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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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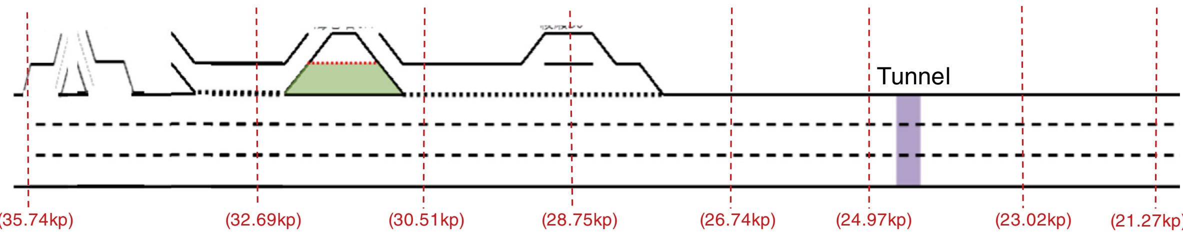

Fig. 1. Section structure of the part of the Tomei Expressway included in our study.

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

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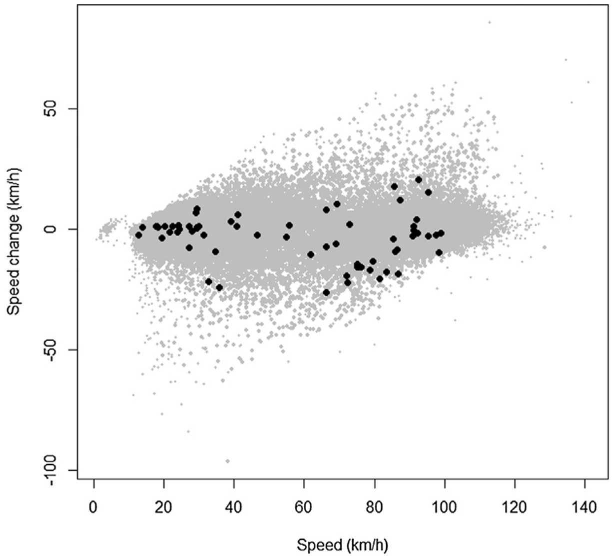

Fig. 2. Scatterplot of speed and speed change (black points show the occurrence of traffic accidents).

Our paper adds to the existing literature in two ways. First, in our analysis, we include the time-varying 5-min mean speed of the vehicles and the change in this speed using section-based monitoring data. Second, we include the interaction between the speed and the speed change using a two-dimensional additive Poisson model.

3. Methodology

We applied a generalized additive model (GAM) to consider and implement a nonlinear relationship between the dependent variables and the accident rates [22]. The GAM is a generalized linear model in which the linear predictor is given by the user as a specified sum of smooth functions of the covariates and a conventional parametric component of the linear predictor. As traffic accidents are rare events, we estimated the function using the Poisson model [22]. A one-dimensional model is expressed as follows.

$$\log(E(y_{it})) = s_1(x_{1it}) + s_2(x_{2it}) \tag{1}$$

Further, a two-dimensional model is expressed as follows.

$$\log(E(y_{it})) = s(x_{1it}, x_{2it}) \tag{2}$$

where $E(y_{it})$ is the expected value of the (independent) response variables y_{it} assuming a Poisson distribution, i is the section, t is the time, s_1 and s_2 are the smooth functions, and s is a thin plate smooth function of covariates x_1 and x_2. These models are typically fit using penalized likelihood maximization, where the model (negative log) likelihood is modified by adding a penalty for each smooth function, thus penalizing its "wiggliness." The smoothing parameter estimation problem is solved using the generalized cross-validation (GCV) criterion, and we obtain the degrees of freedom (the trace of the smoother matrix) and chi-square values. We refer to Wood [23] for additional information about this model.

In this paper, the dependent variable is the number of accidents that occur over a 5-min interval at each monitoring section. We use the mean speed and changes in the mean speed over 5 min, the share of large vehicles (see below), time of day, and weather (see Section 4) as covariates. To take the road geometric factors, such as the presence of a tunnel, ramp, or sag, into account, we included section dummies [24,25].

To obtain the per vehicle-kilometer traffic accident rates, the logarithm of vehicle kilometers for each section and time period is used as an offset [26]. In addition, because various combinations of multi-dimensional smooth functions are possible, we used the Akaike information criterion (AIC) to evaluate these models and selected the preferred models [27]. In order to examine the impact of speed change on the traffic accident rates, we present the following three models: (1) a model that only includes the mean speed, (2) a one-dimensional model that includes the mean speed and speed change separately, and (3) a two-dimensional model that includes both the mean speed and the speed change.

4. Data

Because traffic accidents are relatively rare events and we intend to analyze the relationship among speed, speed change, and traffic accidents, we selected the sections and times during which congestion and thus both high speeds and speed changes occur. We included data from weekends and holidays because in Japan, congestion occurs more during the weekends and holidays than on the weekdays, and more accidents occur on these days than on average.

We selected the Tomei Expressway section, between Atsugi and Yokohama-Machida (close to Tokyo), managed by Central Nippon

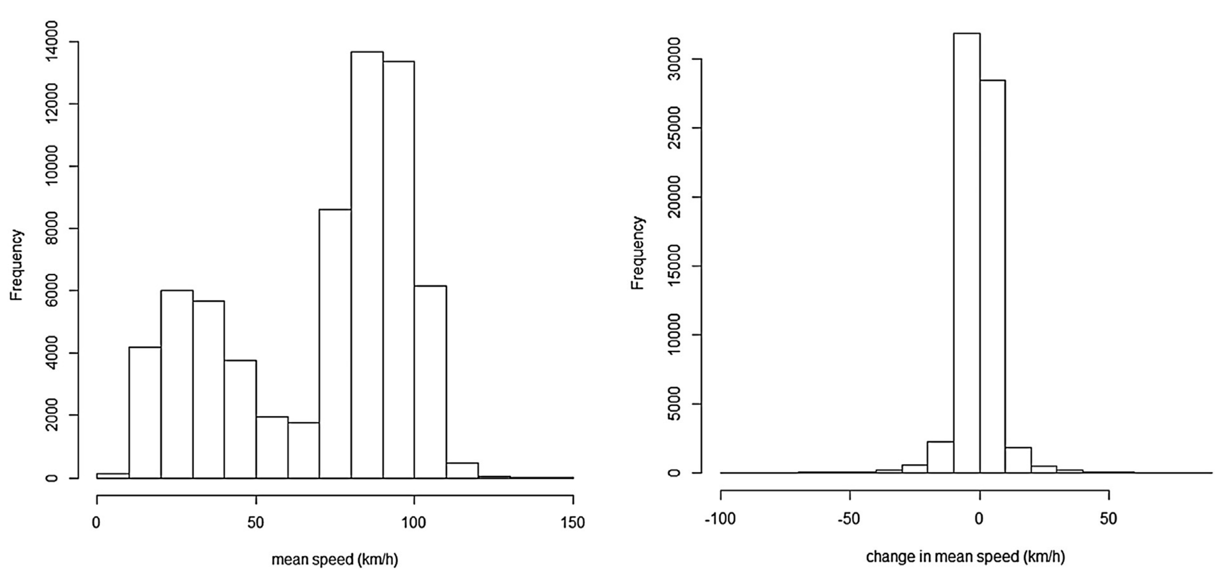

Fig. 3. Histogram of mean speed and its change over the 5-min interval. Left: mean speed (km/h), right: mean speed change over the 5-min interval.

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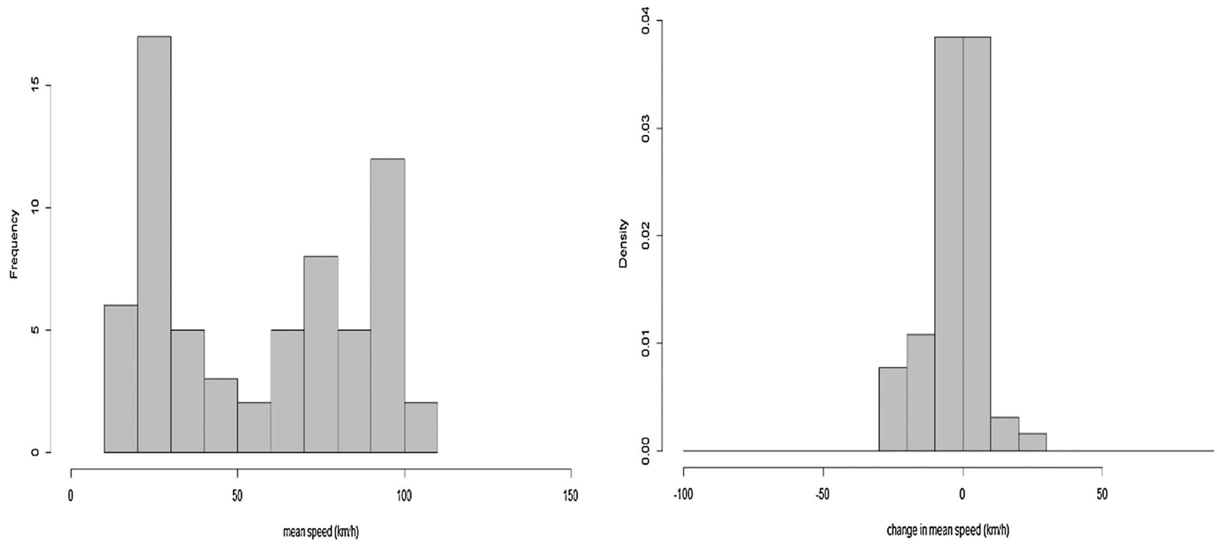

Fig. 4. Histogram of mean speed and its change over the 5-min interval when traffic accidents occur. Left: mean speed (km/h), right: mean speed change over the 5-min interval.

Table 3
Estimation results (additive Poisson model).

	Two-dimensional smooth		One-dimensional smooth		Without speed change	
	Coef.	z-Value	Coef.	z-Value	Coef.	z-Value
Intercept	−7.50	−6.57	−7.51	−6.66	−6.78	−6.21
Cloudy dummy (ref. sunny)	−1.15	−3.22	−1.16	−3.23	−1.17	−3.27
Rainy dummy (ref. sunny)	*−0.31*	−0.59	*−0.47*	−0.89	*−0.50*	−0.07
LR*	*0.31*	0.37	*0.37*	0.43	*0.51*	0.62
Time	−0.43	−5.78	−0.43	−5.86	−0.48	−6.61
Flat (ref. downgrade)	*−3.43*	0.00	*−3.67*	0.00	*−3.17*	0.00
Upgrade (ref. downgrade)	*0.50*	1.91	*0.68*	2.64	0.73	2.82
	edf**	Chi sq.	edf	Chi sq.	edf	Chi sq.
Smooth function						
s (speed, speed change)	17.91	119.1				
s (speed)			5.35	40.52	5.34	57.15
s (speed change)			5.40	34.75		
Sample size	142,286					
Deviance explained (%)	17.0	14.4	11.8			
AIC	1177	1192	1213			
AIC(0): null model	1327					

*LR: large-vehicle share. **edf: estimated degrees of freedom (the trace of the smoother matrix. See Wood [22] for details.)
It should be noted that s preceding a variable label indicates the application of a smooth function.
Italic indicates that the zero hypothesis cannot be rejected at the 5% significance level.
A null model is a model with only an intercept and no other variables.

Expressway Co. Ltd. (see Fig. 1). We analyzed traffic data across Sundays and holidays in 2013 and 2014, for the period 13:00–20:00 along both the inbound and the outbound directions. This choice was attributed to our observation that most congestion occurs between 13:00 and 20:00. In this road segment, there are eight traffic count points. The average length of each section is approximately 2 km[1]. The longitudinal gradients of these sections are divided into the following 3 categories: downgrade (at least 5 m per 1000 m), flat (less than 5 m per 1000 m), and upgrade (at least 5 m per 1000 m) gradients.

The speed and length of each vehicle is measured using double vehicle detection loops. Vehicles longer than 5.5 m are classified as large vehicles. The data is aggregated at intervals of 5 min, giving the traffic volume, mean spot speed, and the percentage share of large vehicles as part of the whole traffic volume. Along the freeway section, there is one motorway exit/ramp. Because of lack of data on intensities of specific time intervals, which we included in our analysis, we assume the intensities to be the same on both sides of the ramp. In other words, we assume that the volume of traffic leaving and entering the expressway is equal. Accident data, as well as weather conditions (sunny/cloudy/rain), were provided by Central Nippon Expressway Co. Ltd.[1]

Excluding the missing values, we used approximately 142,284 samples (observations refer to the 5-min time intervals) for the model estimations. Tables 1 and 2 show some statistics describing the road conditions[2]. The number of traffic accidents is 78, and data suggest that multiple accidents did not occur in the 5-min interval. Multiple

[1] The distance between the data collection points (around 2 km) might be too long for the analysis.

[2] An important question to be answered is "which 5-min period should be used as the explanatory variable"? The selection of this 5-min interval is based on the changes in the mean speed. If this change is less than 10 km/h, we use the same period as the explanatory variable. If the change in the mean speed decreases by more than 10 km/h (approximately 2 standard deviations of the mean speed change), we use the "before 5-min interval" as the explanatory variable. In addition, traffic accidents are divided into two types: (a) those involving only material damage and (b) those involving material damages in addition to injuries or fatalities. We also estimated a model using only accidents resulting in injury or death, despite only considering 21 cases. Interestingly, in the case of this model, only speed is statistically significant, and not speed change. This may be attributed to the low number of accidents.

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accidents will be observed if time is aggregated over a 1-h interval or more, for example, and not over the 5-min interval. As the dispersion (variance divided by mean) is 0.99, we used a Poisson model, and not a binomial model.

Fig. 2 shows a scatterplot of the mean speeds (x-axis) and changes in the mean speed over 5-min intervals (y-axis). As expected, the mean speed and the change in the mean speed are correlated; the correlation coefficient is 0.18.

Figs. 3 and 4 show the histograms of the mean speeds and their changes over the 5-min interval for all the observations, as well as the histograms obtained during the occurrence of traffic accidents.

Comparing both the figures, we find that traffic accidents are more likely to occur when the mean speed is low (10–30 km/h), probably owing to congestion, and at medium speeds (60–90 km/h). In addition, traffic accidents are more likely to occur when the change in speed is relatively large.

However, in this simple histogram, we cannot analyze the interaction between the mean speed and its change over the 5-min interval. Therefore, as mentioned above, a two-dimensional additive model is applied.

5. Results and discussion

The estimation results are shown in Table 3 and Fig. 5. As the dummy for the ramps/intersections was not statistically significant, we omitted it in the model. Fig. 5 shows the estimated Poisson distribution parameter as a two-dimensional function of speed and speed change using a logarithmic scale. This parameter represents the logarithm of the per vehicle-kilometer accident rate.

Not only speed but also speed change affects the occurrence of accidents. The highest probability of accident is observed when the speed is around 85 km/h, after decreasing from 110 km/h in the previous time interval (5-min before). Another area of high crash probability, which is clearly visible in Fig. 5, is observed when the speed increases to nearly 90 km/h from 65 km/h in the previous 5-min time interval.

On the basis of the estimated model, we re-estimated the number of accidents and compared them with the real number of accidents by year and direction (inbound/outbound), the results of which are summarized in Table 4. The maximum difference is 8 (inbound, 2014), and the maximum difference for the row or column totals is 3 (inbound). These differences are acceptable.

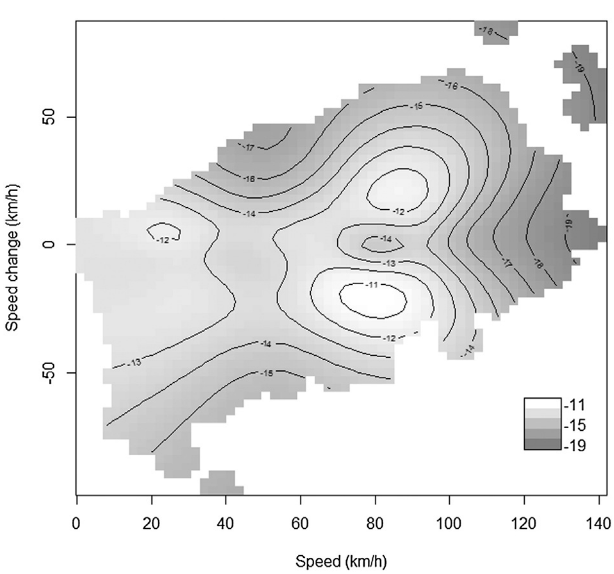

Fig. 5. Estimated parameter (logarithm of per vehicle-kilometer traffic accident rate) as a two-dimensional function of speed and speed change.

Table 4
Validation of the model.

Year direction	2013	2014	Total
Inbound	33/28	29/37	62/65
	(5)	(8)	(3)
Outbound	9/11	7/2	16/13
	(2)	(5)	(3)
Total	41/39	37/39	78/78
	(2)	(2)	(0)

Estimated number of accidents by model/actual number of accidents (difference).

Fig. 6 shows the mean accident rates (per billion vehicle-kilometers) for speed and speed change combinations. We arbitrarily (based on the visual representations) distinguish six areas, based on one or both variables: (1) speed below 35 km/h, (2) speed between 35 and 70 km/h, (3) speed between 70 and 100 km/h and speed change greater than 10 km/h, (4) speed between 70 and 100 km/h and speed change between −10 and +10 km/h, (5) speed between 70 and 100 and speed change below −10 km/h, and (6) speed above 100 km/h.

Fig. 6 shows that if the mean speed is less than 35 km/h, the per vehicle-kilometer accident rate is about two times higher than the overall average accident rate. In addition, if the mean speed is between 70 and 100 km/h and the speed change is less than −10 km/h (i.e., speed decreases by more than 10 km/h), the per vehicle-kilometer accident rate is about 17 times higher than the overall average accident rate. However, if the mean speed is between 70 and 100 km/h and the speed change is between −10 and +10 km/h, the per vehicle-kilometer accident rate is less than half the average value.

Accident rates are higher during sunny weather than when it is cloudy (Table 3). We theorize that this may be the result of less-skilled drivers driving more during the weekends when the sun is shining. Contrary to the findings of Wang et al. [15,16][3,4], we found that rainy weather did not significantly affect the per vehicle-kilometer traffic accident rate as compared to sunny weather (Table 3). Further research is needed to determine if this is truly the case, as well as to reveal the cause of a relatively high accident rate under sunny conditions.

6. Conclusion

In this study, by using real-time mean speed data and by applying a two-dimensional additive Poisson model, we show that not only the mean speeds but also changes in the mean speeds affect the per vehicle-kilometer traffic accident rates. The highest crash probability is observed in 5-min intervals, during which the mean speed reduces from nearly 110 to 85 km/h. Further, high crash probability is obtained when the average speed increases from 65 to 90 km/h. Accident rates are observed to be higher during sunny weather than when it is cloudy.

These results can be beneficial to road authorities and traffic management agencies, because our research is able to provide them with information pertaining to road conditions and high accident rates. For example, this information can be used to warn drivers about congestion ahead. In addition, this information can be useful to road authorities in order to adapt maximum speeds under specific conditions, when it is possible to dynamically change the maximum speed on a motorway.

There are some limitations to this study. In order to collect a large amount of traffic accident data under various traffic conditions, we choose a part of only one expressway, i.e., the Tomei Expressway, and select specific days and time periods. Therefore, it is unclear as to whether our results could also be applied to other freeway sections,

[3] We also collected data on the speed difference between the monitoring station data and the downstream station data. However, the mean speed and speed difference are highly correlated. Therefore, we did not use speed difference owing to collinearity problems [31].

[4] It should be noted that Wang et al. [15,16] did not estimate the per vehicle-kilometer traffic accident rates.

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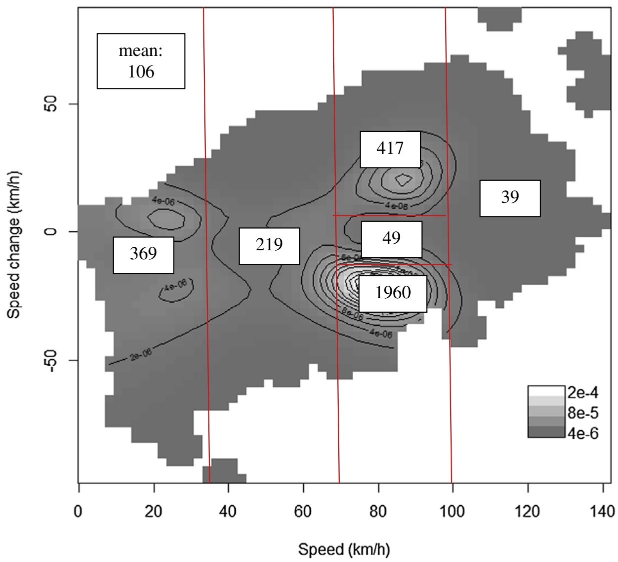

Fig. 6. Mean accident rates per one billion vehicle-kilometers for six speed and speed change classes: (1) speed below 35 km/h, (2) speed between 35 and 70 km/h, (3) speed between 70 and 100 km/h and speed change greater than 10 km/h, (4) speed between 70 and 100 km/h and speed change between −10 and +10 km/h, (5) speed between 70 and 100 and speed change below −10 km/h, and (6) speed above 100 km/h.

days, and time periods. In addition, we did not distinguish between accident types. For example, we did not differentiate between material damage under the conditions of the occurrence of accidents with injuries and/or fatalities, because of the low number of accidents in general and even lower number of accidents with injuries and fatalities (Xu et al. [28–30]—also see Section 2). Finally, we did not analyze the impact of warning systems on the driving behavior (speed and speed changes) and accident rates.

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References

[1] KIM (Kennisinstituut voor Mobiliteitsbeleid), Mobiliteitsbeeld 2015/Den Haag, Kennisinstituut voor Mobiliteitsbeleid, 2015 (in Dutch).

[2] D.J. Finch, P. Kompfner, C.R. Lockwood, G. Maycock, Speed Limits and Accidents, Department of Transport, TRL, Project Report PR 58, Transport research laboratory, 1994.

[3] F.T. Golob, W.W. Recker, V.M. Alvarez, Freeway safety as a function of traffic flow, Accid. Anal. Prev. 36 (6) (2004) 933–946, http://dx.doi.org/10.1016/j.aap.2003.09.006.

[4] SWOV, The relation between speed and crashes, http://www.swov.nl/rapport/Factsheets/UK/FS_Speed.pdf2012 accessed 16.06.02.

[5] M. Abdel-Aty, N. Uddin, A. Pande, M.F. Abdalla, L. Hsia, Predicting freeway crashes from loop detector data by matched case–control logistic regression, Transp. Res. Rec. 1897 (2004) 88–95, http://dx.doi.org/10.3141/1897-12.

[6] F.T. Golob, W. Recker, Y. Pavlis, Probabilistic models of freeway safety performance using traffic flow data as predictors, Saf. Sci. 46 (9) (2008) 1306–1333, http://dx.doi.org/10.1016/j.ssci.2007.08.007.

[7] H. Yeo, K. Jang, A. Skabardonis, S. Kang, Impact of traffic states on freeway crash involvement rates, Accid. Anal. Prev. 50 (2013) 713–723, http://dx.doi.org/10.1016/j.aap.2012.06.023.

[8] S. Roshandel, Z. Zheng, S. Washington, Impact of real-time traffic characteristics on freeway crash occurrence: systematic review and meta-analysis, Accid. Anal. Prev. 79 (2015) 198–211, http://dx.doi.org/10.1016/j.aap.2015.03.013.

[9] D. Lord, F. Mannering, The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives, Transp. Res. A Policy Pract. 44 (2010) 291–305, http://dx.doi.org/10.1016/j.tra.2010.02.001.

[10] L.F. Mannering, C.R. Bhat, Analytic methods in accident research: methodological frontier and future directions, Anal. Methods Accid. Res. 1 (2014) 1–22, http://dx.doi.org/10.1016/j.amar.2013.09.001.

[11] M.M.-I. Imprialou, M. Quddus, D.E. Pitfield, D. Lord, Re-visiting crash–speed relationships: a new perspective in crash modelling, Accid. Anal. Prev. 86 (2016) 173–185, http://dx.doi.org/10.1016/j.aap.2015.10.001.

[12] Y. Zhang, X. Jiang, A. Haghani, B. Haung, Exploring piecewise linear effects of crash contributing factors with a novel Poisson-mixed multivariate adaptive regression splines model, Transp. Res. Rec. 2515 (2015) 17–25 (DOI:10:3141/2515-03).

[13] A. Baruya, A Review of Speed–accident Relationship for European Roads, MASTER Project Report, R1.1.1, Transport research laboratory, 1997.

[14] M.K. Kockelman, J. Ma, Freeway speeds and speed variations preceding crashes, within and across lanes, J. Transp. Forum 46 (1) (2010) 43–61.

[15] L. Wang, M. Abdel-Aty, Q. Shi, J. Park, Real-time crash prediction for expressway weaving segments, Transp. Res. C 61 (2015) 1–10, http://dx.doi.org/10.1016/j.trc.2015.10.008.

[16] L. Wang, Q. Shi, M. Abdel-Aty, Predicting crashes on expressway ramps with real-time traffic and weather data, Transp. Res. Rec. J. Transp. Res. Board 2514 (2015) 32–38, http://dx.doi.org/10.3141/2514-04.

[17] J. Ma, K.M. Kockelman, P. Damien, A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods, Accid. Anal. Prev. 40 (2008) 964–975, http://dx.doi.org/10.1016/j.aap.2007.11.002.

[18] G.I.M.A. Mothafer, T. Yamamoto, V.N. Shankar, Evaluating crash-type covariances and roadway geometric marginal effects using the multivariate Poisson gamma mixture model, Anal. Methods Accid. Res. 9 (2016) 16–26, http://dx.doi.org/10.1016/j.amar.2015.11.001.

[19] T. Hyodo, T. Yoshii, Y. Takayama, Factor analysis of traffic accident occurrence risk by Poisson regression model on expressway, J. Traffic Eng. 34 (2014) 93–99 (in Japanese).

[20] Y. Zhang, Y. Xie, L. Li, Crash frequency analysis of different types of urban roadway segments using generalized additive model, J. Saf. Res. 43 (2) (2012) 107–114.

[21] A. Pirdavani, E. De Pauw, T. Brijs, S. Daniels, M. Magis, T. Bellemans, G. Wets, Application of a rule-based approach in real-time crash risk prediction model development using loop detector data, Traffic Inj. Prev. 16 (8) (2015) 786–791, http://dx.doi.org/10.1080/15389588.2015.1017572.

[22] N.S. Wood, Generalized Additive Models: an Introduction with R, Chapman & Hall/CRC, Boca Raton, FL, USA, 2006.

[23] N. Wood, Simon, fast stable restricted maximum likelihood and marginal likelihood estimation of semi-parametric generalized linear models, J. R. Stat. Soc. B 73 (1) (2011) 3–36, http://dx.doi.org/10.1111/j.1467-9868.2010.00749.x.

[24] National Highway Traffic Safety Administration (NHTSA), Analysis of Lane-change Crashes and Near-crashes, DOT HS 811 147, 2009.

[25] B. Goñi-Ros, V.L. Knoop, Y. Shiomi, T. Takahashi, B. van Arem, S.P. Hoogendoorn, Modeling traffic at sags, Int. J. Intell. Transp. Syst. Res. 14 (1) (2016) 64–74.

[26] Dalgaard, Peter, Rates and Poisson Regression, Introductory Statistics with R. Springer, New York, 2008 259–274, http://dx.doi.org/10.1007/978–0-387-79054-1_15.

[27] Y. Sakamoto, M. Ishiguro, G. Kitagawa, Akaike Information Criterion Statistics, D, Reidel Publishing Company, Dordrecht, 1986.

[28] C. Xu, A.P. Tarko, W. Wang, L. Pan, Predicting crash likelihood and severity on freeways with real-time loop detector data, Accid. Anal. Prev. 57 (2013) 30–39, http://dx.doi.org/10.1016/j.aap.2013.03.035.

[29] C. Xu, L. Pan, W. Wang, Z. Li, Identification of freeway crash-prone traffic conditions for traffic flow at different levels of service, Transp. Res. A Policy Pract. 69 (2014) 58–70, http://dx.doi.org/10.1016/j.tra.2014.08.011.

[30] C. Xu, W. Wang, L. Pan, F. Zhang, Development of a real-time crash risk prediction model incorporating the various crash mechanisms across different traffic states, Traffic Inj. Prev. 16 (1) (2015) 28–35, http://dx.doi.org/10.1080/15389588.2014.909036.

[31] S. Chatterjee, A.S. Hadi, Regression Analysis by Example, John Wiley and Sons, New York, 2006.

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