1 Introduction

Certification of new aircraft for civilian transportation involves the observance of certain safety requirements established by regulatory authorities. The Federal Aviation Administration [FAA], for example, requires the demonstration through a real simulation experiment that full evacuation to the ground, \textit{i.e.} all passengers and crew, is possible within 90 seconds, when only half of the existing emergency exits are available [5, 8]. Besides being costly, such full-evacuation trials expose participants to high risks of severe injuries [8, 6]. It is also questionable whether those trials accurately represent real emergency situations [10].

The use of computer simulations offers the advantages of (i) low cost, (ii) safety, and (iii) possibility of representing various evacuation scenarios. Although such models have already been adopted by the building and maritime industries for certification purposes, this is not a reality for the aeronautical industry [2].

A more extensive use of computer models is still hindered by the difficulties of faithfully representing real evacuation scenarios \textit{in silico} [3, 6, 7, 12]. Emergency evacuation situations are inherently uncertain but, until very recently, few authors have addressed randomness in aircraft evacuation simulation [1, 3, 4, 6].

Efforts have been made to make simulation models more realistic. A recent simulation study considered the joint effects of uncertainty in physical characteristics of passengers, emergency exit availability, as well as non-optimal – thus, more realistic– decision-making process in route/exit selection [10] in various aircraft evacuation scenarios. The authors assessed the factors that have important effect on total evacuation time and were able to predict the expected evacuation time for each simulated evacuation scenario.

Nonetheless, in real situations, one does not know which emergency scenario is taking place. In practice, one wishes to be able to formulate probabilistic statements such as ‘there is a 99% chance that maximum emergency evacuation time is 90s’, regardless of the actual emergency evacuation scenario in question. Therefore, it is important to be able to combine the probability of observing a particular evacuation time –say, the maximum– with the uncertainty that a certain evacuation scenario will occur.

This work builds upon previous investigation [10]. The present main contribution is the construction a simulation-based probabilistic forecasting model that combines different emergency scenarios for predicting the total evacuation time. Instead of obtaining a single predicted value for total evacuation time along with confidence bands for a given emergency scenario, the probabilities of a range of evacuation times is produced across different possible emergency scenarios. Thus, the use of a probabilistic forecasting model allows one to obtain a more complete, reliable and accurate prospect of what might happen in real evacuation situations.
2 Methodology

The cabin layout used in the simulation is based on a Boeing 767-300 aircraft cabin, discretized into 0.5m x 0.5m nodes, which represent cabin elements, such as seats, aisles, and emergency exits, as illustrated in Fig. 1. An agent-based simulation approach is adopted: each passenger is modeled as an independent agent that interacts with other passengers and obeys a set of basic rules. The model is implemented in the open agent-based modeling environment NetLogo [13]. The statistical analysis of the results is carried out using the statistical software R along with the computing environment RStudio [9].

Passengers’ physical characteristics, decisions and actions affect the evacuation dynamics of the aircraft. Such factors have an inherently probabilistic behavior that need to be considered in order confer more reality onto the simulation. These features have been addressed previously by the authors and the modeling strategy is described in details in [10]. Exit availability also plays an important role in the evacuation process, since the interaction of passengers with the cabin environment may influence their behavior.

The simulation experiment is carried out according to a full factorial design with two factors, namely (i) exit availability and (ii) exit selection. Four scenarios are considered with respect to exit availability: (i) Scenario 1: certification configuration with available exits on one side of aircraft; (ii) Scenario 2: only Type-A exits are available, on both the left and right sides of the aircraft; (iii) Scenario 3: only Type-III exits are available ; and (iv) Scenario 4: two Type-A exits at front section and two Type-III exits at the middle section are available. The evaluated scenarios are represented in Table 1. The exit selection rule is given in terms of a probability \( p \), evaluated at three levels, and controls the passengers’ decision-making process, reflecting their level of knowledge of the aircraft cabin layout, as thoroughly described in [10]. A total of 200 computer simulation runs were executed for each of the 12 evacuation scenarios, corresponding to all combinations of factor levels.

3 Results and Discussion

ANOVA (analysis of variance) was performed to test for statistical significance of the considered factors on the evacuation time. The ANOVA results are presented in Fig. 2 Exit availability (EXIT) has significant effect on evacuation time; exit selection (PROB) alone does not, even though there is statistically significant interaction between these two factors. Thus, factor PROB is dropped from the analysis.

The boxplots in Fig. 3 give a visual summary of the distributions of evacuation times computed for each simulated evacuation scenario. Boxplots are based on robust summary statistics. The “box” represents the interquartile range; the vertical line within the box indicates the median; the horizontal lines extending from the box correspond to the range of observed values within 1.5 times the interquartile range from each quartile, marked by the two hinges at each extremity. The boxplots in Fig. 3 reveal that the time necessary for complete evacuation depends on which set of exits are available. Greater evacuation times are expected for scenarios with smaller exit capacity, such as Scenario 3. However, it is interesting to notice that, although Scenarios 1 and 4 have the same exit capacity, Scenario 4 seems to be much more challenging than Scenario 1, which is adopted in certification trials. In fact, the results from Tukey’s multiple comparison statistical procedure [11] indicate that all pairs of evacuation scenarios tested are different from each other, as illustrated in Fig. 4, at an overall 95% confidence level, since the confidence intervals for each pair of scenarios do not include zero.

In practice, one does not know which emergency scenario is actually taking place. Therefore, it is necessary to obtain probabilistic information regarding total evacuation time regardless of the specific emergency evacuation scenario. Thus, a simulation-based probabilistic forecasting model for total evacuation time is obtained by combining the responses from the different tested emergency scenarios. The probabilistic forecast may be represented as an empirical probability distribution of evacuation time, such as displayed...
Fig. 1 Example of evacuation simulation for the Boeing 767-300 aircraft. Black dots represent the passengers; brown cells are the seats; blue cells correspond to the internal structures of the aircraft (obstacles); the white cells are the unconstrained areas (aisles and legroom); and, finally, the red cells correspond to the available emergency exits [10].

Table 1 Exit availability scenarios considered for the simulation experiments. The cabin layout corresponds to a Boeing 767-300 aircraft. In the table, “o” represents an available and “x” an unavailable exit. ‘R’ and ‘L’ refer to right and left sides, respectively [10].

<table>
<thead>
<tr>
<th>Scenario 1:</th>
<th>Scenario 2:</th>
<th>Scenario 3:</th>
<th>Scenario 4:</th>
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<tbody>
<tr>
<td>L1-L2-L3-L4</td>
<td>L1-L1-R1-L4-R4</td>
<td>L2-R2-L3-R3</td>
<td>L2-R2-L4-R4</td>
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<tr>
<td>R x x x x</td>
<td>o x x o x</td>
<td>x o o x x</td>
<td>x o x x o</td>
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<tr>
<td>L o o o o</td>
<td>o o o o x</td>
<td>o o o o x</td>
<td>x x o o o</td>
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Fig. 2 ANOVA output from statistical software RStudio [9].

Fig. 3 Boxplots of evacuation times for each scenario simulated.

in Fig. 5 and Fig. 6. The histogram in Fig. 5 corresponds to a discrete approximation of the probability distribution of evacuation time, while Fig. 6 gives the non-parametric smoothed estimate of the same probability distribution. The data points are represented by the rug plots on the horizontal axes in both graphs. It is interesting to notice that, when evacuation times are combined in a single probabilistic forecast, more information is gained. Instead of having the estimate of a single value, like the mean evacuation time, or hopefully an interval estimate for that quantity, the empirical distribution gives the total range of evacuation times observed in the simulations as well as the corresponding frequencies of occurrence. For the simulations performed, it is possible to infer that, although the majority of evacuation times observed are smaller than 100 seconds, there is non-negligible occurrence of events in which the evacuation time concentrate around 135 seconds, associated with an evacuation scenario with lower exit capacity.
4 Concluding Remarks

The present work proposed a simulation-based probabilistic forecasting model for the total evacuation time, considering various emergency scenarios. The probabilistic forecast is represented as an empirical probability distribution of evacuation time, which efficiently expresses the intrinsic uncertainty of the emergency evacuation process simulated. Various evacuation scenarios and passengers’ attitudes toward decision-making strategies were considered, in order to confer more realism to simulations.

By combining the simulated evacuation times obtained from different emergency configurations into a single probabilistic forecasting model, more information is gained, since the empirical distribution provides the analyst not only with a point or interval estimate of commonly monitored responses like, for example, the mean evacuation time, but also gives the the total range of evacuation times observed in the simulations, as well as the corresponding frequencies of occurrence. Thus, the use of a probabilistic forecasting model allows one to obtain a more complete, reliable and accurate prospect of what might happen in real evacuation situations.

References


5 Contact Author Email Address

Denise Ferrari: denise@ita.br
Rodrigo Giarola: giarolarpgs@fab.mil.br
Luis Santos: luis.castro@embraer.com.br

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