Tunnelling and Underground Space Technology 59 (2016) 100–104

Contents lists available at ScienceDirect

Tunnelling and Underground Space Technology

journal homepage: www.elsevier.com/locate/tust

Exploring factors affecting injury severity of crashes in freeway tunnels

Zhuanglin Ma [a,*], Steven I-Jy Chien [a,b], Chunjiao Dong [c], Dawei Hu [a], Ting Xu [a]

[a] School of Automobile, Chang'an University, Xi'an 710064, Shaanxi, China
[b] John A. Reif, Jr. Department of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark 07102, NJ, USA
[c] Center for Transportation Research, The University of Tennessee, Knoxville 37996, TN, USA

ARTICLE INFO

Article history:
Received 3 April 2014
Received in revised form 6 June 2016
Accepted 19 June 2016

Keywords:
Injury severity
Freeway
Tunnel
Crash
Generalized ordered logit model

ABSTRACT

Identifying and understanding factors which affect crash injury severity is critical for developing plans to ensure traffic safety in freeway tunnels. Potential factors, such as traffic volume, tunnel environment, geometric design, and weather were considered to predict the likelihood of injury severity. A generalized ordered logit model is developed by using police-reported crash records of selected freeway tunnels in China. The results indicate that five factors are significantly related to injury severity, which include Season, Time of Day, Location of Crash, Tunnel Length, and Adverse Weather. The summer season seems discouraging the probability of sustaining fatal injuries. The likelihood of no injury crashes seems to increase during night-time. Crashes occurred near tunnel entrance/exit tend to be more severe than those occurred inside the tunnels. Tunnel length and weather were also found positively affecting the likelihood of injury severity.

1. Introduction

Due to some attributes associated with tunnels (i.e., dark, narrow and monotonous), driving in a tunnel, especially a long one, may cause anxiety comparing to driving in an open road section (PIARC, 2008). Before entering a tunnel, the reflection of sun light from the tunnel portal might result in temporary ocular blindness. After entering the tunnel, drivers need to adapt to abruptly change in light condition, which leads to poor sight condition. After exiting the tunnel, different light conditions and/or unexpected weather conditions (i.e., rain, icy, snow, lateral wind, etc.) will dangerously distract drivers' attention and challenge drivers' responses in a short time period. In addition, poor geometric and environmental conditions as well as congested traffic characteristics in the tunnel shall also be concerned. Therefore, tunnels may be prone to a relatively larger number of crashes compared to open road sections along the freeway. Theses crashes could result in different levels of injury severities, ranging from minor property damages to sever fatal crashes.

To classify levels of injury severity, the KABCO crash injury scale was commonly applied. Injury severity was classified into five levels, including fatal injury, incapacitating injury, non-incapacitating injury, possible/invisible injury, and no injury. Unfortunately, the medical report does not attach to the police-reported crash records in China. Therefore, the crash injury severity associated with each crash was unknown. The purpose of this paper is to develop a sound model to predict the likelihood of injury severity for crashes occurring in freeway tunnels. With that the relationship between potential factors and injury severity must be explored.

Various methods have been applied to analyze the injury severity data. Artificial neural networks (ANN) and statistical modeling approaches were commonly used. Abdel-Aty and Abdelwahab (2004) developed an ANN to predict driver injury severity conditioned on the premise that a crash has occurred. The ANN performance was assessed and outperformed a calibrated ordered probit model. Similar results were found by Delen et al. (2006) and Ma et al. (2009a) where they used an ANN to establish the relationship between driver injury severity and potential factors. The ANN outperformed traditional statistical approaches, yet it was not widely applied because the significance of potential factors on injury severity was unable to quantify.

Traditional statistical modeling approaches are classified as ordered and unordered categories. Many researchers attempted to use ordered categorical models to analyze the relationship between potential factors and injury severity. O'Donnell and Connor (1996) used the ordered logit and ordered probit models to determine the effect of variations of crash and road user related attributes on the probability of each injury severity level.

* Corresponding author.
E-mail address: mazhuanglin@126.com (Z. Ma).

http://dx.doi.org/10.1016/j.tust.2016.06.013
0886-7798/

Kockelman and Kweon (2002) used the ordered probit model to examine the risk of different injury levels sustained under all crash types (i.e., two-vehicle crashes, and single-vehicle crashes). The results suggested that pickups and sport utility vehicles are not safer than passenger cars under single-vehicle crash condition. For two-vehicle crashes, however, pickups and sport utility vehicles are attributed with less severe injuries for drivers but more severe injuries for passengers. Abdel-Aty (2003) used the ordered probit model to examine the relationship between driver injury severity levels and many potential factors at open road sections, signalized intersections, and toll plazas. Later, Abdel-Aty and Keller (2005) used the ordered probit model to predict the injury severity at signalized intersections. It was found that a combination of crash-specific information and intersection characteristics achieved the greatest prediction accuracy. Eluru et al. (2012) used the ordered logit model to assess the impact of various factors on injury severity of accidents at highway-railway grade crossings. It was found that the key factors influencing injury severity include driver age, time of the accident, presence of snow/rain, vehicle role in the crash and drivers' action prior to the crash. Hao et al. (2016) applied the ordered probit model to explore the effects of injury severity for motor vehicle drivers at highway-rail grade. The common drawback of the ordered models is that the effects the coefficient β are constrained across injury outcome levels (Eluru et al., 2008; Wang and Abdel-Aty, 2008; Eustace et al., 2011; Savolainen et al., 2011). Therefore, if one or more factors have different impact on different levels of injury severity, the results from the ordered categorical model may be misleading.

On the other hand, unordered categorical models have also been widely used in analyzing injury severity. Khorashadi et al. (2005) used a multinomial logit approach and found significant differences of risk factors between urban and rural driver injuries involving large trucks. Eustace et al. (2011) used a multinomial probit model to identify risk factors related to fatalities or severe injuries involving motorcyclists, and the results showed that nine risk factors increased the probability of severe injuries, including horizontal curves, graded sections, single-vehicle collisions, major roadways, being a motorcycle rider, being female, speeding, and riding under the influence of alcohol/drug. However, the unordered models ignore the ordinal nature of injury severity data which may result in biased or even nonsensical estimates (Eustace et al., 2011; Khorashadi et al., 2005; Shankar and Mannering, 1996; Ulfarsson and Mannering, 2004).

To preserve the ordinal nature of injury severity data and relax the parallel-line assumption, generalized ordered logit models, also known as partial proportional odds models, were applied in analyzing injury severity. Wang and Abdel-Aty (2008) used the partial proportional odds model to identify factors of four types of ramp-lane arrangements on injury severity. Mergia et al. (2013) used the generalized ordered logit model to examine potential factors of injury severity at freeway junctions (i.e., merge and diverge areas). Abegaz et al. (2014) used the partial proportional odds model to determine possible factors that might influence the injury severity in Ethiopia. Ma et al. (2015) used the partial proportional odds model to examine influence factors of injury severity on rural two-lane highways in China.

In this study, we attempt to explore the contribution factors on injury severity of crashes in freeway tunnels using a generalized ordered logit model. The proposed ordinal logit model has been recognized as a capable approach to overcome the limitations of traditional ordered models. This paper is organization as follows. Section 2 describes the methodology used to explore potential factors affecting injury severity of crashes in freeway tunnels. The data collection and preparation are discussed in Section 3, and Section 4 describes the analysis results and findings. Finally, conclusions of this study are drawn in Section 5.

2. Methodology

This paper aims to evaluate the relationship between contributing factors and injury severity of crashes in freeway tunnels. The injury severity is categorized into three levels in decreasing severity, such that 1 represents fatal injury, 2 represents injury, and 3 represents no injury. The generalized ordered logit model was developed to estimate injury severity because it can overcome the limitations of the conventional ordered logit/probit and the unordered methods (Savolainen et al., 2011). The generalized ordered logit regression model was also commonly applied (Williams, 2006; Wang and Abdel-Aty, 2008; Wang et al., 2009; Mergia et al., 2013; Abegaz et al., 2014; Ma et al., 2015), because it can deal with the variability of the regression coefficients across outcome levels while the ordinal nature of the corresponding variables may be maintained. The generalized ordered logit model can be expressed as Eq. (1):

$$\mathrm{P}(\mathrm{Y} \leqslant \mathrm{j}|\mathrm{x}) = \frac{\exp\left(\mu_{\mathrm{j}} - \mathbf{x}^T \boldsymbol{\beta}_{\mathrm{j}}\right)}{1 + \exp\left(\mu_{\mathrm{j}} - \mathbf{x}^T \boldsymbol{\beta}_{\mathrm{j}}\right)} \tag{1}$$

where $P(Y \leqslant j|x)$ is the cumulative probability of the event $(Y \leqslant j)$, satisfying the condition $\sum_{j=1}^{J} P(Y = j|x) = 1$; Y is the multinomial response variable with J outcomes; J is the number of outcome levels or categories of injury severity, and $J = 3$ in this study; $\boldsymbol{x}$ is a vector of observed explanatory variables; μ_j is an unknown threshold or intercept parameters, satisfying the condition $\mu_1 \leqslant \mu_2 \leqslant \ldots \leqslant \mu_J$; $\boldsymbol{x}^T$ is a transpose vector of observed explanatory variables; and $\boldsymbol{\beta}_j$ is a vector of unknown regression coefficients.

From Eq. (1), the probabilities injury severity denoted as Y of injury severity levels (i.e., 1, 2 or 3) can be expressed by cumulative probability distributions as formulated as Eqs. (2)–(4), respectively. Thus,

$$\mathrm{P}(\mathrm{Y} = 1|\mathrm{x}) = \mathrm{F}(\mu_1 - \mathbf{x}^T \boldsymbol{\beta}_1) \tag{2}$$

$$\mathrm{P}(\mathrm{Y} = 2|\mathrm{x}) = \mathrm{F}(\mu_2 - \mathbf{x}^T \boldsymbol{\beta}_2) - \mathrm{F}(\mu_1 - \mathbf{x}^T \boldsymbol{\beta}_1) \tag{3}$$

$$\mathrm{P}(\mathrm{Y} = 3|\mathrm{x}) = 1 - \mathrm{F}(\mu_2 - \mathbf{x}^T \boldsymbol{\beta}_2) \tag{4}$$

For a variable with three possible outcomes, the comparison can be analyzed by grouping the three outcome levels into two sets. For $j = 1$, the results represents outcome level 1 vs. outcome level 3 (i.e. fatal injury vs. no injury). Similarly for $j = 2$, the results represents outcome levels 2 vs. outcome level 3 (i.e. injury vs. no injury). A positive coefficient indicates that the likelihood of injury severity level increases as the associated independent variable increases. On the other hand, a negative coefficient indicates that the likelihood of injury severity level increases as the associated independent variable decreases.

The likelihood ratio (LR) test and the significance of coefficients in a regression model are typical measures of model performance. These measures were applied to formulate the proposed model. The LR test result indicates whether a global null hypothesis for a specific model should be rejected, which can be determined by Eq. (5):

$$\rho^2 = 1 - \frac{l(\beta)}{l(0)} \tag{5}$$

where $l(\beta)$ is the log-likelihood value of the fitted model, and $l(0)$ is the log-likelihood value of the model without variables included.

If the value of ρ^2 is more than 0.2, it indicates that the proposed model has sufficient explanatory and predictive power (Shankar and Mannering, 1996; Ulfarsson and Mannering, 2004).