7th International Conference on Performance-Based and Fire Safety Design Methods

"Required Safe Egress Time: Data and Modeling"

Jason D. Averill, Paul Reneke, and Richard D. Peacock
National Institute of Standards and Technology (NIST)

Abstract

This paper identifies sources of uncertainty in RSET (required safe egress time) calculations, with focus on data and modeling. A model for efficiently calculating the range of egress solutions for a particular design is presented. Three recommendations for future research are proposed. First, future data collections and model inputs should utilize distributions. Second, future data collections should focus on emergency evacuation data rather than fire drill data. Finally, modeling output should utilize cumulative distribution functions to visualize the range of egress solutions.

Overview

The two central concepts of performance-based design, ASET (available safe egress time) and RSET (required safe egress time), are separate degrees of freedom, each of which can be optimized to achieve performance objectives. The principal thesis of this paper is that, while calculation and analysis of ASET has made great strides in the past 40 years (see Salley, et al 2007 for analysis of the predictive capabilities of fire models), calculation and analysis of RSET has stagnated at best, or possibly regressed over the past 40 years. This assessment is not the result of inactivity or lack of effort on behalf of the egress research community, but more a statement of the challenging nature of RSET subject matter. Advancement of RSET methodology requires (a) robust data for model input and validation, as well as (b) modeling methods which adequately reflect the present knowledge base and inherent uncertainty of occupant egress. While the interface between RSET and ASET (i.e., toxicity) remains a critical link, the scope of this paper will focus on the analysis of RSET.

Evacuation Data

Existing data sets for model inputs and model validation are limited, both in quantity and quality. While the paucity of data is widely established, the quality limitations of the existing evacuation data manifest themselves through several aspects: the temporal, contextual, and realistic nature of evacuation data. Temporal factors can be divided into two categories: physical and mental. Physical temporal factors are those associated with changing human demographics. In the United States, the physiological profile of the typical citizen has changed significantly over the past 20 years (for example, see Ogden 2006). The profile changes would be expected to result in slower overall occupant movement speed; however, a conclusive link between physiological trends and evacuation speeds has not yet been established. There exists sufficient question about the quality of the existing data that Pauls has requested to the SFPE Handbook editors that some egress data be removed from future editions of the handbook (Pauls 2007).

Mental temporal factors include recent events which may influence the decision-making of an occupant regarding evacuation performance. For example, the National Fire Protection Association's (NFPA) Fire Protection Research Foundation (FPRF) survey of high-rise building occupant attitudes captured specific (sometimes regional) events which influenced respondents' attitudes towards evacuation and fire safety (FPRF 2007), while NIST linked occupants' memories of the 1993 attack to their decision-making at the World Trade Center (WTC) towers in 2001 (NIST 2005). This would suggest that future occupant behaviors, and therefore the findings in the NFPA survey (or any other survey of occupant attitudes), could be significantly modified by a major life-loss event.

Contextual factors are those associated with the specific context that each of the occupants are responding to during the data collection. For example, office workers evacuating a high-rise building may behave differently than retail shoppers evacuating a store. The office workers may be familiar with the building, may be trained in the evacuation procedures, and may observe pre-existing workplace social norms. Retail shoppers may not be familiar with the store layout (particularly the location of emergency exits), likely have not been trained on the emergency procedures, and may observe the social norms associated with being in a public place. These contextual factors may limit the applicability of a data collection.

Finally, the realism of most evacuation data collections is unknown. The majority of evacuation data available is either pedestrian observations in public places or evacuations from structures during fire drills. In either circumstance, the utility of non-emergency data collections in predicting decision-making and movement speeds of occupants during a fire or other building emergency is highly uncertain. Further, there is a dearth of emergency evacuation data and the generalizing these data is difficult due to the many contextual factors present in genuine emergency factors which would not be expected to be present in future emergencies. The evacuation at the World Trade Center proceeded more slowly than data from evacuation drills would imply (NIST 2005). The source or sources of the difference between the observed emergency evacuation data and the fire drill data has not been identified, though many hypotheses exist.

Distributions of Data

Distributions are generally more informative than means or other single summary statistics. Figure 1 shows the distribution of occupant speeds during fire drill evacuations for two buildings: a 6 story building (with and without firefighter counterflow), and an 11 story building (no counterflow). It is readily apparent from the distribution curves that there are differences in movement speeds between the evacuees in each of the three buildings. Simply reporting a mean occupant descent speeds for each event (as shown in Table 1) reveals less information about the nature of those differences Therefore, publication of future egress data sets should focus on presentation of the distributions of the data. Additionally, egress models should accept distributions of data as input parameters and visualize solutions as distributions, as demonstrated in the next section.

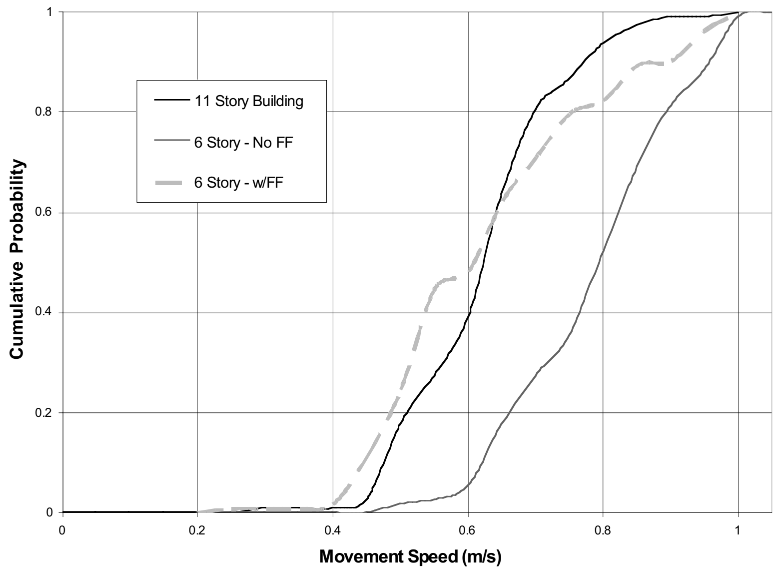


Figure 1: Cumulative Distribution of Occupant Descent Speed in 11 Story Building

Building	6 Story w/ FF	6 Story – No FF	11 Story
Mean Descent Speed (m/s)	0.73	0.83	0.63

Table 1: Mean Descent Speeds for Occupants During 3 Building Evacuations

Proposed Egress Model

Egress models have proliferated with the growth of modern computing, with over 30 available at last count (Kuligowski 2005). However, as discussed above, input data and validation sets are limited. Given that the primary goal of modeling is generally to provide insight into a problem rather than a specific answer (which may or may not be achievable), an egress modeling method which embraces uncertainty and visualizes the range of outcomes would best frame the problem for both designers and reviewing authorities. Therefore, we propose the Modified-Markov Modeling (M^3) approach. As the mathematical motivation and visualization methods are presented below, bear in mind that the primary objective is to understand the range of likely evacuation outcomes as a function of the *distributions* of possible initial conditions and processes.

The current state of the art for egress modeling is to attempt to predict what individuals will do given their local conditions. In addition to the desire for improved prediction and analysis of occupant evacuation, rapid increases in computational power and availability of limited behavioral data are the driving forces for this effort. This has resulted in a variety of more sophisticated models (Kuligowski 2005). While the new class of models have a variety of methods for representing the buildings and locations of individuals, they generally calculate results from a given set of "people" and initial locations the locations of individuals at each instant of time.

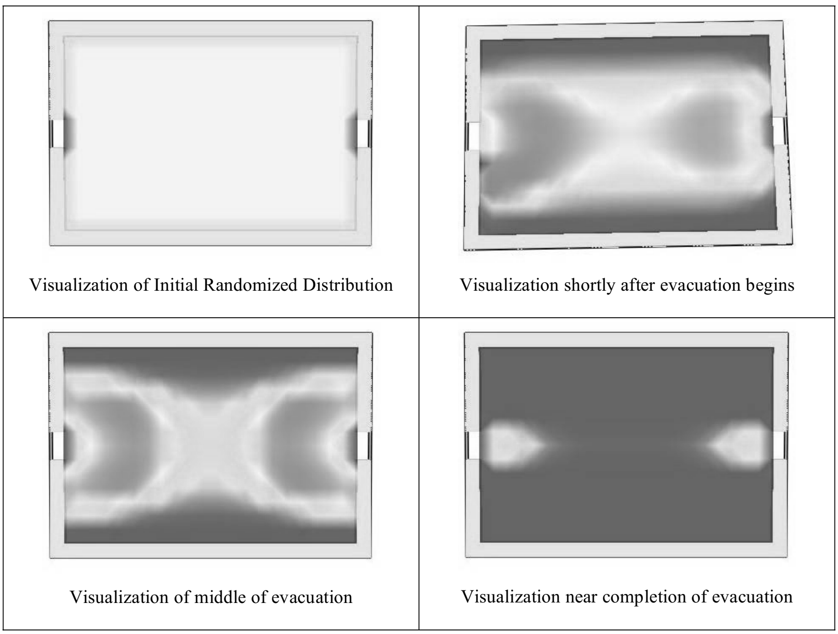
One concern about these models beyond a lack of quality data to test them against is that they give a very specific time for when the building has been completely evacuated for a very specific set of input conditions. It is unlikely that one or even a small number of runs can capture all the possible situations in which the building might be evacuated. A number of people are working or have worked on this issue. Lord, et al, (Lord 2005) in a project supported by NIST, addressed the problem by making thousands of individual runs varying the input parameters and then using all the runs together to develop a cumulative distribution function to estimate the probable maximum egress time as well as the average egress time.

Aside from the complexity and laborious nature of running a model thousands of times to produce a distribution of overall evacuation probabilities, there is a more fundamental question of the viability or usefulness of addressing egress by modeling individual people. While modeling the people directly is a very intuitive option, there are other ways to look at the problem. An alternative approach is to view the problem from a probabilistic point of view, utilizing expected means and variations.

Model Thoery

A typical grid-based egress model divides buildings up into cells. The occupants are randomly assigned to a particular cell. First, add up the number of times each cell is occupied during each time step in each of the combinations and divide the sum by the total number of runs made. The result will be the fraction of the runs each cell was occupied for each time step. That number is the expected value for each cell at each time step. Visualization software then creates a time sequenced movie of the expected values for the building.

For example, imagine a large square room in which occupants are randomly distributed. Prior to the initiation of evacuation, the expected value of the fraction of the time you would find a particular cell occupied would be relatively uniform (upper left of figure 1). On two opposing walls of the room are the two exits, one in each wall. According to the rules of the visualization, dark blue corresponds to an expected occupied fraction of 0.0 and red corresponds to an expected occupied fraction of 1.0. Upon initiation of evacuation, one would expect that the area in the center of the room and along the walls that do not have exits would turn blue (an expected value of 0.0), as shown in the upper right of Figure 1. As occupants make their way to the exits, the area in front of each exit will tend toward a red visualization. Over time, the red semi-circles will first grow, then shrink, and finally disappear into blue as the building empties (see the bottom row of Figure 1).



Visualization of Initial Randomized Distribution

Visualization shortly after evacuation begins

Visualization of middle of evacuation

Visualization near completion of evacuation

Figure 2: Theoretical Evacuation of Single Room with Two Exits

Qualitative verification of the thought experiment implies the possibility of laws that describe how the expected values evolve, thereby allowing one run of a model to generate all the information the untold number of simulations required for the more traditional model. Having the expected values for each of the cells along with the correlations between the cells would allow us to calculate the probability that the population in the room was above a specific number as well as give us the average number of people in the room at any given time during the scenario.

This method provides the same information in one run of the model that would require hundreds or thousands of runs using conventional evacuation models. Markov chains were developed to address similar problems. However, Markov chains cannot be directly applied to the egress problem because of size of buildings. For example for a single room that breaks down to a 10 x 10 set of grid points would need a state vector with a length of 2^{100}. The solution quickly becomes computationally prohibitive and does not adequately characterize the scale of a real building. The solution to this problem is to develop rules that control how the expected values evolve based on local conditions.

The proposed simplification is to assign a small subset of the grid points around every grid point to be that grid point's local space and save the state space for that local space with its associated grid point. Then for each grid point, the each local space evolves simultaneously with all other overlapping local spaces. There are several distinct advantages of this formulation. While the correlation between any two grid points within a local space is defined by the state vector, two grid points that are in the intersection of two local spaces must have the same correlation in both subspaces. Two grid points that are not contained in at least one subspace can have any correlation coefficient. Specifically, any two grid points with any expected values can always have a correlation of 0.0. However, if theory and experimental data says that two grid points that are not in a common subspace should have a certain correlation it is possible to evolve the two points in such a way as they will approach that correlation. This allows for a direct way to include large scale observed phenomena into the modeling frame work.

Further, this formulation allows the mean and variance to be calculated for the building as a whole and any space within the building. If the number of people in the building is a random variable with a normal distribution, then given the mean and variance at time t_i, it is possible to calculate the probability that the number of people in the building is below any given value n. These parameters are directly computed in a single calculation, in a time substantially faster than averaging traditional models in serial manner.

Example

The first example is a building with a few features to demonstrate how the model will respond. The scenario is a very simplified night club building with a large dance hall. The main is at the top Figure 2, which then follows An L-shaped corridor connects the entrance to the dance hall the to the main entrance of the building which includes a cloak or mud room. At the bottom right of the dance hall is an emergency exit that leads to the main entrance. It is assumed this exit is obscure enough that only people near it realize it is there. To the left of the main entrance to the dance hall is an exit door that follows a narrow hall and exits the building at the bottom. At time zero it is assumed that all people in the building are in the dance hall and are uniformly distributed around the hall. A very large number of times the room was randomly filled with a number of people and then averaged. The average number of times each grid in the room was occupied is multiplied by the maximum density of people that can be in the room (assumed to be 3.0 people/m^2).

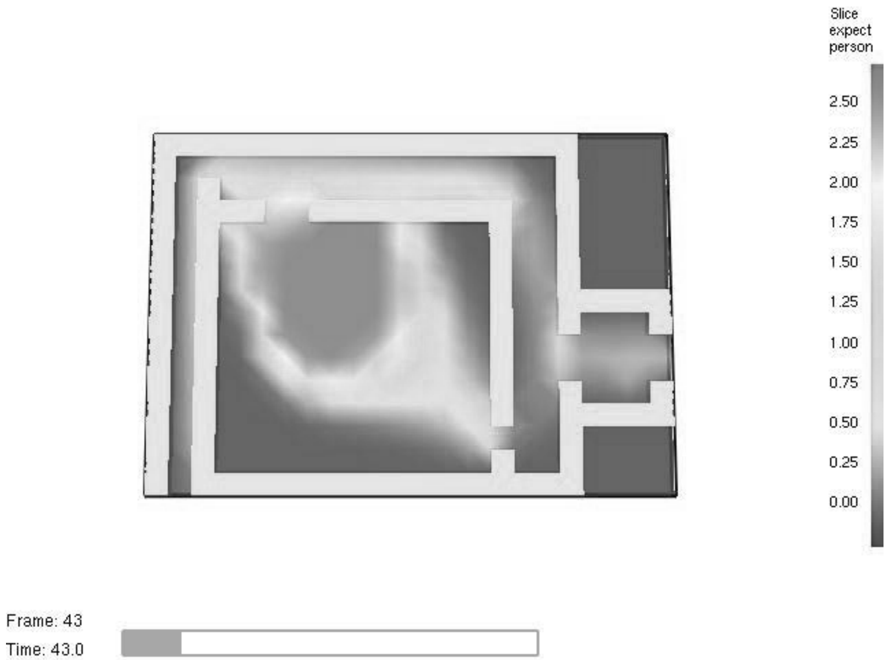


Figure 3: Example Evacuation (Early)

Figure 2 shows a time early in the evacuation. Once again, red indicates that the probability of the space being occupied is (on average) very high, while blue indicates a low probability. There is a concentration of people near the main entrance to the Near the smaller door from the dance hall the expected number of people is a lot lower but the exit would still be used at this point. In the hallway there are expected to be a significant number of people although the density is expected to be a lot lower than in the dance hall and they have not yet reached the main exit.

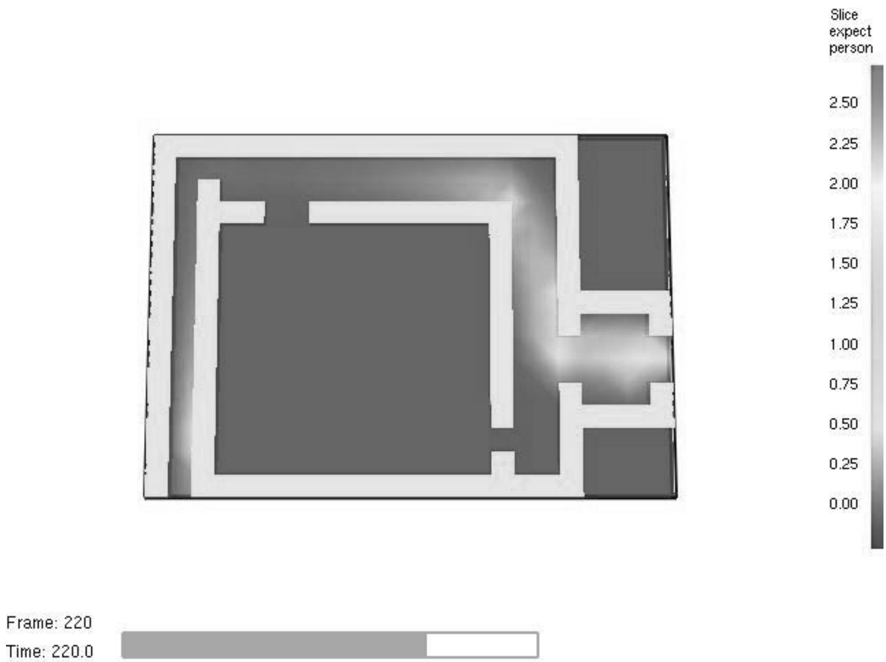


Figure 4: Example evacuation near completion

Toward the end of the evacuation, as show in Figure 3, what few people remain in the building are congregated near the main entrance or in the mud room. A smaller number of people would be expected in the exit hall, while the dance hall would have a low expected occupant density.

Figure 4 shows the cumulative distribution function (cdf) of the probability that (a) the dance hall and (b) the whole building will be empty. Observe that the dance hall is expected to be empty (cdf of 1.0) prior to any probability that the whole building would be empty. The advantage of displaying the cdf is that one could identify a point in time where the model predicts a 95 % chance that the building will be empty. Further, the shape of the distribution is informative. For example, a shallow slope to the cdf would indicate a great sensitivity of the evacuation time to the input parameters. A steep slope, by contrast, would indicate insensitivity to variations in the input parameters.

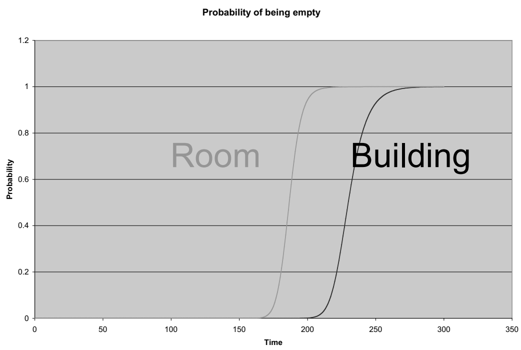


Figure 5: Cumulative Distribution of Probabilities that the Dance Hall and Whole Building will be Evacuated

Conclusions and Recommendations

Predictive models in any scientific field represent the extent of knowledge in that field. Without the ability to predict some aspect of a future event it is difficult to assess if the theory is correct. Theory generally dictates the kinds of measurements that should be taken in experiments. For example, because of our understanding of gravity, one would not take detailed measurements of the colors of the objects dropped to test acceleration due to gravity. A more relevant example of the power of the theoretic paradigm has on experimental measures can be found in large-scale fire experiments. Early computer fire modeling utilized the two zone approximation. Therefore, in many experiments, a few thermocouples spaced vertically could adequately characterize the temperatures in the compartment for the purposes of model validation. As computational fluid dynamics models become more prevalent in fire protection engineering, it is influencing the number and location of temperature measurements that are made in large-scale fire experiments.

Thus, knowledge of the modeling paradigm is critical to collecting appropriate egress data. Early evacuation modeling efforts were based on predicting the maximum possible flow of people. Typically, the input quantities were based on average values such as the density of people and the rate of flow of people. The similarity of these models to fluid flow resulted with the models being referred to as "hydrodynamic" models. Hydrodynamic models remain popular and are still described in the Society of Fire Protection Engineers Handbook. Generally, these models produce a minimal time to evacuate the building given a set of initial conditions for building load and movement speed. Simplistic optimization of evacuation time generally requires a safety factor to give a number that could be used as a maximum time to evacuate a building.

The quality of RSET calculations is dependent upon the availability applicability of the data to support input parameters In order to advance the quality of RSET calculations, we recommend three future directions. First, modelers and researchers collecting egress data should use (or report) distributions to describe evacuation behaviors and travel speeds. From a purely analytical perspective, distributions are superior to averages because they provide information about the range of observations, the shape of the curve of the observations, along with more conventional measures such as the mean. Further, distributions reinforce the fact that there is no average occupant. For example, to simply use the mean speed, excludes the impact of the slower on the faster occupants. Further, there is a distribution of walking speeds as a function of density. Occupants would be expected to tire (slow down) after prolonged periods of walking, as might be observed in high-rise building evacuation. The point at which occupants begin to tire may be a function of age, health, or context. From a behavioral perspective, the number of activities and occupant performs prior to initiating evacuation is a distribution.

Second, future evacuation data collection should focus on collection of emergency evacuation data. Continued reliance on fire drill data imposes uncertainty about the applicability of the data. However, due to the low probability of a particular building being evacuated under emergency circumstances, it is difficult to design a system to capture real-time evacuation data. The prevalence of security cameras in buildings may make some aspects of the data collection feasible (i.e., movement speeds, particularly near the main exit), however, pre-movement activities and distributions are unlikely to be captured. Filtering of data through the memories of occupants (a posteriori data collection) may also introduce significant uncertainty.

Finally, modelers should present evacuation results as a cumulative distribution function. This recommendation is a corollary of the first recommendation about using distributions in data collection and model inputs. Even without leveraging the advantages of the proposed M^3 method, a modeler can produce CDF curves by using monte carlo or other statistical techniques to convey the range and shape of the egress solution space. It is particularly important to convey these uncertainties to authorities-having-jurisdiction, building owners, and architects in order that the critical decisions they make are based upon a complete understanding of the uncertainty inherent in the RSET calculations.

References

Averill, J., Mileti, D., Peacock, R., Kuligowski, E., Groner, N., Proulx, G., Reneke, P., and Nelson, H. "Federal Building and Fire Safety Investigation of the World Trade Center Disaster: Occupant Behavior, Egress, and Emergency Communication" NIST NCSTAR 1-7. September 2005.

Kuligowski, E. D.; Peacock, R. D. "Review of Building Evacuation Models." NIST Technical Note 1471; 153 p. July 2005.

Lord, J. B.J. Meacham, A. Moore, R. Fahy, and G. Proulx. 2005. "Guide for evaluating the predictive capability of computer egress models" NIST GCR 06-886. December. Gaithersburg, MD: National Institute of Standards and Technology, Building and Fire Research Laboratory

Ogden CL, Carroll MD, Curtin LR, McDowell MA, Tabak CJ, Flegal KM. Prevalence of overweight and obesity in the United States, 1999-2004. JAMA 295:1549-1555. 2006.

Jake Pauls. Oral Testimony at ICC Final Action Hearings. May 24, 2007. Rochester, NY.

Proulx, G. "Movement of People: The Evacuation Timing." Section 3, Chapter 13 of 3rd Edition of the SFPE Handbook of Fire Protection Engineering. DiNenno, Editor-in-Chief. National Fire Protection Association. Quincy, MA (2002).

Salley, M. H.; Dreisbach, J.; Hill, K.; Kassawara, R.; Najafi, B.; Joglar, F.; Hammins, A.; McGrattan, K. B.; Peacock, R. D.; Gautier, B. "Verification and Validation: How to Determine the Accuracy of Fire Models." Fire Protection Engineering, No. 34, pp. 34 - 44, Spring 2007.

"Public Perceptions of High-Rise Building Safety and Emergency Evacuation Procedures." Prepared by Mia Zmud and submitted to the Fire Protection Research Foundation. July 2007. Quincy, MA. Available at nfpa.org.