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A Stochastic Approach for Simulating Human Behaviour During Evacuation Process in Passenger Trains

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Abstract. In this paper we present a stochastic approach for modelling passenger performances during evacuation process in passenger trains. The paper is divided into two parts. The first part describes the identification of variables and data collection. This process allows obtaining statistical samples of predefined random variables (personal responses, non-emergency actions, walking speeds, etc.). Then, statistical methods to determine the input and outputs for a stochastic analysis are proposed. In the second part, results from EvacTrain®, a stochastic model for passenger trains, were compared with other evacuation models and an announced evacuation drill. Results suggest that predicted evacuation times can be strongly dependent on the activities of individuals whose actions interrupt the continuous movement of other passengers within the aisle and the time spent by each passenger to negotiate the train steps. The advantages of using a stochastic approach for modelling passenger behaviours are discussed.

Keywords: Evacuation Model, Behavioural Variables, Data Collection, Passenger Trains

1. Introduction

There has been very little research carried out that analyses the evacuation process in passenger trains. First studies were conducted by the National Institute for Standards and Technology (NIST) [1]. Egress calculations were performed to estimate the minimum necessary egress time by using egress modelling for an upright rail car with a maximum capacity of 72 passengers. As the report states, different assumptions were considered showing the lack of empirical data and the absence of a specific tool that permits to simulating a passenger performing activities, such as collecting belongings, investigating the fire, etc., instead of simply exiting the car. Another contribution was carried out by the Department of Fire Safety Engineering (Lund University) publishing a report about safety conditions in case of fire in an intercity train [2]. However, inputs regarding the characteristics and

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passenger behaviours were assumed and the model limitations to represent the specific conditions of this kind of scenarios were highlighted. One of the attempts to simulate evacuation in rail vehicles was performed in [3]. In the agent based model, passengers are modelled as adaptive agents obeying rules of behaviour and the collective behaviour of the group emerges through the interaction of the passengers, between them and the environment. However, it is not clear if the proposed model can simulate the responses and activities of passengers.

The attempts to analyze the passenger behavioural parameters during evacuation processes are really scarce. A special mention is required for the developed studies done by the Fire Safety Engineering Group (FSEG) at University of Greenwich with a series of evacuation experiments in an overturned rail vehicle [4]. Due to the limited number of tests, the results about passenger flow rates are just indicative more than definitive. In Boston, on August 2005, The Federal Railroad Administration (FRA) in collaboration with the Massachusetts Bay Transportation Authority (MBTA) conducted a series of evacuation experiments to a platform in an intercity train [5]. The experiments were performed with normal and emergency lighting systems. The results (flow rates through the exits and evacuation times) did not show differences in evacuation times under these two lighting conditions. Another research work was performed to obtain passenger performance data by conducting a series of evacuation experiments in a metro train [6]. The obtained results made reference to flows through the available doors in one side of the train and the strategies adopted by passengers to leave the train (from the train level to the rail level): "jumping", "Sitting" or "Sitting on a side".

At the moment, one of the most interesting proposals is being developed by the METRO Project [7], a multidisciplinary project developed by nine entities whose aim is protection of underground rail mass transport systems. The project is divided into seven Work Packages. The aim of the work package WP2 (Lund University and Stockholm Public Transport, Sweden) is to develop a series of submodels, which will be implemented into current evacuation models to reproduce the specific conditions of rail vehicles.

From the current results it can be concluded that: (1) the current egress models cannot represent the specific characteristics of trains, and research using evacuation modelling makes assumptions and simplifications and (2) empirical data of passenger behaviours are really scarce. The existing data are mainly referred to exit flow rates. Therefore, an extensive data collection is necessary to quantify the behavioural variables and passenger responses.

This paper explores passenger performances during evacuation process in trains with specific interior configurations—seat rows on both sides with an aisle in the middle of the coach—and no deteriorating environmental conditions. In the first part, behavioural variables and empirical data-sets of passenger performances were collected. Then, statistical methods to determine the input and outputs for a stochastic analysis are proposed. The second part discusses this specific set of behavioural random variables and their application in EvacTrain®, a stochastic egress model for passenger trains.

2. Behavioural Variables

Nowadays, it is well known that human performances can play a key role during evacuation process. One of the most important tasks in safety science is to predict and quantify human performances and prevent inappropriate behaviours to ensure an efficient and safe evacuation. This is particularly important inside trains, where the space is limited.

As soon as the train passengers have been warned about the emergency, their actions before and during evacuation movements, such as preparing for evacuation, gathering information, waiting for others, etc. may cause a block in the aisle and interrupt the continuous movement. This leads to the following question. How do we simulate additional behaviours of passengers?

In order to reproduce any actions the occupants might perform during the evacuation process, most egress models-mainly designed for buildings- assume a pre-evacuation time as the time in which individuals will wait in their initial position before beginning evacuation movements. Other models assign a sequence of behavioural actions (a "behavioural itinerary") to the occupants in order to simulate an interruption in the evacuation process. However, this "behavioural itinerary" is assigned by the user before the simulation begins rather than being predicted by the model [8].

But the actions performed by passengers change amongst individuals. Furthermore, these actions and their impact are unknown prior to an event. For that reason deterministic approaches have problems to analyse all the possible behaviours and their effects on the evacuation process.

A probabilistic approach can be an alternative to solve the problem [9]. We cannot predict the certain actions that individuals may perform given an emergency situation. However, we can predict by stochastic analysis based on reliable data, the impact of multiple combinations of these actions in predicted evacuation times.

The development and the increasing use of stochastic models lead to the selection of a random nature for the input and output variables. Therefore, there is a need to define the stochastic quantitative parameters. In this section behavioural variables of passengers are identified and empirical data-sets of passenger performances were collected. Then, statistical methods to determine the input and outputs for a stochastic analysis are proposed.

2.1. Identification of Variables

Figure 1 shows the sequence of passenger response and the identified variables during evacuation process in trains.

As shown Figure 1, the pre-movement time is broken into two time intervals (variables).

t_{pr}: **Personal response time**. The time spent by each passenger in standing up once he/she receives the emergency notification by the crew member or PA (Public Address System)

t_1: **Delay time within the aisle**. The time elapsed from t_{pr} to the purposeful movement to the exit. This variable is considered part of the pre-movement time.

During this period of time, passengers can perform different actions such as collecting belongings, getting dressed, checking the seat area, waiting, etc. These activities can be performed within the aisle thus interrupting the continuous movement

But not every passenger performs a delay time within the aisle. For this reason we define P_{t1} as the *Probability of passenger delay time within the aisle*. This variable can be defined as follows:

$$P_{t1} = P(t_1 \neq 0|SA) \tag{1}$$

where SA, passenger stays in the aisle; P_{t1} is the probability that the delay time within the aisle is different to 0 once the passenger reaches the aisle.

In some situations the pre-movement time variables (t_{pr} and t_1) can be overlapped i.e. passenger undertakes different actions before standing up (shot down laptops, information exchange, etc.). In the present analysis, this behaviour had been combined and measured as t_{pr}. On the other hand, despite some passengers can have available space to access the aisle and start evacuation movement, they decide to wait for crew members or for other passengers. This behaviour has been assumed as t_1. In some cases, the passenger stands up and starts evacuation movement without undertaking any other activity, therefore $t_1 = 0$.

The end of t_1 denotes the beginning of the Travel Time.

Figure 1 shows how during the Travel Time another time intervals for train evacuation can be identified:

***t_2*: Delay time to collect the baggage**. The time spend by (some) passengers picking up his/her suitcases from baggage compartment within the aisle (see Figure 2). But not all passengers are likely to perform this action. For this reason, a probability is defined as P_{t2} *Probability of passenger delay time to collect the baggage*. This variable can be defined as follows:

$$P_{t2} = P(t_2 \neq 0|SC) \tag{2}$$

where SC, passenger stops in front of the baggage compartment.

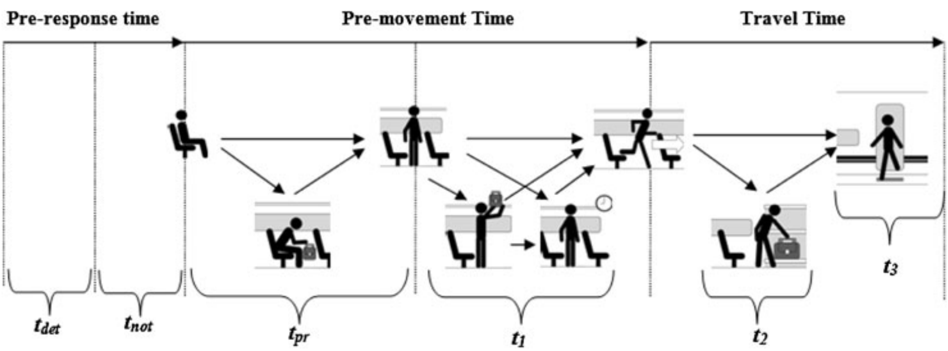

Figure 1. Sequence of passenger response.

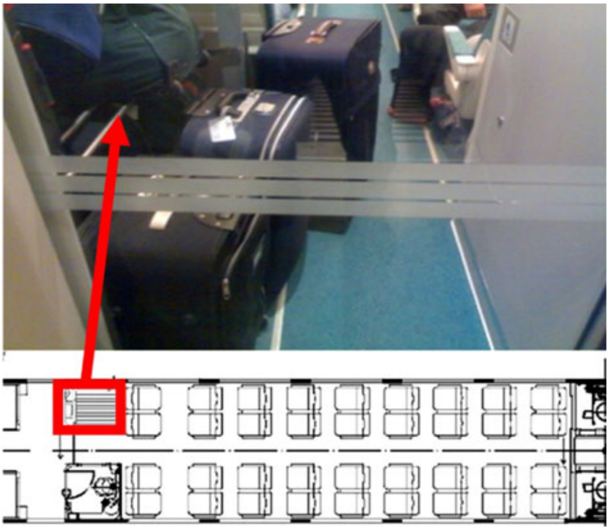

Figure 2. Location of baggage compartment.

This means that P_{t2} is the probability that the delay time to collect the baggage is different than 0 due to the condition that the passenger passes in front of the baggage compartment.

***t3:* Delay time to negotiate exit** This variable is the time spent by each passenger to negotiate the exit. This variable depends on passengers (abilities, baggage), the exit design and how they behave in response to it [10]. For instance, evacuation through platform, sidewalk, emergency ladder or a ramp can produce different values for t_3. In fact, even in the most favourable scenario (platform), the distance and the height of platform respect to the train floor can vary. Other scenarios (emergency ladder or a ramp) are more complex and will generate a higher delay time to negotiate the exit.

***Ws* Unimpeded walking speed** This variable represents the unimpeded walking speed of each individual through the aisle inside the train.

Its value depends on the psychological and physical features of each passenger, the belongings they carry with them. The experimental nature of this variable is checked by measuring the time spent to walk down the aisle of a certain length. In this case the relation density vs walking speed are not considered due to restricted spaces inside the train and the queue discipline conditions.

2.2. Data Collection

2.2.1. Evacuation Drills. Data collection was obtained from two evacuation drills conducted by RENFE Operadora (Spanish Railroad Administration). More detailed information about the evacuation drills can be found in [11].

The first evacuation drill took place on 7th July 2007. The train involved was a high speed train S 103 200 m long with 8 passenger coaches and capacity for 316 passengers. The drill involved 83 workers from Renfe Operadora (Spanish Railroad

Figure 3. Passengers performing actions during evacuation drills.

Administration). Some of the participants had jackets and hand bags. It should be noted that they were not carrying any luggage. The drill was not previously announced in order to provide more realistic information about crew and passenger performance. The procedure consisted of a managed evacuation from three coaches to the platform through one exit once the vehicle had stopped.

The drill was documented by a video camera following the crew member intervention during the evacuation process. The further video processing (frame by frame) permitted to collect data related to the variables t_{pr} and t_1 (see Figure 3).

The second drill took place on 19th September 2009. It involved a high speed train S 130 (198 m long). It has 11 passenger coaches with a capacity for 299 passengers. The drill involved 218 participants. The passenger did not carry luggage, however most of them had jackets and hand bags. This was an announced evacuation drill. It consisted of a simulated fire in one of the coaches and the relocation procedure was performed coach by coach along the length of the train before the train stopped inside a rail tunnel. Once the train had stopped, the doors were automatically open.

The drill was documented with two fixed video cameras (see Figure 4)—one camera inside a passenger coach and other camera in front of the exit. The further video processing permitted to obtain the walking speed (W_s) during the relocation procedure and the delay time to negotiate exit (t_3).

Additionally, a dataset of unimpeded walking speeds of passengers in the aisle was obtained inside a high speed train (Alvia S 130) during 8 journeys in normal conditions. The time spend by different passengers walking down the aisle of a passenger coach length was manually measured with a total of 74 samples.

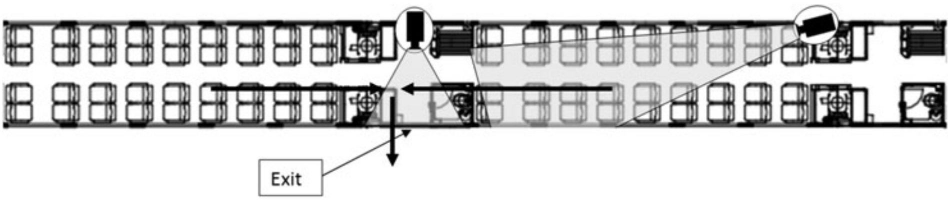

Figure 4. Location of video cameras during the evacuation drill.

2.2.2. Experiments. In order to increase the samples of behavioural variables, individual experiments were conducted at laboratory of GIDAI Group at University of Cantabria. A total of 22 participants (12 males and 10 females) aged between 20 and 70 were recruited. They were not pre-informed about the experiment. In order to measure the estimated personal response time (t_{pr}), each individual was exposed to the following pre-recorded voice message: "Attention please, Attention please, this is an emergency, leave the train by the nearest exit". This voice message lasted 7 s.

Some of participants were performing different actions such as using laptops, reading or listening music on their personal music device before hearing the voice message. It was observed that, depending on the activities, participants spent time preparing for evacuation. Of particular note, some of the participants spent time by switching off their laptops (closing all the applications) thus increasing significantly their response time. Then, the times of participants performing the following discrete actions were measured:

- (t_1) Delay time within the aisle: (1) Putting on jacket and (2) Collecting hand bag from overhead baggage rack.
- (t_2) Time at luggage compartment: (1) Collecting a large suitcase and (2) Collecting a small suitcase.
- (t_3) Personal time to negotiate exit steps: (1) Normally, (2) Carrying a large suitcase and (3) Carrying a small suitcase.

2.3. Statistical Methods

The basis of stochastic approach is the application of Monte Carlo methods. For this reason it is necessary to know the distribution functions of the random variables (t_{pr}, t_1, t_2, t_3 and W_s) and their probability of occurrence (P_{t1} and P_{t2}).

The possibility to combine the samples of data from video recordings and experiments in order to increase the sample size is analyzed and the Mann–Whitney non-parametric test is performed in assessing whether the two samples come from the same distribution. The Hypothesis that the two samples of each variable come from the same distribution is accepted with a significance level of 0.05. The PDF (Probability Distribution Function) of a random variable can be achieved by fitting data for a known distribution. Otherwise data can be achieved by density estimation. This process consists in the application of goodness of fit tests. According to the egress literature reviewed log-normal and normal distributions are the most usually applied for human performance data. For this reason, for assessing whether a given distribution is suited to dataset, the following specific tests and their underlying measures are used [12–14]:

- D' Agostino's K-square normality test (for samples greater than 25).
- The Anderson–Darling normality test (for samples smaller than 25).
- Hypothetical log-normal test applying the same test above.
- The Anderson–Darling uniformity test (normally test modified).

Specific tests are considered because they have more power. Otherwise, data can be achieved by density estimation. From the multiple methods of density estimation, such as Kernel density estimation (used to smooth samples), the histogram method is considered to provide an easier and suitable application for Monte Carlo simulations. In order to obtain the probabilities P_{t1} (time to prepare) and P_{t2} (time at baggage compartment), a Bernoulli trial was performed based in real observations [12]. The results for P_{t1}, P_{t2} and their Wilson score intervals with a significance level of $\alpha = 0.05$. By using the data collection approach and tests outlined above, the following data are obtained displayed in Figure 5 and Table 1.

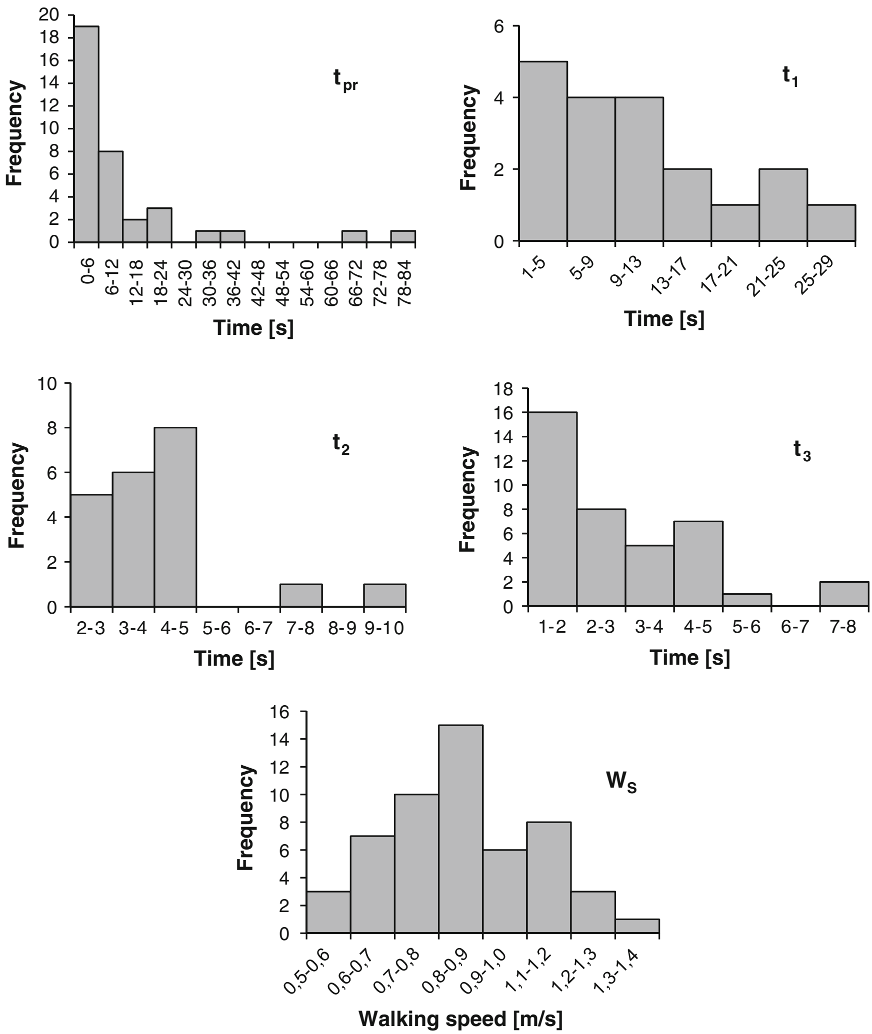

Figure 5. Histograms of random variables.

Table 1
Distributions of Behavioural Variables

	t_{pr} (s)	P_{t1}	t_1 (s)	P_{t2}	t_2 (s)	t_3 (s)	W_s (m/s)
n	79	39	65	37	48	89	74
PDF*	LN		U		LN	LN	N
μ	11.92		12.04		4.38	2.27	0.99
σ	16.25		7.98		2.15	1.26	0.27
p		0.84		0.16			
pmin		0.70		0.076			
pmax		0.93		0.31			
a			1.48				
b			26.06				

PDF probability density function, *LN* log-normal, *U* uniform, *N* normal, *N* number of samples, μ mean, σ standard deviation, *p* probability, *pmin* probability minimum value, *pmax* probability maximum value, *a* minimum value, *b* maximum value

3. Simulations

3.1. EvacTrain®: An Stochastic Model for Passenger Trains

EvacTrain® is an Evacuation Model developed by GIDAI Group of University of Cantabria [9, 15]. The model was developed with the purpose to capture and process stochastic variations in evacuation times by using Monte Carlo methods in order to simulate the random characteristics, decisions and actions of passengers. This is an object-oriented model (developed with Microsoft Visual C# 2008 over .NET Framework 3.5 SP1 platform) in which train spaces are represented by a fine network and passengers move throughout the train from one cell space to another (with a cell size of 0.5 × 0.5 m).

Passengers find their way towards the exit by following the information of neighbouring cells. The interaction between passengers resolves around the idea that two passengers cannot be in the same grid/cell at the same time.

A passenger will not move to another occupied grid cell and will wait until the next cell is empty. If more than one passenger is waiting for the same cell (i.e. in merging flows at exit doors) and they have the same characteristics (i.e. walking speed), the model will resolve the conflict randomly to decide which passenger moves first. Due to restricted space conditions, in this first version the model does not consider the relation between walking speed and density.

As Figure 6 shows, cells 11 and 12 are seats, cells 0 are unavailable cells and cell 44 is the exit. All the other cells are available spaces and passengers move from one cell to the next cell towards the exit. However, some grid cells (cell 32 or the cells that passengers immediately use to access the aisle and the cells in front of the baggage compartment) are locations where behavioral actions (delays) may occur. Cells have the potential to cause delay and passengers may or may not perform delay actions, according to a probability of occurrence assigned randomly by the model.

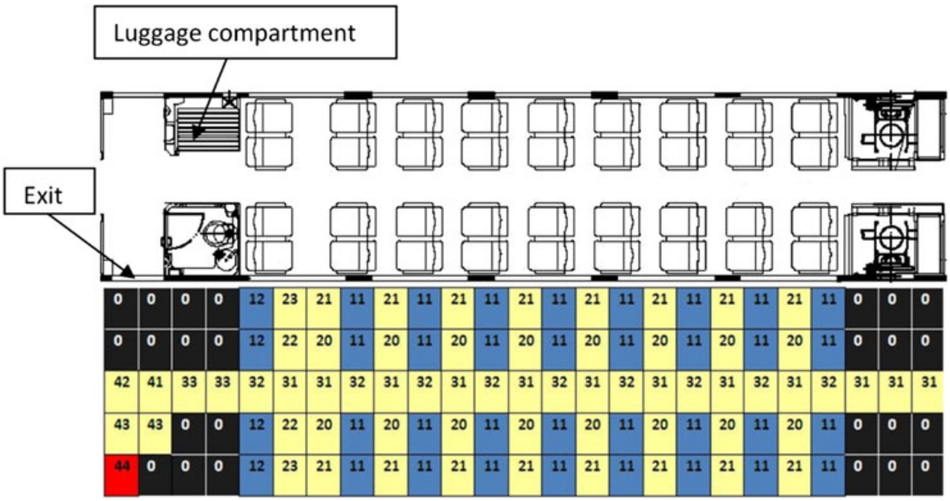

Figure 6. The fine network system and locations where potential delays may occur during evacuation in a passenger coach.

Furthermore, the time spent by each passenger performing each action (in the aisle) is assigned randomly by the model as well, according to distributions. Monte Carlo methods are used to assign stochastic parameters to each individual.

The modeling method is a microscopic approach which incorporates the probability of passengers performing actions in addition to their movement towards the exits [16, 17]. The model permits to statistically treat the sample of total evacuation times and fit it to a known distribution (if possible). Otherwise, density estimation is given.

The main output parameter is the percentile of egress times (0.90, 0.95 and 0.99). The model also provides other statistical characteristics: mean, variance, maximum and minimum values. The resulting model is quick and easy to set-up and the results of thousands of simulations can be obtained in real-time.

3.2. Comparison with an Evacuation Drill

The results from stochastic model are compared with a fire drill in a passenger train conducted by RENFE Operadora (Spanish Railroad Administration). The simulated fire started in a lounge coach while the train was still operating. Passengers were warned about the emergency before the train stops inside a rail tunnel. No baggage was involved in the process.

The data from the drill was obtained by two fixed video cameras in position and the evacuation time of 40 passengers through one exit door was recorded. The input information provide to the model involved the train layout, the number of passengers through the exit and outflow (0.58 per/s) and the time spend in opening the train doors (53 s). Table 2 shows the comparison of results of 100 runs for each case simulated by using the stochastic model.

Table 2
Predicted Egress Times from EvacTrain® Model in Comparison with an Evacuation Drill

	Mean (s)	SD (s)	Min. (s)	Max. (s)	Percentile 95% (s)
Evacuation drill	121	–	–	–	–
Simulation of drill: P_{t1} = 0.3–0.5; Flow = 0.58 per/s	120	13	104	170	152
Default: P_{t1} = 0.3–0.5; Flow = 0.44 per/s	137	13	117	178	171
Default: P_{t1} = 0.7–0.9; Flow = 0.44 per/s	169	23	123	274	224

The second row in Table 2 shows the results from the simulation of drill. The third and fourth rows in Table 2 represent the impact of imputing different probabilities of P_{t1} and the flow through the exit door by default.

Due to the fact that baggage was not included in the trial, participants only carried their jackets and handbags. Because of this reason, it was necessary to calibrate the probability of occurrence for t_1 (P_{t1}) from 0.7–0.9 to 0.3–0.5 and the flow rate through the train exit from 0.44 per/s to 0.58 per/s in order to simulate the same conditions of the evacuation drill. In this case, the average predicted evacuation time obtained by EvacTrain and the evacuation time from actual drill are very close (first and second rows in Table 2). However, results from model described in third and fourth rows suggest that, if baggage is considered, the predicted evacuation times could increase from 12% to 28% (third and fourth rows in Table 2) when compared to evacuation drill.

3.3. Comparison with Other Models (STEPS, FDS + Evac and PathFinder)

A behavioural comparison is performed in order to check the effect of actions performed by passengers in predicted evacuation times using three egress models: STEPS [18], FDS + Evac [19] and PathFinder [20]. The first problem in the comparison was to set up the same inputs for the egress models. STEPS FDS + Evac and PathFinder do not include delays during evacuation-passengers stopping in the aisle- as the EvacTrain do. These models only consider one parameter: premovement time as the time in which individuals will wait in their initial position before beginning evacuation movements.

In order to solve this problem, a program was developed using Microsoft Visual Studio 2008. NET Framework 3.5 SP1. The program simulates 1,000 random values for t_{pr}, t_1 and t_2 taking into account the probabilities of occurrence, P_{t1} and P_{t2}. The program then sums all of the values and fits them to a known distribution. The results fit to a log-normal distribution with a mean of 53 s and a standard deviation of 47 s. This pre-movement time and the walking speed used by default in EvacTrain® were also used for STEPS, FDS + Evac and PathFinder simulations.

The comparison is made for a single-exit scenario with involves two coaches and 50 passengers as shown in Figure 7. A total of 100 runs were performed with

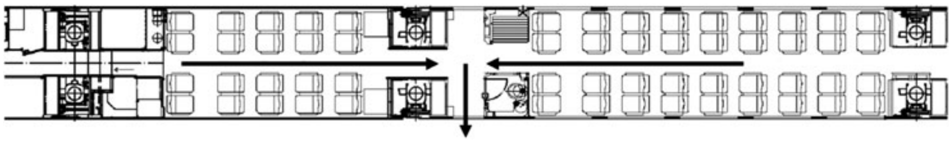

Figure 7. Simulated scenario.

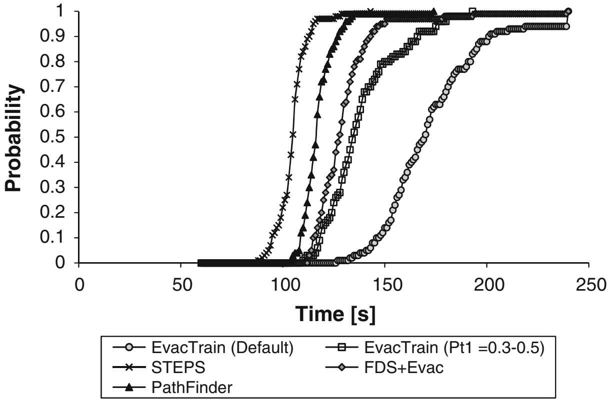

Figure 8. Cumulative distributions functions of evacuation times.

each model to estimate the probable maximum egress time as well as the average egress time.

Figure 8 shows the cumulative distribution functions of evacuation times. The predicted evacuation times vary among each model. It can be seen that results from STEPS, FDS + Evac and PathFinder have lower predicted evacuation times in comparison with the results of EvacTrain®. Predicted evacuation times of STEPS and PathFinder have a low variability with a mean of 105.25 s and a standard deviation of 7.69 s and a mean of 117.74 s and a standard deviation of 8.62 s respectively.

The predicted evacuation times of FDS + Evac are longer with a higher variability, with a mean of 130.40 s and a standard deviation of 17.52 s. In the stochastic evacuation model, the evacuation times are strongly dependent on the activities of individuals whose actions interrupt the continuous movement of other passengers within the aisle. This phenomenon, which cannot be well represented in the other models, produces longer evacuation times.

The results of EvacTrain® show a wide range of possible evacuation times. This is expected for a stochastic model because of the intrinsic uncertainty in such complex systems. In the simulated case with a probability of passengers delay time within the aisle (P_{t1}) between 0.3 and 0.5, the average predicted evacuation time is 140.53 s with a standard deviation of 26.03 s. In this case the predicted evacuation time is similar to FDS + Evac results.This suggests that "social force" algorithm can represent interactions between passengers and their effects in narrow spaces.

When two passengers try to access the aisle at the same time, there is conflict that produces an interruption in the continuous movement within the aisle thus increasing the evacuation times. In the simulated case with a probability (P_{t1} = 0.7–0.9), the predicted evacuation times from stochastic model are longest with a mean of 177.74 s and a standard deviation of 38.10 s when applying the default input values. In this case, the stochastic model simulates the worse case where the probability of each passenger blocking the aisle (P_{t1}) is between 0.7 and 0.9.

Apart from the passenger actions that may interrupt the continuous movement within the aisle, we identified another dominant parameter. This variable is the flow rates through the train steps. Current evacuation models assign door capacities based on observed human behavior data and standards for buildings [21–24]. However the flow rates based on passenger performance data applied by default in EvacTrain®, are lower. Furthermore, the model considers flow rates as a random variable in order to simulate the personal time to negotiate train steps with a mean value of 2.27 s and a standard deviation of 1.26 s (average flow of 0.44 per/s). This is done by assuming this parameter as random variable more than a value based on density correlation. Results from comparison suggests that currently, evacuation models–particularly those primarily designed for buildings–can make simplifications about the behaviour of passengers and are likely to produce inaccurate results in passenger trains evacuation analysis.

4. Conclusions

In this paper a collection and analysis of data sets to support evacuation modelling in trains have been presented. The specific behavioural variables and a collection of empirical data-sets have been defined. In order to make this calculation, we attempt to answer two questions: (1) what actions a passenger may take and (2) how long it takes to perform each action. Then, statistical methods to determine the input and outputs for EvacTrain®, a stochastic evacuation model that specializes in these particular scenarios, have been proposed.

EvacTrain has been partially validated with an evacuation drill. Then results from EvacTrain® have been compared with STEPS, FDS + Evac and PathFinder. Current egress models allow the user to input distributions of pre-movement times. However, the consideration and application of this parameter inside trains should be reviewed.

The proposed model takes into account passengers stopping in the aisle, or being stopped in the aisle by the behaviors of others. This cannot be simulated by current egress models (mainly designed for buildings).

Results from simulations showed that:

- The specific characteristics of passenger trains make hard to use the currently available evacuation models.
- EvacTrain® model, based on the Monte Carlo Method, permits to represent the random character of evacuation processes.

- Evacuation process in trains is not a simple matter of movement and more behavioural factors should be taken into account for evacuation analysis. New parameters should be considered and new approaches should be done in order to obtain reliable and accurate results.

Acknowledgments

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