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Gas dynamic analogous exposure approach to interaction intensity in multiple-vehicle crash analysis: Case study of crashes involving taxis

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ABSTRACT

Exposure is a frequency measure of being in situations in which crashes could occur. In modeling multiple-vehicle crash frequency, traditional exposure measures, such as vehicle kilometrage and travel time, may not be sufficiently representative because they may include situations in which vehicles rarely meet each other and multiple-vehicle crashes can never happen. The meeting frequency of vehicles should be a better exposure measure in such cases. This study aims to propose a novel Gas Dynamic Analogous Exposure (GDAE) to model multiple-vehicle crash frequency. We analogize the meeting frequency of vehicles with the meeting frequency of gas molecules because both systems consider the numbers of the meetings of discrete entities. A meeting frequency function of vehicles is derived based on the central idea of the classical collision theory in physical chemistry with consideration of constrained vehicular movement by the road alignments. The GDAE is then formulated on the basis of the major factors that contribute to the meeting frequency of vehicles. The proposed GDAE is a more representative proxy exposure measure in modeling of multiple-vehicle crash frequency because it further investigates and provides insight into the physics of the vehicle meeting mechanism. To demonstrate the applicability of the GDAE, zonal crash frequency models are constructed on the basis of multiple-vehicle crashes involving taxis in 398 zones of Hong Kong in 2011. The GDAE outperforms the conventional time exposure in multiple-vehicle crash modeling. To account for any unobservable heterogeneity and to cope with the over-dispersed count data, a random-parameter negative binomial model is established. Explanatory factors that contribute to the zonal multiple-vehicle crash risk involving taxis are identified. The proposed GDAE is a promising exposure measure for modeling multiple-vehicle crash frequency.

1. Introduction

In road safety, crash frequency modeling is an important and useful tool for identification of factors that contribute to crash frequency. Remedy measures or policies can be formulated and implemented on the basis of the identified factors

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to enhance road safety. Depending on the purpose of the given study, crash frequency models in terms of different categories, such as the sites of interest (e.g., intersections, road segments, highways, and zonal networks), the numbers of vehicles involved (e.g., single and multiple vehicles), the vehicle types (e.g., motorcycles, taxis, and trucks), and injury severity (e.g., slight-injury and killed or seriously injured), can be established.

1.1. Exposure to crash risk

Exposure measures are the essential elements that are tightly linked to all kinds of crash frequency models. Exposure has been defined differently over the decades. Chapman (1973) defined exposure as the number of opportunities for crashes of a certain type to occur over a given time in a given area. Wolfe (1982) later offered a modified definition of exposure as simply being in a situation that incurs some risk of being involved in a crash and expressed risk as the number of crashes that take place in the same situation in a certain period divided by exposure. More recently, Elvik (2015) defined an event-based definition of exposure in which each event with the potential to generate a crash is interpreted as a trial, as defined in probability theory. Although certain levels of differences lie in these definitions, they all serve the single purpose of determining crash risks or accident rates that indicate the relative risk levels of various traffic situations (Wolfe, 1982).

Broadly speaking, the exposure measure is rather conceptual, and direct measurement may not be feasible in many situations. In practice, although the use of exposure measures is constrained by the availability and quality of data (Naci et al., 2009), various proxy measures have been developed and used in different crash frequency analyses, including population and fuel consumption (Amoh-Gyimah et al., 2017; Fridstrøm et al., 1995), traffic volume (Chiou and Fu, 2015; Heydari et al., 2017; Qin et al., 2004, 2006; Wong et al., 2007), travel time (Chipman et al., 1993; Imprialou et al., 2016), vehicle-miles traveled (Li et al., 2003; Pei et al., 2016), potential conflict counts (Bie et al., 2005), and quasi-induced exposure (Huang and Chin, 2009; Jiang et al., 2014; Stamatiadis and Deacon, 1997).

In general, zonal-level exposure measures such as population are suitable for zonal crash frequency models, and micro-level exposure measures such as traffic flows are more frequently used in modeling crash frequencies at specific roadway entities such as road segments and junctions. For instance, Lee et al. (2015) used zonal population as exposure measure to develop macroscopic multivariate crash analysis reporting models. It was anticipated to efficiently help policymakers allocate resources to improve road safety for different zones. Similarly, Amoh-Gyimah et al. (2017) incorporated population and vehicle-kilometers in a macroscopic crash model and investigated the effects of spatial variations in the unobserved heterogeneity. The results showed that when the spatial variability is considered, an increase in the population of young people increased the crash risk, although the parameter of this variable was negative. For crash risk at road segments, Pei et al. (2012) estimated the travel distance and travel time across 112 road segments in Hong Kong using global positioning system (GPS) data and investigated the influence of these two exposure measures on the relationship between speed and crash risk. Their results revealed a positive correlation between the average speed and crash risk when the distance exposure was adopted. In contrast, average speed had a negative correlation to the crash risk when the time exposure was used. Tulu et al. (2015) investigated pedestrian crash frequency for two-way two-lane rural roads in Ethiopia by considering the product of vehicle volume and pedestrian volume as the exposure measure and established a random-parameter negative binomial model. A nonlinear effect of the exposure measure was found, and the modeling results indicated that the proportion of the daily crossing volume by pedestrians younger than 19 years of age could be used to explain pedestrian exposure in further studies. However, these exposure measures are highly aggregated measures that may not adequately represent exposure to crash risk. For instance, a greater zonal population is not necessarily equivalent to a greater number of commuters, and a greater number of commuters does not mean that all of them are exposed to situations that could possibly develop into a crash (e.g., a pedestrian walking on a street without any vehicles). Similarly, Qin et al. (2006) also pointed out that the conventional aggregated exposure measures do not account for temporal variations in traffic.

Because different types of crashes have different causes, exposure to these traffic hazards (crash risk) may vary. To better identify the factors that contribute to the crash risk, it is of great importance to use a more representative exposure measure for the model development. Many researchers attempted to formulate different kinds of exposure measures by using disaggregated data and considering the mechanism for a potential crash. In a study concerning crash rate prediction in two-lane highway segments, Qin et al. (2004) formulated different exposure functions for single-vehicle crashes and multiple-vehicle crashes in three directions: the same direction, opposite directions, and intersecting directions. The disaggregated flow for each direction of the highway and the segment length were used for the formulations. The results showed that most of the proposed exposure functions had linear relationships with the crash frequency of their corresponding crash types, whereas the conventional exposure measure, vehicle-miles traveled, had nonlinear relationships with the crash frequencies. This finding revealed that their proposed exposure functions would be more representative than vehicle-miles traveled in these scenarios. Instead of using hourly traffic volume, Miranda-Moreno et al. (2011) applied disaggregated flows by movement type and vehicle type in their study of crash risk at intersections. They proposed that the movement types exhibited by vehicles and bicyclists at an intersection may have different effects on the crash risk. Disaggregated flows were used to formulate three exposure measures: aggregated flows, motor vehicle flows aggregated by movement type, and potential conflicts between motor vehicles and cyclists. The products of the different combinations of conflicting disaggregated flows were considered to indicate the conflicting volumes. Similar concepts have been included in a more advanced model—the latent class model with Bayesian inference—to study the unobserved heterogeneity in pedestrian and cyclist crashes (Heydari et al., 2017).