INTEGRATED TRAVEL DEMAND MODELS FOR EVACUATIONS: A BRIDGE BETWEEN SOCIAL SCIENCE AND ENGINEERING

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ABSTRACT

Since 9/11, the Indian Ocean tsunami and hurricane Katrina, the number of papers that are being published related to mobility simulation in evacuation conditions has significantly increased. Though several topics have been developed, they tend to be implemented with an isolated and non-system approach and for specific kinds of dangerous events. This work aims to present a classification and specification of demand models for mobility simulation in evacuation conditions under different evacuation scenarios, in respect to different temporal conditions. A general framework is proposed to support the analysis of dangerous events, in respect of type and effects, especially in time. Three different temporal evolutions are identified and systematized: event developments and the relative conditioning on the system; user modification of behavior; and planning and management evolution. Leaving from the integrated temporal evolutions, the user behavior in the system context is analyzed and specific models are developed. The importance of SP surveys to analyze user behavior in evacuation conditions is highlighted and a hybrid class of surveys, termed SP with a physical check, is introduced. An integrated demand model is specified and calibrated for a dangerous event with effects on travel demand, with diffuse effects in space and delayed in time, according a behavioral approach.

Keywords: Evacuation, temporal axis, behavioral demand models.

1 INTRODUCTION

Demand models are a fundamental tool for solving most problems in transport systems planning and management. Such models are based on various assumptions and can be subdivided in relation to different elements: type of choice simulated by the model, with an implicit or explicit algorithm; approach taken for simulating travel demand, i.e. the reciprocal conditioning of decisions; basic assumptions of the models, which can be behavioral if they derive from explicit assumptions about user choice behavior, or descriptive otherwise. In most cases, these models belong to discrete choice models, which are defined in respect of the decision maker, choice set, attributes and parameters, and random residuals. Discrete choice models are usually derived under the assumption of utility-maximizing behavior by the decision maker and are applied to simulate several choices involving transport and mobility, such as mode choice, path choice and car ownership [1–4]. Hybrid discrete choice models with the impact of different normalization approaches on parameter recovery in a simulated environment are proposed in Raveau *et al.* [5]; multiple-discrete continuous choice models are analyzed in Castro *et al.* [6]. The most common methodology used to simulate transport demand is the four-step process that considers generation, distribution, mode and route choice [7]; for a general approach to the general theme of demand–supply interaction, the work of Russo and Vitetta [8] can be considered.

When a dangerous event occurs, in evacuation conditions, demand models specified and calibrated in ordinary conditions cannot be directly applied for several reasons: multiplicity of decision makers, which could be the generic user or a public decision maker (e.g. a mayor); definition of choice set, which may differ for evacuation scenarios and for decision makers; statistical and probabilistic aspects; and attributes and parameters [9].

© 2014 WIT Press, www.witpress.com
ISSN: 2041-9031 (paper format), ISSN: 2041-904X (online), http://journals.witpress.com
DOI: 10.2495/SAFE-V4-N1-19-37

Moreover, in evacuation conditions the analyst should consider two different types of conditions: (i) the presence of constraints set by the public decision maker, in order to reduce system management costs, maximize the system utility (safety, security) and reduce traffic incidents, according to a system optimum approach, and (ii) the absence of constraints.

In recent years, the production of demand models simulating evacuation conditions has greatly increased. The availability of real data related to specific kinds of dangerous events has led to the development of a discrete number of demand models and DSS that support the simulation of user evacuation. In most cases, such models are based on a statistical approach and there is no preliminary analysis of the effects of the dangerous event in question.

A dangerous event can be classified in relation to [10]:

- the kind of event, which can be natural or anthropogenic;
- effect in a transport system, which may be on demand, supply, or demand–supply interaction;
- effect in space, which can be punctual or diffuse;
- effect in time, which can be immediate or delayed.

It is crucial to consider the behavior of users, to recognize their attitude to how the event evolves and the relevant public decisions taken, if any.

Then it is possible to identify three different temporal evolutions:

(1) event developments and the relative conditioning on the system;
(2) user modification of behavior;
(3) planning and management evolution.

(1) Event developments and the relative conditioning on the system

In demand analysis, a delayed or immediate approach is considered, in relation to the time gap available between the time at which it is known that certainty the dangerous event will happen and the time when the event starts its effects on the population in a specific place. In relation to Fig. 1:

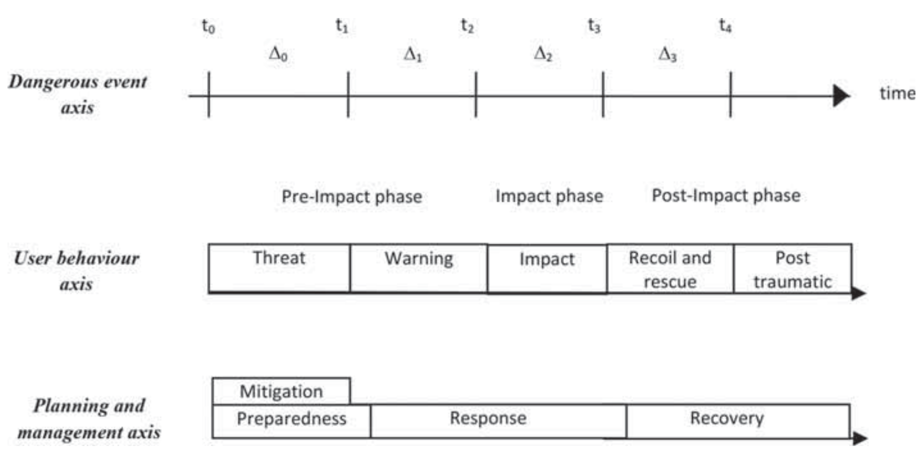

Figure 1: Temporal axis for emergency conditions.

t_0 is the initial instant at which it decides to plan;
t_1 is the time at which it is known that the dangerous event certainly will happen or forecasted to do so or happens in a different place and starts its propagation;
t_2 is the time at which the threat occurs, becomes a dangerous event and starts its direct effects, in the place where the concerned people stay;
t_3 is the time at which the final effect occurs and people cannot be rescued;
t_4 is the time at which the dangerous event ceases its direct effects on the population.

The time interval between the times t_i and t_{i+1} is defined as Δ_i.

If $\Delta_1+\Delta_2= (t_3-t_1)>>0$, a delayed approach is considered and during this gap there is the possibility to evacuate the population and then reduce the effect when the event occurs. In these cases, such as tsunamis, hurricanes, some kinds of landslides and flash floods, evacuation could be implemented and executed in the time $\Delta_1+\Delta_2$.

In Table 1, Δ_i intervals are proposed for several dangerous events. For hurricanes, for example:

Δ_0, that is the interval between t_0 and t_1, the time, respectively, at which a hypothetical public decision maker (e.g. the mayor) decides to plan evacuation from a given area and at which it may be known when the hurricane will be in the considered area;
Δ_1, that is the interval between t_1 and t_2, the time at which the hurricane reaches the given area;
Δ_2, that is the interval between t_2 and t_3, the time at which the hurricane starts its effects;
Δ_3, that is the interval between t_3 and t_4, the time at which the hurricane ceases its direct effects on the population.

(2) User behavior modification in time

This time classification follows that proposed by John Leach's dynamic disaster model, which indicates three phases and five stages during an emergency condition, from which user behavior emerges: a pre-impact phase (Threat Stage and Warning Stage), an impact phase and a post-impact phase (Recoil stage, Rescue stage and Post-traumatic stage), as reported in Vorst [11]. In each phase and stage a specific human behavior has been supposed to be a psychological response to a disaster.

Table 1: Specification of Δ_i intervals for several kinds of dangerous events.

Example	Δ_0	Δ_1	Δ_2	Δ_3
Tsunami	$\neq 0$	$\neq 0$	$\neq 0$	≈ 0
Hurricane	$\neq 0$	$\neq 0$	$\neq 0$	$\neq 0$
Twin Towers	$\neq 0$	$\neq 0$	$\neq 0$	$\neq 0$
Bomb	$\neq 0$	$\neq 0$	$\approx 0/\neq 0$	≈ 0
Exploding tanker	$\neq 0$	$\neq 0$	$\neq 0$	$\neq 0$
Chemical pollution	$\neq 0$	$\neq 0$	$\neq 0$	$\neq 0$
Volcanic eruption	$\neq 0$	≈ 0	$\neq 0$	$\neq 0$
Earthquake	$\neq 0$	0	0	0

In respect of the classification reported in Fig. 1, it may be proposed that:

- the pre-impact phase occurs in $[t_0, t_2)$ and is subdivided in two stages
  Threat stage, which corresponds to the interval $[t_0, t_1)$;
  Warning stage, which corresponds to the interval $[t_1, t_2)$;
- the impact phase occurs in $[t_2, t_3]$;
- the post-impact phase occurs from t_3 and is subdivided into three stages
  Recoil stage and Rescue, which corresponds to the interval $(t_3, t_4]$;
  Post-traumatic stage, which corresponds to the interval (t_4, t_n) with t_n being the generic final time of the post-traumatic event, coincident with the post-traumatic stage.

Different user behavior corresponds to each stage: in the first phase $[t_0, t_1)$ the risk estimation is very low, as is the probability of evacuating, since the risk is not perceived; the second phase $[t_1, t_3]$ is influenced by stress and denial of life-threatening risk, behavior is reflexive and mechanical; during the last stage (t_3, t_n), strong irrational emotions are expressed and emotional disorders are developed. The differences in user behavior between ordinary and emergency conditions are synthesized in the human factor by Vorst [11], who highlights the need to represent it in each evacuation model.

(3) Planning and management evolution
In respect of the introduced time classification, emergency planning activities, defined at international level [12–14] and operated by the civil and public military force, can be classified as:

- mitigation, comprising activities carried out in advance of an emergency event;
- preparedness, comprising events to ensure, if an emergency occurs, that communities, resources and services are capable of responding to the effects;
- response, comprising activities to control, limit or modify the emergency and to reduce its consequences;
- recovery (community), including activities to support reconstruction of physical infrastructure after the emergency situation.

In conclusion, three kinds of temporal evolution can be considered (Fig. 1), corresponding to three different types of analysis, related to:

- the temporal evolution of a dangerous event (dangerous event axis), with the specification of the time interval in which effects on the population are possible;
- the user behavior response, given a dangerous event (user behavior axis);
- the emergency planning activities to reduce the exposure component of the risk (emergency planning and management activities axis).

This work focuses on dangerous events with delayed effects in time ($\Delta_1+\Delta_2>>0$). Given this class of dangerous event, this paper seeks to analyze the literature in question highlighting if papers deal with event evolution, user behavior modification in time, planning and management evolution. Starting from the analysis of models found in the literature, the paper has the following objectives:

- to propose a general framework able to support the analysis of dangerous events, in respect of its kind and effects, especially in time;
- to propose a demand model specified and calibrated for a dangerous event with effects on transport demand, with diffuse effects in space and delayed in time.

In the following it is presented:

- a state-of-the-art/practice review of existing demand models for evacuation conditions;
- a database and survey to analyze user behavior in evacuation conditions;
- specification of an integrated model system, according to descriptive and behavioral approaches;
- the main conclusions and future working objectives.

2 LITERATURE REFERENCE ON TRAVEL DEMAND MODELS FOR EVACUATIONS

In this section the recent literature is examined, focusing on dangerous events that predominantly produce effects on demand, with diffuse effects in space and delayed effects in time. The proposed paper would like to discuss only the travel demand model just before the route choice; in this way it is complementary to other relevant papers analyzing the route choice and the different context of congestion that in turn generate different link flow solutions [15–19].

Previous contributions are classified according to the following elements.

- The kind of dangerous event, distinguishing natural and anthropogenic events.
- The simulated choice, in comparison with the consolidated four-step model: in particular, the paper focuses on the presence of an integrated system able to simulate generation (with or without departure time), distribution and transport mode choice.
- The time classification: the temporal axes to be considered in the paper are reported, referring to the three temporal axes previously defined.
- The basic assumption of the model: the descriptive approach can be distinguished from the behavioral approach, which is introduced if specific hypotheses on user behavior are supposed.
- Calibrated parameters: the presence of technical parameter calibration is verified.

This work mainly considers papers that deal with dangerous events having effects predominantly on transport demand, analyzing generation and scheduling, destination and transport mode user decisions. In relation to route choice, a large number of papers have been proposed in the literature. In this section only a few of these are recalled [15, 17, 18] and readers are suggested to refer to specific papers for a complete analysis. Daganzo and So [20] propose a strategy for managing evacuation networks that are classified as non-anticipative, that is not rely on demand forecast; adaptive, that is based on real-time traffic information; and decentralized, because all the information is available locally.

Some works consider a general point of view of the exiting researches. Sorensen [21] in a reference paper examines the progress on USA hazard warning system, but highlights the necessity to develop research to obtain a more reliable integrated warning system reducing the knowledge gap. Lindell and Prater [22] underline that social scientist research, that approaches to the population behavior, has been poorly integrated with transportation engineers development of evacuation models. Pel *et al.* [23] examine the state-of-the-art models for evacuations and pose some suggestions specifically on travel behavior simulation. Murray-Tuite and Wolshon [24, 25] update the overview of research on evacuation transportation modeling and re-underline the gap between the behavioral science and engineering. A wide analysis of natural disasters that have affected millions of people in the recent years are reported in Brebbia [26]; a focus on the flood risk is proposed in Molinari, Menoni and Ballio [27].

2.1 Generation

In this section the recent literature simulating generation demand in evacuation conditions is synthetically described. Generation demand is estimated in two steps: (1) estimation of total evacuation demand, i.e. the total number of people that need to be evacuated, and (2) estimation of the time profile of evacuation, i.e. departure times of batches of evacuees.

A first classification of generation and scheduling model is proposed in Sbayti and Mahmassani [28], who classify simultaneous and staged evacuation: in simultaneous evacuation, evacuees are advised to evacuate immediately to their destinations; in staged evacuation, evacuees are advised when to evacuate so as to minimize the network time. For the staged evacuation, Chen and Zhan [29] show that staging evacuation in phases is essential in communities where the street networks have a Manhattan-type structure and the population density is high.

The two steps are generally carried out using simplified methods and relationships such as mean demand generation, participation rates and assumed temporal profiles rather than rigorous estimation of demand using comprehensive urban transportation planning models and demand profile optimization [28]. For example, the most common method of estimating evacuation demand is to use participation rates in evacuation zones. These rates vary according to the severity of the storm and are based on past observed behavior. Some researchers report the use of response curves, sensitive to the characteristics of the hurricane, time of day and type and timing of evacuation order, to simulate evacuation demand. These curves are subjectively established based on past evacuation behavior and relate the proportion evacuating to the time from an evacuation order being issued.

Dow and Cutter [30] examine aspects of household evacuation decision making that potentially affect transportation planning for future evacuations. Four specific issues are considered: number of vehicles per household; the timing of evacuees' departures; distances traveled in the evacuation; and the role of information in the selection of specific evacuation routes. Wilmot and Mei [31] compare the relative accuracy of alternative forms of trip generation of evacuation traffic. Participation rate, logistic regression and various forms of neural network models were estimated and tested using a data set of evacuation behavior collected in southwest Louisiana, following Hurricane Andrew. Solis *et al.* [32] examine a set of econometric models to analyze the determinants of household hurricane evacuation choice for a sample of 1355 households in Florida. Hasan and Ukkussuri [33] present a mixed logit model of household hurricane evacuation behavior using original data from hurricane Ivan.

Alsnish *et al.* [34, 35] examine by means of an SP experiment the behavior in evacuation and calibrate a multinomial and a mixed logit in the case of a bushfire.

Wilmot and Fu [36] assume that the decision whether and when to evacuate is made simultaneously. They postulate that this joint decision is an issue that is considered repeatedly prior to it being taken. In other words, they suggest that each household reviews the conditions surrounding a storm continually as it approaches, each time deciding not to evacuate until, if a threshold is reached in their evaluation, a decision is made to evacuate at a certain time. To model this process, they propose the use of a model which they term 'sequential logit model'. In Russo and Chilà [37], dynamic approaches are proposed to simulate user decisions in evacuation conditions. Among dynamic models, sequential dynamic discrete choice models [38, 39] represent a special class and are proposed with sequential tests to ascertain whether current decisions are directly influenced by the most recent previous decisions, also in emergency conditions.

2.2 Distribution

In typical evacuation planning models, evacuees are assigned to pre-determined destinations that are based primarily on the geographical context and their activities. One approach in the literature concerns relaxation of the constraint of assigning evacuees to pre-fixed destinations. In other words, instead of assigning the demand to pre-fixed destinations, evacuees are directed to the nearest safe destination outside the impacted area. This can be achieved by directing evacuees to one dummy destination beyond the existing destinations and letting the optimization approach (user or system) find the shortest route to this dummy destination.

Chiu *et al.* [40] and Han *et al.* [41] propose the One-Destination evacuation model in which the traditional road network with m origins to n destinations is modified to a network with m origin to one destination. Chiu *et al.* [40] applied a system optimal dynamic traffic Cell Transmission Model to a simple evacuation event to solve the evacuation destination-route-flow-staging problem for non-notice emergency events.

A disaggregate choice model for hurricane evacuation was developed with post-Hurricane Floyd survey data collected in South Carolina in 1999 by Cheng *et al.* [42]. A multinomial logit model was used to investigate the effect of risk areas in the path, or projected path, of a hurricane, and socio-economic and demographic characteristics on destination choice behavior.

An important result was obtained by Hasan *et al.* [43], who verified the transferability of the parameters of the evacuation choice models over different hurricane contexts in similar regions.

2.3 Mode choice

Demand models for evacuation conditions focus on one mode of evacuation (predominantly cars) with little attention to multi-modal evacuation using both cars and mass transit [40, 44]; this topic is still largely uncovered in most emergency evacuation studies. This shortcoming is particularly important in cities where the percentage of the population using mass transit is significant. For example, in Toronto a significant portion of the population uses public transit particularly within, towards and outside the downtown core. This portion of the population does not have access to automobiles during the day or at all. Abdelgawad and Abdulhai [44] show that using the readily available transit capacity is therefore essential not only to serve the transit captives but also to improve the evacuation process and reduce network clearance time by moving people *en masse*. The authors propose a general framework able to simulate evacuation demand both by private cars and public transport.

2.4 Comparison of existing models

From examining the literature it emerges that:

1. Some recent general work underline the research gap between behavioral sciences and engineering [22, 24];
2. in most cases, a complete set of integrated tools for assessing demand is lacking;
3. the availability of RP data related to dangerous hurricane events has produced, in recent years, an increase in statistical papers based on historical data, able to simulate only a specific kind of demand in evacuation conditions, which could be transferred only in similar contexts;
4. some papers deal with human behavior in emergency conditions, such as works proposed by Vorst [11], Hasan and Ukkussuri [33], Pel *et al.* [18, 23] and analyze the

psycho-behavioral research in the field of evacuation and underline the importance of behavioral approach in future research, especially in relation to the repeated binary logit model;
5. no paper has proposed the analysis of dangerous events in time, hence the response of user behavior is constrained between the evolution of the event and planning activities;
6. some papers propose an integrated analysis of temporal evolution of dangerous events, planning activities and user behavior.

In the next sessions, two different temporal evolutions are contemporary considered: the modification of the user behavior's decision and the system management related to the dangerous event evolution. A general model to approach the evacuation simulation is proposed, putting a bridge between behavioral science and engineering.

3 AN INTEGRATED SYSTEM OF TRAVEL DEMAND MODELS FOR EVACUATION CONDITIONS

Starting from the analysis of the literature in terms of state of the art/practice relative to travel demand models for evacuation, in respect of different elements, previously described, in this section the following is proposed:

- a general framework which supports the specification of a demand model in evacuation conditions, considering a generic dangerous event, anthropogenic or natural, that predominantly produces effects on demand, with diffuse effects in space, for immediate or delayed effect in time, in respect of consolidated multi-step models (Fig. 2);
- an integrated system of models, specified in the case of dangerous events with delayed effects in time and diffuse in the space, in an area involving a population of 800–1000 people (e.g. a truck with dangerous goods, a chemical industrial accident, a terrorist attack inside a school, an unexploded bomb), according to the behavioral approach; a simplified statistical mode, to support operators of public administrations, students, and so on, is reported in Russo and Chilà [9].

In Fig. 2 different cases are proposed and for each step of the decision-making process the presence or otherwise of constraints is considered. In comparison with the temporal axis

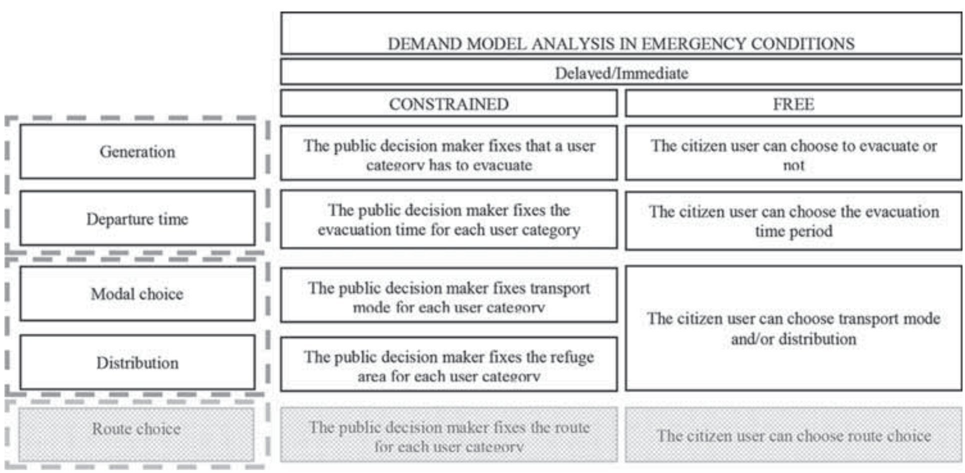

Figure 2: General framework of the travel demand model in evacuation conditions.

proposed in the introduction, in the presence of constraints the temporal axis of planning and management activities by public decision makers predominates over user decisions, but in both cases (constraints or not), the user behavior axis is conditioned by the temporal axis of the dangerous event.

The integrated system of models is subdivided into the following macro-models:

- generation with departure time;
- modal choice with distribution;
- route choice.

The generation model gives the level of demand in the study area according to the reference period and user category. Modal choice gives the number of users taking a given transport mode from a certain origin to a certain refuge area, among the alternatives, namely walking, cars, buses and emergency vehicles for particular categories of users. In relation to destination choice, it is worth pointing out that, in comparison with ordinary conditions, when the destination is a homogeneous area including several elementary destinations, in emergency conditions, alternatives are discrete points fixed by a decision maker [9]. The traditional Newtonian method is not very effective at representing user behavior in emergency conditions. In most papers, evacuees are assigned to pre-determined destinations that are based primarily on the geographical context and their activities. However, the distribution model could be applied to:

- simulate user distribution among different point destinations fixed by a public decision maker (e.g. the mayor);
- simulate user distribution between fixed point destinations and other areas not fixed by a public decision maker, but considered safe by users.

For the distribution model, in emergency conditions and in the absence of constraints, it is supposed that the decision maker chooses the refuge area together with the transport mode or, alternatively, he/she chooses the transport mode first and then the destination. Finally, it is showed that in evacuation conditions the consolidated order of the multi-step model could vary and, for example, the choice of transport mode could be made before the destination choice.

The last level of the Fig. 2 is shaded because the proposed paper would like to discuss only the travel demand model just before the route choice, as previously specified.

3.1 Generation model

Given an emergency scenario, the generation model simulates the mean number of people to evacuate in the study area in the reference period.

Herein demand of people present willing to evacuate can be specified according to a behavioral binary model.

It is assumed that constraints are absent and:

- the citizen user as the decision maker;
- a choice set including the evacuate or not evacuate alternative;
- attributes and parameters related to socio-economic characteristics and alternative specific attributes (ASA);
- a behavioral approach, with random residual ε_j independently and identically distributed according to a Gumbel random variable of zero mean and parameter θ.

In the following the specification of systematic utility for the alternatives is proposed:

$$V_{evacuate} = \beta_{Woman} \cdot Woman + \beta w_{\_PU} \cdot W\_PU + \beta_{DL} \cdot DL + \beta_{CO} \cdot CO + \beta_{Centre} \cdot Centre$$
$$V_{not\ evacuate} = \beta_{R} \cdot R + \beta_{NOFL} \cdot NOFL + \beta_{Age\_25–65} \cdot Age\_25–65 + \beta_{ASA\_NE} \cdot ASA\_NE$$

with

Woman	dummy equal to 1 for woman, 0 otherwise;
W_PU	dummy equal to 1 for public sector employees, 0 otherwise;
Centre	dummy equal to 1 if the origin is in the central zone, 0 otherwise;
DL	dummy equal to 1 for users with a driving licence, 0 otherwise;
CO	dummy equal to 1 for users owning vehicles, 0 otherwise;
R	dummy equal to 1 for residents, 0 otherwise;
NOFL	dummy equal to 1 for unemployed, 0 otherwise;
Age_25–65	dummy equal to 1 for people with ages in the 25–65 age class, 0 otherwise;
ASA_NE	ASA for the *not evacuate* alternative.

3.2 Modal choice model with distribution model

The modal choice model gives the number of users choosing a given transport mode from a certain origin to a certain refuge area; the distribution model gives the probability of trips undertaken by users going to a certain refuge area, given departure from zone r and time period h. Herein modal choice and distribution are probably constrained for school staff and weak user categories. For the remaining categories it is proposed:

- a modal choice model;
- a distribution model;
- a modal choice with distribution model.

For the modal choice model the constraint absence is supposed and

- the citizen user as is considered as the decision maker;
- a choice set which includes the alternatives car and pedestrian;
- attributes and parameters related to level of service, socio-economic characteristics and ASA, variables which account for quality characteristics or those not explicitly included in the attributes;
- a behavioral approach, with random residual ε_j independently and identically distributed according to a Gumbel random variable of zero mean and parameter θ.

The systematic utility for the alternatives is a function of:

$$V_{Pedestrian} = f(T_{RP}, D, Pedestrian, E_i, Woman)$$
$$V_{Car} = f(T_{RC}, D, Car, L, CWork)$$

with

T_{RP}	time on pedestrian network;
T_{RC}	time on road network;
Pedestrian	dummy for pedestrian alternative;
D	linear distance between origin and refuge area;
E_i	dummy equal to 1 for users of age in the range i;

Woman dummy equal to 1 for woman users, 0 otherwise;
L dummy for skill level of employees;
CWork dummy equal to 1 if the worker uses a car to go to work, 0 otherwise.

For the distribution model, a refuge area fixed by the public decision maker is supposed and

- the citizen user is considered as the decision maker;
- a choice set which includes the alternatives *refuge area fixed* by public decision maker (RAF) or *other refuge area* (RAO);
- attributes and parameters related to level of service, socio-economic characteristics and ASA;
- a behavioral approach, with random residual ε_j independently and identically distributed according to a Gumbel random variable of zero mean and parameter θ.

In relation to the choice set considered, it is showed elsewhere [9] that users, during evacuation, are inclined to reach areas not only indicated by a public decision maker but especially considered safe by themselves. Indeed, about half the users reach the areas fixed by the public decision maker. Hence, to represent other destinations, a generic *other refuge area*, referred to as RAO, is introduced.

The systematic utility for the alternatives is a function of:

$$V_{RAF} = \mathrm{f}(Z_r, D)$$
$$V_{RAO} = \mathrm{f}(L, Woman)$$

with
Z_r dummy origin zone;
D linear distance between origin and refuge area
Woman dummy equal to 1 for woman users, 0 otherwise;
L dummy for skill level of employees.

For modal choice with the distribution model the absence of constraints is supposed and

- the citizen user as decision maker;
- a choice set which includes the alternatives car with refuge area (C,RA) and pedestrian with refuge area (P,RA);
- attributes and parameters related to level of service, socio-economic characteristics and ASA, variables which account for quality characteristics or those not explicitly included in the attributes;
- a behavioral approach, with random residual ε_j independently and identically distributed according to a Gumbel random variable of zero mean and parameter θ.

The systematic utility for the alternatives is a function of:

$$V_{P,RA} = \mathrm{f}(T_{RP,RA}, D_{RP,RA})$$
$$V_{C,RA} = \mathrm{f}(T_{RC,RA}, D_{RC,RA})$$

with
$T_{RP,RA}$ time on the pedestrian network;
$T_{RC,RA}$ time on the road network;
$D_{RP,RA}$ distance on the pedestrian network;
$D_{RC,RA}$ distance on the road network.

4 EXPERIMENTATION

The international literature related to evacuation conditions proposes studies which focus, in most cases, on hurricanes. For this kind of dangerous event, large data collections allow the demand model to be estimated by means of RP (revealed preference) surveys. RP surveys include preferences inferred from observations of a decision maker's actual choices, in relation to real contexts. RP data are not available for all dangerous events. Hence, models specified for hurricane evacuation, which are derived from observation of past evacuation behavior, cannot be directly transferred to the simulation of other dangerous events. For this purpose, SP (stated preference) surveys may be carried out, which represent stated behavior of users in relation to hypothetical contexts [45]. Various alternatives as a basis for constructing optimal designs for stated preference studies are proposed in Yu *et al.* [46].

Naser and Birst [47] confirm the importance of SP data to specify and calibrate demand models for evacuation conditions, recalling a wider class of stated surveys termed stated response (SR). SR surveys, according to a large number of studies, can provide predictions of choice behavior to a satisfactory degree. There are four general classes for SR survey techniques based on the nature of the questions and the expected behavioral outcome: stated preference, stated tolerance, stated adaptation and stated prospect. According to the literature taxonomy [48]:

- in stated preference (SP) surveys, respondents are forced to choose or give a trade-off between predetermined options, which are expressed in terms of packages of attributes or as behavioral alternatives in the face of a given set of constraints;
- in stated tolerance (ST) surveys, respondents are asked to identify the nature and level of constraints comprising the limits of acceptability of behavioral outcomes;
- in stated adaptation (SA) surveys, respondents are allowed to imagine for themselves how they would behave in the new situation of interest;
- in stated prospect (SPro) surveys, respondents are asked under what circumstance they would be likely to change their travel behavior and how they would go about it.

Train and Wilson [49] introduced SP-off-RP questions, in which information is asked differently from SP surveys. According to this approach, the alternatives and the choice of respondents in a real-world setting are observed, and respondents are asked whether they would choose the same alternative or switch to another alternative if the attributes of the chosen alternative were less desirable in ways specified by the researcher and/or the attributes of non-chosen alternatives were more desirable in specified ways.

Between RP and SP surveys, in this work a hybrid class of surveys, termed SP with a physical check, is introduced. In order to obtain useful data for demand model calibration, given a kind of dangerous event, evacuation trials in the context of the SICURO research project are carried out [9]. During evacuation trials, RP data have been obtained, even if they are affected by the laboratory effect, because each user participating in evacuation trials knows that he/she does not run any real danger. Therefore, RP surveys during evacuation trials are a statement of behavior in emergency conditions, like SP surveys with physical check.

In this section the following are proposed:

- the main results obtained from RP and SP with physical check data;
- calibrated parameters obtained for proposed models.

4.1 Data: RP and SP with physical check

In order to evaluate user behavior in respect of formal transportation decisions, data obtained from a real experiment in the urban area of Melito Porto Salvo in the province of Reggio Calabria (Italy) are considered.

The following were carried out:

- a survey to ascertain the socio-economic characteristics of the study area, including RP and SP data, to estimate the usual number of users present and their willingness to evacuate;
- a pre-test, where an area with only public offices and one school is evacuated,
- a test, where the whole area is evacuated.

The data obtained from the pre-test and test are referred to as SP with physical check data.

The survey was carried out with data related to buildings and users present in the study area, subdivided into the following categories:

for buildings

- residential;
- public;
- private business;
- school;

and for users

- residents;
- employees;
- occasional customers;
- teachers and students;
- weak users.

In Table 2, the main indicators obtained for the study area are proposed. The study area is 4.3 ha and was subdivided into 11 discrete traffic zones. During the experiment, information was obtained with manual/automatic tools, 30 video cameras and by interviewing evacuated users.

4.2 Model estimation

In this section the proposed system of models is described. The generation model was calibrated using the maximum likelihood method. In Table 3 the calibrated parameters, obtained for a morning reference period, according to the behavioral approach, are reported.

Table 2: Buildings and residents in the studying area.

User category	Number	Building	Number
Residents	255	Residential	135
Employees	212	Public	27
Occasional customers	170	Private (shop, ...)	44
Teachers and students	159	School	1
Weak users	5		

Table 3: Behavioral generation model for evacuation willingness.

Parameter		Alternative	Value	t-Statistic	Value	t-Statistic
$\beta_{Age\_25–65}$	25–65 Age class	ne			–0.344	(–1.1)
β_{NOFL}	Unemployed	ne	1.398	(1.2)	1.272	(1.1)
β_{R}	Residents	ne	0.814	(2.8)	0.882	(2.5)
β_{W_PU}	Public sector employees	e	0.644	(2.0)	0.665	(1.7)
β_{Woman}	Woman	e	0.439	(1.5)	0.518	(1.8)
β_{ASA_NE}	ASA_NE	ne			–0.353	(–0.8)
β_{Centre}	Origin in central zone	e	0.628	(0.8)	0.652	(0.9)
β_{DL}	Dummy for driving licence	e	0.649	(2.7)	0.623	(2.1)
β_{CO}	Dummy for vehicle ownership	e	–0.142	(–0.5)		
	Initial likelihood		–230.125		–230.125	
	Final likelihood		–201.377		–200.779	
	ρ^2		0.125		0.128	

e: to evacuate, ne: not to evacuate

On considering the behavioral approach, it is noted that the most significant parameter is that of residents in the study area, which has a positive sign and is associated to alternative 2 (not evacuate). The parameter public sector employees is also very significant and bears a positive sign for alternative 1 (evacuate), representing the trend to evacuate from the public office. Another significant parameter is related to the driving licence, which has a positive sign and, as might be expected, represents the trend to evacuate. The parameter origin in central zone is characterized by a positive sign and represents the trend to evacuate if the user is located in a zone with a high percentage of public offices, commercial shops and so on. Considering the gender of the users, the parameter woman, introduced in specifying evacuation alternatives, has a positive sign, expressing the trend to evacuate. The sign of unemployed, introduced in the alternative not evacuate, expresses the trend to stay at home. By contrast, the sign of age in the 25–65 age class parameter is negative and expresses the trend for people of this age to evacuate.

The modal choice model and distribution model were calibrated using the maximum likelihood method. In Table 4, the results are shown for the modal choice model, in relation to car and pedestrian alternatives; in Table 5 the results obtained are for distribution model, considering the alternatives refuge area fixed by public decision maker or other refuge area.

In relation to the modal choice model, calibrated parameters of the model show that the trend to use the car to evacuate is higher for high-income employees who use their car to go to work. The distance parameter negatively influences the trend to choose walking as an alternative. By contrast, people aged below 45 years and women prefer to choose the pedestrian alternative. In relation to the distribution model, it is showed that while women and medium–high income for employee parameters represent the trend to reach the refuge area fixed by the public decision maker, the origin in a central zone (Z10) expresses the trend to reach another refuge area, not fixed, but considered safe by the user.

Table 4: Modal choice model.

Parameter		Alternative	Value	t-Statistic
β_{WE}	Dummy employee age lower than 45 years	Pedestrian	3.07	(1.9)
β_{DRC}	Distance on the pedestrian network between origin and refuge area	Pedestrian	–0.01	(–1.9)
β_{L3}	Dummy employee's high income (high skill level)	Car	1.18	(0.7)
β_{CWork}	Dummy equal to 1 if the user uses his/her car to go to work, 0 otherwise	Car	0.30	(0.5)
β_{Woman}	Dummy like 1 if the user is a woman, 0 otherwise	Pedestrian	1.94	(1.3)
Initial likelihood				–14.56
Final likelihood				–7.58
ρ^2				0.57

Table 5: Distribution model.

Parameter		Alternative	Value	t-Statistic
α_{Woman}	Dummy equal to 1 if the user is a woman, 0 otherwise	RAF	2.85	(3.3)
α_{L2}	Dummy if the employee's income is medium–high (medium–high skill level)	RAF	0.27	(0.4)
α_{Z10*}	Dummy of origin equalling zone 10	RAO	1.48	(3.9)
Initial likelihood				–39.51
Final likelihood				–25.81
ρ^2				0.35

Z10* is a central zone of the considered area, in which most of the public offices are present. RAF, Refuge area fixed by public decision maker, RAO, Other refuge area.

The model proposed was validated by verifying the reasonableness and the significance of estimated coefficients, as well as the model's capability to reproduce the choices made by a sample of users. All these activities can be completed with appropriate tests of hypotheses for a sample of users.

5 CONCLUSIONS

In this work a synopsis of models from the recent literature dealing with evacuation conditions has been proposed, pointing out that, in most cases, models are specified for a specific kind of dangerous event and are not directly applied to simulate a generic evacuation condition, defined only by the evolution of the event. Generally, models are specified according to a descriptive approach, which is unable to consider human behavior in emergency conditions. There are a substantial number of papers dealing with a specific formal transportation decision, few of which propose a general structure able to simulate all transportation decisions. Finally, some papers have proposed an integrated analysis of the evolution of dangerous events, planning activities and user behavior.

Starting from such considerations, in this work the following have been proposed:

- an introductory framework able to support the analysis of dangerous events, in respect of their kind and effects, especially in time;
- a demand model specified and calibrated for a dangerous event with effects on transport demand, with diffuse effects in space and delayed in time, according a behavioral approach.

The importance of SP surveys is highlighted to analyze user behavior in evacuation conditions and then to specify and calibrate models able to reproduce the decision process during a dangerous event.

Future objectives are related to a calibration of behavioral models from SP data, evidencing the role of public management in the risk reduction and of type of information to the users.

ACKNOWLEDGMENTS

The SICURO research project was organized by the Laboratory for Transport Systems Analysis of Mediterranea University of Reggio Calabria and funded by the Calabria Regional Authority.

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