Accident Analysis and Prevention 120 (2018) 295–303

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Effects of modal shares on crash frequencies at aggregate level

Mehdi Mohammadi[a], Gholamali Shafabakhsh[a,*], Ali Naderan[b]

[a] Department of Civil Engineering, Semnan University, Semnan, Iran
[b] Department of Civil Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

ARTICLE INFO

Keywords:
Safety planning
Crash generation
Crash mode split
Macro model
Negative binomial

ABSTRACT

Introduction: Long-range transportation plans often involve proposals for improvements/ changes in different modes of travel. This means that modal share of trips generated at each traffic analysis zone (TAZ) by mode of travel needs to be predicted/ forecasted for safety evaluation purposes. The objective of this research study is to develop a series of aggregate crash prediction models (ACPMs) that relate with the modal split step of the conventional four-step demand models.
Method: The models are developed utilizing network and vehicular, socio-economical, trip production/attraction and trip frequencies by mode at TAZ-level as explanatory variables in a generalized linear regression with the assumption of a negative binomial error structure. Crash frequencies are split into total crashes (TC) and severe crashes (SC).
Results: The models prove promising in estimating crash frequencies upon changes in modal shares, which is essential in safety assessment of alternate transportation demand management (TDM) scenarios. Trips made in car, bus, and bus Service mode became significant in the estimated TC and trips made in car, taxi, school service, bus service and moped mode became significant in the estimated SC ACPMs.
Conclusions: The ACPMs may be used from two different points of view. First and most appropriate use is to consider these as tools to forecast future crash frequencies and develop long-term plans to counteract. In the second point of view, ACPMs act as the primary planning tool to identify how any increase in a specific mode-ridership will contribute to crash frequencies. This is of great interest in developing plans that involve increased use of a specific mode.
Practical application: As modal shares are forecasted in certain years into the future by the modal split step of demand modeling, crash frequencies could also be forecasted and safety implications of mobility improvement scenarios (e.g. increased number of trips by bus, car, etc.) would be evaluated.

1. Introduction and background

Transportation planners are often concerned with plans that directly or indirectly affect modal use in urban trips (Meyer and Miller, 2001), while a major issue in evaluation/ prioritization step is to estimate safety implications of proposed policies and plans (Washington et al., 2006). This requires safety analysis and modeling abilities at macro-level that target the overall performance of network and enable the planner to forecast safety figures into the future. On the other hand, future growth in modal use is a major concern in planning efforts, especially in developing countries. There is a general understanding that changed policies and plans will contribute to changing multiple long-term issues related to sustainability, efficiency and also safety of transportation in urban environments (Tasic and Porter, 2016). In other words, planners wish to shift trips from a certain mode of travel to another (e.g. from private automobiles to public buses). These plans should be evaluated to see if the modal shift is in the benefit of the trip makers from a safety point of view.

Evaluating the safety performance of urban transportation network at an aggregate (macro) level is approached by many researchers. Tasic et al. (Tasic and Porter, 2016) explored the relationship between access to multimodal transportation (spatial features, socio-economic characteristics, land use mixture, street network patterns and multimodal facilities) and safety outcomes in urban environments in census tract level. Amoh-Gyimah et al. (Amoh-Gyimah et al., 2016) used Annual Average Daily Traffic (AADT) data, population and housing data and land-use data to developing macro-level pedestrian and bicycle crashes model in second level Statistical Area of Melbourne. Li et al. (Li et al., 2013) using Road network data, Traffic data, and Socio-demographic data versus California county-level crash data to developing spatial

* Corresponding author.
E-mail addresses: mmahdii@semnan.ac.ir (M. Mohammadi), shafabakhsh@semnan.ac.ir (G. Shafabakhsh), naderan@srbiau.ac.ir (A. Naderan).

https://doi.org/10.1016/j.aap.2018.08.019
Received 7 May 2017; Received in revised form 20 August 2018; Accepted 21 August 2018

safety macro-model. Ukkusuri et al. (Ukkusuri et al., 2012) investigated the role of built environment on pedestrian crash frequency at census tract level. Chang et al. (Chang et al., 2011) analysed the relationship between Density of Surgeons and deaths from motor vehicle crashes (MVC) based on general practitioners, urbanicity of the county, and socioeconomic status of the county for US Counties. Huang et al. (Huang et al., 2010) tried to detecting county-level variations of crash risk in Florida by explicitly controlling for exposure variables of daily vehicle miles traveled and population using county level data. Quddus (Quddus, 2008a,b) developed a series of relationships between area-wide different traffic casualties and the contributing factors associated with ward characteristics in census wards level from the Greater London metropolitan area. Hadayeghi et al. (Hadayeghi et al., 2003) and (Hadayeghi et al., 2007) developed macro-level crash prediction models that estimate crash frequencies in traffic analysis zones (TAZs) as a function of land use, traffic and network characteristics. Lovegrove and Sayed (Lovegrove and Sayed, 2006) provided guidelines for practical application of aggregate crash prediction models (ACPMs). they have developed their models based on socio-demographic, network and transportation demand management data. Lord and Persuad (Lord and Persaud, 2004) developed a tool that would allow the estimation of crashes on digital or coded urban transportation networks during the planning process. Chatterjee et al. (Chatterjee et al., 2003) developed regression models using link-length and daily traffic to forecast future crash frequencies. Washington et al. (Washington et al., 2006) developed a series of ACPMs in order to forecast future crash frequencies in urban TAZs of Arizona. Their models included population by age cohort; vehicle-kilometers traveled (VKT); network length by type and other related variables. The ability of ACPMs to forecast future crash frequencies at macro level was also reported by Hadayeghi et al. (Hadayeghi et al., 2006).

Different formulations were used based on the purpose of study and nature of available data. When the data are over-dispersed the negative binomial (NB) model structure with a log-link function being the most favored (Gomes and Vieira, 2013; Ukkusuri et al., 2012; Hadayeghi et al., 2007; Kim et al., 2006; Qadeer Memon, 2006; Maher and Summersgill, 1996). when the data are not over-dispersed the poisson structure (Daniels et al., 2010; Lord et al., 2010, 2005) being the most favored.

Also some other modeling technique such as zero-inflated poisson and negative binomial (Malyshkina et al., 2010; Lord et al., 2007, 2005) and gamma (Daniels et al., 2010; Lord et al., 2005) were used in literature.

More complex models such as simultaneous estimation of NB models (de Guevara et al., 2004); Random effects model (Amoh-Gyimah et al., 2016; Yu et al., 2013); multivariate Poisson model (Ma and Kockelman, 2006); multivariate NB model (Winkelman, 2003); multivariate Poisson-lognormal model (Park et al., 2010; El-Basyouny and Sayed, 2009); full-Bayes hierarchical models with spatial effects (Vandenbulcke et al., 2014; Huang et al., 2010; Aguero-Valverde et al., 2006; Quddus, 2008a,b); geographically weighted Poisson regression models (Li et al., 2013; Hadayeghi et al., 2010); neural network (Abdelwahab and Abdel-Aty, 2002); bayesian neural network (Xie et al., 2007), and support vector machine (Li et al., 2008) were also estimated in previous researches.

Close estimation of model coefficients in spatial and non-spatial NB models was found by Quddus (Quddus, 2008a,b), and he suggested that same variables become significant in both models. On the other hand, simpler models with ordinary least square (OLS) estimation that provide more understandable results were also used by some researchers, e.g. linear regression (Clark and Cushing, 2004), linear regression with a spatial lag parameter (Levine et al., 1995), and log-linear models (Washington et al., 2006; Wier et al., 2009).

Variables used in previous studies were aggregated at different levels such as state (Noland, 2002), county (Li et al., 2013; Chang et al., 2011; Huang et al., 2010; Aguero-Valverde et al., 2006), TAZ (Abdel-Aty et al., 2013; Pulugurtha et al., 2013; Huang et al., 2013; Wang et al., 2012; Abdel-Aty et al., 2011; Naderan and Shahi, 2010a,b; Hadayeghi et al., 2007), ward (Quddus, 2008a,b), census block (Tasic and Porter, 2016; Ukkusuri et al., 2012; Levine et al., 1995) and even a grid of 0.1 square miles (Kim et al., 2006). Compared to non-spatial models, it has been suggested that spatial models provide better estimation results in smaller aggregation units, while they show rather identical results at higher aggregations (Aguero-Valverde et al., 2006; Quddus, 2008a,b).

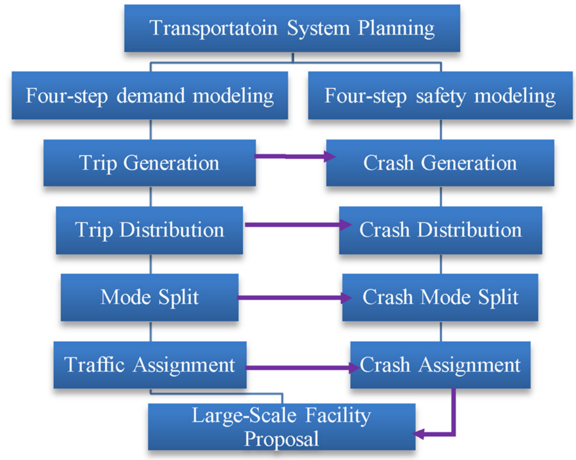

Fig. 1. Four-step safety modeling (Naderan and Shahi, 2010a,b).

Crash generation models (CGMs) were developed based on results of trip generation models that related trip frequencies made from/ to a TAZ by different purposes to crash frequencies in each TAZ (Naderan and Shahi, 2010a,b). The purpose of those models was to forecast future crash frequencies upon future changes in frequencies of different trip purposes (Naderan and Shahi, 2010a,b). These models may be used to develop four-step safety planning models similar to the process followed in four-step demand modeling (Naderan and Shahi, 2010a,b). Fig. 1 depicts the idea of inter-relating transportation and safety planning. The concept behind this figure is that each trip generated in a TAZ by a certain mode of travel (produced in or attracted to a TAZ) will be subject to a probable risk of crash.

The primary purpose of this paper is to estimate ACPMs that would predict crash frequencies based on trip frequencies by modes of travel. This provides a set of policy-related variables: number of trips by mode and their impact on crash frequencies. As modal shares are forecasted in certain years into the future by the modal split step of demand modeling, crash frequencies could also be forecasted and safety implications of mobility improvement scenarios (e.g. increased number of trips by bus, car, etc.) would be evaluated.

2. Data processing

This study is based on the transportation databases from city of Mashhad, Iran (MTTO, 2009). City of Mashhad is the second largest city of Iran with 2.67 million residents (in 2008) and an area of 195 square kilometers, and is divided into 253 TAZs. In Iran, transportation master plans done in cities with more than 100,000 population and should be updated each 5 years. Mashhad transportation master plan studies updated by conducting a comprehensive household travel survey in 2008 as last time, and zonal trip productions/ attractions per mode are available. Four-step demand models are also recalibrated to forecast future trip frequencies.

The data which use in macro level modeling must be accessible in point type (with precise geographical latitude and longitude) for data aggregation purpose. On the other hand, these types of data are not commonly recorded continually in developing countries such as Iran.