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Uncertainty in Egress Models and Data: Investigation of Dominant Parameters and Extent of Their Impact on Predicted Outcomes – Initial Findings

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INTRODUCTION

Computer egress modeling is becoming a common tool in the building design industry. Models can provide insight into the movement of people through buildings, and sometimes provide a visual tool that is useful for presentation of a design to architects, clients, and authorities.

The reality of egress modeling is that current methods of calculation must somehow account for a degree of human behavior that is not necessarily predictable. Most egress models attempt this through use of correlations based on available data, or through the addition of safety factors to the model results.

When using an egress model in building design, there are many uncertain variables, among them:

- Number of building occupants
- Occupant characteristics (size, age, etc.)
- Movement speeds
- Pre-movement times
- Familiarity with the building

However, as discussed by Fahy at the *National Research Council Workshop to Identify Innovative Research Needs to Foster Improved Fire Safety in the United States*,[1] there is severe lack of data for use in predicting evacuation times from buildings, and for the data that do exist, there has been little or no identification or assessment of uncertainty and variability, or of the impact of the uncertainty or variability on the predictive capability of egress models. Notarianni[2] and others have discussed the importance of identifying and addressing uncertainty, as the failure to do so can lead to misapplication of models, and of the results obtained from the models as used in design and performance evaluations.

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SCOPE OF RESEARCH

To begin addressing the above concerns, a three-year research has begun under a grant from the National Institute for Standards and Technology, Building and Fire Research Laboratory (Grant 60NANB2D0138) that aims to improve the predictive capabilities of egress models by:

- Collecting data sets for use in and for verification of the predictive capabilities of egress models,
- Beginning to identify sources, type, magnitude and importance of uncertainty and variability in data for egress models,
- Beginning to identify the actual range of input variables used in egress models, and to identify sources, type, magnitude and importance of uncertainty and variability in data (input) for egress models, and
- Beginning to compare egress models (two models) based on above parameters on a "blind" evacuation scenario (using a data set not used for the uncertainty analysis identified above).

This paper addresses the scope completed in year one of this project:

- Collect and analyze data sets from previous evacuation and research work.
- Assess two egress models, EXIT89 and STEPS, to determine dominant variables; sources, types, magnitudes and importance of uncertainty and variability; and how the models differ.
- Assess models against a data set and compare model results.
- Identify sources and type of uncertainty and variability in data (model inputs).
- Begin to identify appropriate treatment of uncertainty and variability based on model specifics.

The goals of this work are to:

- Apply and refine a method of uncertainty analysis to computer egress modeling
- Identify "cross-over" variables that may have an impact on the results of the egress model that is significant enough to cause a change in an engineer's design of a building.
- Provide building engineers with guidance in the appropriate use of computer egress models.

METHODOLOGY

A five-step process is being used to carry out the study, as detailed below:

Step 1: Construction & of Base Models

Construction of base models: STEPS and EXIT89 are being investigated in this study, as they represent grid-based and node-based calculations (respectively). Computer models were built using data from a 6-story (plus basement) office building in London, Ontario ("the London building"). This stage of the work included validation of the models for use with this type of building.

Step 2: Identification of Variables and Possible Values

EXIT89 and STEPS each contain a number of variables that can be modified by the user. These variables were identified, along with their possible range of input values. Distribution curves of possible variable inputs were formed using data from a review of the available literature.

Step 3: Monte Carlo Analysis

A Monte Carlo analysis was used to generate values for the STEPS model input variables. This type of analysis consisted of generating a large number of scenarios by randomly sampling values from the distribution curves formed in Step 2. These scenarios were then run using STEPS. Future work will involve a similar analysis using EXIT89.

Step 4: Statistical Analysis of Computer Model Results

A statistical analysis was performed to determine the uncertainty associated with the STEPS input variables for the office building, with a concentration on their effect on the total evacuation time for the building.

Step 5: Identification of Significant Variables

Using the results of the statistical analysis, the significance of several variables has been identified, as discussed in the results below.

RESULTS

Step 1: Construction of Base Models

STEPS and EXIT89 were used to model the London building, for which data was available from an actual evacuation. The modelers were provided with information regarding the building geometry, the number of occupants on each floor of the building, and the pre-movement times for many of the building occupants.

Three different approaches were taken to assigning pre-movement times to the occupants:

- The maximum observed pre-movement time (51 sec) was assigned to every building occupant
- People were broken into groups by floor, and each group was assigned the average observed pre-movement time for that floor.
- Each individual in the model was assigned an observed pre-movement time.

Preliminary results indicate that STEPS and EXIT89 both provide good approximations of the travel time from the London building, given that the modeler knows the number of people that were present on each floor, and their pre-movement times. As shown in Figure 1 below, there was little difference between the three pre-movement time distributions used in the STEPS model; similar results were obtained using EXIT89.

The actual total evacuation time of the London building was 226 seconds. The three initial STEPS simulations predicted total evacuation times of between 222 and 226 seconds; the three initial EXIT89 simulations predicted total evacuation times of between 199 and 203 seconds. This would seem to indicate that both programs are appropriate tools for modeling egress in office buildings similar in characteristics to the London building. In addition to predicting the total evacuation time within 0% - 12% of the actual observed time, both models were able to predict the number of people who had left the building at any given time during the evacuation with reasonable certainty, given the exact occupant load and information regarding pre-movement times.

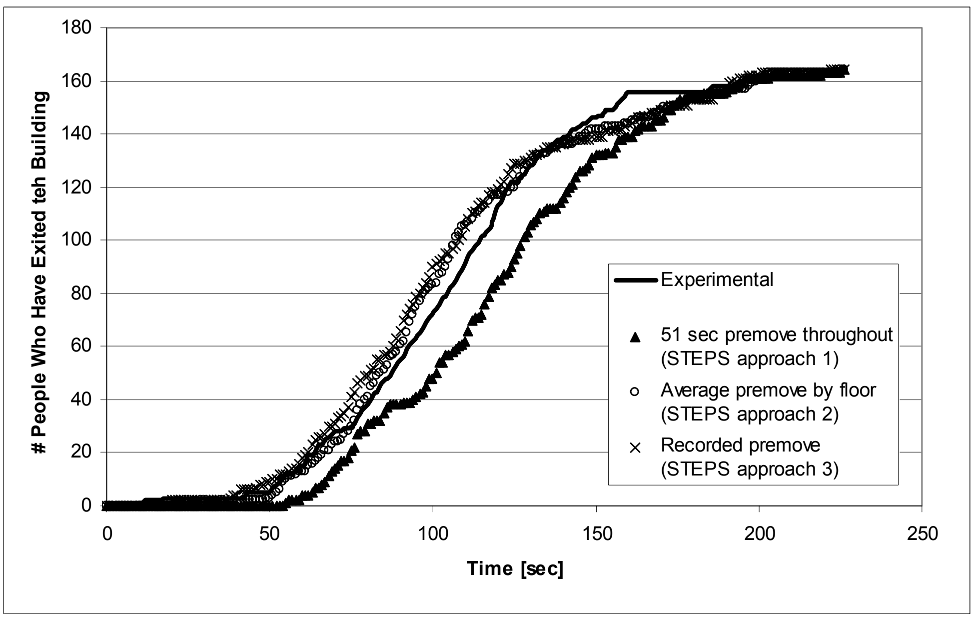

Figure 1: STEPS Model, Number of People Left in London Building Over Time, Experimental vs. Various Simulated Conditions

Based on these initial test simulations, STEPS 2 through 5 were completed based on the assumption that all occupants on a given floor have the same pre-movement time, rather than assigning different pre-movement times to each individual.

Step 2: Identification of Variables and Possible Values

A number of variables were identified that could be modified within STEPS and EXIT89. Included in these variables are building geometry (number of floors, furniture layout, number of exits, stair width, etc.), occupant characteristics (number of people, age distribution, walking speeds, pre-movement times, patience, etc.), and model-specific variables (grid spacing, time step, etc.).

Building geometry was not modified in this initial study. All simulations assumed that the geometry was the same, as observed during the actual evacauation of the London building. Future work may investigate geometry changes, such as varying door and stair widths, or blocking exits.

Distribution curves of values were formed for many variables representing occupant characteristics or model-specific variables. When available, experimental observations reported in available literature were used to form these distribution curves. A sample distribution curve for pre-movement times is provided in Figure 2.

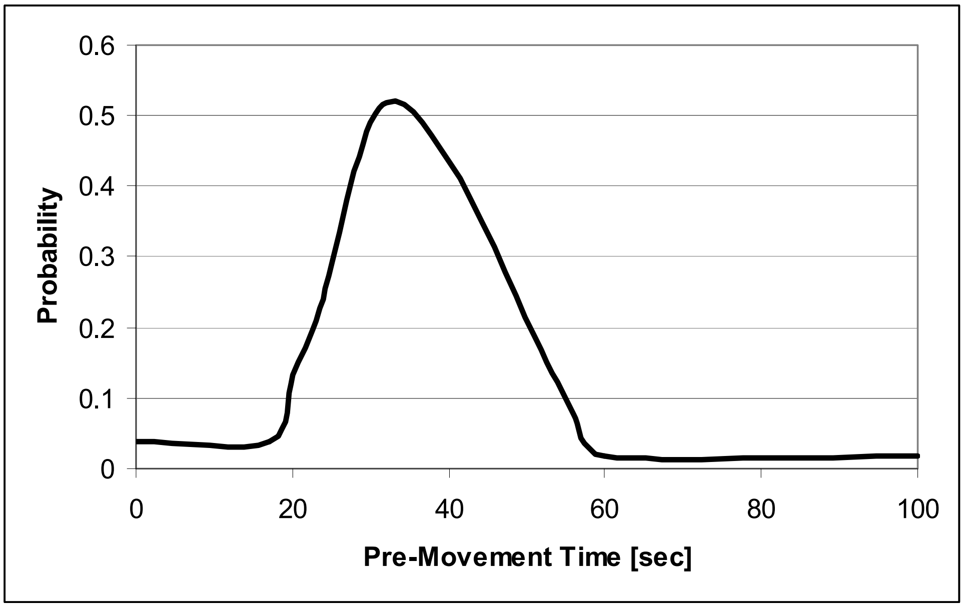

Figure 2: Sample Distribution Curve of Values for Pre-Movement Time (in seconds) for Occupants of Office Buildings. Formed from NRC "London Building" Data and Purser[3]

One of the factors limiting the field of egress modeling is the relative scarcity of data for some occupant characteristics. Future work is required to expand upon the literature review begun in this study. In addition, techniques should be developed to combine statistical information from that is already available from different studies, but in varying formats. Some research has been done in the fields of risk management[4] and weather forcasting[5] investigating the combination of data from multiple sources.

Many of the STEPS model-specific variables do not represent quantifiable properties that can be obtained experimentally. Among these are people's patience, model randomness, time-step, lock-solver depth, patience coefficient, walking coefficient, and queuing coefficient. Coefficients were randomly assigned values between 0 and 1 for each simulation, while time-step was varied between 0.01 and 5 seconds, and lock-solver depth was varied between 1 (default) and 10.

Because of time constraints, this initial study did not investigate the effect of varying grid size in STEPS simulations. This will be modeled during the remaining scope of this study.

Step 3: Monte Carlo Analysis
An initial set of 300 STEPS input files were created and run using the Monte Carlo method. Variable values were randomly chosen from the distribution curves formed in step 2 of the analysis.

Step 4: Statistical Analysis of Computer Model Results
The output from the 300 STEPS simulations were analyzed using a method described by Notarianni[6]. A cumulative distribution function was created to display the probabilities associated with an estimated evacuation time for the London building. This was accomplished by graphing each evacuation value against its rank, as displayed in Figure 3.

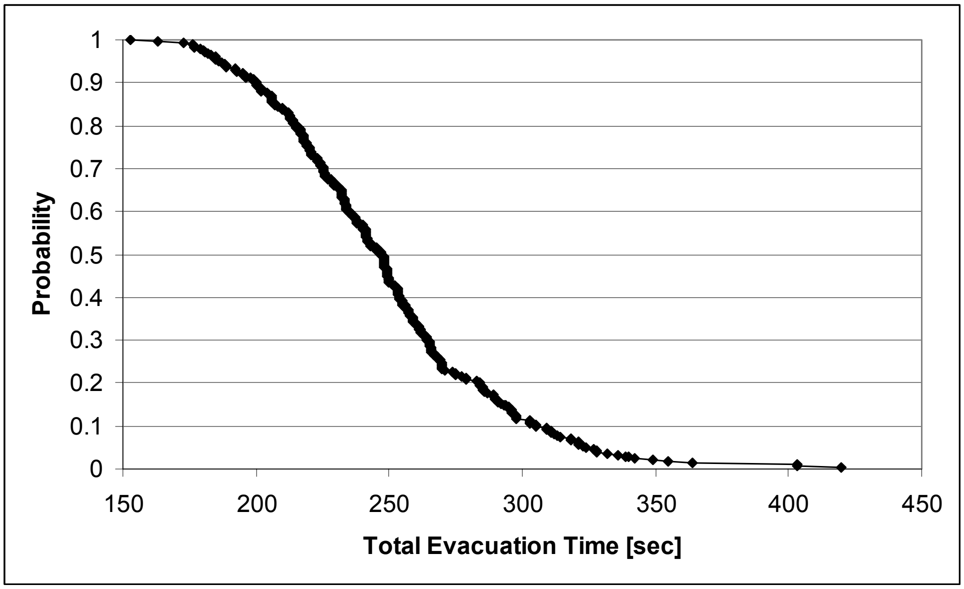

Figure 3: Cumulative Distribution Funtion of Total Evacuation Time

This graph provides the probabilities that are associated with a range of evacuation times. For example, according to this analysis, there is a 70% chance that it will take 225 seconds or more to evacuate the London building. Therefore, if the acceptable level of uncertainty were 5%, it would be prudent to design fire/life safety systems for the building that could maintain tenable conditions for at least 325 seconds.

Step 5: Identification of Significant Variables
Using a method identical to that described above, it is possible to view the simulation data in a way that identifies the significance of the variables that were randomly chosen in the Monte Carlo analysis of step 3. Cumulative distribution functions were formed for each of the tested variables, comparing different values of the variables with each other.

Occupant Load
Figure 4 provides a cumulative distribution function that reflects the effect of the total building occupant load on the total evacuation time for the building. The two series represent simulations with a low occupant load (0-20% of the maximum number of people simulated) and a high occupant load (80-100% of the maximum number of people simulated). This figure provides some insight into the effect of occupant load on total evacuation time. For probabilities between

0.3 and 0.7, it appears that evacuation times may be *faster* with higher occupant loads. This is somewhat counter-intuitive, and bears further investigation in future studies, including use of a greater number of samples to reduce statistical uncertainty.

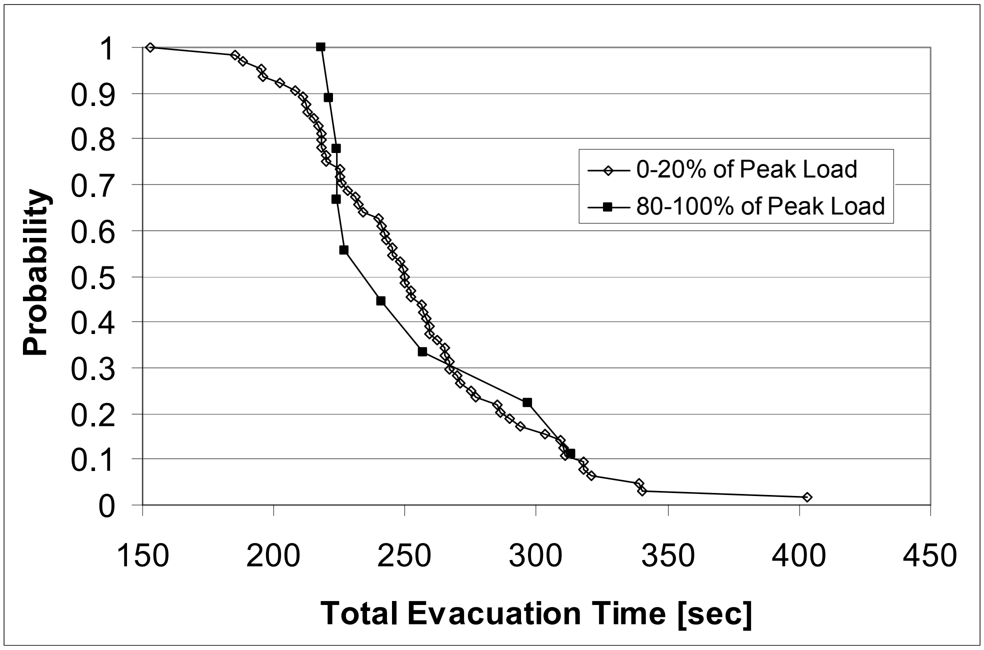

Figure 4: Cumulative Distribution Funtions of Total Evacuation Time for Two Total Building Occupant Loads

An alternate method of displaying the data in Figure 4 is to graph the difference in the two series. Figure 5 represents the difference in total evacuation times, subtracting the 0-20% of peak load series from the 80-100% of peak load series.

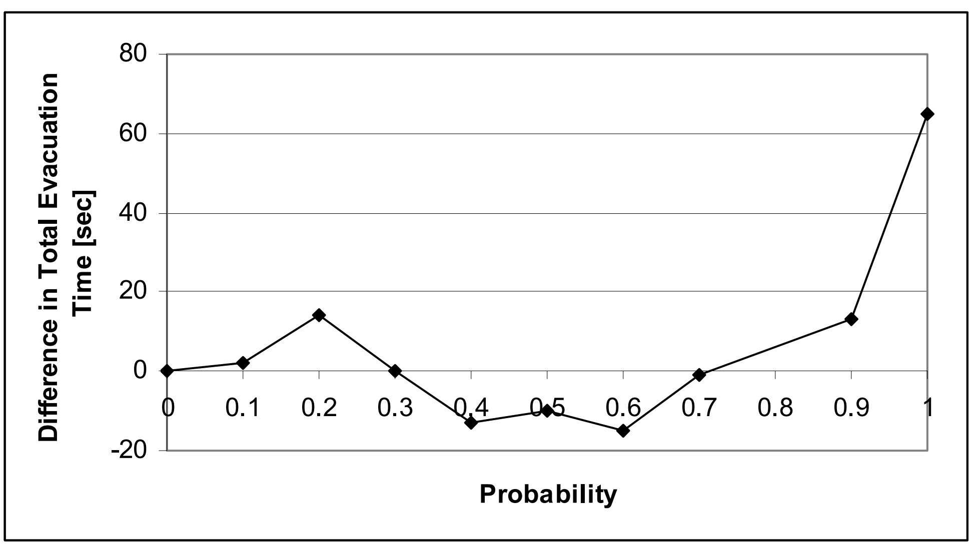

Figure 5: Sensitivity of Total Evacuation Time to Total Building Occupant Load

Figure 5 indicates that as the probability threshold increases from 0.7 to 1.0, the effect of the occupant load on the total evacuation time increases rapidly. This would seem to suggest that, as one would anticipate, the total occupant load used in the design of a building would have a significant effect on the total evacuation time when considering probability thresholds of greater than 0.7.

The occupant load data was also analyzed by floor; preliminary findings seem to suggest that the occupant loads of the ground floor and top floors have a more significant impact on the total evacuation time than the occupant loads of the middle floors of the building or the basement.

Pre-Movement Time

The results of the analysis indicate that pre-movement time may have a significant impact on the total evacuation time of the building in some cases, and should be included in egress analyses. Figure 6 demonstrates a cumulative distribution function of total evacuation time based on first floor pre-movement time ranges of 0 to 25 seconds and 75 to 100 seconds. In general, using higher pre-movement times (75 to 100 sec) on Floor 1 resulted in total building evacuation times that were 20-30 seconds greater than those obtained using lower pre-movement times (0 to 25 sec) on Floor 1.

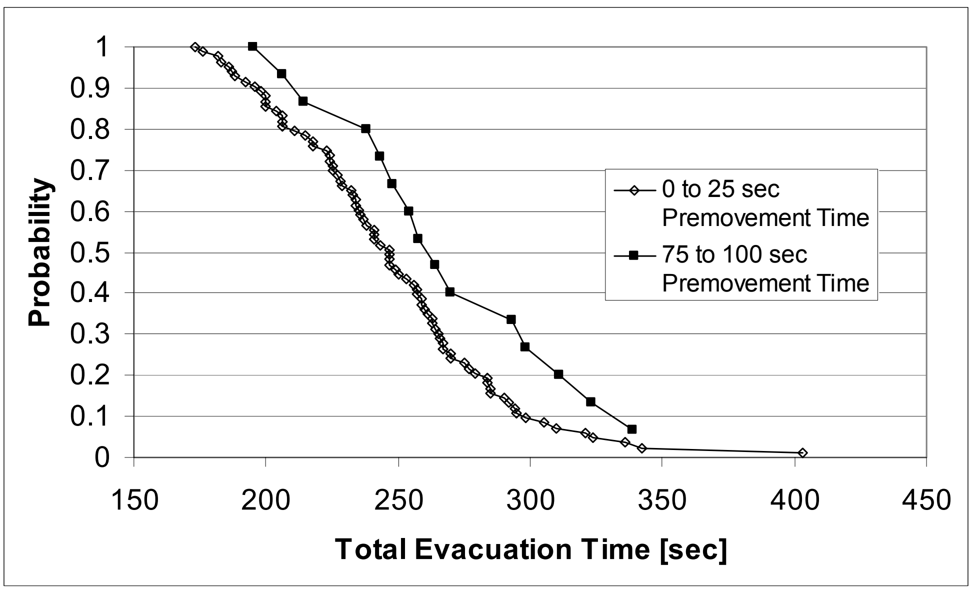

Figure 6: Cumulative Distribution Funtions of Total Evacuation Time for Two Pre-Movement Time Ranges on Floor 1

It was noted that the effect of pre-movement time varied by floor. The results suggest that there are times when greater pre-movement times may actually *decrease* the total amount of time required to evacuate the building. For the basement and Floor 1, a longer pre-movement time correlated to a longer evacuation time. In Floors 2-4, increasing the pre-movement times seemed to have a negligible effect on the total building evacuation time. On the upper floors (Floor 5 and Floor 6), increasing the pre-movement time seemed to result in *shorter* total building evacuation times. This may reflect an increase in the speed of evacuation due to a decrease in queuing in the stairs. A cumulative distribution function for the Floor 6 pre-movement times is provided in Figure 7 below.

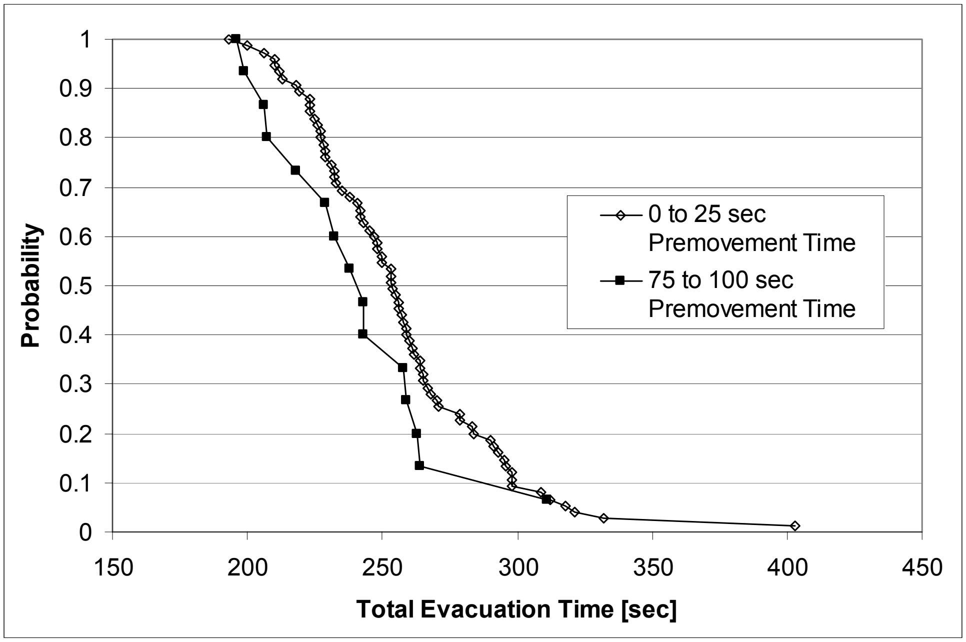

Figure 7: Cumulative Distribution Funtions of Total Evacuation Time for Two Pre-Movement Time Ranges on Floor 6

Demographics & Walking Speed

The initial results of this study indicate that in buildings similar to the London building, demographics play a fairly insignificant roll in the overall total evacuation time. This also correlates to occupant walking speed, which was correlated to each person's age during the STEPS simulations.

This finding is likely due to the fact that the distribution of ages was fairly limited in range, as most office buildings have relatively low populations of elderly or disabled persons. Future stages of this study will investigate other types of buildings, which may be more significantly affected by the population age and walking speeds.

Door Flow Rate

STEPS allows a flow rate to be applied to doorways within the model. This can be set at any user defined value, and is not one of the default STEPS settings. A range of 0.1 persons/meter/second (p/m/s) to 1.3 p/m/s was tested; the results of the simulations indicate that the door flow rate is significant for probabilities of less than 0.2, but is fairly insignificant above 0.2, as indicated in the figure below.

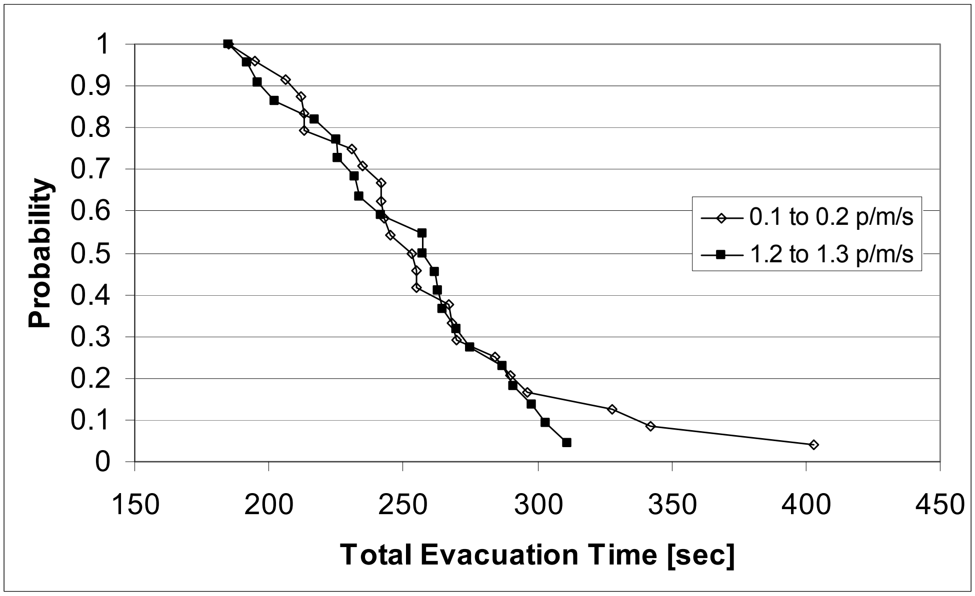

Figure 8: Cumulative Distribution Funtions of Total Evacuation Time for Two Ranges of Door *Flow Rates*

Patience
STEPS allow a value to be signed to each person indicating their patience, on a scale from 0 to 1. Initial results indicate that this variable may have a minimal impact on the simulation results.

STEPS Coefficients
The STEPS software has three coefficients labeled "Patience Coefficient" (default value of 0.1), "Walking Coefficient" (default value of 1.0), and "Queing Coefficient" (default value of 1.0). These coefficients can have a value between 0 and 1, and have an effect on the decision process of each building occupant, which determines the exits to which people will travel.

The results of the analysis suggest that the Patience and Walking coefficients tended to effect the total evacuation time by approximately 5-10%. The fastest total evacuation times were achieved when these variables were set to values close to 1.0. Therefore, it would seem that the default value for the Patience coefficient (0.1) would tend to result in a longer evacuation time, but the default value for the Walking coefficient would tend to result in shorter evacuation times.

The Queuing coefficient seemed to have a significant impact on the results of the STEPS simulations. Figure 9 provides a graph of the sensitivity of the total evacuation time to the Queing coefficient. This graph was prouced by subtracting the total evacuation times achieved with a low (0 to 0.1) queing coefficient from those with a high (0.9 to 1.0) coefficient. The results indicate that the significance of the queing coefficient was quite high at a probability near 0, but rapidly diminished as the probability approached 0.6.

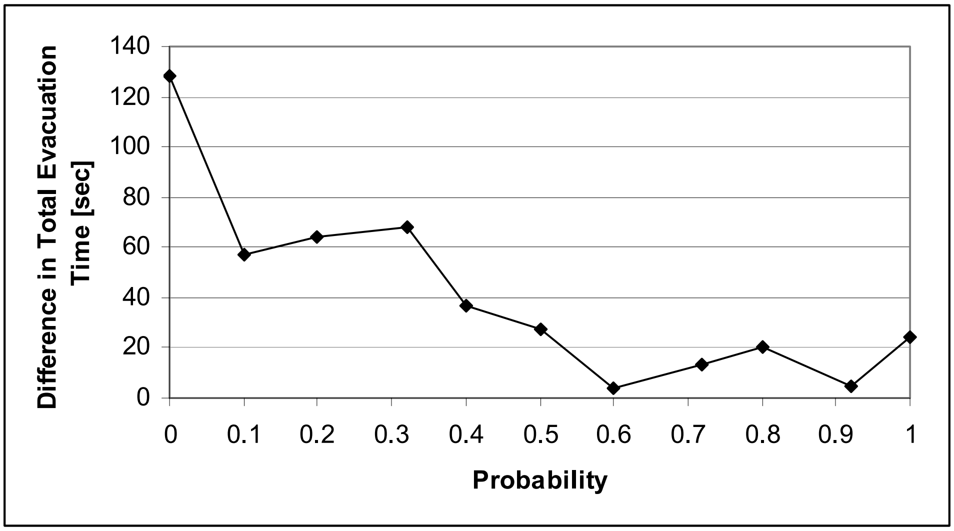

Figure 9: Sensitivity of Total Evacuation Time to Queing Coefficient

Time Step

The analysis results seem to suggest that within a range of 0 to 5 seconds, the time step chosen for STEPS simulations is insignificant. The cumulative distribution function in Figure 10 shows that there was very little difference seen between runs with a time step of between 0 and 1, and runs with a time step of between 4 and 5. The effect of the time step on computer simulation time was also investigated. Figure 11 indicates that size of the time step had very little effect on the amount of time that it took to compute each simulation.

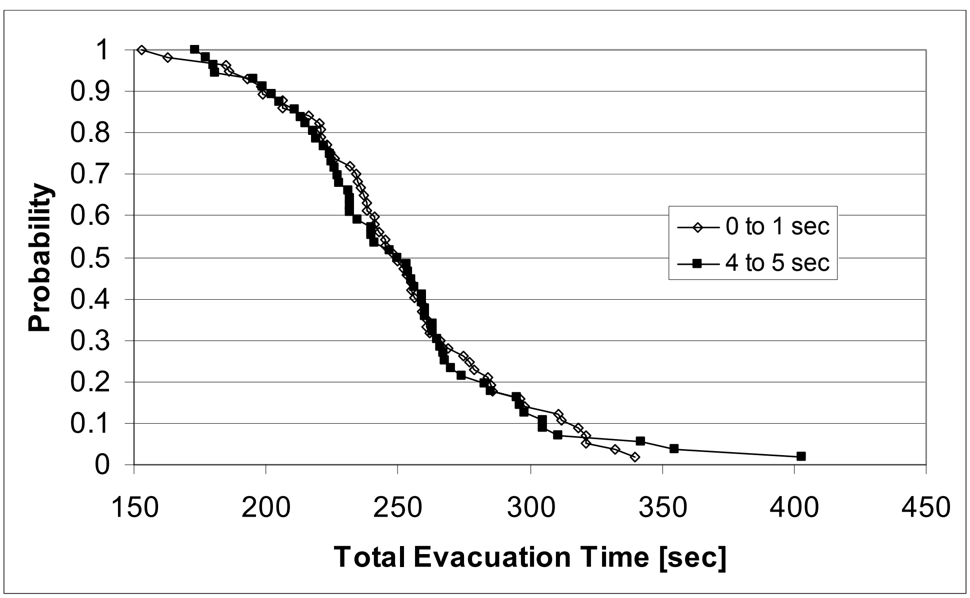

Figure 10: Cumulative Distribution Funtions of Total Evacuation Time for Two Time Step Ranges

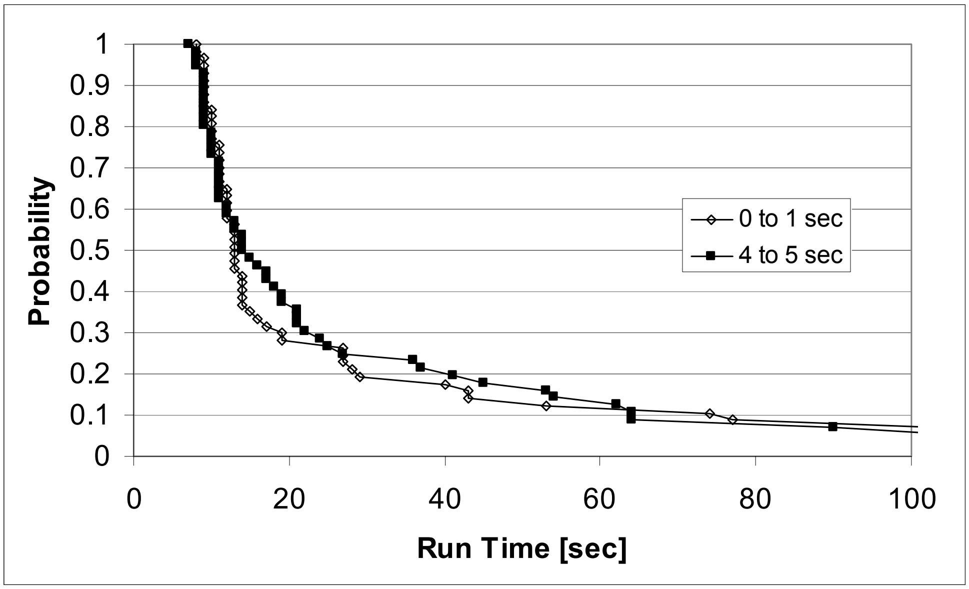

Figure 11: Cumulative Distribution Funtions of Computer Simulation Time for Two Time Step Ranges

Locks Solver Depth

STEPS contains a variable known as "Locks Solver Depth", which determines the maximum number of iterations that will be used to find a solution when a circular lock occurs in the simulation. This analysis investigated a range of values from 1 to 10 for the Lock Solver Depth; initial results suggest that the value of this variable is significant at probabilities of greater than 0.9. Therefore, when it is desired that the uncertainty of a problem is within this range, the value of the Lock Solver Depth should be included in an analysis. Preliminary findings indicate that this may increase the computational time needed to reach a solution by more than 400% when a value of 10 is used rather than the default value of 1.

CONCLUSIONS

A study has been conducted to apply the method of Notarianni[7] to computer egress modeling. This method uses a Monte Carlo techinque to evaluate the uncertainty associated with simulation of evacuation times from a building. An analysis has been completed using the computer egress model "STEPS" for a 6-story office building in London, Ontario. A similar analysis is underway using the computer egress model "EXIT89".

Several variables have been identified as having a statistically significant impact on the total evacuation time for the London building. Among the more significant variables for this analysis are:

- Occupant loads
- Pre-movement times
- Queing Coefficient
- Locks Solver Depth

Future work will involve the modeling of other types of buildings; this will help to determine both the effectiveness of the methodology and the validity of STEPS and EXIT89 for various types of scenarios.

In addition, future analysis will be needed to investigate the significance of grid size on STEPS simulations, and the effecte of larger numbers of simulations on the statistical analysis.

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