Developing Population Behavioral Parameters Influencing Earthquake Disaster Preparedness and Planning: A Genetic Algorithm Approach

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Abstract: Earthquake disasters occur unexpectedly providing no time to alert the public and result in great infrastructure damage in addition to severe threats to public safety. There have been many studies performed on emergency evacuation planning and management, however few of them addressed the modeling of the demand on the transportation system after evacuation orders are issued in response to an earthquake event. Knowing the behavior of the evacuating population has a significant impact on the ability to provide reliable models that capture the operational conditions of the transportation systems during the different stages of the regional emergency. This paper presents the results of an interview survey that was used to identify the different behavioral aspects related to the surveyed population intended response to evacuation orders in the aftermath of a major earthquake. The data from the survey were mainly utilized to identify the compliance rates with evacuation orders and the demand on the roadway network. Trip generation models were developed to relate that demand with the household category of the evacuation population. In addition, due to the dynamic nature of the emergency evacuation, the mobilization time needed by the evacuees to start the evacuation trip was analyzed. This study also used genetic algorithm to optimize the sigmoid function that is used to describe the evacuation trip mobilization curves for the case study scenario. The results from the analysis showed that it is important to use different evacuation trip rates for single-family and multifamily evacuating households. The study revealed that compliance rates with evacuation orders and the number of vehicle used for evacuation were dependent on the HH category. Also, this study developed functions for evacuation mobilization times for the case study earthquake hypothetical scenario were shorter compared to other types of emergencies and case studies available in the literature. This research was fully funded by a research grant provided by the Scientific Research Support Fund (SRSF)-Jordan, all thanks for making this project possible.
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1.Introduction

In cases of regional emergencies, especially those associated with little to no warning time, evacuating the affected population is considered to be one of the most important response measures. The effective management of the transportation system in support of emergency evacuation efforts proved to be critical in mitigating their adverse impacts especially on regional levels. Those regional emergency events are mainly categorized based on the cause of the threat (natural or man-made) in addition to the warning time available to the population. The different transportation measures related to the regional emergency are usually associated with the different phases of the emergency event which include the pre-disaster, during the disaster and the post-disaster phases (Saba and Rehman, 2012a,b). The major fields of research related to transportation system modeling under evacuation conditions are communication of information, dynamic evacuation planning and human behavior (Richter *et al.*, 2013).

Evacuation simulation models play an important role in planning, analyzing, and understanding the different aspects of emergency evacuations. Modeling the transportation system performance under evacuation conditions relies heavily on understanding the travel behavior under those conditions. The main purpose for analyzing travel behavior is to develop models that have the ability to replicate, as accurately as possible, the travel flows generated by users of the transportation system. Also, those models should be able to capture the changes in the transportation system users' travel patterns as a result of changes in the conditions of the transportation system. Most of the modeling and simulation tools used for evacuation modeling are based on the four-step model.

The availability of the data necessary for developing functional evacuation simulation models is one of the major problems faced by many researchers. This study aimed to generate the data needed for building those models, especially data related to estimating the demand on the transportation system during the emergency event and the population compliance rates. It focused on developing the needed human behavior data for estimating the demand on the transportation system under evacuation conditions. In addition, this study focused on identifying values of the trip loading functions parameters for the scenario under study and compared the developed functions with those available in the literature.

2. Research Background

Developing emergency evacuation models is considered to be an important part of the preparedness and planning efforts for different disaster scenarios that provide guidance regarding the most effective response to a specific emergency scenario. Emergency evacuation simulation models differ from conventional models because they usually involve moving a large number of users over a large area during a limited time period. It is vital to analyze the travel behavior to be able to build simulation models that produce relatively accurate traffic flows on the transportation system under emergency evacuation conditions. Most of the modeling and simulation tools used for evacuation modeling are based on the four-step model which consists of four major stages are related to the user's trip decision-making process. The four stages are trip generation, trip distribution, modal split, and traffic assignment (Naser *et al.*, 2010, Saba et al., 2012).

2.1 Evacuation Demand

The main focus of this study is to develop the models needed to estimate the demand on the transportation system under emergency evacuation conditions and compare those models to other studies available in the literature. The models developed for evacuation travel demand estimation relate the decision to evacuate and timing of the evacuation trip to different social and hazard factors. Hence, the modeling of demand on the transportation system during regional emergency events is affected by many factors and assumptions related to the nature of the hazard and the properties of the affected population. The literature suggests that some of the most important factors affecting the evacuation demand include previous hazard experience, frequency of the hazard, available warning and the impact risk of the hazard. In addition, several studies showed that previous hazard experience had inconsistent effect on the compliance with evacuation orders (Murray-Tuite *et al.*, 2013).

There are two steps needed for estimating the evacuation demand needed to for effective simulation of the transportation system under emergency evacuation conditions. The development of the evacuation demand begins by estimating the number of households that will comply with evacuation orders and then followed by the determination of the evacuation trip departure time (Wilmot *et al.*, 2004). The estimation of the demand for travel is mainly based on the number of Households (HH) and family size since the HH is the basic unit of evacuation. There are many factors that influence the public compliance rates with evacuation instructions. Some of them are related to different behavioral aspects, while others are associated with the nature of the emergency itself. The compliance rates are usually high in incidents involving hazmat or in major storm surge areas, whereas for small storms or river floods they are usually low (Sorensen *et al.*, 2006).

The number of households that will comply with the evacuation orders and the number of vehicles per household are estimated based on surveys of the population or direct data collection during the different phases of the emergency event. Several techniques are used to develop those rates; however, studies showed that logistic regression and neural network models provided relatively accurate results. To estimate the participation rates in the emergency evacuation, most of the developed behavioral models are based on historical data, especially data obtained from hurricane evacuations (Chang *et al.*, 2003).

The literature suggests that public response rates to emergency evacuation improve when the orders to evacuate are issued by a source the public perceives to be credible (Sorensen *et al.*, 2006). Hobeika et al. (1994) assumed a 100% response rate but he didn't consider the evacuation demand form regions surrounding the at risk area. On the other hand, Lindell et al. (2002) developed an evacuation response function using regression analysis rates for hurricane type events (Naser *et al.*, 2010). His function was for hurricane event related evacuations where it was based on the category of the at-risk area and the hurricane category (Lindell *et al.*, 2007), the function is shown in equation (1).

$$Y = 33.78 - 19.72\, x_1 + 2.87\, (x_1)^2 + 31.39\, x_2 - 2.84\, (x_2)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\, Equation\ (1)$$

Where,

Y: % compliance with the instructions to evacuate
X_1: Risk area category
X_2: Hurricane category

From studies mainly performed for hurricane type events, an average of 1.3 vehicles per HH were used in the evacuation. Ruch and Schumann (1997) estimated the number of evacuating vehicles to be 1.35 based on a behavioral survey for the study area. Also, Prater et al. (2000) reported a rate of 1.34 vehicles per HH for Hurricane Bret (Lindell *et al.*, 2007). Those studies also showed that only an average of (1-2) % needed official assistance (Sorensen *et al.*, 2006).

2.2 Evacuation trip loading rates

The emergency evacuation is a dynamic process in its nature; therefore it is not suitable to use static assignment procedures in evacuation modeling. Hence, most of the evacuation simulation models are based on the dynamic traffic assignment procedures which distribute time-dependent trips on the routes (Lammel *et al.*, 2010). Those trips need to be distributed over time after their numbers are identified by developing functions for the trip loading curves. Those trip loading rates will have a significant impact on the congestion levels, clearance time and other operational conditions of the transportation system under emergency evacuation situation. The most commonly functional form used is the sigmoid curve (S-curve) which is used to identify the cumulative percent of evacuation trips taking place with time (Sorensen, 2000). Radwan et al. developed a sigmoid function shown in equation (2), while Hobeika and Kim used a function that is equivalent to the function proposed by Radwan et al. with β = 45 minutes (Hobeika *et al.*, 1998).

$$P\ (t) = \frac{1}{\{1+e^{(-\alpha\,(t-\beta))}\}}\ \ldots\ldots..Equation\ (2)$$

Where,
$P\ (t)$: % of evacuating trips at time (t)
α: slope of the curve
β: median departure time

Cova and Johnson (2002) utilized Poisson distribution to represent the overall evacuating vehicles departure times based on 5-minute time increments (Lindell *et al.*, 2007). The US Army Corps of Engineers developed trip loading rates for hurricane evacuation which are shown in figure (1). The figure illustrates three categories of trip loading rates (Fast, Medium and Slow) along with data obtained from hurricane Opal evacuation in the U.S. (Murray *et al.*, 2013). The trip loading curves developed by some of the researchers for different researchers are illustrated in figure (2).

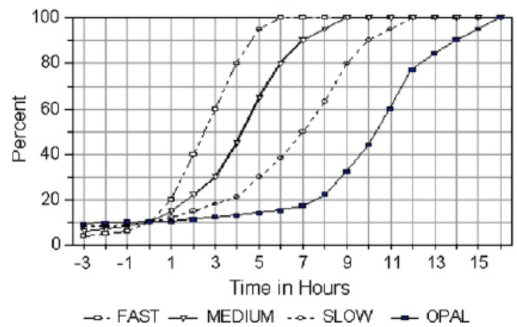

Figure (1): US Army Corps of Engineers hurricane evacuation trip loading rates along with data from hurricane Opal
(Source:Murray et al., 2013)

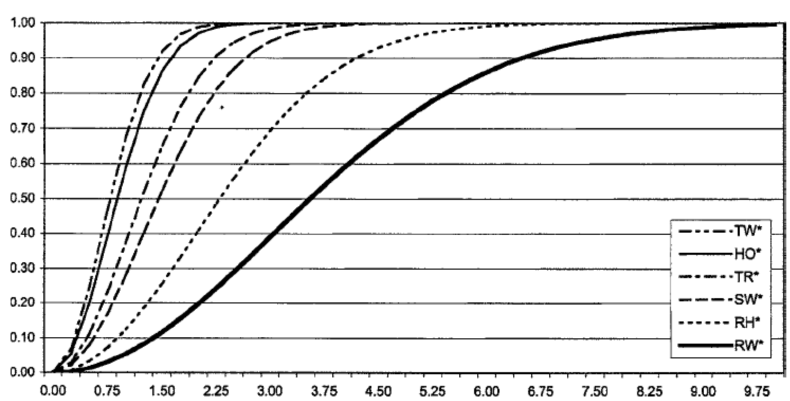

Fig. 1. Departure time curves for Tweedie et al. (1986) (TW*); Hobeika et al. (1994) (HO*); Lindell et al. (2002a) transients (TR*); Southworth and Chin (1987) (SW*); and Lindell et al. residents at home (RH*) and residents at work (RW*)

Figure (2): Evacuation trips loading curves
(Source:Lindell et al., 2007)

2.3 Genetic Algorithms

In this work, we apply the Genetic Algorithm for optimizing the parameters of the Sigmoid function used for estimating the Evacuation trip loading rates. The Genetic Algorithm is a heuristic search algorithm that was first introduced by John Holland (1975) and his students, it is based on the concept of natural selection and genetics where it mimics the processes needed for evolution in natural systems. GA follows the principal of survival of the fittest as illustrated in figure (3). The GA models are most commonly used for problems that do not have pre-specified method of solution, making them suitable for many real-life optimization problems.

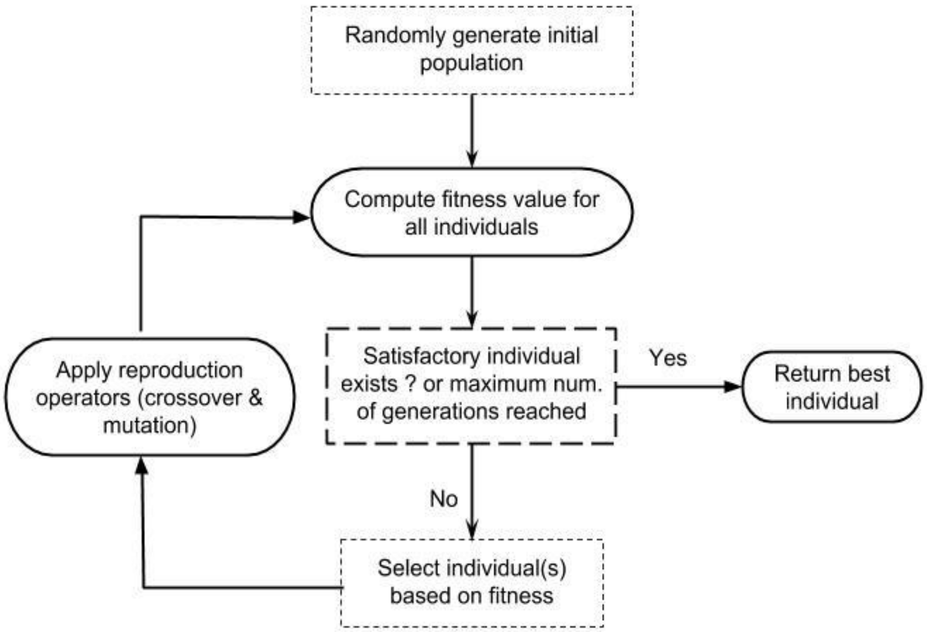

Figure (3): Basic GA evolutionary process

The GA models utilize the genetic operations of selection, crossover and mutation to modify the obtained problem solution and select the most suitable solution that will be used in the following generations. The literature shows that GA has been found to provide convergence to near optimum solutions rapidly for a variety of problems (Sheta *et al.*, 2001). However, GA do not guarantee that a convergence to a single best solution for a given problem despite the fact that it's processing leverage will make it an efficient search tool.

GA doesn't deal with a single solution but they deal by their nature with populations of individual solutions where each of these populations is represented by a number of chromosomes formulated in the form of a finite linear string of symbols. The application of GA begins by the random generation of an initial population of individuals which are decoded and evaluated on the basis of the fitness function used for the problem before moving to the next step. After that, a crossover operator is applied to exchange the genes between two selected individuals to form new population individuals. Finally, a mutation operator is applied usually to very small portion of the population making random changes in them. The main advantage of the mutation operator is to maintain the diversity of the generations and avoid the algorithm from being trapped in local minima.

3. Methodology and Case Study

This study focused on developing evacuation human behavior functions needed for modeling the transportation system under evacuation conditions. The developed functions influence the reliability and accuracy of the evacuation models because of their significant effect on the changes in the demand for travel on the transportation system during emergency evacuations. The case study area used for this paper is the Abdali zone in Amman, the capital of Jordan, where it was selected due to its location within the city of Amman and the dense traffic patterns in the area. In addition, the selected area contains many of the sensitive entities such as the Parliament, Public Security Directorate, Civil Defense Directorate, in addition to many other ministries and institutes. The Abdali covers an area of approximately 15 square kilometers and it houses a major development where it is being branded the new downtown for the city of Amman. The case study area is shown in figure (4) along with the major roadway network in the area.

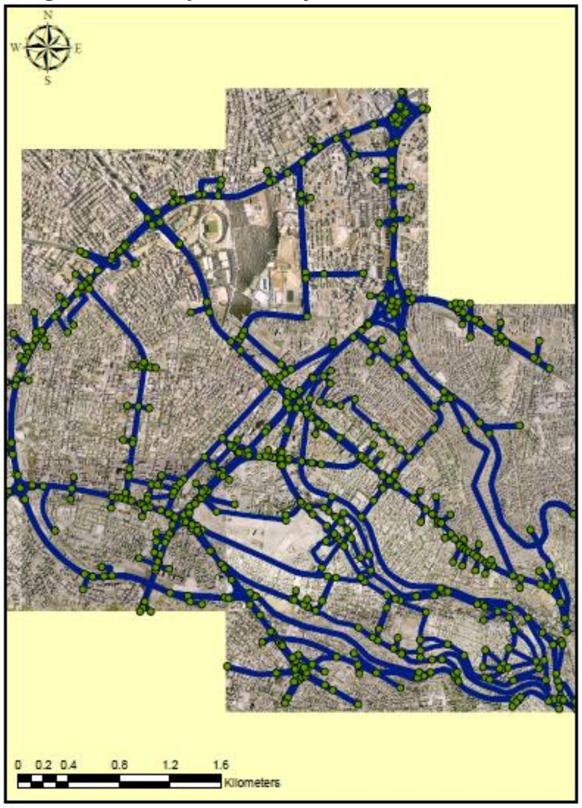

Figure (4): Case study area and major roadway network

The case study scenario selected for this paper was a hypothetical emergency evacuation in the aftermath of a major earthquake that affected the study area. For the purposes of this study human behavior data during the hypothetical emergency event were collected to develop functions for trip generation rates, evacuees' response rates and evacuation trip loading rates which are not readily available in the literature. The regional evacuation caused by the occurrence of an earthquake was selected for this study due to the recent recurrences of similar events in the region and the lack or related data in the literature for such events.

The surveys most commonly used in developing travel behavior parameters are categorized as revealed preference (RP) or stated response (SR) surveys. RP surveys are used to collect data that describe actual behavior of the transportation system users while SR surveys are used to collect data on the response of those users to a hypothetical scenario. The survey used for this study falls within the SR survey category since participants were asked to provide their responses to a hypothetical emergency scenario. There are always concerns related to the reliability of the data obtained from SR surveys since respondent behavior may be different when faced by the actual conditions. On the other hand, the literature shows that data obtained using SR surveys provided valid estimations of human behavior parameters (Travel Survey Manual, 1997).

To produce the data needed for evacuation scenario modeling, a stated response public survey was performed where respondents were interviewed and asked about information related to the hypothetical emergency evacuation scenario. The survey was performed over five stages; planning, design, field implementation, data preparation, and data analysis (Travel Survey Manual, 1997). The scope of the survey along with the required data analysis types were determined in addition to the hypotheses and relations that need to be examined. The survey was then implemented and the results were coded into Microsoft Office Access database using a visual basic form developed for this study and the obtained data were tested and cleaned to maintain usable data for processing and analysis.

The survey used for this study consisted of nine questions in addition to a map illustrating the evacuation area and the possible evacuation destinations. The questions were selected to provide the following information about the evacuees' behavior in response to the selected scenario:

- Compliance rates with the orders to evacuate.
- The estimated time needed to evacuate.
- Number of vehicles to be used in the evacuation.
- Evacuation destination.
- Type of household.

The population selected for the survey included people who are living or working within the boundaries of the study area shown in figure (4) which includes approximately 41,000 households. The needed sample size was determined according to equation (3) and using a 95% level of confidence (Travel Survey Manual, 1997) where it was determined to be 381. A total of 703 people were interviewed providing the needed sample size for analysis. The summary of the obtained data and the analysis of the results are discussed in detail in the following section.

$$S = \frac{P\,(1-P)}{\left(\frac{A^2}{Z^2}\right) + \left(\frac{P\,(1-P)}{N}\right)} \;\ldots\ldots\text{Equation (3)}$$

Where,
S: Sample size
N: Population size
P: Estimate of the interested people in the population (as a conservative estimate a value of 50% was used)
A: Level of accuracy (0.05 was used)
Z: Number of standard deviations of the sampling distribution

4. Results

After the data from the population sample were collected, they were tested and cleaned to maintain usable data only to be used in the analysis. The results of the data analysis are summarized in the following sections.

4.1 Trip Generation

The demand for travel over the transportation system is defined by the number of evacuating trips in addition to the distribution of those trips over the evacuation period. To estimate the number of evacuation trips data about the compliance rates with the orders to evacuate and the number of vehicles that will be used for evacuation by the surveyed sample were collected. The analysis of the trip generation data obtained from the surveyed sample is summarized in table(1).

Table 1: Compliance of households (HH) with orders to evacuate.

Total HH that will comply (%)	473 (67%)	Total HH that will not comply (%)	230 (33%)
Single-family HH that will comply (%)	209 (59%)	Single-family HH that will not comply (%)	143 (41%)
Multifamily HH that will comply (%)	264 (75%)	Multifamily HH that will not comply (%)	87 (25%)

As can be seen from table (1) most of the surveyed sample (67%) stated they will comply with the evacuation orders if they were issued by the authorities. Also, the table shows that people who reside in a single-family HH had lower compliance rates than those living in multifamily HH. When the survey participants were asked to provide reasons for not complying with evacuation orders, most of the single-family HH residents stated they wanted to stay in their residence to protect it and minimize any potential damage to the property. To estimate the number of evacuating trips on the transportation system it is important to determine the number of vehicles that will be used for the evacuation by the household members. The average number of vehicles used for evacuation was 1.2 vehicles per household, and the numbers of those vehicles per household category are summarized in table (2).

Table 2: Number of vehicles used for evacuation per HH category

# of vehicles	# of single-family HH	%	# of multifamily HH	%
0	0	0%	43	16%
1	112	54%	207	79%
2	83	40%	14	5%
3 or more	14	6%	0	0%
Total	209	100%	264	100%
Average/HH	1.53		0.89	

To analyze the effect of the HH category on the average number of vehicles used for evacuation, the Chi-squared test was used at a confidence level of 95%. The hypothesis used for testing was:
Null hypothesis: Ho: The two classifications are independent
Alternative hypothesis: Ha: The two classifications are dependent

Test statistic: $\chi^2 = \sum \frac{[n_i - E_i]^2}{E_i} \ldots \ldots .. Equation\ (4)$

Reject if $\chi^2 > \chi^2_{(0.05)}$ for degrees of freedom equal to [(r-1)*(c-1)]

Where,

Eij = $\frac{(\text{RiCj})}{n}$

r : The number of categories of the first classification
c : The number of categories of the second classification
n : The total sample size
k: The number of categories

The results from the analysis of the data provided in table (2) are summarized in table (3). Based on the data analysis at (α = 0.05) and (D.F. = 3) the χ^2 = 129.733, null hypothesis is rejected and that indicates that different HH's categories used different average number of vehicles for evacuation. Based on the analysis of the case study data the estimate of the number of evacuation trips generated by HH's within the evacuation area is given by equation (5).

Table 3: Chi-Square test for number of vehicles used for evacuation by HH category.

HH Type	Number of vehicles used for evacuation				
	0	1	2	3 ≤	Total
Single family HH	0	112	83	14	209
	19.00	140.95	42.86	6.19	
	19.000	5.47	37.591	9.870	
Multi-family HH	43	207	14	0	264
	24.00	178.05	54.14	7.81	
	15.042	4.708	29.760	7.814	
Total	43	319	97	14	473

$N = (1.53 * SF) + (0.89 * MF) \ldots Equation\ (5)$

Where,
N: The number of evacuating vehicle trips
SF: Number of single family HH complying with the evacuation orders
MF: Number of multi-family HH complying with the evacuation orders

4.2 Trip Loading Rates

After developing the models to estimate the number of evacuating trips, the trip loading rate functions were developed based on the feedback of the surveyed population regarding the needed time to mobilize after the evacuation orders are issued. The literature shows that the most common functional form used to represent the evacuation trip loading rates is the sigmoid function. Sigmoid functions are applied to relate the percent of the evacuating trips with the time period after the evacuation orders are issued. To fit the data obtained from the surveyed sample into a sigmoid functional form, the Genetic Algorithm (GA) was used.

The data obtained was used to develop three mobilization time curves; for the general population, for people who had previous experience with emergency evacuations and others who had no such experience. The general functional form used is represented in equation (6). GA was applied for optimizing α and β parameters of the model for the three curves. GA tuning settings are summarized in table (4). The best α and β parameters obtained through the evolutionary cycle of the GA for the sigmoid functions are summarized in table (5) while the final obtained functions for both experienced and non-experienced surveyed samples are illustrated in figure (5). The comparison between the general function developed for study with other functions available in the literature are shown in figure (6).

$$P(t) = \frac{1}{1 + e^{(\alpha(t-\beta))}} \quad \ldots\ldots.. Equation\ (6)$$

Where,

P (t): % of evacuating trips at time (t)

t: time after the evacuation orders were issued (minutes)

α, β: function constants

Table (4): GA parameter settings

Parameter	Value
Generations	1000
Stall generations	500
Population size	50
Selection method	Stochastic uniform
Crossover probability	80%

Table (5): Developed functional models parameters

Parameter	Functional Model		
	General	Non-experienced	Experienced
α	-0.1425	-0.1267	-0.0973
β	19.5606	17.4012	9.8311

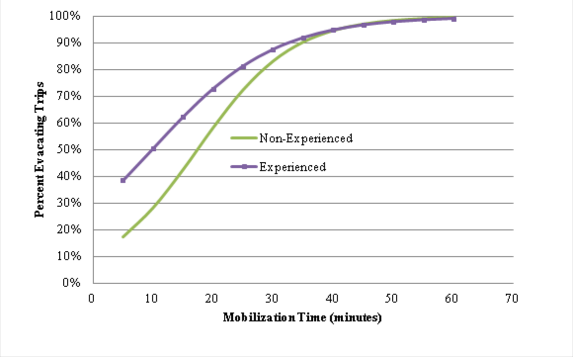

Figure (5): Evacuation mobilization time curves for different surveyed samples

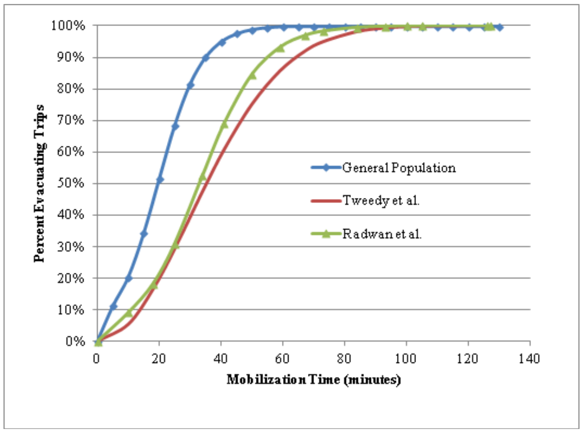

Figure (6): Evacuation mobilization time curves for different case studies

As it can be seen from figures (5) and (6), the evacuation mobilization time after the evacuation orders are issued is relatively short in the case of earthquake related evacuations. This could be attributed to the very short notice time and the severity of the threat, therefore, using the parameters developed in the literature for other cases will lead to overestimating the mobilization time. This in turn will result in underestimating the congestion levels and delays on the roadway network under emergency evacuation conditions which could affect the safety of the evacuating at-risk population. In addition, the figures show that people who had previous experience with emergency evacuations were faster to respond to the evacuation orders than others who had no such experience.

5. Discussions

Estimating the conditions of the transportation system during regional emergency events is critical for emergency preparedness, where the development of evacuation plans should be done well in advance of the occurrence of the emergency event. Modeling the transportation system under emergency evacuation conditions is one of the major tools used to support decision making and capture the changes in the transportation system users' travel patterns as a result of changes in the conditions of the transportation system during regional emergencies. The reliability of the transportation models developed is highly dependent on the ability to accurately capture different human behavior parameters needed for modeling.

This study aimed to develop the human behavior data needed for evacuation modeling for a major earthquake scenario. That data were needed for trips generation and trips loading rates, which are critical for developing accurate and reliable evacuation models. In addition, the data obtained were used to identify the population compliance rates with evacuation orders. The data obtained by this study revealed that compliance rates with evacuation orders and the number of vehicle used for evacuation were dependent on the HH category. Also, this study revealed that evacuation mobilization times for the case study earthquake hypothetical scenario were shorter compared to other types of emergencies and case studies available in the literature. Therefore, using the evacuation modeling parameters developed in the literature for other cases will lead to overestimating the mobilization time. This in turn will result in underestimating the congestion levels and delays on the roadway network under emergency evacuation conditions which could affect the safety of the evacuating at-risk population.

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