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The optimal time to evacuate: A behavioral dynamic model on Louisiana resident data

Nayel Urena Serulle*, Cinzia Cirillo

Department of Civil and Environmental Engineering, University of Maryland, College Park, MD 20742 United States

A R T I C L E I N F O

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A B S T R A C T

Understanding what affects the decision process leading to evacuation of a population at risk from the threat of a disaster is of upmost importance to successfully implement emergency planning policies. Literature on this is broad; however, the vast majority of behavioral models is limited to conventional structures, such as aggregate participation rate models or disaggregate multinomial logit models. This research introduces a dynamic discrete choice model that takes into account the threat's characteristics and the population's expectation of them. The proposed framework is estimated using Stated Preference (SP) evacuation data collected from Louisiana residents. The results indicate that the proposed dynamic discrete choice model outperforms sequential logit, excels in incorporating demographic information of respondents, a key input in policy evaluation, and yields significantly more accurate predictions of the decision and timing to evacuate.

1. Introduction

In the event of a threat, the potentially affected population goes through a cognitive process by which they estimate probabilities and consequences of the threat and their potential actions. In this sense, such population goes through four stages of reaction: collection, evaluation, decision, and implementation (Williams, 1964). In the first stage, the population collects information on the threat, mainly through disaster warning messages. Then, the information is evaluated, generally based on the perceived *personal* relevance (Perry et al., 1981). Finally, a decision is made and implemented within a selected timeframe. These stages also serve as the basis for more current behavioral theories and models, such as the Protective Action Decision Model, which divides the rational thinking into pre-decisional processes and core perceptions—threat, protective action, and stakeholder perceptions (Lindell & Perry, 2004; 2012). The transition through this complex cognitive process makes travel demand for evacuation different from ordinary travel behavior. In order to understand travel needs in threatening situations, it is necessary to gather knowledge on evacuation behavior. For this, research to comprehend evacuation must move beyond understanding the characteristics of those who evacuate and those who do not, towards an understanding of what factors are crucial in determining the forces behind evacuation travel demand (Dash & Gladwin, 2007; Lindell et al., 2005, Xu et al., 2016, Yamada et al., 2016).

Recent literature has also pointed out that the evacuation process is a dynamic process and that a temporal dimension should be accounted for when modeling evacuation during a disastrous event (Pel et al., 2011a). This will help identify when people evacuate, what type of information and which channel is the most appropriate to evacuate the population in a timely manner, and would eventually help decision makers to better organize resources and personnel over time.

* Corresponding author.
E-mail addresses: ing.urenaserulle@gmail.com (N. Urena Serulle), ccirillo@umd.edu (C. Cirillo).

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This research proposes behavioral methods based on discrete choice models to estimate the decision to evacuate over time. It adds to existing approaches by explicitly modeling the optimal time to evacuate as the results of a succession of decisions, where the respondents evaluate both present and expected future conditions.

The remaining of this paper is organized as follows. Section 2 provides a review of the literature surrounding behavior during evacuation, and dynamic modeling both in transportation and in related fields. Section 3 describes the methodological framework. Section 4 offers a simulated case study, where static and dynamic estimation of individual choices are compared. The dataset used for model estimation and related descriptive statistics are in Section 5. Model estimation results and model validation are presented in Section 6. Conclusions and future development from the analysis proposed are given in Section 7.

2. Literature review

2.1. Modeling behavior during evacuation

The literature related to disaster events and to model for emergency situations has grown substantially in recent years. In this Section we concentrate on papers that are mainly concerned with behavioral models during emergency situations. Published research (Dash & Gladwin, 2007), has found that factors such as age of the decision maker (Mileti et al., 1975; Gruntfest et al., 1978; Perry R. W., 1979), presence of kids or seniors in the household (Carter et al., 1983; Gladwin & Peacock, 1997), gender (Bolin et al., 1996; Fothergill, 1996; Bateman & Edwards, 2002), disability (Van Willigen, Edwards, Edwards, & Hessee, 2002), ethnicity (Drabek & Boggs, 1968; Perry & Greene, 1982; Perry & Mushkatel, 1986), and income (Schaffer & Cook, 1972; Sorensen et al., 1987; Bolin, 1986) all have an influence on evacuation outcomes. Additionally, previous experience (Hutton, 1976; Baker, 1979; Perry et al., 1982; Sorensen et al., 1987) and geographic location (Simpson & Riehl, 1981; Gladwin & Peacock, 1997) affect the evacuation decision-making process. Similarly, Charnkol and Tanaboriboon (2006) found that, as expected, permanent residents, larger families, people living further away from the seashore, people that haven't directly or indirectly experienced a disaster event, and people without disaster knowledge are less likely to have a faster response time (i.e., time required to physically travel to safer area) than their counterparts; the same results are found when other types of threats and disasters are evaluated.

However, the correlation between the cited factors and the decision to evacuate should not be completely generalized as they may change from study to study (and/or location by location). Baker (1991) highlighted the previous specifically for demographic variables. A recent statistical meta-analysis by Huang et al. (2015) shows the significance and consistency of these (and other) variables over 49 evacuation studies. Their findings are summarized in Table 1, where the correlation indicates the likelihood effect of the variable and the consistency indicates how often it is found to be significant or not throughout the sampled studies. The reader is referred to Carnegie and Deka (2010), Lindell and Prater (2007) and Murray-Tuite and Wolshon (2013) for a more comprehensive review of the array of factors that have been reported to influence evacuation decision.

The suggestion of incorporating time into evacuation modeling is found throughout the literature (Pel et al., 2011a). Identifying what will get people to evacuate in a timely manner would enable more robust traffic-clearing models during threats and disasters. A common practice in hurricane evacuation travel demand estimation is to estimate the total evacuation demand and departure time through simple relationships such as means, rates, and distributions rather than the more sophisticated mathematical relationships observed in urban transportation planning (Mei, 2002). These estimates are generally determined by applying an exogenous response curve stating the percentage of departures in each time interval (Pel et al., 2011b). Response curves have been extensively studied; however there is still a debate about the distribution it should follow: instantaneous departure (Chen & Zhang, 2004; Chiu et al., 2006), a uniform distribution (Liu et al., 2006; Yuan et al., 2006), a Poisson distribution (Cova & Johnson, 2002), a Weibull distribution (Lindell et al., 2002) or sigmoid curve (Kalafatas & Peeta, 2009; Xie et al., 2010), to mention a few. The drawback of the response curve approach is that there is no clear behavioral basis to justify the method (Pel et al., 2011a).

An area that requires much additional effort is the translation of the considerable amount of knowledge on evacuees' behavior during the time of crisis into reliable quantitative measures of the timing of evacuee mobilization (Southworth, 1991). Behavioral models based on discrete choice analysis have been suggested to study different types of choices during an emergency or evacuation: time to evacuate, path to safe zones, or mode choice (Sadri et al., 2014).

2.2. Dynamic discrete choice models

Dynamic models estimate decisions as a sequence of discrete choices where at each time period the decision maker chooses the utility-maximizing alternative. In his seminal work, Rust (1987) developed a regenerative optimal stopping model of bus engine replacement based on accumulated mileage, in which at each time period the decision-maker is faced with the decision of whether to replace the engine of a public transportation bus or to wait one more period, risking unexpected engine failure. The model allows for recurrent participation of the buses by resetting their mileage to zero after their engine is replaced––hence the term regenerative. Rust estimates the utility based on the expected cost of operation of each alternative, where expected accumulated mileage is given by a draw from an exponential distribution. Other influential