by

$$P_f = \int_0^{\infty}\int_{t_{av}}^{\infty} f(\lambda,t) f(\gamma,t_{av}) dt dt_{av} = \int_0^{\infty} e^{-\lambda t_{av}^{\alpha}} \alpha\gamma t_{av}^{\alpha-1} e^{-\gamma t_{av}^{\alpha}} dt_{av} = \frac{1}{1+\lambda/\gamma} \tag{4}$$

Equation (4) shows that P_f is only determined by λ/γ, and has no relationship with α. Since parameters λ and γ are positive variables, λ/γ can be related to various factors by using an exponential link function as shown in Equation (5). Correspondingly, P_f can be written in the form of Equation (6).

$$\lambda / \gamma = e^{-\beta_h x_h} \tag{5}$$

$$P_f = \frac{1}{1+e^{-\beta_h x_h}} \tag{6}$$

In Equations (5) and (6), $\boldsymbol{\beta_h}$ and $\boldsymbol{x_h}$ are vectors of unknown parameters and explanatory variables, respectively, related to P_f. Variables discerned to affect drivers' task load and action complexity need to be included in $\boldsymbol{x_h}$.

Formulating the Probability of Encountering an Obstacle Vehicle P_o

A right-turn vehicle becomes an obstacle vehicle for the opposite through vehicles if its turning movement interrupts the smooth movement of the through vehicles. The right-turning vehicle's hazardous movement is normally caused by driver misjudgment. The misjudgment probability is closely related to the frequency of disturbances, such as legally crossing pedestrians/bicyclists, stop/deceleration of leading vehicles, conflicts with opposite left-turn vehicles and so on. However, an emerging disturbance may not necessarily lead a right-turning vehicle to an obstacle vehicle. Only disturbances occurring within a certain time period may cause the right-turning vehicle to become an obstacle. This time period is called "effective time". Since the occurrence of disturbances is discrete, nonnegative, and random, it is a Poisson arrival process. In such a process, intervals between arrivals are independent and follow the same exponential distribution (Pitman, 1993). Let's consider a disturbance j whose arrival rate is η_{dj}, and effective time is t_{dj}. Then, its density function is

$$f(t) = \eta_{dj} e^{-\eta_{dj} t} \qquad \text{for t>0} \tag{7}$$

According to the memoryless property of the exponential distribution, the probability of occurrence of a disturbance j within t_{dj} is independent of the elapsed time. Therefore, the probability of the right-turning vehicle to encountering the disturbance j within t_{dj} can be calculated by Equation (8).

$$P_{dj} = \int_0^{t_{dj}} \eta_{dj} e^{-\eta_{dj} t} dt = 1 - e^{-\eta_{dj} t_{dj}} \tag{8}$$

Since any of the disturbances can cause the right-turning vehicle to become an obstacle vehicle, the probability of a through vehicle to encountering an obstacle vehicle, P_o, is equivalent to the probability that at least one disturbance occurs within the effective time period. Therefore, P_o can be expressed as follows.

$$P_o = 1 - \sum_j (1 - P_{dj}) \tag{9}$$

Replacing P_{dj} by Equation (8), a simpler form of P_o can be obtained as shown in Equation (10)

$$P_o = 1 - e^{-\sum_j \eta_{dj} t_{dj}} \tag{10}$$

In Equation (10), $\sum_j \eta_{dj} t_{dj}$ should always be positive and be affected by a set of variables. Thus an exponential link function can be employed to reflect the effects of explanatory factors as shown in Equation (11).

$$\sum_j \eta_{dj} t_{dj} = e^{\boldsymbol{\beta}_o \mathbf{x}_o} \tag{11}$$

Then P_o becomes

$$P_o = 1 - e^{-e^{\boldsymbol{\beta_o x_o}}} \tag{12}$$

In Equations (11) and (12), $\boldsymbol{\beta_o}$ and $\boldsymbol{x_o}$ are vectors of unknown parameters and explanatory variables of disturbance frequencies respectively. $\boldsymbol{\beta_o}$ does not change with locations, while $\boldsymbol{x_o}$ varies from place to place.

The Integrated Formulation of the AG Accident Risk Model

Replacing P_o and P_f in Equation (1) by Equation (6) and Equation (12) respectively, and adding subscripts denoting intersection (i) and leg (k), we get an integrated AG accident risk model formulation as shown in Equation (13). We can see that the model contains not only road environmental related factors, but also human related factors. This is the main distinction from most existing models.

$$P_{AGik} = P_{oik} P_{fik} = \frac{1 - e^{-e^{\boldsymbol{\beta_o x_{oik}}}}}{1 + e^{-\boldsymbol{\beta_h x_{hik}}}} \tag{13}$$

Estimation Strategy

To simplify the problem, it is assumed that vehicles within a traffic stream have consistent AG accident risk – P_{AGik}. Then, the number of accidents that occur within this stream follows a binomial distribution,

$$P(n_{ik}) = \binom{f_{ik}}{n_{ik}} P_{AGik}^{n_{ik}} (1 - P_{AGik})^{f_{ik} - n_{ik}} \tag{14}$$

where f_{ik} : through traffic volume of intersection i, leg k.

n_{ik} : number of AG accidents occurred within f_{ik}.

Since an AG accident is normally a very rare occurrence, P_{AGik} should be very small, while traffic volume f_{ik} is very large. Consequently, Poisson distributions can be used as very good approximations to binomial distributions (Pitman, 1993):

$$P(n_{ik}) = \frac{m_{ik}^{\ n_{ik}} \cdot e^{-m_{ik}}}{n_{ik}!} \tag{15}$$

with Poisson distribution parameter

$$m_{ik} = E(n_{ik}) = f_{ik} \cdot P_{AGik} \tag{16}$$

Poisson distribution models have been commonly used for predicting total numbers of accidents. They are usually the fist choice when modeling traffic accidents because of the nonnegative, discrete and random features of accidents. Poisson models, however, have only one distribution parameter, requiring that the distribution's expectation and the variance be identical. However, in most of cases, accident data are overdispersed, and the applicability of the Poisson models is therefore limited. An easy way to overcome this difficulty (i.e. the mean must be equal to the variance) is to add an independently distributed error term, ε_{ik}, to the log transformation of Equation (16). That is:

$$\ln m_{ik} = \ln(f_{ik} P_{AGik}) + \varepsilon_{ik} \tag{17}$$

Assume $\exp(\varepsilon_{ik})$ is a Gamma distributed variable with mean 1 and variance δ. Substituting Equation (17) into Equation (15) yields

$$P(n_{ik} \mid \varepsilon_{ik}) = \frac{e^{(-f_{ik}P_{AGik}\exp(\varepsilon_{ik}))} \cdot (f_{ik} P_{AGik} \exp(\varepsilon_{ik}))^{n_{ik}}}{n_{ik}!} \tag{18}$$

Integrating ε_{ik} out of Equation (18), we can directly derive a negative binomial distribution model as the following:

$$P(n_{ik}) = \frac{\Gamma(n_{ik} + \theta)}{\Gamma(n_{ik} + 1)\Gamma(\theta)} \left(\frac{\theta}{f_{ik} \cdot P_{AGik} + \theta}\right)^{\theta} \left(\frac{f_{ik} P_{AGik}}{f_{ik} \cdot P_{AGik} + \theta}\right)^{n_{ik}} \tag{19}$$

where $\theta = 1/\delta$. The expectation of this negative binomial distribution equals the expectation of the Poisson distribution shown in Equation (16). Its variance is changed to be

$$V(n_{ik}) = E(n_{ik})[1 + \delta E(n_{ik})] \tag{20}$$

Since δ can be larger than 0, the constraint of the mean equaling the variance in the Poisson model is released. Therefore, the negative binomial distribution can deal with overdispersed data. By applying accident observations to Equation (19), the risk model can be calibrated using the maximum likelihood estimation.

DATA

About 150 four-legged signalized intersections were randomly selected within the Tokyo Metropolitan area at the beginning of this study. This selection was based only on considerations of intersection size, surrounding land use pattern, and crossing angles (vertical or skewed) of the approaches. Intersection accident histories were not considered. The purpose of such a selection was to obtain samples representing the normal situations of intersection traffic safety in Tokyo.

Since the occurrence mechanism of AG accidents was considered in our risk model, very specific data, such as AG accident number of each approach, traffic volume by direction, surrounding land use pattern and etc., were needed to calibrate the model. The existing accident data, however, were too aggregated to meet our needs. Thus, all accident data used in this study were obtained from the original accident records, the first-hand documents with site figures and specific descriptions about each accident. To guarantee the quality of the accident data, the number of accidents at each intersection approach was verified with the accident map made by the Department of Construction. Since some of the sample intersections did not have complete original accident records or have various traffic regulations, only 81 intersections qualified for this study.

For the current study, the unit of observation was defined as an intersection approach (leg) and the time period was 4 years, from 1992 to 1995. All the applicable AG accidents were cataloged according to their movements before collisions, and assigned to the corresponding approaches, to which the through vehicles belonged. Traffic flow data were obtained from reports of annual site surveys ("Traffic", 1992-1995), conducted by the Tokyo Metropolitan Police Department, and highway census data ("Report", 1997). Traffic control information and safety improvement histories were extracted from the corresponding database and documents. Road and environment related factors were selected according to the findings of previous studies and our logical inference. For each observation, a total of 72 possible explanatory variables, affecting either P_o or P_f, were collected or converted from other variables.

For convenient variable interpretation, specific terms such as entering approach, opposite approach and so on are used and the illustration of these terms is given in Figure 1.

ESTIMATION RESULTS AND DISCUSSION

The AG accident risk model, shown in Equation (13), is estimated by MLE. The log-likelihood function used for model estimation is given in Equation (21).

$$l(\boldsymbol{\beta_h}, \boldsymbol{\beta_o}, \theta) = \sum_{i=1}^{115}\sum_{k=1}^{4} \ln\left(\frac{\Gamma(n_{AGik}+\theta)}{\Gamma(n_{AGik}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{ik}\cdot\frac{1-e^{-e^{\boldsymbol{\beta_o x_{oik}}}}}{1+e^{-\boldsymbol{\beta_h x_{hik}}}}+\theta}\right)^{\theta}\left(\frac{f_{ik}\cdot\frac{1-e^{-e^{\boldsymbol{\beta_o x_{oik}}}}}{1+e^{-\boldsymbol{\beta_h x_{hik}}}}}{f_{ik}\cdot\frac{1-e^{-e^{\boldsymbol{\beta_o x_{oik}}}}}{1+e^{-\boldsymbol{\beta_h x_{hik}}}}+\theta}\right)^{n_{AGik}}\right) \qquad (21)$$

In total, 19 explanatory variables were found to significantly affect the AG accident risk at the p=0.15 level. Of the 19 variables, 9 had impacts on P_f and 10 had impacts on P_o. The estimation outline information is given in Table 1. The likelihood ratio index was calculated according to Equation (22), in which $l(\boldsymbol{\beta}_c, \theta)$ represents the log-likelihood value at convergence, and $l(\boldsymbol{C}, \theta)$ denotes the log-likelihood value obtained when assigning zeros to all the coefficients for explanatory variables in $\boldsymbol{\beta}_c$ except those corresponding to the constant terms.

$$\rho^2 = 1 - \frac{l(\beta_c, \theta)}{l(\mathbf{C}, \theta)} \tag{22}$$

Table 1 Fitness of the AG accident risk model

Sample number: 324
Log likelihood at convergence, $l(\beta_c,\theta)$: -480.38
Log likelihood with constants only, $l(\mathbf{C},\theta)$: -875.40
Likelihood ratio index, ρ^2: 0.451

Factors Affecting P_f

In Table 2, factors affecting the probability of a through-vehicle driver's reaction failure, P_f, are listed with the estimated coefficient values and their significant levels (shown by the *t*-ratio). The sign of each coefficient indicates the effect direction, increasing (positive) or decreasing (negative), on the AG accident risk. Four explanatory variables were found to decrease the AG accident risk and five were discerned to increase it.

The principle for selecting causal factors in β_h was whether they affected drivers' information load for process, action complexity and ease of perceiving dangers. Since the number of turning vehicles is proportional to the lane-change frequency of an approach, more left-turning vehicles should require more attention from through-vehicle drivers on the approach. In this case, the attention of the through-vehicle drivers may be detracted from the opposite right-turning vehicles. This results in a shorter APRT for through-vehicle drivers, and a corresponding increase in P_f. (Actually, the right-turning volume of the entering approach was also expected to have a similar effect on the attention of through-vehicle drivers. However, it did not turn out to be significant, possibly because of its correlation with the opposite right-turning volume.) Intersections in the central business district (CBD) may have higher levels of visual noise that detract drivers' attention. Thus, intersections located in the CBD had a higher P_f. Motorcycles tend to travel on the left side of automobile flows. This makes it difficult for motorcycle drivers to see right-turning vehicles. Thus, the APRT of motorcycle riders tend to be shorter than that for drivers of other vehicles. There is a similar effect from additional right-turn lanes in the opposing approach. Vehicles on the outside right-turn lanes may block the detection of vehicles on the inside right-turn lanes. If an inside-lane vehicle that is blocked from detection hazardously makes a right turn, the APRT for the arriving through-vehicle driver may be very short. The effect of the speed limit of the entering approach on P_f is obvious. Since stop distance is proportional to vehicle speed, the higher the speed, the shorter the APRT a driver can receive. A shorter APRT implies a higher P_f.

Table 2 Estimation results of factors affecting P_f in the AG accident risk model

Parameters in P_f model (β_h)	Estimate	t-ratio
Constant	-13.739	-13.175
Left-turn volume in thousands of the entering approach	0.030	1.044
Average time headway in seconds of through traffic flow of the entering approach	-0.018	-1.486
Speed limit of the entering approach	0.029	2.430
Large vehicle ratio of the entering approach	-0.017	-1.332
Total entering lane number of the entering approach	-0.460	-4.191
Motorcycle ratio of through traffic at the entering approach	2.411	1.070
Angle of the entering approach and opposite approach (0 if within ±30°, 1 otherwise)	-1.451	-1.816
The existence of more right-turn lanes (1 if have more than 2 right-turn lanes, 0 otherwise)	0.513	2.161
Intersection location (1 if in CBD, 0 otherwise)	1.503	1.660

Similarly, we can interpret the four decreasing factors by observing their contributions to the APRT/NPRT ratio. Leading vehicles normally restrict a following vehicle driver's sight. A longer gap between two consecutive vehicles can reduce such an effect. Thus longer average time headway for through traffic implies a better sight field. Similarly, the width of the entering approach is proportional to the number of lanes. The wider the entering approach, the better vision a through-vehicle driver may have. Since a better vision corresponds to a larger APRT, a decreasing effect for these two factors is expected. The angle of the entering approach and through approach was also found to decrease P_f. People tend to think that irregular-shaped intersections contain more complex information than regular-shaped intersections, and the increased complexity should have increasing effect on the NPRT. If, however, the existing angle may seriously reduce through-vehicle speed, and hence increase the APRT, a net decreasing effect on P_f is not impossible. In this way the effect of a large-vehicle ratio on the entering approach can be explained. Large vehicles, such as trucks or buses, block the vision of following vehicles and hence shorten the APRT. On the other hand, drivers tend to keep a longer distance from a leading large vehicle in order to maintain a reasonable sight distance, which may result in a longer APRT. The net effect, however, may depend on driver behavior as well as intersection service level.

Factors Affecting P_o

The factors affecting P_o are listed in Table 3. Again the signs of the estimated factors are consistent with their effects on P_o. Of the 10 explanatory variables, six have an increasing effect and four have a decreasing effect on P_o.

Most of the intersections are of regular-shape, i.e. approaches cross perpendicularly. Drivers have become used to such intersections, and tend to drive based on their experience at regularly-shaped intersections. Hence their judgments and actions may be less exact when driving at irregularly-shaped intersections. Consequently, the angle of the opposing approach and the right approach increases P_o. The increasing effect of the opposing-approach slope may be due to the less stable speed and poor sight angle of the right-turning vehicles. For right-turning vehicle drivers, whether or not to conduct the right-turn movement depends on the through-traffic headway of the entering approach. If the headway is large, conflicts between the opposing right-turn flow and the through traffic flow may be more frequent. In another case, when right-turn flow is heavy, delay time for right-turning vehicles can be longer. Longer delay time may encourage risky right-turn behavior. Thus it is easy to understand why longer through-traffic headways or more right-turning vehicles increase P_o. The result that an increase in median width increases P_o seems to contradict common sense. However, if we note that a wider median worsens the sight angle of the right-turning drivers, the increasing effect becomes understandable. Similarly, if the angle of the entering approach and the opposing approach is beyond ±15°, right-turning vehicle drivers have difficulties judging the movement of opposing through vehicles and therefore are more likely to make mistakes.

Since four-phase control separates right-turn green time from through traffic green time, conflicts between through traffic flow and opposing right-turn flow can be significantly reduced. If we change a signal's control pattern from two-phase control to four-phase control, AG accidents can be significantly decreased. The existence of a pedestrian overpass at the right approach also reduces P_o as the conflicts between pedestrian flow and right-turn flow are sufficiently lowered. When there are more through lanes on the entering approach, right-turning vehicle drivers from the opposing approach tend to be more conservative as they know that it takes longer to complete the right turn and the chance to find an acceptable gap is rare. Consequently we found a lower P_o for approaches with more through lanes. The finding that intersections located in the CBD had a lower probability of encountering an obstacle vehicle was consistent with the findings of Poch and Mannering (1996) and Wang *et al* (2002). This finding can be attributed to a number of factors including long-term efforts toward safety improvement and stricter enforcement of traffic regulations in CBD areas.

Table 3 Estimation results of factors affecting P_o in the AG accident risk model

Parameters in P_o model (β_o)	Estimate	t-ratio
Constant	-3.883	-4.445
Through lane number of the entering approach	-0.225	-1.715
Angle of entering approach and opposite approach (0 if within ±15°, 1 otherwise)	0.329	1.661
Slope of the opposite approach (0 if within ±3%, 1 otherwise)	0.308	1.448
Angle of opposite approach and right approach (0 if within 75° and 105°, 1 otherwise)	0.273	2.177
Intersection location (1 if in central business district (CBD), 0 otherwise)	-1.688	-1.813
Signal control pattern (0 for two-phase control, 1 for four-phase control)	-0.431	-1.800
Pedestrian overpass at right approach (1 if there is, 0 otherwise)	-0.438	-1.307
Right-turn traffic volume in thousands (4 years) of the opposite approach	0.179	6.014
Average time headway in seconds of through traffic of the entering approach	0.074	5.119
Road median (0 if none, 1 if less than 2 meters wide, and 2 if wider than 2 meters)	0.566	5.131

Other Factors Estimated in the Model

The reciprocal of the negative binomial dispersion parameter, θ=3.685, with t=3.143. This implies that our choice of using negative binomial estimation was correct. Along with the coefficients, average values of both the probability of encountering an obstacle vehicle (P_o) and the probability of the through-vehicle driver's failure (P_f) were also estimated and are shown in Table 4. The average probability of encountering an obstacle vehicle (P_o) was estimated as 0.123, more than 723,000 times higher than the estimated probability of driver failure of 1.7E-6. This explains why obstacle vehicles were often encountered at intersections, but very few AG accidents actually occurred. Drivers have very low failure probability in dealing with obstacle vehicles.

Table 4 Estimation results of other factors in the AG accident risk model

Other Parameters in the model	Estimate	t-ratio
Reciprocal of negative binomial dispersion parameter ($\theta=1/\alpha$)	3.685	3.143
Average probability of encountering an obstacle vehicle (P_o)	0.123	1.391
Average probability of the failure of through vehicle drivers (P_f)	1.70E-06	1.474

SUMMARY

The increasing trend of traffic accidents makes it an urgent task to find effective countermeasures against traffic accidents in Japan. To assess the potential utility of various countermeasures, we need models to estimate the possible changes of traffic accident risks resulting from such improvements. This paper addressed this practical issue by applying a new methodology for intersection AG accident modeling.

Unlike most existing accident models, the AG accident risk model developed here considered the occurrence mechanism of intersection AG accidents. Based on a microscopic analysis of hundreds of original records of intersection AG accidents, we found that the occurrence of AG accidents was usually due to the hazardous turning movement of opposing right-turn vehicles and the ineffective reaction of arriving through-vehicle drivers. A right-turning vehicle becomes an obstacle vehicle when its turning movement interrupts the smooth movement of opposing through vehicles. For a randomly selected vehicle in the through traffic flow of an intersection approach, the probability of having an AG accident is the product of the probability of encountering an obstacle vehicle (P_o) and the probability of its driver failing to respond effectively (P_f), as P_o and P_f are usually independent.

Both P_o and P_f were formulated based on their probabilistic characteristics. Since the probability of drivers' failure was formulated based on their perception reaction time distribution, human effects, which account for more than 95% of accidents, were clearly taken into account. Such quantitative evaluation results on human effects are very desirable for countermeasure selections.

The AG accident risk model was successfully estimated by a modified negative binomial regression. The estimated negative binomial distribution parameter was found to be significantly different from zero, showing that the data were over dispersed and the Poisson regression was inappropriate. Several explanatory variables were found to affect AG accident risk significantly through P_o or/and P_f. Most of the estimation results were consistent with our expectations, and this indicated that our modeling methodology was reasonable.

Since we did not simply use the canonical linear or log-linear formulation, factors affecting both P_o and P_f but in different directions could also be reflected. These estimation results may help traffic engineers evaluate the effects of accident causal factors quantitatively and effectively. However, further studies are needed for the temporal and spatial transferability of the model before applying it in practice.

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