Risk Simulation Analysis of the Vehicle Velocity in Reduced Visibility Conditions at Bridge-Tunnel Transition Sections

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Abstract: Due to the characteristics of both highway bridge-tunnel structures and facilities, bridge-tunnel transition section (BTTS) is an environment ally precarious place heavily influenced by external factors, such as topography and local weather. This is truer in reduced visibility conditions, such as fog, when road traffic accidents increase dramatically. This paper presents an assessment of road traffic safety at BTTS in reduced visibility conditions. In line with research objectivity, we employ the 8-Degrees of Freedom (8-DoF) Motion Platform for Driving Simulator, owned by Tongji University (Shanghai, China), to test the motion parameters of eighteen drivers when they drive through BTTS. Such experiment serves to analyze the principal performance of their driving speed behavior on the one hand, and on the other, the characteristics of speed deviation at different visibility levels (VLs). The tested results reveal VL's effects on vehicle's running speed, operating speed, as well as speed coefficient of variation. In addition, based on Multinomial Logistic regression model, we propose the model of vehicle velocity risk control at different VLs at BTTS. The key findings include: 1)the higher the VL, the faster the average vehicle velocity; 2) when the visibility distance is 150 meters, drivers drive at a speed close to when they drive in sunny days; 3) VL generates considerable effects on the 85th percentile speed and speed coefficient of variation. Our findings provide support for conducting researches driving risk control.

Keywords: bridge-tunnel transition section (BTTS), visibility level (VL), driving simulation, vehicle velocity, driving risks.

1. INTRODUCTION

As one of the important modern engineering constructs functioning to shorten driving distance and optimize road linearity, bridge and tunnel is a common facility in mountain highway. Due to the characteristics of its structures and facilities, bridge-tunnel transition section (BTTS) is an environment ally precarious place heavily influenced by external factors, such as topography and local weather. This is truer in reduced visibility conditions, such as fog. When drivers drive through the BTTS, it is difficult for them to react quickly to the traffic environment and to decrease the speed properly. This fact is among the main causes of the dramatic increase of traffic accident at BTTS.

There have been substantial researches, both in China and around the global, on traffic safety issues at independent bridge, tunnel, and tunnel group. Related reports and writings cover a wide range of topics, including traffic accident prevention, temporal and spatial distributions of traffic accident, its situations, automotive types, road traffic injuries and mortality, economic loss, traffic congestion, early warning, and assessment of the traffic accident [1-6]. In contrast, studies on traffic safety issues at BTTS are limited in both quantity and topic. To be precise, most researchers focus on assessing the traffic safety [7-9], but few pay attention to the traffic environment [10], drivers' driving behaviors [11], operating speed [12], and characteristics of traffic flow [13].

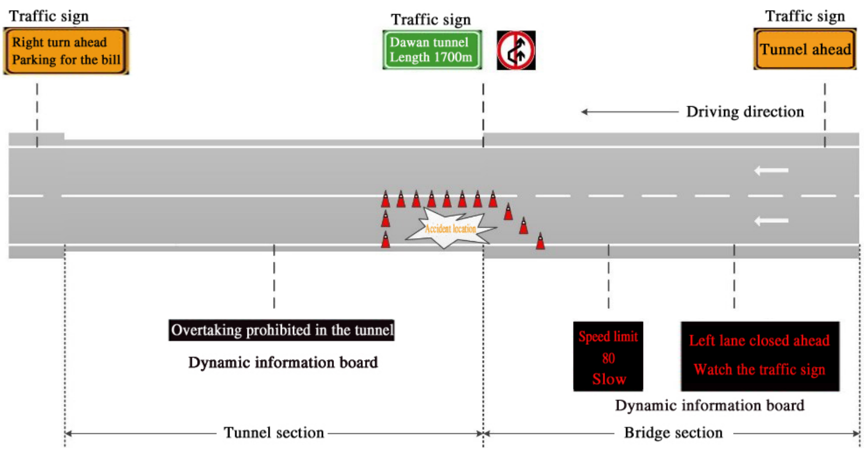
Findings from previous studies suggest that in reduced visibility conditions at BTTS, driving environment and speed changing are among the leading causes of traffic accidents [10]. From the perspective of driving simulation-based vehicle velocity risk studies, and treating the driving simulation technique as an efficient means for conducting experiment and analysis [14,15], this paper presents a risk simulation analysis of vehicle velocity in reduced visibility conditions (i.e. fog) at BTTS. It has significance and pragmatic values for our works on fixing expected running speed, expected vehicle safety distance, and criteria for setting speed limits in LV conditions, as well as for traffic safety improvement design.

2. Experiment Design and Data Analysis Methods

2.1. Scenario Design of the Road Segment for the Experiment

The road segment selected for the experiment is 3.0 kilometers in length, in which tunnel section and bridge are1.7 and 0.8 kilometers long respectively. The design speed for the overall road segment is 80 km/h. The carriageway, traffic line marking, and emergency lane are 3.75, 0.15, and 2.5 meters in width respectively. Figure 1 illustrates the detailed scenario design.

Figure 1: The scenario design of driving simulation experiment at BTTS



2.2. Visibility Level (VL) Setting

Drawn on the meteorological visibility theory, and the concept of visibility in foggy conditions defined by the transportation sector of China, our driving simulation experiment sets up four gradient levels of visibility. The visibility distance of each level is 50 meters, 100 meters, and 150 meters, in addition to sunny days, as indicated in Table 1.

Table 1: VL Setting

Reference No.	1	2	3	4
Visibility Level (VL)	N/A	150	100	50

2.3. Methods

The experiment adopts the UC-Win/Road driving simulation software package, and the assorted driving simulator to monitor and collect data of drivers' driving behavior. Figure 2 presents the experiment scenario.

A total number of eighteen people were selected to participate in the experiment, half of whom are professionally trained drivers. To ensure that the results of driving simulation experiment in reduced visibility conditions not be influenced by uncertain factors, the participant drivers have attained complete rest before the experiment got started. Pre-experiment works also include some brief training that we provided to them, so that they became fully cognizant as to how to operate the driving simulator correctly. The installation and testing of eye tracker ensued. This is followed up by a fiveminute free driving, to ensure that all the eighteen drivers have fully adapted themselves to the driving simulation scenario in foggy conditions prior to the commencement of the formal experiment.

Figure 2: Driving simulation experiment

2.4. Data Analysis Methods

In the driving simulation experiment, drivers were allowed to drive freely. Under such circumstance, we were able to examine the effects different VLs produced on several indicators including running speed, accelerated speed, and lane departure. These eighteen drivers performed differently at different VLs. The experiment examines the VL's effects on the running speed through the lenses of the variations of lane, speed, and the vehicle stability. By means of monitoring and collecting different indicator data of driving speed, accelerated and decelerated speed, steering wheel performance, lane departure, and lane shift, etc., we analyze drivers' principal driving behaviors, including their driving speed, accelerated speed, lane departure, etc. at BTTS at different VLs. Through analyzing vehicle's operating properties, we also propose the indicators of the characteristics of driving behaviors, fix criteria for safety risks assessment, frame risks assessment model, in addition to examine different VLs' quantitative relations with both the characteristics of driving behaviors and driving risks.

3. Properties of the Vehicle Velocity at Different VLs

3.1. Simulation Analysis of the Principal Properties of Speed

The abovementioned experiments conducted in the scenarios of different visibility conditions lead us to the formation of box plot of speed (Figure 3) and continuous plot of average speed (Figure 4). As the box plot shows, at each VL, the average speed rises notably along with the increasing of VL. In relatively reduced visibility conditions (e.g. visibility distance is between 50-100meters), however, the speed deviation appears to be minor. This is likely because the drivers' driving behaviors have been greatly influenced by the visibility conditions, and in turn chose to drive cautiously. In contrast, when the visibility distance reaches 150meters, the average driving speed gets faster, and the speed deviation is large. Thus, we infer that such visibility level is most likely to cause traffic accident.

Figure 3: Box plot of speed at different VLs

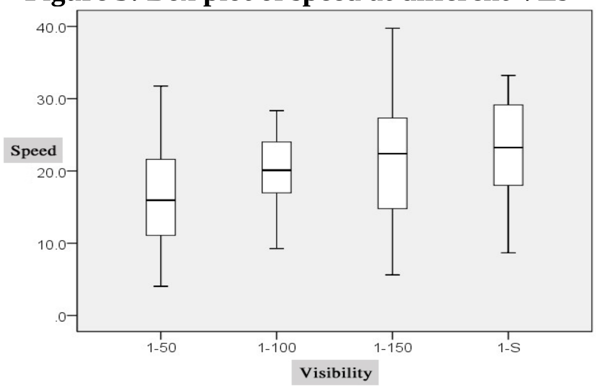
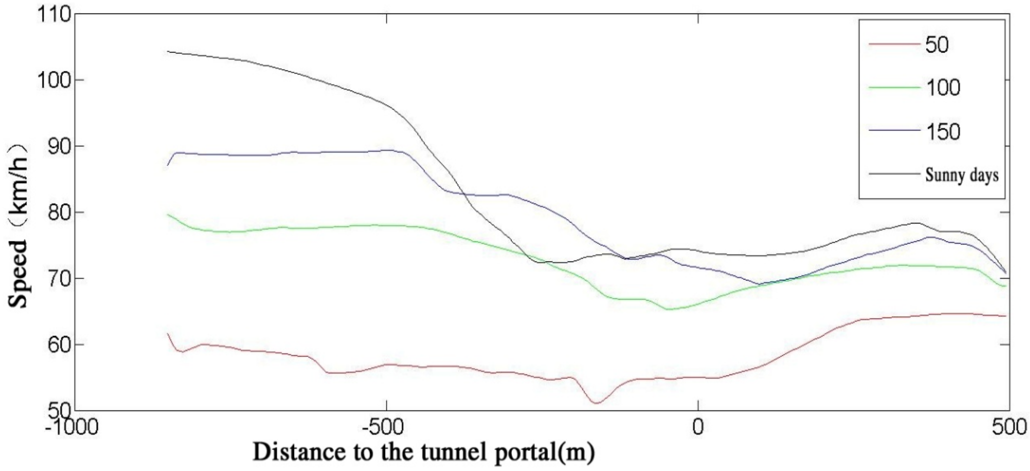


Figure 4: Continuous plot of average driving speed at different VLs at BTTS

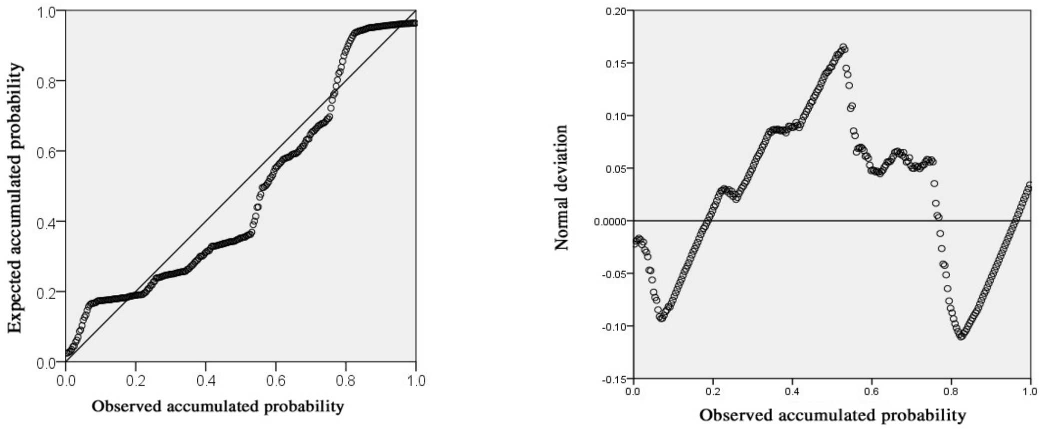


As Figure 4 indicates, visibility conditions generate great influence on drivers' average driving speed: the higher the visibility, the faster the speed. Noteworthy, when the visibility distance is 150 meters, drivers drive at a speed close to when they drive in sunny days. This is mainly because in such visibility condition, all signs which require drivers' optical judgment for safety driving are within their eyeshot, and their own driving skills and response capability are adequate to tackle with emergent situations in time. In other words, fogs produce minor effect on them.

3.2. VL's Effects on Speed Indicators

In order to confirm the relations between speed and speed-related statistics in various driving simulation scenarios, we employ the variance analysis method to test whether significant variance between average driving speed, 75th percentile speed, and 25th percentile speed exist. Normal distribution test was undertaken in SPSS through the K-S (Kolmogorov-Smirnov) single sample test method. The results indicate that both the average speed and the lower and the upper quartile speed do not fully comply with the normal distribution. This is likely because of the K-S test's over-sensitiveness when the sample quantity is large. To verify the speed distribution, and confirm whether the variance analysis method is plausible, we have drawn probability plot to scrutinize the relationship between actual cumulative probability and theoretical cumulative probability. Figure 5 is the probability plot in scenario1-50(visibility distance is 50 meters).

Figure 5: Analytical results of 1-50 normal probability plot of the average speed

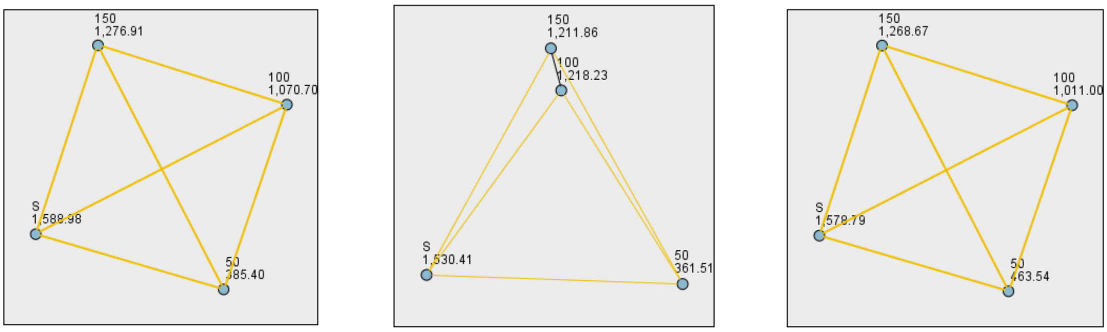


(a)1-50 Normal probability plot **(b)1-50 Normal probability plot of the average speed**

As shown in Figure 5, the cumulative probability of average speed in scenario 1-50 does not comply with the cumulative probability of normal distribution. Moreover, the normal deviation in the normal probability plot is too large, exceeding 0.05. Hence, we infer that the distribution of average speed in scenario 1-50 does not meet the normal distribution. Normal distribution tests were conducted in other scenarios as well, all of which failed to meet the conditions of normal distribution.

Therefore, we use K-W (Kruskal-Wallis H) in nonparametric method to conduct variance test on average speed, the lower and the upper quartile speed in different scenarios. The tested results are as shown in Figure 6. Each spot in the Figure indicates the sample's average value. The yellow-color line segments in various samples represent the status of statistical significance, while the black-color ones represent the status of statistical insignificance.

Figure 6: VL-based pairwise comparison results of the Kruskal-Wallis H test



(a)average speed **(b) speed in the bottom quartile P25** **(c)speed in the top quartile P75**

The VL-based pairwise comparison results derived from the Kruskal-Wallis H test suggest that drivers' average driving speed, the lower, and the upper quartile speed differ greatly at different VLs. Drivers' driving speed is influenced by vision at different VLs. In low visibility conditions, drivers usually decelerate the speed for safety consideration; and in relatively high visibility conditions, they would accelerate to ensure the pass speed. Thus, all speed indicators and visibility conditions are in direct proportion, with only one exception. The difference of the lower quartile speed in the situation when the visibility distance is100meters and when the visibility distance is 150meters is not of statistical significance. Because in these two VLs, drivers demonstrate similar level of cognition associated with vision's effects on driving safety, and in turn are inclined to driving at a relatively lower speed for safety considerations.

4. The Indicator Confirmation of Speed Risk Assessment and Correlation Analysis

4.1. The Indicator Confirmation of Speed Risk Assessment and Model Framing

Based on the data analysis of the operating speed at BTTS, and speed changing's effects on road safety, we use a series of indicators of driving speed properties for speed risk assessment. Findings from previous studies suggest that speed deviation directly influences road safety [16]. When the highway traffic conditions are good, drivers drive at a steady speed, whereas when the highway traffic conditions are poor, vehicle velocities turn to be more deviated. In calculating the speed coefficient of variation, we take into consideration the effects of the standard deviation of driving speed and the expected speed in terms of speed deviation. Furthermore, researches reveal a close correlation between speed coefficient of variation and the probability of traffic accident.

To frame the indicator model of speed risk control at BTTS, we analyze the effects various speeds and accelerated speeds have produced on driving safety. We select several key parameters as independent variables of the model. The selection criteria mainly include drivers' driving speed, accelerated speed, speed deviation, the 85th percentile speed, as well as speed coefficient of variation. The definitions of independent variables are as follows:

(1)The 85th percentile speed: the 85th percentile value of driving speed of the same driver in a driving simulation scenario;

(2)Speed coefficient of variation: ratio of the standard deviation of driving speed to average driving speed of the same driver in a driving simulation scenario. The calculation process is illustrated as follows.

The standard deviation of driving speed refers to the standard deviation of speed on the road segment. Its value can be obtained by two consecutive steps. First, calculating the driving speed V85; second, based on the number of collected sample speed, using the equation (1) to calculate the standard deviation of driving speed σ which is correspondent to the driving speed V85 in each intercept.

$$\sigma = \sqrt{\frac{\sum\left(V_i - \overline{V}\right)^2}{n-1}} \tag{1}$$

In equation (1), n refers to the number of monitored and collected speed. In practice, there could only be a limited number of spots designed for measurement. Changes of any values would generate significant effects on the standard deviation σ. Therefore, the standard deviation of driving speed σ possesses certain defects. We introduce C_V, the speed coefficient of variation for the road segment, to overcome these defects:

$$C_V = \frac{\sigma}{\mu} \tag{2}$$

In equation (2), μ refers to the average speed.

4.2. Indicator Model of Speed Risk Control

This paper employs Multinomial Logit Model (MLM) to establish speed risk assessment model. The MLM is a transitional form between binary Logit regression model and ordinal Logit regression model. It is usually adopted in the situation when there are more than two categories of ordinal response variables. It is a natural extension of Logit regression model.

As regards the non-ordinal response variables of J category, when j=1,2,……, the MLM can be described through the Logit expression below:

$$\ln\left[\frac{P(y=j\,|\,x)}{P(y=J\,|\,x)}\right] - \alpha_j + \sum_{k=1}^{K}\beta_{jk}x_k \tag{3}$$

In the MLM, Logit derives from contrasting non-repetitive category pairs in the response variables. If there are J categories in response variables, there are J-1 number of Logit in the MLM, which can be expressed through the equations (4):

$$\begin{aligned}
&\ln\left[\frac{P(y=1\,|\,x)}{P(y=J\,|\,x)}\right] - \alpha_1 + \sum_{k=1}^{K}\beta_{1k}x_k \\
&\ln\left[\frac{P(y=2\,|\,x)}{P(y=J\,|\,x)}\right] - \alpha_2 + \sum_{k=1}^{K}\beta_{2k}x_k \\
&\cdots \\
&\ln\left[\frac{P(y=J-1\,|\,x)}{P(y=J\,|\,x)}\right] - \alpha_{J-1} + \sum_{k=1}^{K}\beta_{(J-1)k}x_k
\end{aligned} \tag{4}$$

The last category, namely (J), functions as a reference. Given that:

$$
\begin{aligned}
&P(y=1 \mid x)+P(y=2 \mid x)+\ldots+P(y=J \mid x) \\
&=P(y=J \mid x)\left[1+\sum_{j=1}^{J-1} e^{\alpha_j+\sum_{k=1}^{K}\beta_{kj}x_k}\right] \\
&=1
\end{aligned} \tag{5}
$$

For the response variables possessing J numbers of categories, the probability of classifying the j[th] category of the dependent variable can be estimated through the equation (6):

$$
P(y=j \mid x)=\frac{e^{\alpha_j+\sum_{k=1}^{K}\beta_{kj}x_k}}{1+\sum_{j=1}^{J-1} e^{\alpha_j+\sum_{k=1}^{K}\beta_{kj}x_k}} \tag{6}
$$

We adopt the backward-stepping method to choose proper model(s). This work comprises of two steps. First, we included all the variables to the model, to test whether any of them can be excluded. After excluding the variables with the highest significance level of the likelihood ratio statistics, we re-tested the models left. These procedures were repeated until no more variables should be excluded according to the test criteria. The second step of the experiment is to test whether those variables outside the model are qualified to be included in the model. After those variables the likelihood ratio statistic of which is of the lowest significance level were included in the model, we tested all the models anew. Similarly, these procedures were repeated until all the variables met the inclusion or exclusion criteria.

The information of Multinomial Logistic regression model fitting is as listed in Table 2. Our analysis suggests that the interpolation of log likelihood is approximate to the Chi-Square distribution. The Chi-Square distribution is at significance level=0.002, which means in 99.8% of the scenarios, models with predictive variables could provide better information than that with pure constants. Pseudo R-squared tested results are as listed in Table 3. The R-squared statistic of McFadden is less than 0.2, indicating a good status of the model fitting.

Table 2: Model fitting information

Model	Model Fitting Criteria	Likelihood Ratio Test		
	-2 log likelihood	Chi-square	df	Significance level
Intercept	120.573	-	-	-
Final	103.926	16.647	4	.002

Table 3: Pseudo R-squared statistics

Cox &Snell	.249
Nagelkerke	.285
McFadden	.138

The confirmation of the estimated values of parameters is based on multinomial Logistic regression model. The values are as listed in Table 4.

Through the correlation analysis, we frame indicator model of driving speed risk control at BTTS as follows:

$$
R=f(V,V_{85},C_V) \tag{7}
$$

$$
V=g_1(X) \tag{8}
$$

$$V_{85} = g_2(X) \quad (9)$$

$$C_V = g_3(X) \quad (10)$$

In the equations (7), (8),(9), and (10), R refers to critical speed on horizontal curve sections; V to drivers' driving speed; V_{85} to the85th percentile speed; C_V to speed coefficient of variation; and X to VL.

Table 4: The Estimated Values of Parameter

Visibility	B	Standard Deviation	Wald	df	Significance Level	Exp. (B)	confidence intervals of Exp. (B) 95%	
							Min.	Max.
Intercept	6.711	2.354	8.130	1	.004	-	-	-
V_{85}	-.245	.083	8.836	1	.003	.782	.665	.920
Speed coefficient of variation	-4.920	6.105	.650	1	.420	.007	4.644E-08	1146.425

5. CONCLUSION

Drawn on the results derived from driving simulation experiment, this paper analyzed the characteristics of drivers' driving speed behaviors, accelerated speed behaviors, and speed deviation at different VLs, leading us to the principal conclusions:

(1)Visibility conditions greatly influence the average vehicle velocity: the better the former, the faster the latter. Noteworthy, when the visibility distance is 150 meters, drivers drive at a speed close to when they drive in sunny days.

(2)Visibility-based pairwise comparison results of the Kruskal-Wallis H Test indicate that drivers' average speed, the lower and the upper quartile speed differ greatly at different VLs. Drivers' driving speed is influenced considerably by vision. In reduced visibility conditions, drivers usually choose to decelerate the speed for safety driving; in relatively high visibility conditions, they would accelerate to ensure the pass speed.

(3) By means of establishing multinomial logistic regression model, we revealed the relations between different visibility levels and predictive indicators; the VL has significant relations with both the 85th percentile speed and speed coefficient of variation.

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References

[1] Amundsen F.H. and Ranes G.. "*Studies on traffic accidents in Norwegian road tunnels*", Tunneling and Underground Space Technology, Vol. 15/1, pp. 3-12, (2000).
[2] KIRCHER K and AHLSTROM C. "*The Impact of Tunnel Design and Lighting on the Performance of Attentive and Visually Distracted Drivers*", Accident Analysis and Prevention, Vol. 47, pp. 153-161, (2012).
[3] GUO Wei, PAN Xiaodong and JIANG Shuhao. "*Relative Difference Function-based Traffic Safety Assessment of Tunnel Groups*", Journal of Tongji University: Natural Science, Vol. 41/1, pp. 101-105, (2013).

[4] MA Zhuanglin, ZHANG Yiyi and YANG Yang. "*Research on models for predicting severity of traffic accident in highway tunnel*", China Safety Science Journal, Vol. 25/5, pp. 75-79, (2015).
[5] HU Yueqi, LIU Haoxue and ZHU Tong. "*Research on visual characteristics of drivers driving through extremely long expressway tunnel* ", China Safety Science Journal, Vol. 27/6, pp. 31-36, (2017).
[6] YI Hongcheng. "*The Research on the Influence Mechanism and Control Method of Crosswind Effects on Long-span Bridge Traffic Safety* ", Hefei University of Technology, 2017,Hefei.
[7] Yujia TIAN, Hong CHEN and Baixiu LIU. "*Safety Evaluation of Bridge-Tunnel Sections on Mountainous Expressway Based on Bayesian Network* ", Integrated Transportation Systems Green • Intelligent • Reliable, pp. 875-882, (2010).
[8] WU Hongbo, ZHEN Dongxiao and ZHOU Ronggui. "*Safety Evaluation Techniques for Tunnel-Bridge Linkage Sections on Freeways in Mountainous Areas* ", Journal of Highway and Transportation Research and Development, Vol. 29/12, pp. 125-132, (2012).
[9] PAN Xiaodong, FU Zhibin and YU Zewen. "*The Connecting Section Between Tunnels and Bridges in Mountainous Highway Traffic Safety Evaluation Model*", Highway Engineering Vol. 37/3, pp. 1-5, (2012).
[10] Xiao Dianliang. "*Assessment Methods of Operational Safety Rating of Bridge-Tunnel Group in Mountainous Expressway*", China Academy of Transportation Sciences, 2014, Beijing.
[11] Dianliang Xiao, Yong Fang and Yanning Zhang. "*Analysis of driving behavior at the bridge-tunnel transition section in reduced visibility situations*", 2017 4th International Conference on Transportation Information and Safety, ICTIS 2017-Proceedings, pp. 581-588, (2017).
[12] MANSER M P and HANCOCK P A. "*The Influence of Perceptual Speed Regulation on Speed Perception, Choice, and Control: Tunnel Wall Characteristics and Influences*", Accident Analysis and Prevention, Vol. 39, pp. 69-78, (2007).
[13] NI Na, PAN Binghong and WANG Lei. "*Research on traffic flow characteristics of bridge and tunnel intensive section in mountainous expressway*", Journal of Railway Science and Engineering, Vol. 14/4, pp. 852-861, (2017).
[14] Joo S, Oh C and Jeong E. "*Categorizing bicycling environments using GPS-based public bicycle speed data*", Transportation Research Part C：Emerging Technologies, Vol. 56, pp. 239-250, (2015).
[15] Bella F, Calvi A and D'Amico F. "*Analysis of driver speeds under night driving conditions using a driving simulator*", Journal of Safety Research, Vol. 49/6, pp. 45-52, (2014).
[16] YAN Ying. "*Research on operating speed prediction model and application of freeway*", Tongji University, 2009, Shanghai.