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Impact of vehicle speeds and changes in mean speeds on per vehicle-kilometer traffic accident rates in Japan

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ABSTRACT

Speed and speed variation are widely believed to be key issues in the understanding of traffic accidents. However, there has not been a substantial amount of research that focuses on the interaction between the mean speed and the change in the mean speeds. In this paper we use a five-minute continuous monitoring data of the mean speed on an expressway in Japan. Applying a two dimensional additive Poisson model, we show that not only mean speeds but also changes in mean speeds affect per vehicle-kilometer traffic accident rates. The highest probability of an accident occurs when speed reduces from 110 to 85 km/h. Another area of high accident probability occurs when the average speed increases from 65 to 90 km/h. In addition, we found that accident rates are higher when there is sunny weather, rather than when it is cloudy.

1. Introduction

It is important to decrease the rate of traffic accidents to reduce not only human casualties but also medical expenses, damages of vehicles and road facilities, congestion due to accidents, and other economic losses (such as losses of production). To illustrate this, in the Netherlands—a relatively safe country—the damages due to accidents were estimated to be 12.2–14.5 billion EUR, which is approximately 2% of their GDP [1]. Therefore, policy makers, road authorities, and traffic management agencies have been working on accident reduction.

Researchers have conducted numerous studies to investigate the factors associated with traffic accidents. Speed is widely believed to be a key factor for understanding traffic accident rates and accident severity [2,3]. High speeds reduce the drivers' ability to respond when necessary because drivers' need time to process information, decide whether to react, and finally execute a reaction if required. Because braking and reaction distances are proportional to the square of speed [4], risk increases drastically with speed. Therefore, the possibility of avoiding a collision decreases with an increase in speed. In addition, the severity of an accident increases with speed, because energy also increases quadratically with respect to speed ($E = 1/2MV^2$). On the other hand, in the case of congested conditions, the collision probabilities are relatively high as the inter-vehicular distance and time are often short. Therefore, the relationship between the mean speed and the accident rates per vehicle-kilometer is unclear.

Traffic volume changes over time. If this volume exceeds the capacity, the mean speed decreases; subsequently, if the traffic volume decreases, the mean speed increases. Real-time speed variations among vehicles and/or differences between the upstream and the downstream speeds are also considered to be the fundamental factors that influence the occurrence of accidents (i.e., accident rates) [5–8]. When the rate of variation in speed increases, it is imperative for the drivers to adjust their vehicle speed more frequently; in this case, the drivers are more likely to make a misjudgment while maintaining a safe separating distance from the other vehicles.

To the best of our knowledge, in the previous research, the mean speed and change in the mean speed or variance of speeds are treated as separate variables. However, it is possible that both variables interact, for example, because at high speeds, the changes in the vehicle speed can be more risky than those at relatively low speeds. On the other hand, it is possible that at high but constant speeds, the accident rates are relatively low. In this study, we, therefore, apply a two-dimensional model to consider an interaction between the mean speed and its change over 5-min intervals.

To model real-time accident risks and to analyze rare events in general, researchers often make estimates using the Poisson and related models [9,10]. An additive Poisson model has been applied [12] to consider the nonlinear relationship between speed and accident risk [11]. However, this model does not predict the correlation (and thus the cross effects) between speed and speed change. A two-dimensional additive Poisson model can provide a solution to this problem; however, to the best of our knowledge, this model has not been applied to estimate

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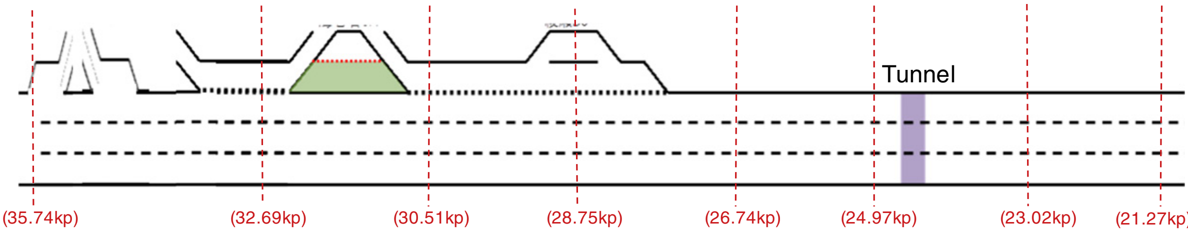

Fig. 1. Section structure of the part of the Tomei Expressway included in our study.

the effect of the interaction between the mean speed and the change in the mean speed on the accident risks.

The objective of this study is to bridge these gaps. More specifically, we adopt 5-min intervals of continuously monitored mean speed data from an expressway in Japan and analyze the impacts of mean speed and its change in the 5-min interval at the occurrence of a crash over a given segment of motorway on the per vehicle-kilometer accident rates by applying a two-dimensional additive Poisson model.

In Section 2, we provide an overview of the previous research in this area, as well as show the main gaps in literature, allowing us to position our contribution to the literature. In Sections 3 and 4, we describe our method and the obtained data, respectively. In Section 5, we present the results of our study, and in Section 6, we summarize our main conclusions.

2. Overview of the literature, gaps, and added value of this paper

In this section, we provide an overview of the literature that discusses the relationship between the vehicle speed and the number of accidents, as well as crash prediction modeling.

Baruya [13] reviewed studies carried out between 1949 and 1994. On the basis of an approach presented by Finch et al. [2], Baruya concluded that a decrease in speed by 1 mph reduces the accident rate by 3.7 (motorways)–5.7% (rural roads).

Since 2001, real-time data has been used to predict the occurrence of crashes. Adbel-Aty et al. [5] showed that the variable that most significantly predicts crash occurrence is the 5-min (10 consecutive 30-s) average occupancy, defined by the proportion of an observational period during which the loop senses a vehicle, observed at the upstream station 5–10 min before crash occurrence, along with the 5-min coefficient of variation of speed observations at the downstream station during the same time interval. Golob et al. [6] showed the existence of a strong relationship between the traffic flow conditions, as obtained from 40 consecutive 30-s observations, and the likelihood of traffic accidents (crashes), in terms of the type of crash. The key traffic flow conditions that affect safety are the mean traffic volume, median speed, and temporal variations in the traffic volume and speed. However, in a study on the accident rates in Southern Californian freeways, Kockelman and Ma [14] did not find a relationship between changes in the 30-s speed patterns prior to crash occurrences. Yeo et al. [7] defined section-based traffic states as follows: free flow (FF), back of queue (BQ), bottleneck front (BN), and congestion (CT). They then determined the traffic states of all the freeway sections on the basis of the speeds at the upstream and downstream ends of each section. The results of their analysis show that the accident rates in the BN, BQ, and CT states are approximately five times higher than the accident rate in the FF state. Wang et al. [15] studied real-time crash prediction for weaving segments. Higher speed differences between the beginning and end of the weaving segments result in higher crash risks. In addition, wetness on pavement surfaces was found to increase the crash risk by 77%. Using Bayesian logistic regression models, Wang et al. [16] showed that the logarithm of the vehicle count, average speed in a 5-min interval, and visibility are significant factors that affect the occurrence of crashes on expressway ramps.

More recently, statistical methods that take rare events into consideration have improved, resulting in a better understanding of traffic crashes. We provide some examples, presenting only the models (and not the results). Ma et al. [17] applied a multivariate Poisson-lognormal regression model to take crash injury severity simultaneously into account. Mothafer et al. [18] developed a multivariate Poisson gamma mixture model. However, speed was not included in these analyses. Hyodo et al. [19] analyzed the per vehicle-kilometer traffic accidents in the following three traffic phases: free flow, synchronized flow, and wide moving jam, depending on the flow-density relationship, and they applied a Poisson regression model. Zhang et al. [12] applied an additive Poisson model to consider the nonlinear relationship between an explained variable and the explaining variables. However, the dependent variable in their analysis was the number of traffic accidents per road-kilometer. They did not model the per vehicle-kilometer accident rates. In addition, they did not include either speed or interactions between the independent variables in their analysis.

Next, we discuss recent research that is more related to our work and briefly summarize the main findings. Imprialou et al. [11] applied Poisson regression to study accidents of different types, using the traffic volume, speed, road geometry, and spatial correlations as variables. They showed that the number of accidents, divided by the vehicle-hours per kilometer, had a convex relationship with speed. Considering this nonlinear relationship, Zhang et al. [20] and Zhang et al. [12] applied an additive Poisson model to solve the problem. However, they did not include speed and speed change in their analysis. By applying a rule-based classifier analysis, Pirdavani et al. [21] showed that crash occurrence has a significant correlation with the traffic volume, average speed, the standard deviation of speed at the upstream loop detector station, and the difference in the average speed at the upstream and downstream loop detector stations. We believe that this method is useful in analyzing the variables that are related to the accident rates. However, it is difficult to calculate the elasticity of these variables in the context of rule-based models.

Table 1
Descriptive statistics of four explanatory variables.

	Min.	1st QT	Median	Mean	3rd QT	Max.	SD.
Traffic volume	1	213	252	255.6	302	523	67.0
Mean speed (km/h)	1	80.2	93	82.93	97.9	147	24.3
Speed change (km/h)	−116	−2.3	−0.10	−0.13	2.1	85.9	5.4
Large vehicle share	0.003	0.09	0.13	0.17	0.20	1	0.12

Table 2
Descriptive statistics of other variables (total: 142,284).

Variable		Counts	Share (%)
Occurrence of traffic accidents in 5 min	No	142,206	99.9
	Yes	78	0.1
Weather	Sunny	94,491	66.4
	Cloudy	38,536	27.1
	Rain	9257	6.5
Longitudinal gradient	Down	76,278	53.6
	Flat	11,143	7.8
	Up	54,863	38.6