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GUIDE FOR EVALUATING THE PREDICTIVE CAPABILITIES OF COMPUTER EGRESS MODELS

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Prepared for
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Notice

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INTRODUCTION

To begin addressing the issue of uncertainty and variability in egress data and in computational models for egress analysis, a three-year research study began in September 2002 under a grant from the National Institute for Standards and Technology, Building and Fire Research Laboratory (Grant 60NANB2D0138), *Uncertainty in Egress Models and Data: Investigation of Dominant Parameters and Extent of Their Impact on Predicted Outcomes*. The primary goals of this work were to:

- Understand sources of uncertainty and variability in egress models.
- 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.

The results of this three-year research study are provided in this document, broken into several informational appendices.

2. SUMMARY OF WORK

Year 1 Summary (September 2002 – September 2003)

In Year 1, sources and types of uncertainty and variability were identified for the selected models, STEPS and EXIT89, and an assessment of the models against a set of baseline data was undertaken. In addition, steps were taken to identify variables that could be adjusted in each model that could lead to uncertainty and variability. A literature review was begun to start gathering as much data as possible for the variables that were identified for each of the models.

Year 2 Summary (September 2003 – September 2004)

In Year 2, the literature review was completed, and distribution curves were developed for all of the variables that were identified during the first year of work. This data is included in the attached Appendix B.

The distribution curves were then used as input for Monte Carlo analyses of an office building (the "London Building") and an apartment building (the "Calgary Building") using both STEPS and EXIT89. The results of these analyses were used to determine the statistical significance of each variable, and to identify potential "cross-over" variables that may warrant close monitoring during use of computer egress models.

Year 3 Summary (September 2004 – December 2005)

The work in Year 3 involved undertaking a blind test of the two evacuation models and developing the guidance document for use with egress models. The Year 3 effort also included the presentation and publication of papers at the *3rd International Symposium on Human Behaviour in Fire* (1-3 September 2004 in Belfast, Northern Ireland) and the *5th International Conference on Performance-Based Codes and Fire Safety Design Methods* (6-8 October 2004 in Luxembourg). These papers are attached as Appendices D and E.

3. DOCUMENT FORMAT

The purpose of this document is to convey the lessons learned during this study to the design community in a format that can be used as a guide for evaluating the predictive capability of egress models. The following items have been compiled in this single document in order to facilitate use of the information gained during the course of this grant:

Appendix A - Draft Standard Guide for Evaluating the Predictive Capability of Computer Egress Models

The bulk of Appendix A contains the language provided in ASTM (American Society for Testing and Materials) E 1355 – 97, *Standard Guide for Evaluating the Predictive Capability of Deterministic Fire Model*. Where appropriate, new language has been suggested that applies specifically to computer egress models rather than deterministic fire models.

Annex A to this appendix provides a step-by-step example of how to apply the recommendations of the guidance document when using a computer egress model (in this case STEPS) during the design process. It should be noted that although this particular example used STEPS, it is meant to provide an example of a step-by-step process that can be used for any computer egress model.

Appendix B – Literature Review

Appendix B contains all of the data collected during the literature review. This appendix contains the data in tabular format as well as graphically in the resulting distribution curves. A list of references is provided.

Appendix C – Summary of Modeling Results

Appendix C contains a summary of the modeling that was performed using EXIT89 and STEPS during the 3-year grant. A brief summary of the findings of the simulations are provided for each of the buildings that were analyzed.

Appendix D – Submission to the 5th International Conference on Performance-Based Codes and Fire Safety Design Methods

Appendix D contains a paper that was is published in the proceedings of the 5th International Conference on Performance-Based Codes and Fire Safety Design Methods, SFPE, Bethesda, MD, October 2004. The paper is entitled “Uncertainty in Egress Models and Data: Investigation of Dominant Parameters and Extent of Their Impact on Predicted Outcomes – Initial Findings**”,** and provides a summary of the work completed during the first 1.5 years of the grant.

Appendix E – Submission to the 3rd International Symposium on Human Behaviour in Fire

Appendix E contains a paper that was is published in the proceedings of the 3rd International Symposium on Human Behaviour in Fire, Interscience Communications Ltd., September 2004, pp.419-430. The paper is entitled “Investigation of Uncertainty in Egress Models and Data”, and provides a summary of the work completed during the first 2 years of the grant.

4. SUMMARY OF FINDINGS

The analyses that were conducted indicate that there may not be a single set of variables that are significant or insignificant over all egress scenarios. The variables that were determined to be significant or exhibit “cross-over” behavior varied on a case-by-case basis, and depended on the computer model that was being used and the type of building that was being modeled.

After reviewing the data from EXIT89 and STEPS from the three buildings that were modeled with each, some general conclusions can be drawn:

- Both EXIT89 and STEPS provide reasonably accurate total egress times for office and apartment buildings on the order of 6 to 14 stories in height.
- For the types of buildings that were modeled, EXIT89 may under-predict the total evacuation time for a building if prior knowledge of the occupant load is not provided.
- For the types of buildings that were modeled, STEPS may over-predict the total evacuation time for a building if prior knowledge of the occupant load is not provided.
- EXIT89 is generally sensitive to the occupant data that is provided. Varying the number of occupants, size of occupants, and speed of occupants will often have a significant impact on the model results.
- STEPS is generally sensitive to grid-size. Changing the grid from 0.3 meters to 0.6 meters can have a significant impact on the results of the model. Efforts should be taken when using STEPS to use an appropriate grid size and to perform some sensitivity analysis.

There was sufficient variation from one scenario to another in the variables that exhibited significance that it would be difficult to eliminate the need to consider specific variables without future analyses that build off the information provided in this document. Until such analysis can be completed, the method of uncertainty analysis described in this document could be used to evaluate the significance of individual variables and to identify which variables are most significant for building evacuations on a case-by-case basis.

APPENDIX A

Draft Standard Guide for Evaluating the Predictive Capability of Computer Egress Models

A1. SCOPE

1.1. This guide provides a methodology for evaluating the predictive capabilities of an egress model for a specific use.

1.2. The methodology is presented in terms of four areas of evaluation:

  1.2.1. Defining the model and scenarios for which the evaluation is to be conducted,

  1.2.2. Verifying the appropriateness of the theoretical basis and assumptions used in the model,

  1.2.3. Verifying the mathematical and numerical robustness of the model, and

  1.2.4. Quantifying the uncertainty and accuracy of the model results in predicting the course of events in similar occupant movement scenarios.

1.3. *This guide does not purport to address all of the safety concerns, if any, associated with its use. It is the responsibility of the user of this guide to establish appropriate safety and health practices and determine the applicability of regulatory limitation prior to use.*

A2. REFERENCED DOCUMENTS

2.1. Fahy, Rita F., Proulx, Guylene, *Toward Creating a Database on Delay Times to Start Evacuation and Walking Speeds for Use in Evacuation Modeling*, Human Behavior in Fire-Proceedings of the 2nd International Symposium, MIT, March 2001.

2.2. Notarianni, K., "The Role of Uncertainty in Improving Fire Protection Regulation", Thesis, Carnegie Mellon University, 2000.

2.3. Hald, A., *Statistical Theory with Engineering Applications*, Wiley, 1952.

2.4. Proulx, G, Laroche, C.; Pineau, J. Methodology for Evacuation Drill Studies, *Internal Report 730, Institute for Research in Construction, National Research Council Canada*, Ottawa ON, November 1996.

A3. TERMINOLOGY

3.1. *Definitions Specific to This Guide:*

  3.1.1. *model evaluation* – the process of quantifying the accuracy of chosen results from a model when applied for a specific use.

  3.1.2. *model validation* – the process of determining the correctness of the assumptions and governing equations implemented in a model when applied to the entire class of problems addressed by the model.

  3.1.3. *model verification* – the process of determining the correctness of the solutions of a system of governing equations in a model. With this definition, verification does not imply the solutions of the correct set of governing equations, only that the given set of equation is solved correctly.

  3.1.4. *model uncertainty* – the amount or percentage by which a model calculated value may differ from the actual value.

  3.1.5. *model sensitivity analysis* – a study of how changes in model parameters affect the results generated by the model.

  3.1.6. *cumulative distribution function* – the probability that the variable takes a value less than or equal to a specific value

  3.1.7. *correlation coefficient* – a number between -1 and 1 which measures the degree to which two variables are linearly related. A correlation coefficient of 1 indicates that there is a perfect linear relationship with positive slope. A correlation of -1 indicates that there is a perfect inverse linear relationship with a positive slope. A correlation coefficient of 0 indicates that there is no linear relationship between the two variables.

  3.1.8. *scenario* – The definition of a scenario can vary depending on the user of a model. For model developers and those evaluating models, a scenario may often entail comparison of the model results to a set of experimental data. On the other hand, for those using the model as a design tool a scenario may entail a specific set of design conditions that are being evaluated using the model. Throughout this document the term “scenario” has been used to represent either of these cases, depending on the user of this guidance document.

A4. SUMMARY OF GUIDE

4.1. A recommended process for evaluating the predictive capability of egress models is described. The process includes a brief description of the model and the scenarios for which evaluation is sought. Then, methodologies for conducting an analysis to quantify the sensitivity of model predictions to various uncertain factors are presented. Finally, guidance is given concerning the relevant documentation required to summarize the evaluation process.

A5. SIGNIFICANCE AND USE

5.1. The process of model evaluation is critical to establishing both the acceptable uses and limitations of egress models. Rather than attempting to provide a method to evaluate a model in total, this guide is intended to provide a methodology for evaluating the predictive capabilities for a specific use. Validation for one application or scenario does not imply validation for different scenarios. Several alternatives are provided for performing the evaluation process including: comparison of predictions against evacuation experiments, documented emergency events, previously evaluated models, or calculations.

5.2. Engineering, fire service, and legal communities all employ the use of egress models. Sufficient evaluation of egress models is necessary to ensure that those using the models can judge the adequacy of the scientific and technical basis for the models, select models appropriate for a desired use, and understand the level of confidence which can be placed on the results predicted by the models. Adequate evaluation will help prevent the unintentional misuse of egress models.

5.3. This guide is intended for use by:

5.3.1. *Model Developers/Marketers* – To document the usefulness of particular calculation methods possibly for specific applications. Part of the model development includes identification of accuracy and limits of applicability, and independent testing.

5.3.2. *Model Users* – To assure themselves that they are using an appropriate model for an application and that it provides adequate accuracy.

5.3.3. *Developers of Model Performance Codes* – To be sure that they are incorporating valid calculation procedures into codes.

5.3.4. *Approving Officials* – To ensure that the results of calculations using mathematical models stating conformance to the recommendations in this guide, cited in a submission, show clearly that the model is used within its applicable limits and has an acceptable level of accuracy.

5.3.5. *Educators* – To demonstrate the application and acceptability of calculation methods being taught.

5.3.6. This guide is not meant to describe an acceptance testing procedure.

A6. GENERAL METHODOLOGY

6.1. The methodology is presented in terms of four areas of evaluation:

  6.1.1. Defining the model and scenarios for which the evaluation is to be conducted,

  6.1.2. Assessing the appropriateness of the theoretical basis and assumptions used in the model,

  6.1.3. Assessing the mathematical and numerical robustness of the model, and

  6.1.4. Quantifying the uncertainty and accuracy of the model results in predicting the course of events in similar egress scenarios.

6.2. *Model and Scenario Definition:*

  6.2.1. *Model Documentation* – Sufficient documentation of calculation models, including computer software, is necessary to assess the adequacy of the scientific and technical basis of the models, and the accuracy of computational procedures. Also, adequate documentation will help prevent the unintentional misuse of egress models. Details applicable to evaluation of the predictive capability of egress models are provided in Section A7.

  6.2.2. *Scenario Documentation* – Provide a complete description of the scenarios of interest in the evaluation to facilitate appropriate application of the model, to aid in developing realistic inputs for the model, and criteria for judging the results of the evaluation. Details applicable to evaluation of the predictive capability of egress models are provided in Section A7.

6.3. *Theoretical Basis and Assumptions in the Model* – An independent review of the underlying mathematics inherent in a model ensures appropriate application of sub-models which have been combined to produce the overall model. Details applicable to evaluation of the predictive capability of egress models are provided in Section A8.

6.4. *Mathematical and Numerical Robustness* – The computer implementation of the model should be checked to ensure such implementation matches the stated documentation. Similarly, users of the model should be familiar with the mathematical basis of the model, and choose appropriate inputs that fall within its limitations. Details applicable to evaluation of the predictive capability of egress models are provided in Section A9.

6.5. *Quantifying the Uncertainty and Accuracy of the Model:*

  6.5.1. *Model Uncertainty* – Even deterministic models rely on inputs often based on experimental measurements, empirical correlations, or estimates made by engineering judgment. Uncertainties in the model inputs can lead to corresponding uncertainties in the model outputs. Sensitivity analysis is used to quantify these uncertainties in the model outputs based upon known or estimated uncertainties in model inputs. Details of sensitivity analysis applicable to evaluation of the predictive capability of egress models are provided in Section A10.

  6.5.2. *Experimental Uncertainty* – In general, the result of measurement is only the result of an approximation or estimate of the specific quantity subject to measurement, and quantitative statement of uncertainty. When using experimental data this uncertainty should be accounted for.

6.6. *Model Evaluation* – Obtaining accurate estimate of human behavior using predictive egress models involves providing correct model inputs appropriate to the scenarios to be modeled, correct selection of a model appropriate to the scenarios to be modeled, correct calculations by the model chosen, and correct interpretation of the results of the model calculation by those using it as a design tool. Evaluation of a specific scenario with different levels of knowledge of the expected results of the calculation addresses these multiple sources of potential error. Details applicable to evaluation of the predictive capability of egress models are provided in Section A11.

A7. MODEL AND SCENARIO DEFINITION

7.1. Model Documentation – Provide the following information:
  7.1.1. The name and version of the model,
  7.1.2. The list of the model developer(s),
  7.1.3. A list of relevant publications,
  7.1.4. A statement of the stated uses, limitations, and results of the model,
  7.1.5. The type of model,
  7.1.6. A statement of the modeling rigor, including;
    7.1.6.1. The assumptions inherent in the model and the governing equations included in the model formulation, and
    7.1.6.2. The numerics employed to solve the equations and the method by which individual solutions are coupled.
  7.1.7. Additional assumptions of the model as they relate to the stated uses or other potential uses,
  7.1.8. The input data required to run the model
7.2. Scenarios for Which Evaluation is Sought – Provide the following information:
  7.2.1. A description of the scenarios of interest,
  7.2.2. A list of quantities predicted by the model for which evaluation is sought, and
  7.2.3. The degree of accuracy required for each quantity.

A8. THEORETICAL BASIS FOR THE MODEL

8.1. The theoretical basis of the model should be reviewed by one or more experts fully conversant with human behavior and movement but not involved with the production of the model. This review should include:
  8.1.1. An assessment of the completeness of the documentation particularly with regard to the assumptions and approximations.
  8.1.2. An assessment of whether there is sufficient scientific evidence in the open scientific literature to justify the approaches and assumptions being used.
  8.1.3. Empirical or reference data used for constants and default values in the code should also be assessed for accuracy and applicability in the context of the model.

A9. MATHEMATICAL AND NUMERICAL ROBUSTNESS

9.1. Analyses which can be conducted include:
  9.1.1. *Comparison with Actual Evacuations* – If the program can be applied to a situation for which there is a known evacuation time, comparing the results of the model to the actual evacuation time is a powerful way of testing the correct functioning of a model for that type of scenario.
  9.1.2. *Code Checking* – The code can be verified on a structural basis preferably by a third party either totally manually or by using code checking programs to detect irregularities and inconsistencies within the computer code. A process of code checking can increase the level of confidence in the program's ability to process the data to the program correctly, but it cannot give any indication of the likely adequacy or accuracy of the program in use. In cases where the source codes for computer models are proprietary, the model developer should provide documentation as evidence of implementation of a code-checking procedure.
  9.1.3. *Comparison with Hand Calculations* – Hand calculation methods can give good first-order approximations of evacuation times for straightforward scenarios or for parts of complex scenarios. The evacuation times found using hand calculations can be compared to full or partial evacuation times found using a computer egress model. This

method is another useful way to check the functioning of the model for specific scenarios if actual evacuation data is not known or comparable.

A10. MODEL SENSITIVITY

10.1. Evacuation models are typically based on a system of algebraic equations calculating occupant travel time and queuing time while taking into account detection/notification time and pre-movement time of the occupants. To study the sensitivity of these equations, the variations of possible input values and how they affect results should be examined.

10.2. A sensitivity analysis of a model is a study of how changes in model parameters affect the results generated by the model. Model predictions may be sensitive to uncertainties in input data, to the level of rigor employed in the modeling of occupant movement, and to the accuracy of numerical treatments. The purpose of conducting a sensitivity analysis is to assess the extent to which uncertainty in model inputs is manifested to become uncertainty in the results of interest from the model. This information can be used to:

  10.2.1. Determine the dominant variables in the models,
  10.2.2. Define the acceptable range of values for each input variable,
  10.2.3. Quantify the sensitivity of output variables to variations in input data, and
  10.2.4. Inform and caution any potential users about the degree and level of care to be taken in selecting input and running the model.

10.3. Inputs to the model can vary greatly between different choices of evacuation software. However, the types of variables that are present can generally be lumped into 3 basic categories. These consist of:

  10.3.1. *Scenario Specific Data* – Such as the geometry of the building or space, occupant flow rate through exits or other building components, and if the model is grid-based, the grid size chosen to model the scenario.
  10.3.2. *Occupancy Specific Data* – Such as the total number of occupants, the demographics of the population, size of occupants, walking speeds, pre-movement times, occupant patience factors, and other similar variables.
  10.3.3. *Model Specific Data* – Which can include various coefficients and other factors specific to the model being studied.

10.4. Conducting a sensitivity analysis of an egress model is not a simple task. Many models require extensive input data. Time and cost become critical factors in determining the extent of the analysis. A practical problem to encounter when designing a sensitivity analysis experiment is that the number of model runs required will rapidly increase with the number of input parameters and independent variables to be considered. A partial factorial experiment may be adequate in many cases for the purpose of obtaining information on the effect of varying input parameters and consequential interactions considered important.

10.5. An effective model for addressing uncertainty in computer models, including egress models, is the Monte Carlo method. An example of a sensitivity analysis that utilizes the Monte Carlo method is presented in Annex A.

  10.5.1. The first step of a Monte Carlo analysis involves identification of all of the variables that can be input into the computer egress model. Following identification of these variables it is necessary to obtain a collection of data sets of measured egress parameters. Distribution curves can then be formed from the available data, by determining the probability of each of the values occurring. Some references are available that provide an initial collection of data for this purpose.[1,2] In addition, Annex B provides a summary of data related to egress.

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[1] Fahy, Rita F., Proulx, Guylene, *Toward Creating a Database on Delay Times to Start Evacuation and Walking Speeds for Use in Evacuation Modeling*, Human Behavior in Fire-Proceedings of the 2nd International Symposium, MIT, March 2001.

10.5.2. Multiple simulations should be run in order to determine the effect of the variation of input parameters on the output. Selection of the appropriate number of simulations depends on several factors. Hald[3] provides a formula for determining the relationship between the number of runs, n, and the statistical significance of the correlation coefficient.

10.5.2.1.1. $t = \frac{c}{\sqrt{1-c^2}}\left(\sqrt{n-2}\right)$

10.5.2.1.2. The value for t is related to the confidence level, and is typically chosen as 0.95[4]. The value c is a value between 0 and 1 that determines the statistical significance of the correlation coefficients.

10.5.3. After the simulations are run, the output must be analyzed to determine the effect of the variation of the input parameters. The method of Notarianni[5] can be used to conduct this analysis. A cumulative distribution function (CDF) is created to display the probabilities associated with an estimated evacuation time for the structure. This is accomplished by graphing each evacuation value against its rank.

10.5.4. Using this same method 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. This can be done in several different ways.

10.5.4.1. An analysis of the significant variables can be done by plotting the CDF of estimated evacuation times focusing on a specific variable. By plotting the CDFs of both the bottom quadrant and top quadrant evacuation times for the variable on the same graph, the effect of that variable on the output can be seen.

10.5.4.2. Another way to view this data is to plot the difference in the evacuation times for a specific variable. By subtracting the fastest evacuation times from the slowest evacuation times for a variable one can see the effect of the variable on the evacuation time as the probability threshold is increased.

10.5.4.3. In addition to the creation of CDFs, useful information can be gained by evaluating the importance of each variable in relation to the total evacuation time (or any other quantity that is measured). Each variable's importance can be calculated on a scale from -1 to 1, where a correlation coefficient of 1 indicates a very strong direct correlation, 0 indicates no correlation, and -1 indicates a very strong inverse correlation. The value of the correlation coefficient at which a variable becomes statistically significant can be calculated using the equation shown in Section 11.5.2.

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[2] NIST Grant Study 60NANB2D0138

[3] Hald, A., *Statistical Theory with Engineering Applications*, Wiley, 1952.

[4] Notarianni, K., "The Role of Uncertainty in Improving Fire Protection Regulation", Thesis, Carnegie Mellon University, 2000.

[5] Notarianni, K., "The Role of Uncertainty in Improving Fire Protection Regulation", Thesis, Carnegie Mellon University, 2000.

A11. MODEL EVALUATION

11.1. The model should be assessed for a specific use in terms of its quantitative ability to predict the evacuation time of specific building regions and entire structures.

11.2. Model evaluation addresses multiple sources of potential error in the design and use of predictive egress models, including the need to provide correct model inputs appropriate to the scenario being modeled, correct selection of a model appropriate to the scenarios to be modeled, correct calculations by the model chosen, and correct interpretation of the results of the model calculation. Evaluation of a specific scenario with different levels of knowledge of the expected results of the calculation addresses these multiple sources of potential error. It is understood that only one or more of these levels of evaluation may be included in a particular model evaluation.

11.2.1. *Blind Calculation* – The user is provided with a basic description of the scenario to be modeled. This includes supplying the user with information on the geometry of the structure (floor plans, elevations, egress components, etc.) and the type of structure. Additional details necessary to simulate a scenario with a specific model are left to the judgment of the model user. In addition to illustrating the comparability of models in actual end-use conditions, this will test the ability of those who use the model to develop the appropriate input data for the models. An example of a blind calculation is presented in Annex A.

11.2.2. *Specified Calculation* – The user is provided with a detailed description of model inputs including geometry of the structure (floor plans, elevations, egress components, etc.), occupant characteristics, and the range of numerical constants to use that are specific to the model. As a follow-on to the blind calculation, this test provides a more careful comparison of the underlying algorithms in the model with a more completely specified scenario.

11.2.3. *Open Calculation* – The model user is provided with the most complete information about the scenario including the inputs provided with a specified calculation along with actual evacuation data or benchmark model runs completed using the blind calculation or specified calculation with the same model or results from a validated egress model for the same scenario to be modeled. Deficiencies in available input (used for the blind calculation) should become most apparent with comparison of the open and blind calculation.

11.2.4. *Problem Description and Model Inputs* – Different models may require substantially different details in the problem description for each of the three levels outlined above. For example, some egress models are node-based and others are grid-based, which leads to differences in the information that must be provided about the geometry. In addition, some models require the user to provide specific details about the occupants while others do not. For each of the three levels of evaluation, an appropriate problem description sufficient to allow the problem to be simulated is necessary.

11.3. A model may be evaluated using one or more of the following tools:

11.3.1. *Comparison with Evacuation Tests of the Chosen Scenario*

11.3.1.1. Since these types of test are very difficult to conduct, a scenario with documented evacuation test data must be chosen for the model evaluation in order to conduct this comparison. Currently there are no published standards relating to how evacuation data should be collected, but an Internal Report by the National Research Council of Canada describes a methodology for evacuation drill studies.[6]

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[6] Proulx, G, Laroche, C.; Pineau, J. *Methodology for Evacuation Drill Studies*, Internal Report 730, Institute for Research in Construction, National Research Council Canada, Ottawa ON, November 1996.

11.3.1.2. Model predictions can be tested against the evacuation times measured during the test.

11.3.1.3. Where data are available, model predictions should be viewed in light of the uncertainty in the experimental data as compared to the uncertainty in the model results that arise due to uncertainty in the model inputs.

11.3.2. *Comparison with Data from Documented Emergency Events*

11.3.2.1. There are very few emergency events that have been documented to the extent that is necessary for this type of evaluation; therefore, a scenario with documented fire evacuation data must be chosen for the model evaluation in order to conduct this comparison. Currently there are no published standards relating to how evacuation data should be collected, but an Internal Report by the National Research Council of Canada describes a methodology for evacuation drill studies.[7] A literature review of available real-life egress data has been summarized in Annex B of this document.

11.3.2.2. Model predictions can be tested against the evacuation times measured during the emergency event.

11.3.3. *Comparison with Proven Benchmark Models*

11.3.3.1. Care should be taken to determine that the *benchmark* model has been evaluated for the scenarios of interest.

11.3.3.2. Model predictions can be tested against the evacuation times that the benchmark model predicts.

11.3.3.3. Where data are available, model predictions should be viewed in light of the variability of the sensitivity of both model predictions. Initial studies have indicated that the accuracy of model results can vary greatly depending on the type of scenario that is being modeled and the range of input data that is provided. A comparison with two sample computer egress models and some real-life evacuations are provided in Annex C.

11.3.4. *Comparison with Calculations* - For structures with simple egress paths, it is possible to compare the predicted evacuation time of the egress model to hand calculations. This type of comparison could also be completed for portions of buildings with complex egress paths.

11.3.5. *Quantifying Model Evaluation* – The evacuation times would be the measure of comparison for the methods listed above. However, the comparison should not be limited to total evacuation time only. The evacuation time of regions or floors in a structure should also be compared in order to assess the predictive capabilities of the egress model.

11.3.6. Whenever possible, the use of subjective judgments should be avoided and the results of the comparisons should be expressed in quantitative terms.

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[7] Proulx, G, Laroche, C.; Pineau, J. *Methodology for Evacuation Drill Studies*, Internal Report 730, Institute for Research in Construction, National Research Council Canada, Ottawa ON, November 1996.

A12. EVALUATION REPORT

12.1. The following information should be reported. A sample report can be seen in Annex A.

- 12.1.1. Date of the evaluation report.
- 12.1.2. Person or organization responsible for the evaluation.
- 12.1.3. Specific reference information for the evaluation report. References to model documentation, reports of experimental measurements, sensitivity analysis reports, and additional evaluation reports are appropriate.
- 12.1.4. Description of the model and scenarios for which evaluation is sought as outlined in 7.1 and 7.2.
- 12.1.5. A summary of the sensitivity analysis.
- 12.1.6. A summary of the predictive capabilities of the model.
- 12.1.7. Known limitations for the use of the evaluation for other egress scenarios.

A13. KEYWORDS

13.1. evaluation; egress model; sensitivity; uncertainty; validation

ANNEX A

Sample Evaluation Report

A14. INTRODUCTION

This report describes the process and results of an evaluation of the STEPS computer egress model. This evaluation was completed by Arup in September of 2005.

A15. MODEL DOCUMENTATION

A15.1 Model

Simulation of Transient Evacuation and Pedestrian movementS (STEPS), 2.0 Build 0011

Model Developer: Simulation Group of Mott MacDonald

Relevant Publications: STEPS User Manual, Mott MacDonald, United Kingdom

A15.2 Uses, Limitations, and Results:

STEPS is designed to simulate how people move in both normal and evacuation situations within building complexes. The model outputs include evacuation time of the model or area, number of occupants in the whole model or in a specific area of the model, number of occupants that use a specific exit, and occupant density on a specific floor or area.

There are some limitations of the model as well. Since the model is grid based, the model assumes that occupants are the same size as the grid cell that they are occupying, so occupant size and small building dimension changes (such as changing a stair width by a few inches) do not affect the evacuation time. Also, travel speeds are constant regardless of population density.

A15.3 Type of Model

STEPS is a grid based evacuation model. The grid defines the area where occupants can walk. Planes can be created in STEPS and blockages can be formed to indicate walls, etc. Also, floor plans in CAD format can be imported into STEPS as planes. The walls and other obstructions on the floor plan automatically become blockages in the model. A grid is overlaid on top of each plane and if a blockage such as a wall crosses through a grid cell, the cell becomes blocked and occupants cannot use that cell. People can also use paths to move from location to location in STEPS as well. A path is simply a line that spans two points in the model and conveys occupants at a fixed rate of travel.

A15.4 Modeling Rigor

The calculation procedure in STEPS is actually referred to as the decision process in the user's manual. There are two main parts of each occupant's decision process: finding which target (exit or checkpoint) to aim for and finding how to move to the chosen target.

A target is chosen based on the score that it receives. The algorithm that is used to score each target involves the following steps.

- Time needed to reach the target
- Time needed to queue at the target
- Adjustment of the walking time to take into account the time that is not actually walked to reach the end of the queue
- Calculation of the real time needed to reach the end of the queue
- Adjustment of the queuing time to take into account the people that will get out while the person is walking
- Calculation of the real time to queue
- Incorporation of the patience levels
- Calculation of the final score

People will choose the target with the lowest score. In the case of a tied score between targets, people will randomly choose between the targets.

The time needed to reach the target is calculated using the following equation.

$$T_{walk} = D / W$$

Equation 1

Where:

D = Distance to the target

W = Person's walking speed (entered by user)

The equation used to find the time needed to wait in the queue at the target is:

$$T_{Queue} = N / F$$

Equation 2

Where:

N = Number or persons that will reach the target before the current person (found by comparing the walking time of the current person with all the other people on the same plane)

F = Flow rate of the target (entered by user)

Since the time to travel to the end of the queue is shorter than the time to travel to the target, the walking time must be adjusted. The model does this by assuming that people will gather around the target by occupying the cells that are closest to the target and subtracting the travel time adjustment from the time calculated in Equation 1.

$$T_{\mathrm{Re}\,alTimetoWalk} = T_{Walk} - \left(\frac{D2}{W}\right)$$ **Equation 3**

Where:

D2 = Distance of the person just in front of current person from target

Similar to the walking time, the queuing time also needs to be adjusted to reflect the number of people that will pass through the target while the current person is traveling to the target. The queuing time is adjusted using Equation 4.

$$T_{\mathrm{Re}\,alTimetoQueue} = T_{Queue} - \left(\frac{N2}{F}\right)$$ **Equation 4**

Where:

N2 = Number of persons that will reach the target during the time calculated in Equation 3.

When setting up the model the user defines patience levels for each people type in the model. Patience is a number between 0 and 1 that describes how prepared people are to queue at a target. People with a Patience of 0.5 have an unbiased level of patience. People with a Patience higher than 0.5 are considered patient; whereas, people with a Patience lower than 0.5 are considered impatient. Patient people will accept to queue longer than impatient people. The coefficient to adjust the queuing time is calculated using Equation 5.

$$C_{AdjustQueue} = 1 - C_{Patience} * (0.5 - Patience) / 0.5$$ **Equation 5**

Where:

Patience = Patience level of person (entered by user)

$C_{Patience}$ = Coefficient between 0 and 1 (entered by the user)

The estimated to queue takes the adjustment for patience into account and is calculated using Equation 6.

$$T_{EstimatedTimetoQueue} = T_{\mathrm{Re}\,alTimetoQueue} * C_{AdjustQueue}$$ **Equation 6**

The total score for the target is calculated using the travel time from Equation 3 and the estimated queuing time from Equation 6.

$$T_{Total} = T_{\mathrm{Re}\,alTimetoWalk} * C_{Walking} + T_{EstimatedTimetoQueue} * C_{Queuing}$$

Equation 7

Where:

$C_{Walking}$ = Coefficient between 0 and 1 (entered by user)

$C_{Queuing}$ = Coefficient between 0 and 1 (entered by user)

A15.5 Additional Assumptions

The STEPS model assumes that all people are the same size as the grid cell that they are on. Therefore it is not possible to determine the effects of changing building dimensions by small increments (i.e. making a hallway or stair 3 inches wider).

A15.6 Model Inputs

Many of the different inputs that can be specified in STEPS are listed below. Only inputs pertaining to evacuation simulations have been listed (STEPS is also capable of simulating normal conditions). In addition to the inputs listed below, elevators can be added to models in STEPS as well.

A15.6.1 Main Parameters

Number of Runs – Specifies the number of runs that are to be performed when launching the simulation. It has a default value of 1.

Simulation Mode - Evacuation or Normal Conditions can be chosen.

Start Time – Specifies the time at which the simulation starts. The default value is 0.

Time Step – Specifies the time step for the simulation. It has a default of 0.1.

End Time – This is optional and can be used to specify a time to stop the simulation.

Random Level – Coefficient between 0 and 1 that specifies the random level used in the decision process. When it is set to 0 people having multiple choices will always go for the same target. When it is set to 1 people will randomly go for one target or another.

Locks Solver Depth – Specifies how deep STEPS will go when trying to solve circular locks that happen during the simulation. It has a default value of 1.

A15.6.2 Decision Process Inputs

Walking Coefficient – Coefficient between 0 and 1 that is applied to the time to walk to a target, which is calculated during the decision process calculation. Default is 1.

Queuing Coefficient - Coefficient between 0 and 1 that is applied to the time to queue at a target, which is calculated during the decision process calculation. Default is 1.

Patience Coefficient – Coefficient between 0 and 1 that is used in the decision process calculation to adjust the queue time based on a person's patience level. Default is 0.1.

A15.6.3 Distribution Inputs

The distribution inputs are used to set up distributions that can be used to define walking speeds, pre-movement times, etc.:

Name – Specifies name of distribution

Type – Specifies type of distribution. Distribution can be uniform, normal, or log normal. Default is log normal.

Mean – Specifies mean value of the distribution. Default is 0.

Variance – Specifies variance of the distribution. Default is 0.

A15.6.4 People Type Inputs

People Type Inputs are used to specify different people types in the model:

Name – Specifies name of people type.

Color – Specifies color of the person graphic for this “people type”.

Width – Specifies width of people type. Default is 0.5m.

Depth – Specifies depth of people type. Default is 0.3m.

Height – Specifies height of people type. Default is 1.7m.

3D Model – Specifies the 3D model to represent people in the model. People can look like sticks, people, or people in wheelchairs.

Patience – Coefficient between 0 and 1 that describes how prepared people are to queue at a target. People with a Patience of 0.5 have an unbiased level of patience. People with a Patience higher than 0.5 are considered patient; whereas, people with a Patience lower than 0.5 are considered impatient. Patient people will accept to queue longer than impatient people. Default is 0.5.

Walking Speeds – Specifies various walking speeds for the people type. Walking speeds can be a fixed number or based upon a specified distribution. These walking speeds are used when planes and paths are specified. Default is 1.0 m/s.

A15.6.5 People Group Inputs

People Group Inputs are used to specify different people groups using the different people types:

Name – Specifies the name of the people group.

No People – Specifies the number of persons in the people group.

Fractions – Specifies the fractions of each people type in the people group.

Families – optional, used to add families to the model.

A15.6.6 Shape Inputs

Shape Inputs are used when setting up shapes to create items, planes, or blockages. When a DXF or ASE file is imported into STEPS shapes are automatically defined.

Name – Specifies name of shape.

Form – Specifies whether shape is open, closed, or filled. Default is filled.

Contour – Specifies whether the contour of the shape is included or excluded when used as a blockage. Default is included.

Thickness – Specifies shape thickness (only used when shape is not filled).

Shape points – Specify the points of the shape in the model.

A15.6.7 Mesh Inputs

Mesh Inputs are used to set up meshes for the model. It is not recommended to manually define meshes since they are automatically defined. It is recommended to only perform minor modifications on meshes.

A15.6.8 Plane Inputs

Plane Inputs are used to define planes where people will walk during the simulation. DXF and ASE files can be imported into STEPS as planes.

Name – Specifies name of plane

Speed number – Specifies which walking speed will be used by all people types moving on the plane. User enters the index of the walking speed that people will use. Default is 1.

Grid size – Specifies the size of the grid for the plane. Default is 0.5m. It has been proposed that in the future a fine grid option will be implemented that can be used where more than one person can occupy the same cell simultaneously.

Shape – Specifies the shape upon which the plane is based. Default is none.

X, Y, and Z – Specify coordinates of plane.

Width and Length – Specify dimensions of plane in x direction and y direction, respectively.

Angle – Specifies angle of plane. Default is 0, which represents a flat plane.

Information – Specifies what type of information to show on the plane when it is rendered.

Initial State – Plane can be specified as blocked or unblocked. Default is unblocked.

Visible – Specifies whether plane is visible or not. Default is visible.

A15.6.9 Path Inputs

Path Inputs are used to specify paths in the model. A path is basically a line that joins two points in a model.

Name – Specifies name of path.

Speed number – Specifies which walking speed will be used by all people types moving on the plane. User enters the index of the walking speed that people will use. Default is 1.

Minimum Spacing – Specifies the minimum spacing of two people on the path.

Exit to – Specifies the destination type of the path.

X1, Y1, and Z1 – Specifies coordinates of the path entrance.

X2, Y2, and Z2 – Specifies coordinates of the path exit.

Visible – Specifies whether path is visible or not.

A15.6.10 Plane Exits Inputs

Plane Exits Inputs are used to specify exits from a plane:

Name – Specifies name of plane.

Plane – Specifies which plane the exit belongs to.

Initial State – Specifies initial state of the exit. Exit can be open or closed. Default is open.

Tag – Gives a tag number to an exit.

Capacity – Specifies the flow through the exit.

Type – Specifies type of exit. Exit can be a system exit, an exit to another plane, or an exit to a path.

Exit Position – Specifies position of the exit on the plane.

Destination – Specifies position of the exit on the destination plane.

Display Potential Table – Specifies whether potential table is displayed.

Visible – Specifies whether exit is visible or not. Default is visible.

Active – Specifies whether exit is active. Default is active.

A15.6.11 Accesses Inputs

Accesses Inputs are used to restrict access to exits for people types:

People Types – Specifies which people types are affected.

Targets – Specifies which targets are restricted for the chosen people types.

Awareness - Specifies which fraction of the selected people types know about the selected targets. Setting the slider to “none” means that nobody from these People Types knows the Targets. Setting the slider to Total means that everyone from these People Types knows the Targets.

A15.6.12 Blockages Inputs

Blockages Inputs are used to specify blockages on the planes. When a DXF or ASE file is imported into STEPS blockages are automatically defined.

Name – Specifies name of blockage.

Plane – Specifies the plane where the blockage is located.

Type – Specifies the type of blockage.

X1, Y1, X2, and Y2 – Specifies coordinates of blockage.

Block or Unblock – Specifies whether blockage blocks or unblocks the plane. Default is block.

Visible – Specifies whether blockage is visible or not. Default is visible.

Active – Specifies whether blockage is active or not. Default is active.

A15.6.13 People Events Inputs

People Events Inputs are used to specify when and where people will appear during the simulation:

Name – Specifies name of people event.

Time – Specifies the time at which the people event is to occur during the simulation. Default is 0.

People Group – Specifies which people group will be added to the simulation.

Family – Specifies which family will be added (if any are defined).

Delay – Specifies the delay before people will start to move after being added. Delay time can be fixed or based on a distribution.

Initial Aim – Optional input to specify what target people are aiming when they are added to the model.

Add on Path or Add on Plane – Specifies where people are to be added.

Repeat Number – Specifies how many times this people event is to be repeated. Default is 0.

Repeat Time – Specifies the delay between repetitions of the people event. Default is 0.

Active – Specifies whether people event is active or not.

A16. SCENARIO DOCUMENTATION

A16.1.1 Description of Scenario

The scenario used for the sensitivity analysis and the initial test for numerical robustness is called the London Building, a 6 story office building with occupied basement in London, Ontario. An actual evacuation was conducted for this building and all of the information collected from the evacuation was given to the modeler.

The scenario used for the model evaluation blind test is called the Ottawa Building, which is an office building that is 7 stories high with a partial eighth story that does not constitute a full floor and an occupied basement in Ottawa, Ontario. There was an actual evacuation conducted for this building, but the information from the evacuation was not known to the modeler at the time of modeling.

A16.1.2 Desired Model Outputs

Evacuation time for each of the different test buildings.

A16.1.3 Degree of Accuracy

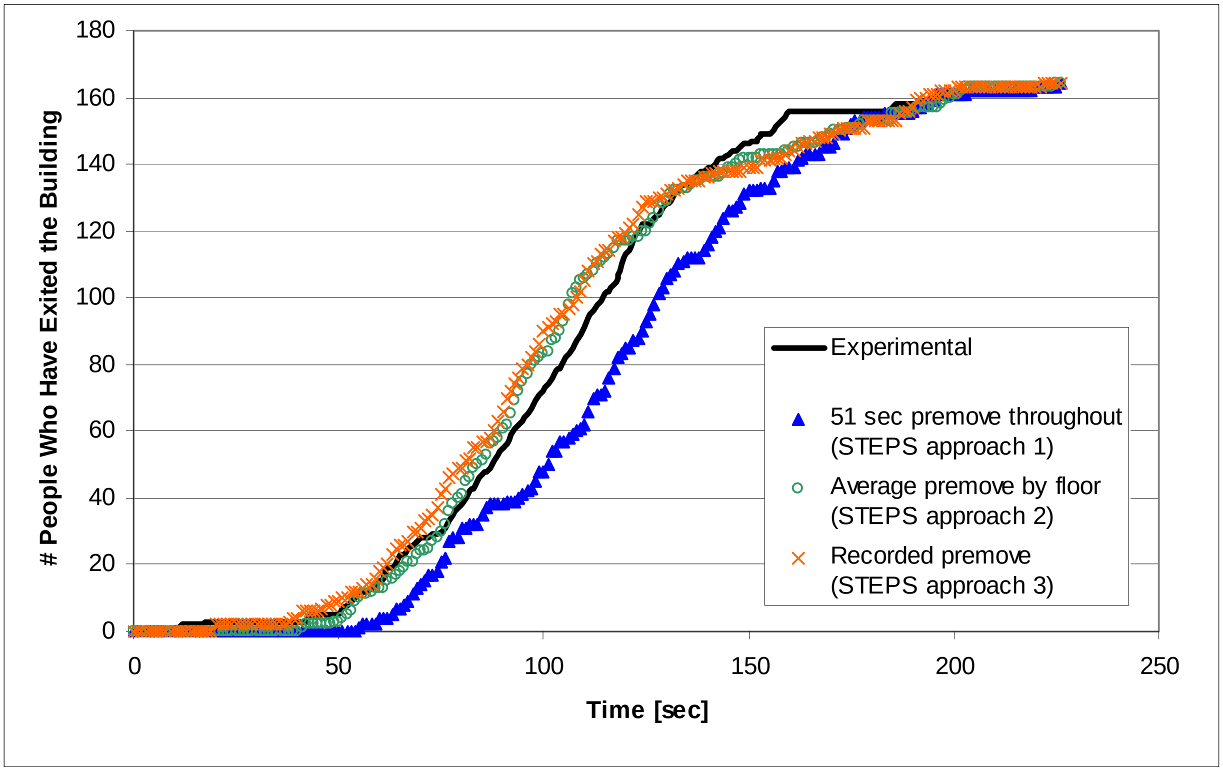
For the purposes of these analyses, it is desirable that the degree of uncertainty be within 10%. (Note this is an example, in reality the degree of accuracy will depend on the specific scenario and stakeholders).

A17. THEORETICAL BASIS FOR MODEL & NUMERICAL ROBUSTNESS

A review of the STEPS model has been completed, including evaluation of the technical documentation and comparison against both real-life evacuation data for an office building and other methods of calculation.

The graph below displays the results of an evacuation simulation, compared against real-life evacuation data from the London Building. Three different methods were employed to determine the best way to input pre-movement time into the model. The three methods were: using a 51 second pre-movement time throughout the building for all occupants (the average in the actual evacuation drill), using the average pre-movement time for each floor that was recorded during the evacuation drill, and applying actual pre-movement times from the evacuation drill and applying them to each occupant. The results of all three are shown in the following graph.

Figure 1: Comparison of STEPS Results with Actual Evacuation Data



Based on this information it appears that STEPS provides a reasonably accurate simulation for this type of building/evacuation. Further data regarding the theoretical basis of the model is contained in the references provided in Appendices D and E.

A18. QUANTIFYING MODEL UNCERTAINTY

A18.1 Model Input

A sensitivity analysis of the egress model STEPS was completed using the case study London office building. Three different types of input data were varied for this analysis: scenario specific data, occupancy specific data, and model specific data.

Please note that where columns have been labeled "% Chance" in the tables below, this represents the likelihood that that particular row of information would be chosen for a particular scenario according to the literature that was available at the time of this study.

A18.1.1 Scenario Specific Data

The scenario specific data that was varied during this analysis was the grid size. Four different grid sizes were used: 0.3 m, 0.4 m, 0.5 m, and 0.6 m.

A18.1.2 Occupancy Specific Data

The input parameters related to the occupants that were varied during this case study were occupant load factors, occupant pre-movement times, occupant walking speed on horizontal surfaces and up and down stairs, and occupant demographics.

The input parameters related to the occupants were varied based on an extensive literature review of egress data from actual evacuations. There were three different types of occupant groups used for the case study: people 18-29 years old, 30-50 years old and over 50 years old. The demographic of the case study office building was based on actual office populations. Table 1 summarizes the occupant demographics of the case study building.

Table 1: Office Demographic Summary

% Chance	[% 18-29 years old]	[% 30-50 years old]	[% > 50 years old]	References
9.09 %	15	66	19	Proulx, et. al., 1999
9.09 %	43	44	13	US Department of Labor, 2004
9.09 %	33.3	44.4	22.2	Arup Westborough
9.09 %	30.8	53.8	15.4	Arup Toronto
9.09 %	0	50	50	Arup Seattle
9.09 %	24.2	59.6	16.2	Arup San Francisco
9.09 %	26.3	64.1	9.68	Arup New York
9.09 %	10.5	73.7	15.8	Arup Los Angeles
9.09 %	25	75	0	Arup Houston
9.09 %	45.5	45.5	9.09	Arup Detroit
9.09 %	34.6	65.4	0	Arup Boston

The population size of the building was specified by floor based on several different occupant loading factors. In all cases, occupants were randomly scattered throughout the floor. The occupant load factors that were used to determine the occupant loading for each of the office floors are shown in Table 2.

Table 2: Office Occupant Load Factor Summary

% Chance	Loading Factor [m^2/person]	References
6.67%	146.4	Data from London Building Evacuation
6.67%	79.7	Data from London Building Evacuation
6.67%	60.3	Data from London Building Evacuation
6.67%	50	Boyce, et. al., 1998
6.67%	41	Data from London Building Evacuation
6.67%	40.9	Data from London Building Evacuation
6.67%	26.5	Data from London Building Evacuation
6.67%	25	Boyce, et. al., 1998
6.67%	22.7	Boyce, et. al., 1998
6.67%	17.2	Boyce, et. al., 1998
6.67%	16.9	Boyce, et. al., 1998
6.67%	11.6	Boyce, et. al., 1998
6.67%	9.29	BOCA, 1999; ICBO, 1997; ICC, 2003; NFPA, 2003; SBCCI, 1999
6.67%	9	BR, 2000
6.67%	6	Building Authority of Hong Kong, 1996

The basement of the London Building was mechanical space, so there were six possible occupant load factors that were used for the basement. The load factors for the mechanical space are in Table 3.

Table 3: Occupant Load Factors for Mechanical Space

% Chance	Loading Factor [m^2/person]	References
16.67%	27.9	BOCA, 1999; ICBO, 1997; ICC, 2003; NFPA, 2003; SBCCI, 1999
16.67%	30	BR, 2000; Building Authority of Hong Kong, 1996
16.67%	0	Actual conditions

The main reason the occupants of the building are split up into three different groups is so that the walking speed could be varied throughout the population. Values for horizontal, upward, and downward walking speeds were found through the literature search. The values used for horizontal walking speeds of the young people group can be found in Table 4. The data points used for upward and downward walking speeds for the young people group can be found in Table 5 and Table 6.

Table 4: 18-29 Years Old Horizontal Walking Speed Summary

% Chance	Walking Speed [m/s]	References
20%	1.2	Boyce, et. al., 1998
20%	1.4	Knoblauch, et. al., 1996
40%	1.5	Knoblauch, et. al., 1996
20%	1.6	Knoblauch, et. al., 1996

Table 5: 18-29 Years Old Upward Walking Speeds

% Chance	Speed [m/s]	References
50%	0.216	Predtechenskii, and Milinskii, 1978
50%	0.6	Fruin, 1987

Table 6: 18-29 Years Old Downward Walking Speeds

% Chance	Speed [m/s]	References
14.29%	0.78	Fahy and Proulx, 2001
14.29%	0.8	Knoblauch, et. al., 1996
14.29%	0.84	Knoblauch, et. al., 1996
14.29%	0.93	Fahy and Proulx, 2001
14.29%	1.13	Knoblauch, et. al., 1996
14.29%	1.14	Knoblauch, et. al., 1996
14.29%	1.3	Knoblauch, et. al., 1996

The values used for horizontal walking speeds of the 30 – 50 years old people group can be found in Table 7. The data points used for upward and downward walking speeds for the 30 – 50 years old people group can be found in Table 8 and Table 9.

Table 7: 30 – 50 Years Old Horizontal Walking Speed Summary

% Chance	Walking Speed [m/s]	References
20%	1.2	Boyce, et. al., 1998
20%	1.22	Knoblauch, et. al., 1996
20%	1.25	Knoblauch, et. al., 1996
20%	1.43	Knoblauch, et. al., 1996
20%	1.5	Knoblauch, et. al., 1996

Table 8: 30 – 50 Years Old Upward Walking Speeds

% Chance	Speed [m/s]	References
50%	0.18	Predtechenskii, and Milinskii, 1978
50%	0.5	Fruin, 1987

Table 9: 30 – 50 Years Old Downward Walking Speeds

% Chance	Speed [m/s]	References
14.29%	0.6	Knoblauch, et. al., 1996
14.29%	0.645	Knoblauch, et. al., 1996
14.29%	0.76	Knoblauch, et. al., 1996
14.29%	0.775	Knoblauch, et. al., 1996
14.29%	0.78	Fahy and Proulx, 2001
14.29%	0.93	Fahy and Proulx, 2001
14.29%	0.97	Knoblauch, et. al., 1996

The values used for horizontal walking speeds of the >50 years old people group can be found in Table 10. The data points used for upward and downward walking speeds for the old people group can be found in Table 11 and Table 12.

Table 10: >50 Years Old Horizontal Walking Speed Summary

% Chance	Walking Speed [m/s]	References
20%	0.91	Knoblauch, et. al., 1996
20%	1.0	Knoblauch, et. al., 1996
20%	1.1	Knoblauch, et. al., 1996
20%	1.234	Knoblauch, et. al., 1996
20%	1.25	Knoblauch, et. al., 1996

Table 11: >50 Years Old Upward Walking Speeds

% Chance	Speed [m/s]	References
50%	0.144	Predtechenskii, and Milinskii, 1978
50%	0.4	Fruin, 1987

Table 12: >50 Years Old Downward Walking Speeds

% Chance	Speed [m/s]	References
14.29%	0.39	Knoblauch, et. al., 1996
14.29%	0.41	Knoblauch, et. al., 1996
14.29%	0.45	Knoblauch, et. al., 1996
14.29%	0.6	Knoblauch, et. al., 1996
14.29%	0.64	Knoblauch, et. al., 1996
14.29%	0.78	Fahy and Proulx, 2001
14.29%	0.93	Fahy and Proulx, 2001

Pre-movement times were also varied by floor during the available document evacuations. Pre-movement time was defined as the time before the occupants start to travel to exits. The times are based on the actual recorded pre-movement times from the evacuation and from Purser (1998). A summary of pre-movement times used in this case study can be found in Table 13.

Table 13: Pre-movement Time Summary

Data Summary	
Number of Sample Points	171
Minimum Time [sec]	0
Maximum Time [sec]	100
Standard Deviation [sec]	17
Mean Time [sec]	36

A18.1.3 Model Specific Data

There were also some input parameters specific to STEPS that were varied during the analysis. These inputs included the patience coefficient, the walking coefficient, the queuing coefficient, the randomness coefficient, lock solver depth, grid size, and occupant patience levels.

The STEPS specific input parameters that were varied throughout the case study (using a normal distribution) are listed below. Each of these parameters is described in more detail above in the model documentation section.

Occupant Patience Level: Between 0 and 1 (inclusive)

Random Level: Between 0 and 1 (inclusive)

Lock Solver Depth: Between 1 and 10 (inclusive).

Walking Coefficient: Between 0 and 1 (inclusive)

Queuing Coefficient: Between 0 and 1 (inclusive)

Patience Coefficient: Between 0 and 1 (inclusive)

A18.2 Analysis

A total of 500 STEPS simulations were run for each grid size (0.3m, 0.4m, 0.5m, and 0.6m) for a total of 2,000 simulations. This number was chosen based on the average time it takes to run a STEPS simulation. With the exception of grid size, inputs were randomly selected from the data sets provided in the previous section, since there were not enough data points to generate distribution curves.

After the 2,000 STEPS simulations were complete, the variable inputs and the resulting evacuation time from each of the simulations were compared to determine the impact each input had on model uncertainty. A summary of the evacuation times can be seen in Table 14. The Cumulative Distribution Function (CDF) of evacuation time is shown in Figure 2.

Figure 2: Evacuation CDF

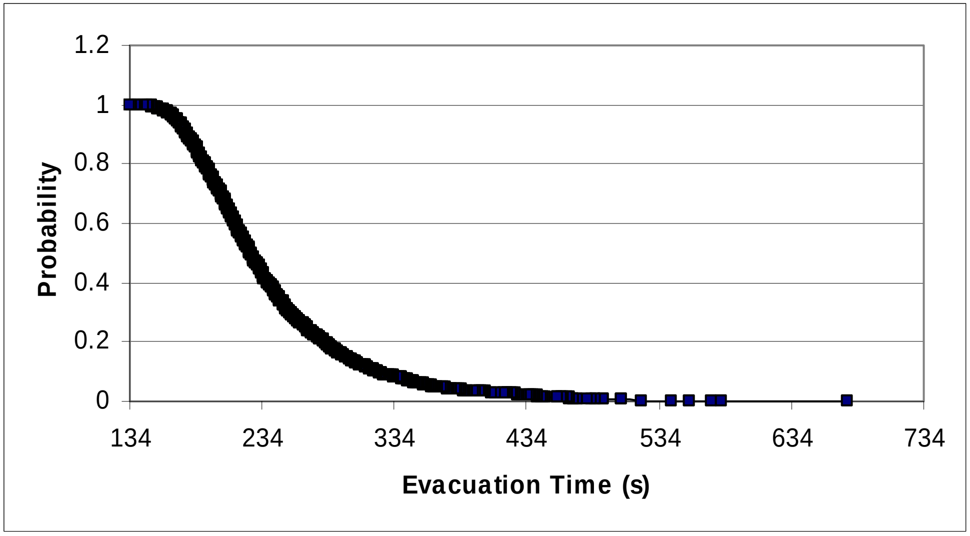
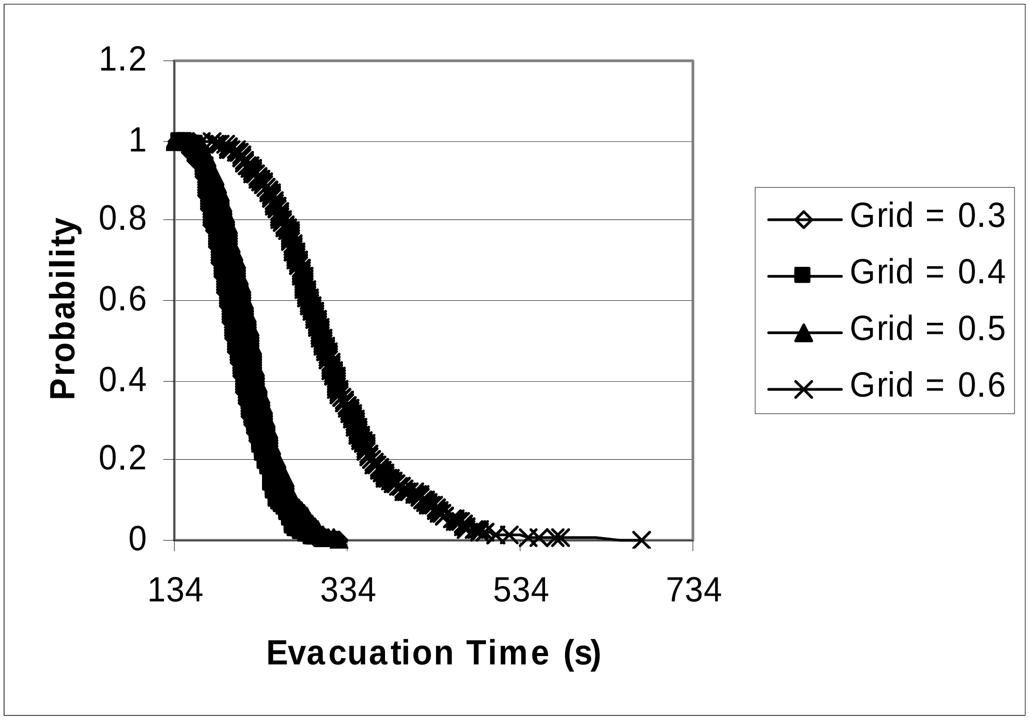


Table 14: Summary of STEPS Results

	Total Evacuation Time [s]
Minimum	134
Maximum	676
Average	241
Mode	186
Median	225
Standard Deviation	64

By comparing the CDFs of the high and low values (or quadrants) of a specific variable, it can be seen how the variable affects evacuation time. Figure 3 below shows the CDF for the four grid sizes used in the analysis. Based on the graph, the simulations with the grid size of 0.6m had much longer evacuation times than the simulations with the smaller grid sizes.

Figure 3: Grid Size CDF



The CDF for the variable lock solver depth is shown in Figure 4, the CDF for walking speed upwards of the young occupant group is shown in Figure 5, and Figure 6 shows the CDF for the percentage of young people.

Figure 4: Lock Solver Depth (LSD) CDF

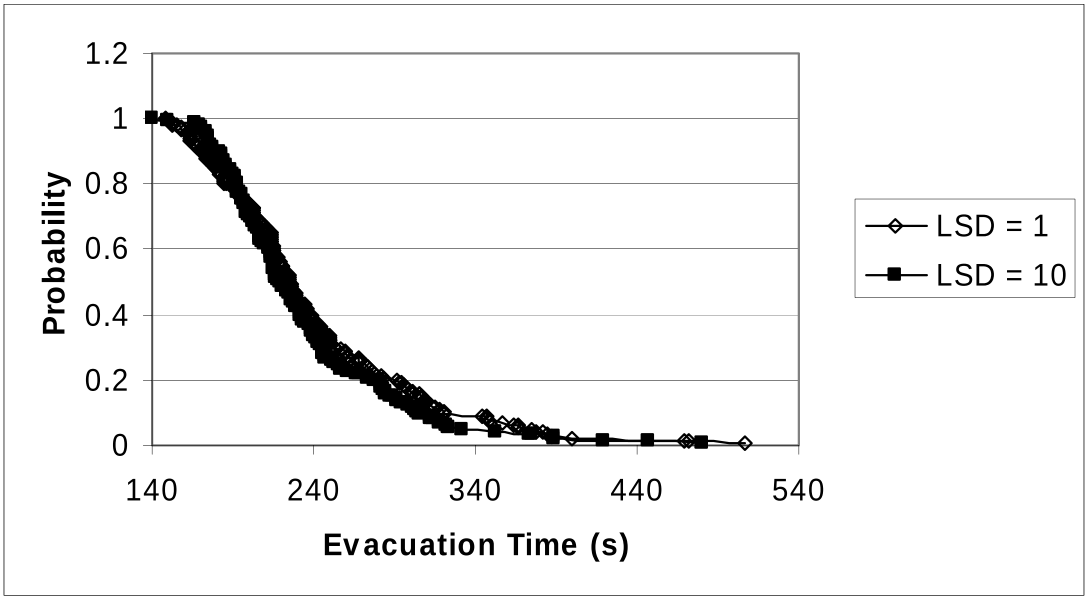


Figure 5: CDF Upward Walking Speed - Young Occupant Group

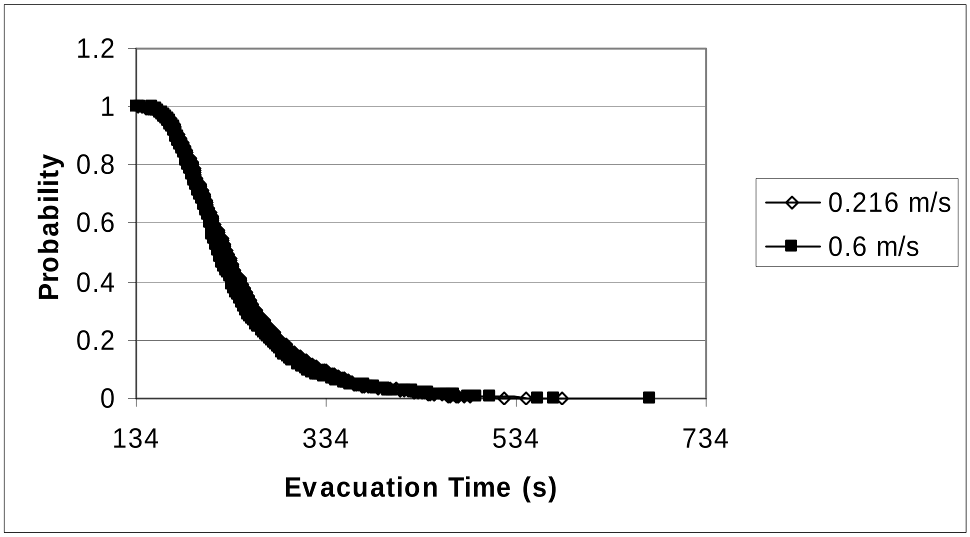


Figure 6: CDF for Percentage of Young People

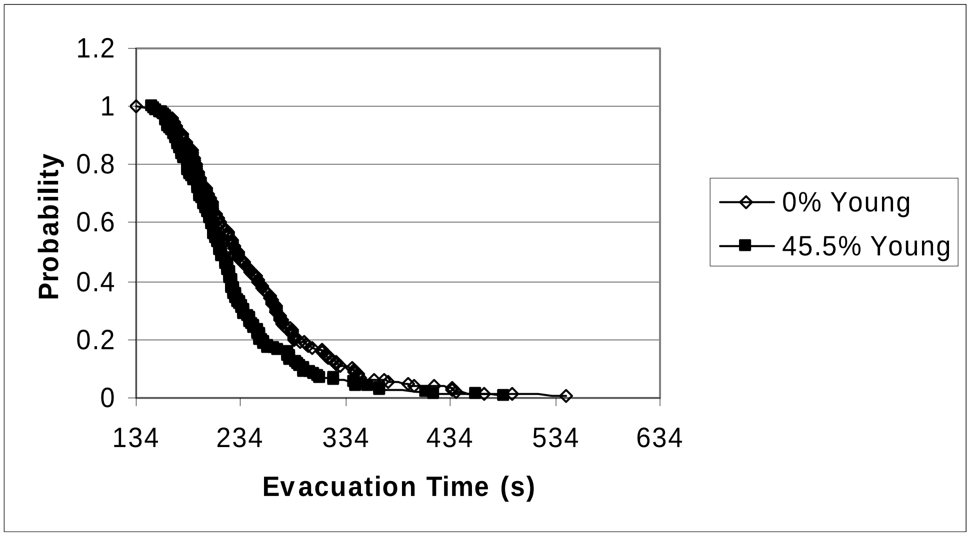


Figure 7 shows the CDF for the variable walking coefficient. The CDFs for the number of occupants on floor 1, the number of occupants on floor 3, and the variable patience coefficient can be seen in Figure 8, Figure 9, and Figure 10, respectively.

Figure 7: CDF of Walking Coefficient

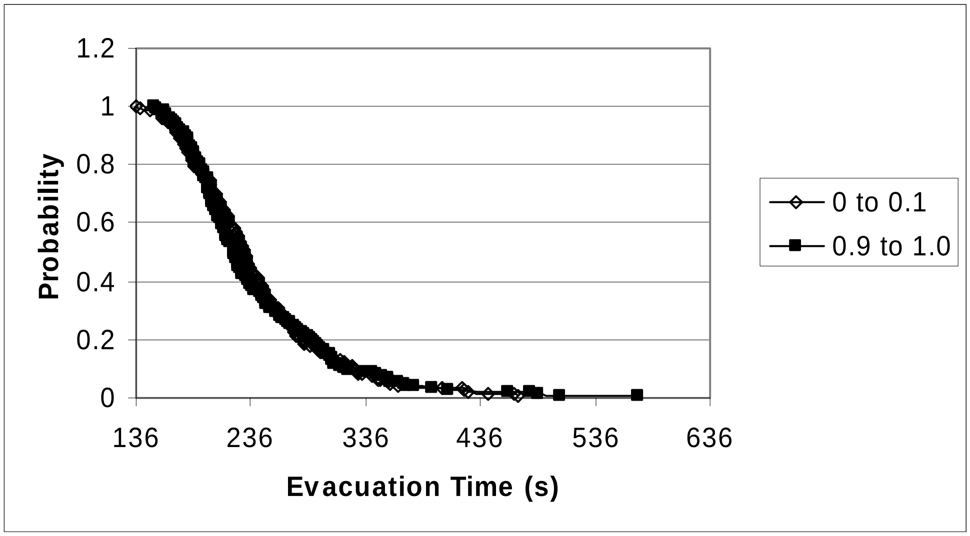


Figure 8: CDF of # Occupants Floor 1

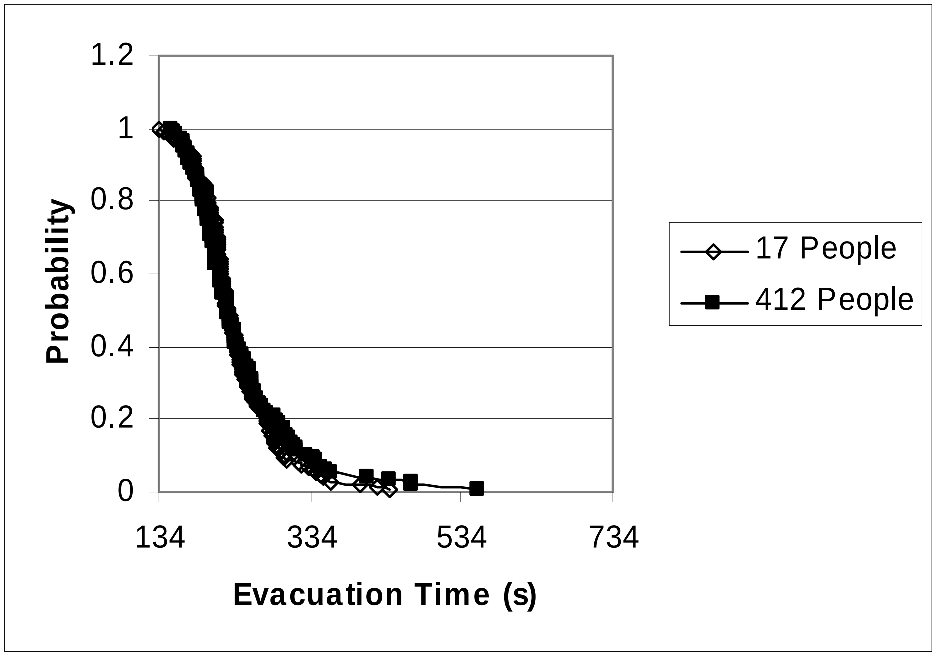


Figure 9: CDF of # Occupants Floor 3

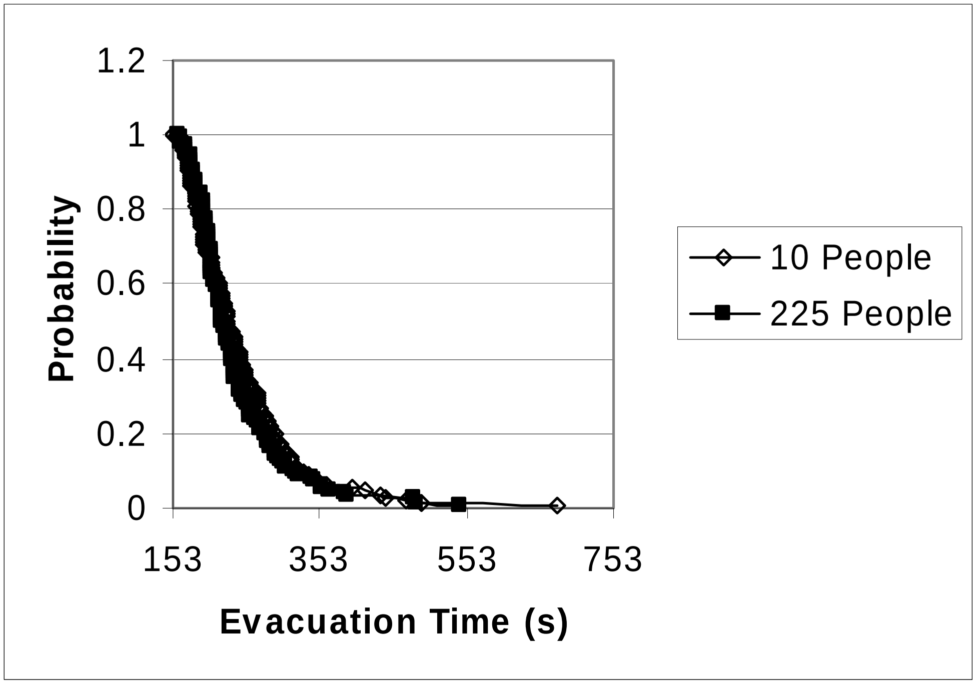


Figure 10: CDF of Patience Coefficient

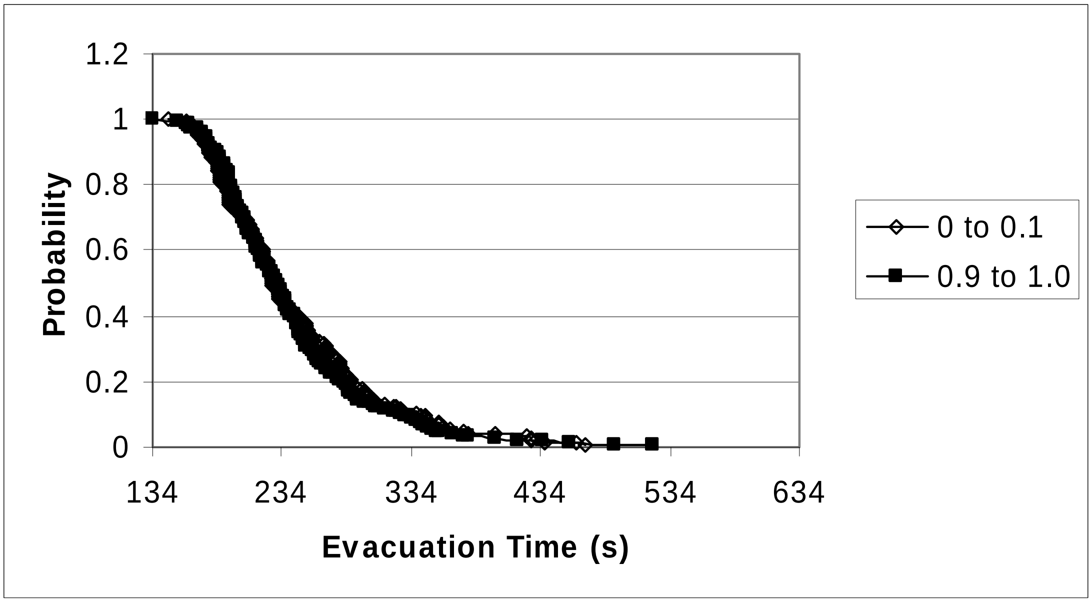
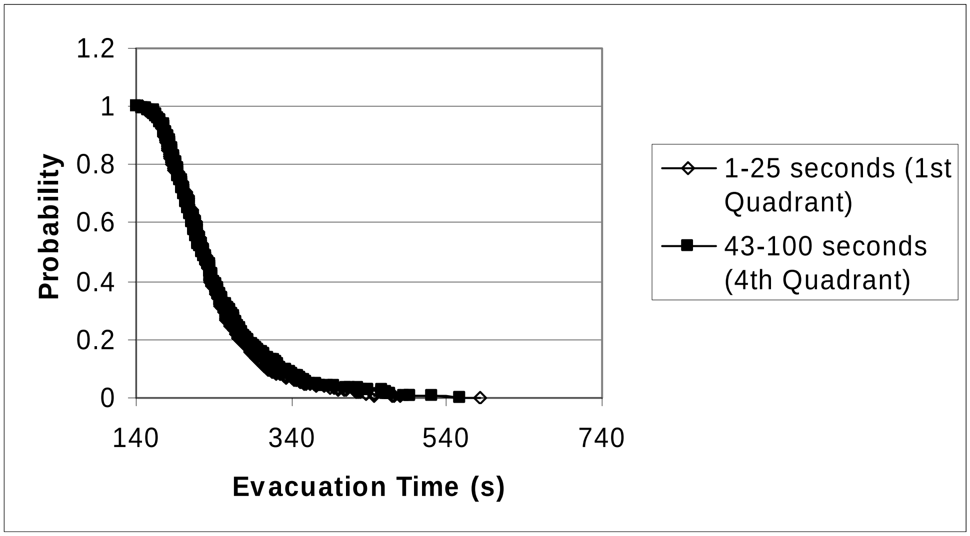


Figure 11shows the CDF for basement pre-movement times. The first quadrant and fourth quadrant are plotted against each other.

Figure 11: CDF for Basement Pre-movement Time



The CDF for downward walking speed of the old occupant group is shown in Figure 12. Figure 13 shows the difference in evacuation time between the maximum and minimum speed values. The figure shows that as the probability threshold increases, the effect of downward walking speed of the old occupant group on the total evacuation time actually decreases.

Figure 12: CDF of Downward Walking Speed of Old Occupant Group

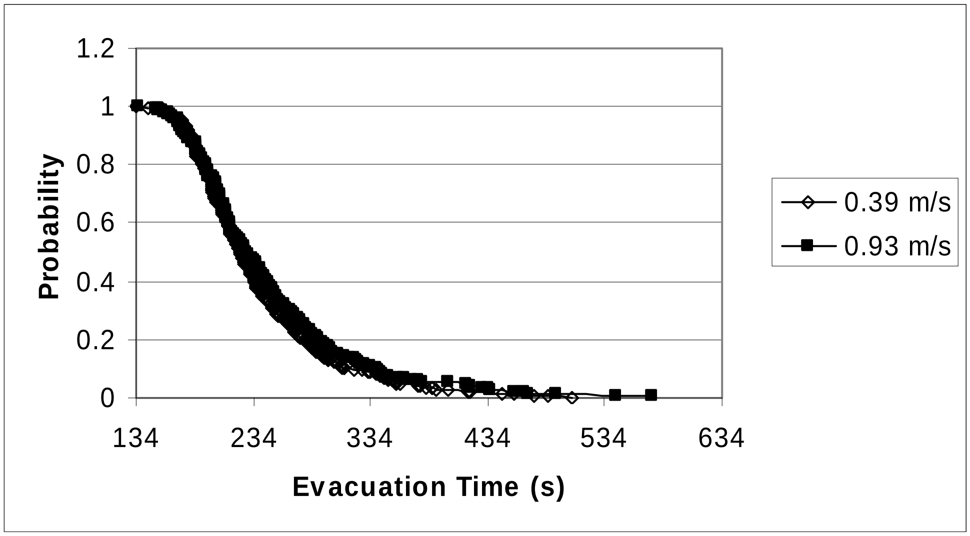
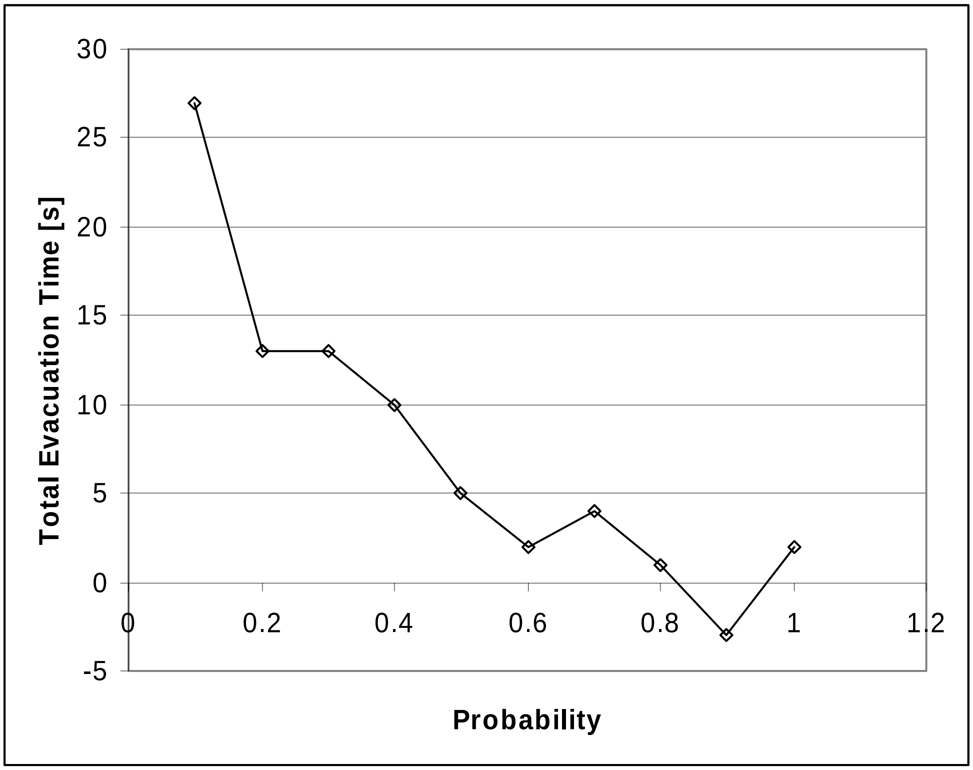


Figure 13: Sensitivity of Total Evacuation Time to Downward Walking Speed of Old Occupant Group



Based on the fact that the total number of simulations was 2000 at a confidence level of 95%, this means that correlation coefficients (described in Section 11.5.4.3 of the guide) with an absolute value of 0.021 are statistically insignificant.

It was found that the statistically significant variables were (in order of significance): grid size, lock solver depth, walking speed – young up, percentage of young people, basement pre-movement time, walking speed – old down, walking coefficient, number of people – floor 1, number of people – floor 3, and patience coefficient. The correlation coefficients for each of these variables can be found in Table 15.

Table 15: Correlation Coefficient Summary

Variable	Correlation Coefficient [absolute value]
Grid Size	0.577
Lock Solver Depth	0.047
Walking Speed – Young Up	0.034
Percentage Young People	0.033
Basement Pre-movement Time	0.032
Walking Speed – Old Down	0.028
Walking Coefficient	0.028
# People Floor 1	0.025
# People Floor 3	0.023
Patience Coefficient	0.021

A19. MODEL EVALUATION – BLIND TEST

The blind test was run by a modeler who knew only the floor plans of the building and the types of occupancies in the building, which is mostly office with some areas for storage, parking, and a cafeteria. The following sections describe the inputs as well as the results of the blind test.

A19.1 Model Input

A blind test analysis of the egress model STEPS was completed using the case study Ottawa office building. The blind test was conducted as a sensitivity analysis, so, the input into the model was varied. As with the sensitivity analysis that was conducted for the London Building, three different types of input data were varied for this analysis similar to the sensitivity analysis: scenario specific data, occupancy specific data, and model specific data. It would not be necessary to have this type of variation in a blind test that does not analyze the sensitivity of the model.

A19.1.1 Scenario Specific Data

Two parameters were varied that relate to the scenario: the grid size and door flow rate. Four different grid sizes were used: 0.3m, 0.4m, 0.5m, and 0.6m. The range of door flow rates that was used was 0.35 to 1.25 occupants per second per meter of width (Fruin, 1987).

A19.1.2 Occupancy Specific Data

The input data used for occupant parameters such as walking speed, pre-movement time, occupant demographics, and occupant loading were taken from the data presented in Annex B.

A19.1.3 Model Specific Data

There were also some input parameters specific to STEPS that were varied during the analysis. These inputs included the patience coefficient, the walking coefficient, the queuing coefficient, the randomness coefficient, lock solver depth, grid size, and occupant patience levels.

The STEPS specific input parameters that were varied throughout the case study are listed below. Each of these parameters is described in more detail above in the model documentation section.

Occupant Patience Level: Between 0 and 1 (inclusive)

Random Level: Between 0 and 1 (inclusive)

Lock Solver Depth: Between 1 and 10 (inclusive).

Walking Coefficient: Between 0 and 1 (inclusive)

Queuing Coefficient: Between 0 and 1 (inclusive)

Patience Coefficient: Between 0 and 1 (inclusive)

A19.2 Analysis

Five-hundred STEPS simulations were created for each grid size (0.3m, 0.4m, 0.5m and 0.6m) for a total of 2000 simulations. This was the largest number of runs that could be completed within the timeline of the project due to current limitations on computer speeds. With the exception of grid size, inputs were randomly selected from the data sets and distribution curves described above.

After all the simulations had completed running, the results of the evacuation time from each simulation was compiled. A summary of these results is shown below in Figure 14 and Table 16.

Figure 14: Evacuation Time CDF

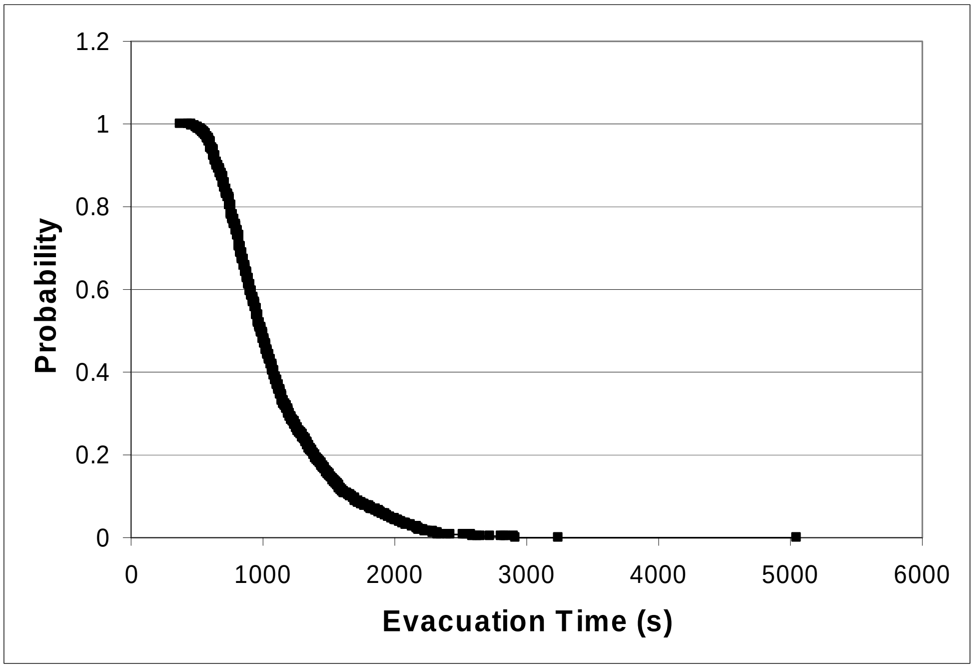


Table 16: Summary of STEPS Results

	Total Evacuation Time [s]
Minimum	377
Maximum	5047
Average	1091
Mode	819
Median	990
Standard Deviation	423

During the actual evacuation 489 occupants evacuated in less than nine minutes during the evacuation drill of the Ottawa building (Proulx, 1996). The evacuation time of the occupants is shown graphically in Figure 15.

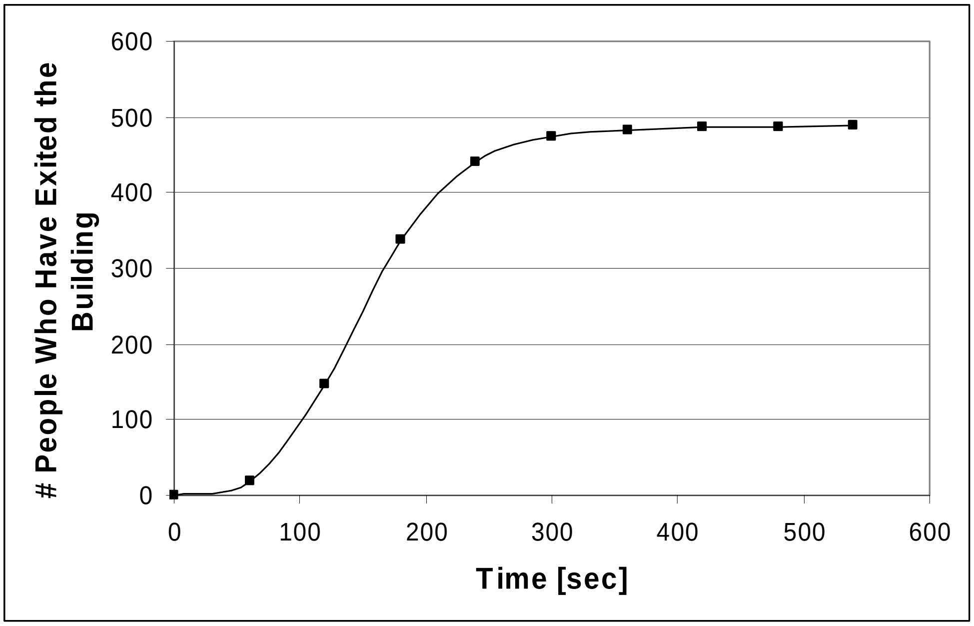


Figure 15: Evacuation Timing of the Ottawa Building

There is a large difference between the actual evacuation time and the time calculated by STEPS for the blind test. However, this probably relates to the number of people that were actually in the building and the number in the model. The total number of people in the model varied between 1293 and 3738 occupants based on office occupant load factors found in literature and building codes (described in Annex B). The low end of this range is more than twice the actual number of people in the office building, which could account for the average evacuation time of the STEPS model being approximately twice the actual evacuation time. The actual occupant load of the building is low for this size of office building, but it could be contributed to by the large number of private offices and the large amount of space devoted to generally unoccupied spaces, such as corridors. Therefore, the discrepancy could be attributed to the input rather than model error.

A20. CONCLUSIONS

There were three different tests described in this evaluation report: an open calculation (where all information about the building is known) using the London Building, a sensitivity analysis using the London Building, and a blind test of the Ottawa Building. As shown in Figure 1 above, the STEPS results track very well with the observations during the actual evacuation of the London Building. The actual evacuation was completed in 226s and the STEPS model predicted evacuation times between 222 and 226s. This indicates that STEPS is a reliable predictor of evacuation time for this type of building and these occupants.

However, comparison of the results of the blind test to the results of the actual evacuation showed that the STEPS model greatly overestimated the evacuation time of the Ottawa Building. This discrepancy could be attributed to the low occupant load in the Ottawa Building as compared to the occupant loads in the literature and building codes. This test demonstrates the importance of choosing reasonable inputs for an egress scenario.

The sensitivity analysis also demonstrates that varying the inputs can greatly affect the results from the model. Changing the grid size had a large impact on the predicted evacuation time because as the grid got larger certain corridors and doorways became blocked and the occupants in the model chose a longer route in order to evacuate the building. Walking speeds, basement pre-movement time, and STEPS specific inputs such as lock solver depth and walking and patience coefficients all significantly affected the evacuation time predicted by the model, but not nearly as much as the grid size did. This analysis shows that it is important to model the building as closely as possible and to check the simulation to make sure that the occupants egress paths make sense.

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APPENDIX B

Literature Review – Egress Data

B1. SUMMARY OF EGRESS DATA

B1.1 General

This annex contains a summary of data relating to egress variables found through an extensive literature search. The variables that were investigated include occupant demographics in office and apartment buildings, occupant walking speeds on horizontal surfaces and up and down stairs, occupant load factors for offices and apartment buildings, and occupant pre-movement times for both offices and apartment buildings.

B1.2 Demographics

Table 17 shows the demographic information that was used to model office buildings during the study. The values shown in the table reflect data from actual offices and statistics. For the purposes of this study, the occupant groups in the table refer to the following ranges in age: young range from 18 – 29, middle aged range from 30-50, old are above 50 years of age. There were eleven total data points found for this variable.

Table 17: Summary of Office Occupant Demographics

% Chance	[% 18 – 29 years old]	[% 30 – 50 years old]	[% > 50 years old]	References
9.09 %	15	66	19	Proulx, et. al., 1999
9.09 %	43	44	13	US Department of Labor, 2004
9.09 %	33.3	44.4	22.2	Arup Westborough
9.09 %	30.8	53.8	15.4	Arup Toronto
9.09 %	0	50	50	Arup Seattle
9.09 %	24.2	59.6	16.2	Arup San Francisco
9.09 %	26.3	64.1	9.68	Arup New York
9.09 %	10.5	73.7	15.8	Arup Los Angeles
9.09 %	25	75	0	Arup Houston
9.09 %	45.5	45.5	9.09	Arup Detroit
9.09 %	34.6	65.4	0	Arup Boston

A fourth occupant group was added to many of the simulations. The fourth occupant group is disabled occupants. Table 18 shows data found for the percentage of disabled occupants in office buildings. These eight data points are from actual office populations.

Table 18: Disabled Occupants in Offices

% Chance	[% Disabled]	References
12.5%	0%	Boyce et. al., 1998
50%	0.5%	Boyce et. al., 1998
12.5%	0.9%	Boyce et. al., 1998
12.5%	5%	Boyce et. al., 1998
12.5%	6%	Proulx, et. al., 1999

In addition to demographic data from office buildings, data for apartment buildings was also of interest for the study. Table 19 shows the demographic information that was used to model apartment buildings during the study. The values shown in the table reflect data from actual apartment buildings and statistics. For the purposes of this study, the occupant groups in the table refer to the following ranges in age: children are under 18, young range from 18 – 29, middle aged range from 30-50, old are above 50 years of age. There were three data points found for apartment demographics.

Table 19: Summary of Apartment Building Occupant Demographics

% Chance	[% Children]	[% Young]	[% Middle-Aged]	[% Old]	References
33.3%	1%	6%	12%	81%	Sekizawa, 1998
33.3%	3.1%	7.9%	21.1%	67.9%	Proulx, 1994
33.3%	6.06%	42.4%	30.3%	21.2%	Proulx et al, 1995

The percentage of disabled occupants in apartment buildings was also important, so the fifth occupant group for the apartment buildings modeled is disabled occupants. Table 20 shows the four data points found for percentage of disabled population in apartment buildings.

Table 20: Disabled Occupants in Apartment Buildings

% Chance	[% Disabled]	References
25%	12.1%	Proulx et al, 1995
25%	17%	Sekizawa, 1998
25%	20%	Proulx, 1994
25%	23%	Proulx, 1999

Since the disabled occupant population varies in age, the overall percentages of each occupant age group should be adjusted to account for this. Table 21 breaks down the disabled population in the United States by age.

Table 21: Percentage of Disabled Population by Age

Age Group	[% Disabled]	Reference
Children (0 – 18)	5.8%	US Census Bureau, 2000
Young (18 – 29)	18.6%	US Census Bureau, 2000
Middle-Aged (30 – 50)	18.6%	US Census Bureau, 2000
Old (50+)	41.9%	US Census Bureau, 2000

B1.3 Occupant Load Factors

In order to determine the building populations for the study, occupant load factors for both office and apartment buildings were found. Table 22 below shows the occupant load factors found for offices. There were thirteen total data points found from actual office populations.

Table 22: Office Occupant Load Factors

% Chance	Loading Factor [m^2/person]	References
8%	50	Boyce et. al., 1998
7%	25	Boyce et. al., 1998
8%	22.7	Boyce et. al., 1998
8%	17.2	Boyce et. al., 1998
7%	16.9	Boyce et. al., 1998
8%	11.6	Boyce et. al., 1998
39%	9.29	BOCA, 1999; ICBO, 1997; ICC, 2003; NFPA, 2003; SBCCI, 1999
7%	9	BR, 2000
8%	6	Building Authority of Hong Kong, 1996

Table 23 shows the occupant load factors found for apartment buildings. Twelve data points were found from actual apartment building populations.

Table 23: Apartment Building Occupant Load Factors

% Chance	Loading Factor [m^2/person]	References
42%	18.6	BOCA, 1999; ICBO, 1997; ICC, 2003; NFPA, 2003; SBCCI, 1999
17%	10	BR, 2000; Charters, 2001
8%	8	BR, 2000
17%	5	BR, 2000; Charters, 2001
8%	4.5	Building Authority of Hong Kong, 1996
8%	3	Building Authority of Hong Kong, 1996

B1.4 Walking Speeds

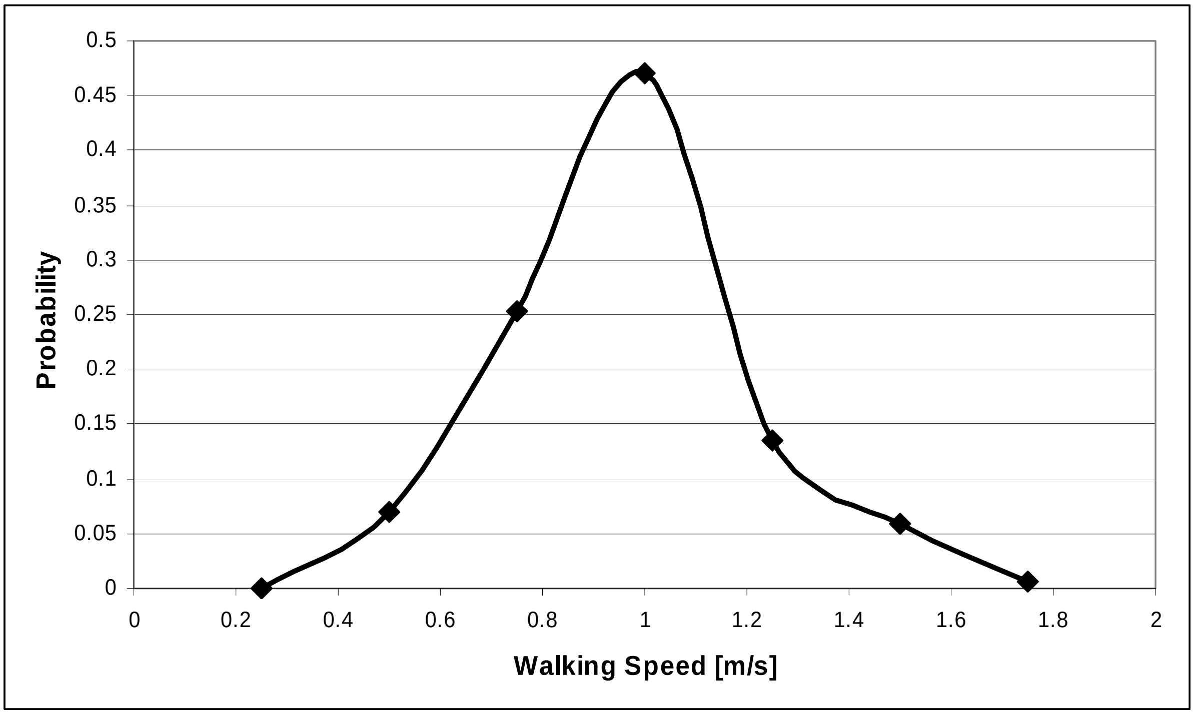
Three different types of walking speeds were of interest for each of the occupant groups: horizontal, upward on stairs, and downward on stairs. The walking speed information was found from a variety of tests that have been conducted, including both evacuation tests and observations of normal walking conditions in public places.

The horizontal walking speed distribution for the children occupant group is plotted in Figure 16 and summarized in Table 24. The data is from two different sources (Fahy and Proulx, 2001; Hokugo, 2001).

Table 24: Summary of Children's Horizontal Walking Speeds

Data Summary	
Data Points	170
Minimum [m/s]	0.28
Maximum [m/s]	1.8
Standard Deviation [m/s]	0.25
Average [m/s]	0.88

Figure 16: Distribution of Children's Horizontal Walking Speeds



The walking speeds for children for downward and upward travel on stairs are shown in Table 25 and Table 26. Nine data points were found for downward travel and two data points were found for upward travel.

Table 25: Downward Walking Speeds for Children

% Chance	Speed [m/s]	References
11.1%	0.45	Proulx, 1995
11.1%	0.36	Fruin, 1987
11.1%	0.76	Fruin, 1987
11.1%	0.18	Predtechenskii and Milinskii, 1978
11.1%	0.27	Predtechenskii and Milinskii, 1978
11.1%	0.33	Predtechenskii and Milinskii, 1978
11.1%	0.42	Predtechenskii and Milinskii, 1978
11.1%	0.53	Proulx et al, 1995
11.1%	0.77	Proulx et al, 1995

Table 26: Upward Walking Speeds for Children

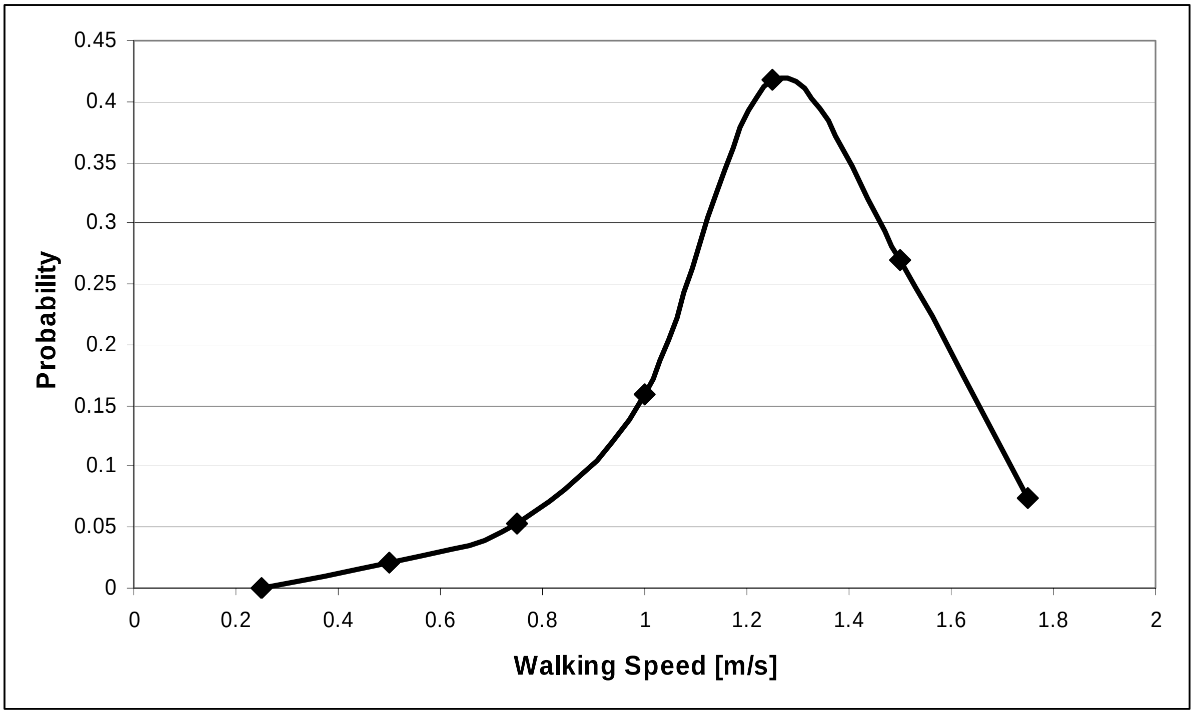
% Chance	Speed [m/s]	References
50%	0.14	Predtechenskii and Milinskii, 1978
50%	0.22	Predtechenskii and Milinskii, 1978

The horizontal walking speeds for the young occupant group are from several different sources (Fahy and Proulx, 2001; Hokugo, et. al., 2001; Fruin, 1987; Predtechenskii, and Milinskii, 1978; Webber, 2001; Al-Obaidi, et. al., 2003; Riley, et. al., 2001; Sandberg, 1997; and Hoel, 1968). The distribution of horizontal walking speeds for the young people group is shown in Figure 17 and the data is summarized in Table 27.

Table 27: Summary of Horizontal Walking Speeds for 18-29 Years Old Occupant Group

Data Summary	
Data Points	1695
Minimum [m/s]	0.25
Maximum [m/s]	1.9
Standard Deviation [m/s]	0.25
Average [m/s]	1.12

Figure 17: Distribution of Horizontal Walking Speeds of 18 – 29 Years Old People Group



The walking speeds for the 18 – 29 year old people group for downward and upward travel on stairs are shown in Table 28 and Table 29. Thirty-one data points were found for downward travel and six data points were found for upward travel.

Table 28: Downward Walking Speeds for 18 – 29 Years Old Occupant Group

% Chance	Speed [m/s]	References
3.22%	0.52	Proulx, 1995
3.22%	0.54	Proulx, 1995
3.22%	0.62	Proulx, 1995
3.22%	0.78	Fahy and Proulx, 2001
6.44%	0.93 (2)	Fahy and Proulx, 2001; Fruin, 1987
3.22%	0.61	Proulx, et. al, 1999
3.22%	0.7	Proulx, et. al, 1999
3.22%	0.72	Proulx, et. al, 1999
3.22%	0.57	Proulx, et. al, 1999
3.22%	0.36	Fruin, 1987
3.22%	0.76	Fruin, 1987
3.22%	0.828	Fruin, 1987
3.22%	0.594	Fruin, 1987
3.22%	0.671	Fruin, 1987
3.22%	0.18	Predtechenskii and Milinskii, 1978
9.66%	0.27 (3)	Predtechenskii and Milinskii, 1978; Webber, 2001
6.44%	0.33 (2)	Predtechenskii and Milinskii, 1978; Webber, 2001
3.22%	0.42	Predtechenskii and Milinskii, 1978
3.22%	0.31	Webber, 2001
9.66%	0.4 (3)	Webber, 2001
3.22%	0.28	Webber, 2001
3.22%	0.35	Webber, 2001
3.22%	0.43	Webber, 2001
3.22%	0.3	Webber, 2001
3.22%	1.2	Proulx et al, 1995

Table 29: Upward Walking Speeds for 18 – 29 Year Old Occupant Group

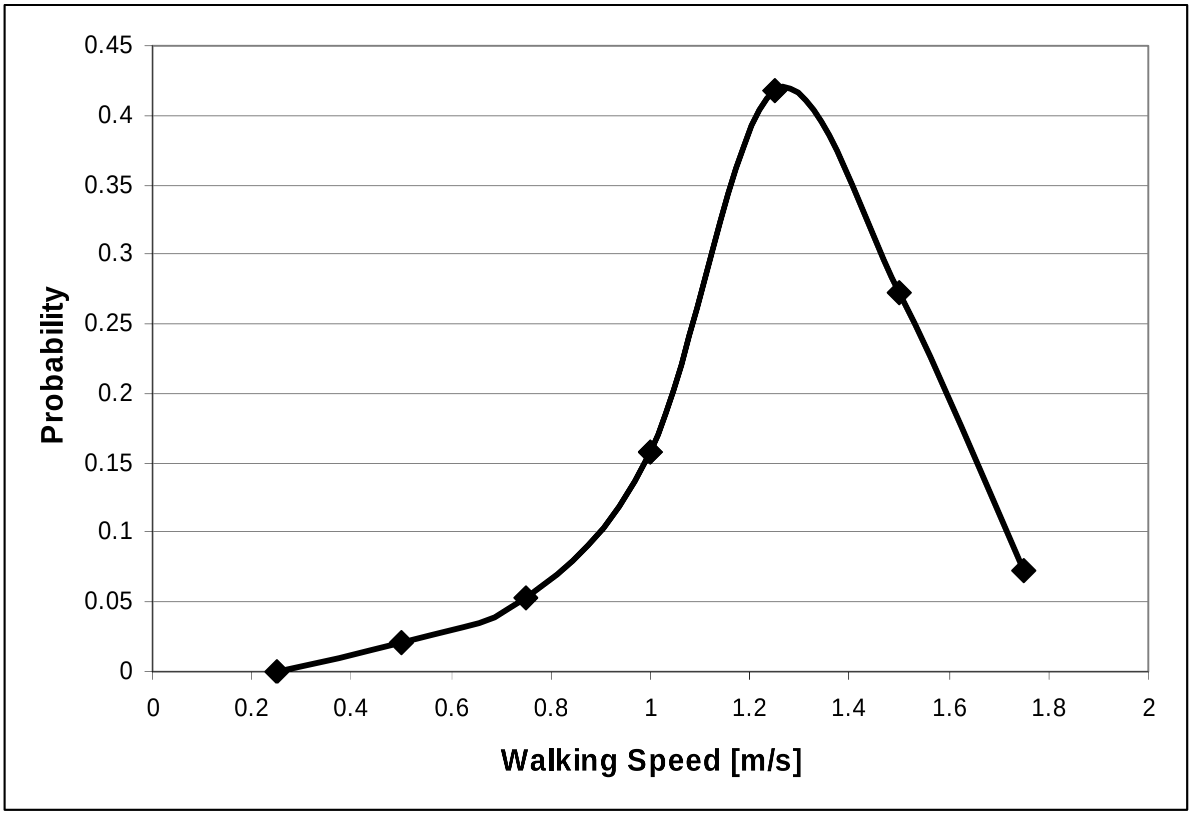
% Chance	Speed [m/s]	References
16.67%	0.14	Predtechenskii and Milinskii, 1978
16.67%	0.22	Predtechenskii and Milinskii, 1978
16.67%	0.56	Fruin, 1987
16.67%	0.54	Fruin, 1987
16.67%	0.61	Fruin, 1987
16.67%	0.56	Fruin, 1987

The horizontal walking speeds for the 30 – 50 years old occupant group are from several different sources (Fahy and Proulx, 2001; Hokugo, et. al., 2001; Fruin, 1987; Predtechenskii, and Milinskii, 1978; Webber, 2001; Riley, et. al., 2001; Sandberg, 1997; and Hoel, 1968). The distribution of horizontal walking speeds for the 30 – 50 years old people group is shown in Figure 18 and the data is summarized in Table 30.

Table 30: Summary of Horizontal Walking Speeds for 30 – 50 Years Old Occupant Group

Data Summary	
Data Points	1683
Minimum [m/s]	0.25
Maximum [m/s]	1.9
Standard Deviation [m/s]	0.25
Average [m/s]	1.12

Figure 18: Distribution of Horizontal Walking Speeds of 30 – 50 Years Old People Group



The walking speeds for the 30 – 50 years old people group for downward and upward travel on stairs are shown in Table 31 and Table 32. Thirty-two data points were found for downward travel and six data points were found for upward travel.

Table 31: Downward Walking Speeds for 30 – 50 Years Old Occupant Group

% Chance	Speed [m/s]	References
3.125%	0.52	Proulx, 1995
3.125%	0.54	Proulx, 1995
3.125%	0.62	Proulx, 1995
3.125%	0.78	Fahy and Proulx, 2001
3.125%	0.93	Fahy and Proulx, 2001
3.125%	0.61	Proulx, et. al., 1999
3.125%	0.7	Proulx, et. al., 1999
3.125%	0.72	Proulx, et. al., 1999
3.125%	0.57	Proulx, et. al., 1999
3.125%	0.36	Fruin, 1987
3.125%	0.76	Fruin, 1987
3.125%	0.691	Fruin, 1987
3.125%	0.508	Fruin, 1987
3.125%	0.65	Fruin, 1987
3.125%	0.813	Fruin, 1987
3.125%	0.18	Predtechenskii and Milinskii, 1978
9.375%	0.27	Predtechenskii and Milinskii, 1978; Webber, 2001
6.25%	0.33	Predtechenskii and Milinskii, 1978; Webber, 2001
3.125%	0.42	Predtechenskii and Milinskii, 1978
3.125%	0.31	Webber, 2001
9.375%	0.4	Webber, 2001
3.125%	0.28	Webber, 2001
3.125%	0.35	Webber, 2001
3.125%	0.43	Webber, 2001
3.125%	0.3	Webber, 2001
3.125%	1.2	Proulx et al, 1995
3.125%	0.81	Proulx et al, 1995

Table 32: Upward Walking Speeds for 30 – 50 Years Old Occupant Group

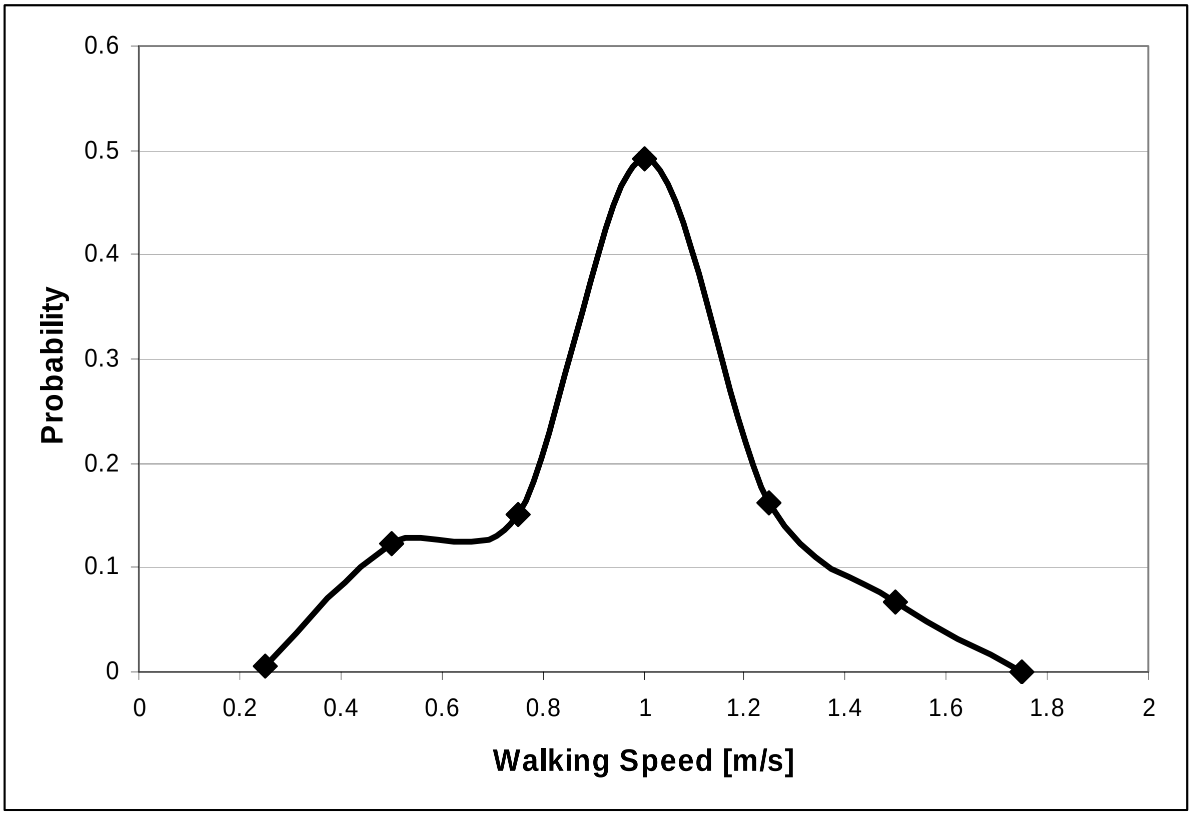
% Chance	Speed [m/s]	References
16.67%	0.14	Predtechenskii and Milinskii, 1978
16.67%	0.22	Predtechenskii and Milinskii, 1978
16.67%	0.51	Fruin, 1987
16.67%	0.48	Fruin, 1987
16.67%	0.59	Fruin, 1987
16.67%	0.54	Fruin, 1987

The horizontal walking speed distribution for the > 50 years old occupant group is plotted in Figure 19 and summarized in Table 33. These values are from several different sources (Fahy and Proulx, 2001; Hokugo, et. al., 2001; Fruin, 1987; Predtechenskii, and Milinskii, 1978; Sandberg, 1997).

Table 33: Summary of Horizontal Walking Speeds for > 50 Years Old Occupant Group

Data Summary	
Data Points	179
Minimum [m/s]	0.25
Maximum [m/s]	1.5
Standard Deviation [m/s]	0.26
Average [m/s]	0.86

Figure 19: Distribution of Horizontal Walking Speeds of > 50 Years Old Occupant Group



There were a total of thirteen data points found for downward walking speed and six for upward walking speed for the > 50 years old occupant group. The downward walking speeds are shown in Table 34 and the upward walking speeds are shown in Table 35.

Table 34: Downward Walking Speeds for > 50 Years Old Occupant Group

% Chance	Speed [m/s]	References
7.69%	0.43	Proulx, 1995
7.69%	0.36	Fruin, 1987
7.69%	0.76	Fruin, 1987
7.69%	0.569	Fruin, 1987
7.69%	0.472	Fruin, 1987
7.69%	0.599	Fruin, 1987
7.69%	0.564	Fruin, 1987
7.69%	0.18	Predtechenskii and Milinskii, 1978
7.69%	0.27	Predtechenskii and Milinskii, 1978
7.69%	0.33	Predtechenskii and Milinskii, 1978
7.69%	0.42	Predtechenskii and Milinskii, 1978
7.69%	0.81	Proulx et al, 1995
7.69%	0.57	Proulx et al, 1995

Table 35: Upward Walking Speeds for > 50 Years Old Occupant Group

% Chance	Speed [m/s]	References
16.67%	0.14	Predtechenskii and Milinskii, 1978
16.67%	0.22	Predtechenskii and Milinskii, 1978
16.67%	0.43	Fruin, 1987
16.67%	0.39	Fruin, 1987
16.67%	0.41	Fruin, 1987
16.67%	0.4	Fruin, 1987

The horizontal walking speeds for the disabled occupant group are from four different sources (Fahy and Proulx, 2001; Hokugo, et. al., 2001; Predtechenskii, and Milinskii, 1978; Boyce, et. al., 1999). The distribution of horizontal walking speeds for the disabled people group is shown in Figure 20 and the data is summarized in Table 36.

Table 36: Summary of Horizontal Walking Speeds for Disabled Occupant Group

Data Summary	
Data Points	35
Minimum [m/s]	0.25
Maximum [m/s]	1.3
Standard Deviation [m/s]	0.24
Average [m/s]	0.77

Figure 20: Distribution of Horizontal Walking Speeds of Disabled Occupant Group

There were a total of fifteen data points found for downward walking speed and three for upward walking speed for the disabled occupant group. The downward walking speeds are shown in Table 37 and the upward walking speeds are shown in Table 38.

Table 37: Downward Walking Speeds for Disabled Occupant Group

% Chance	Speed [m/s]	References
12.5%	0.33	Predtechenskii and Milinskii, 1978; Boyce et. al., 1999
12.5%	0.36	Fruin, 1987; Boyce et. al., 1999
6.25%	0.22	Boyce et. al., 1999
6.25%	0.32	Boyce et. al., 1999
6.25%	0.16	Boyce et. al., 1999
6.25%	0.7	Boyce et. al., 1999
6.25%	0.29	Boyce et. al., 1999
6.25%	0.26	Boyce et. al., 1999
6.25%	0.37	Boyce et. al., 1999
6.25%	0.76	Fruin, 1987
6.25%	0.18	Predtechenskii and Milinskii, 1978
6.25%	0.27	Predtechenskii and Milinskii, 1978
6.25%	0.42	Predtechenskii and Milinskii, 1978
6.25%	0.61	Proulx et al, 1995

Table 38: Upward Walking Speeds for Disabled Occupant Group

% Chance	Speed [m/s]	References
33.33%	0.14	Predtechenskii and Milinskii, 1978
33.33%	0.22	Predtechenskii and Milinskii, 1978
33.33%	0.62	Predtechenskii and Milinskii, 1978

B1.5 Pre-movement Times

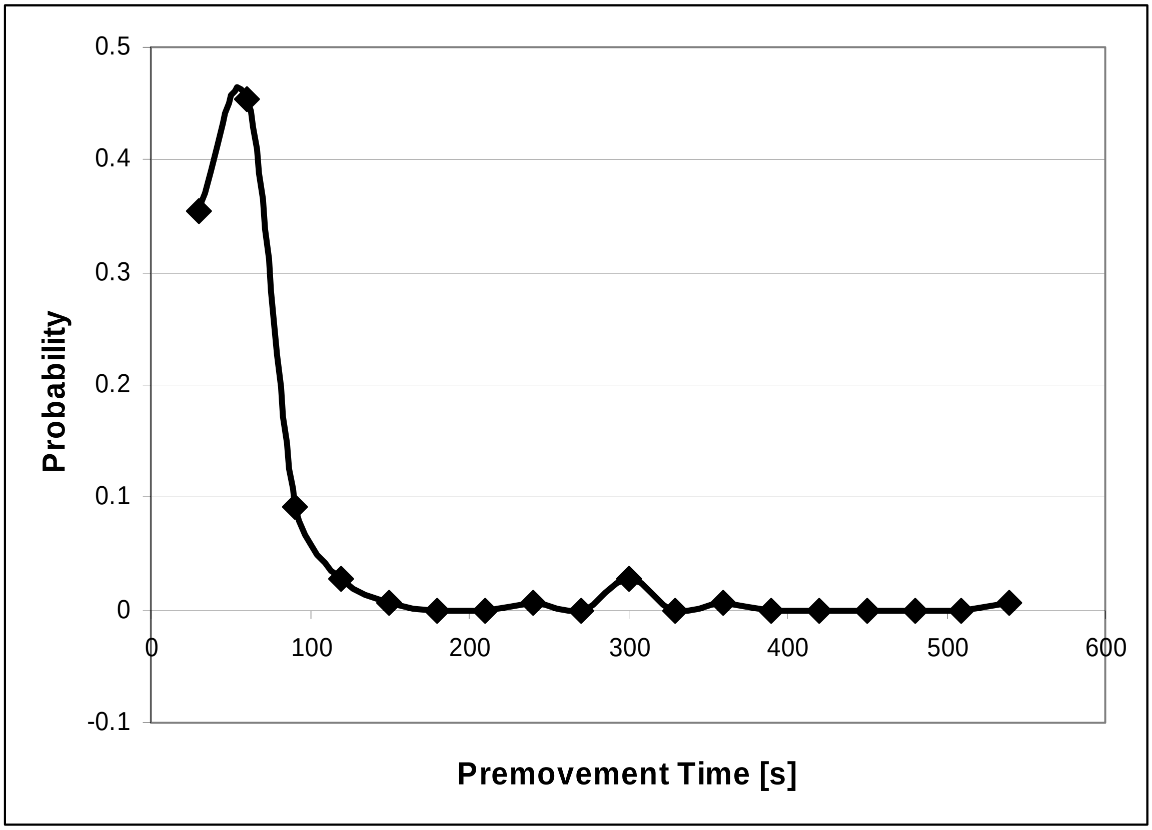
Pre-movement time can greatly affect the evacuation time of a building or structure. Therefore, it was chosen to investigate possible values of pre-movement times for office buildings and apartment buildings.

The data for pre-movement times for office buildings are from several different sources (Charters, 2001; Proulx, et. al., 1999; Fahy and Proulx, 2001; Purser, 1998; Brennan, 1997; Proulx et al, 1996). The distribution of these times is shown in Figure 21 and a summary is shown in Table 39.

Table 39: Summary of Office Pre-movement Times

Data Summary	
Data Points	141
Minimum [s]	0
Maximum [s]	1704
Standard Deviation [s]	165
Average [s]	71

Figure 21: Distribution of Office Pre-movement Times

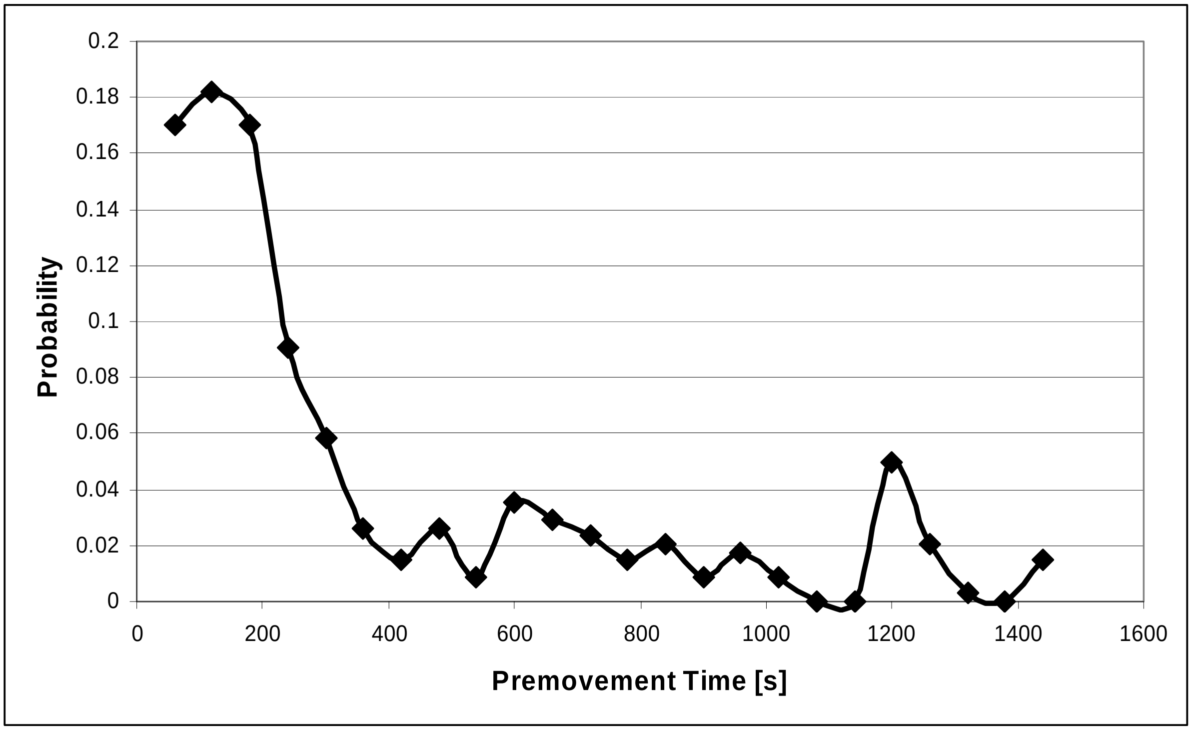


The data for pre-movement times for apartment buildings is summarized in Table 40 and the distribution of the data is shown in Figure 22. The data is from several different sources (Charters, 2001; Proulx, 1994; Fahy and Proulx, 2001; Brennan, 1997; Brennan, et. al., 1997; Proulx et al, 1995).

Table 40: Summary of Pre-movement Times in Apartment Buildings

Data Summary	
Data Points	341
Minimum [s]	13
Maximum [s]	1470
Standard Deviation [s]	376
Average [s]	347

Figure 22: Distribution of Pre-movement Times in Apartment Buildings



B1.6 References

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APPENDIX C

Comparison of EXIT89 and STEPS to Experimental Data

C1. GENERAL

The work conducted under the National Institute for Standards and Technology, Building and Fire Research Laboratory Grant 60NANB2D0138 included performing sensitivity analyses using the computer egress models EXIT89 and STEPS, comparing them with three real-life evacuation scenarios.

The three real-life evacuation scenarios included:

- A 6-story (plus basement) office building in London, Ontario.
- A 14-story apartment building in Calgary, Alberta
- An 8-story (plus basement) building in Ottawa, Ontario

The evacuations were documented by the National Research Council of Canada, information was collected by observers and by videotape. General information regarding the occupant loads at the time of evacuation and the total evacuation times is provided in the table below.

Table 41: Summary of Documented Evacuations

Building	Occupant Load	Time To Evacuate Building
London	164	226 seconds (3.75 minutes)
Calgary	165 (only 33 evacuated)	780 seconds (13 minutes)
Ottawa	489	540 seconds (9 minutes)

The series of summaries below present graphs displaying average evacuation times for the simulations completed with STEPS and EXIT89. It should be noted that a more useful way of looking at results and accounting for uncertainty on a case-by-case basis is to utilize the cumulative distribution functions presented in the Annex of Appendix A. However, the more general “mean evacuation” times have been provided here to provide a very basic summary of the simulations that were completed.

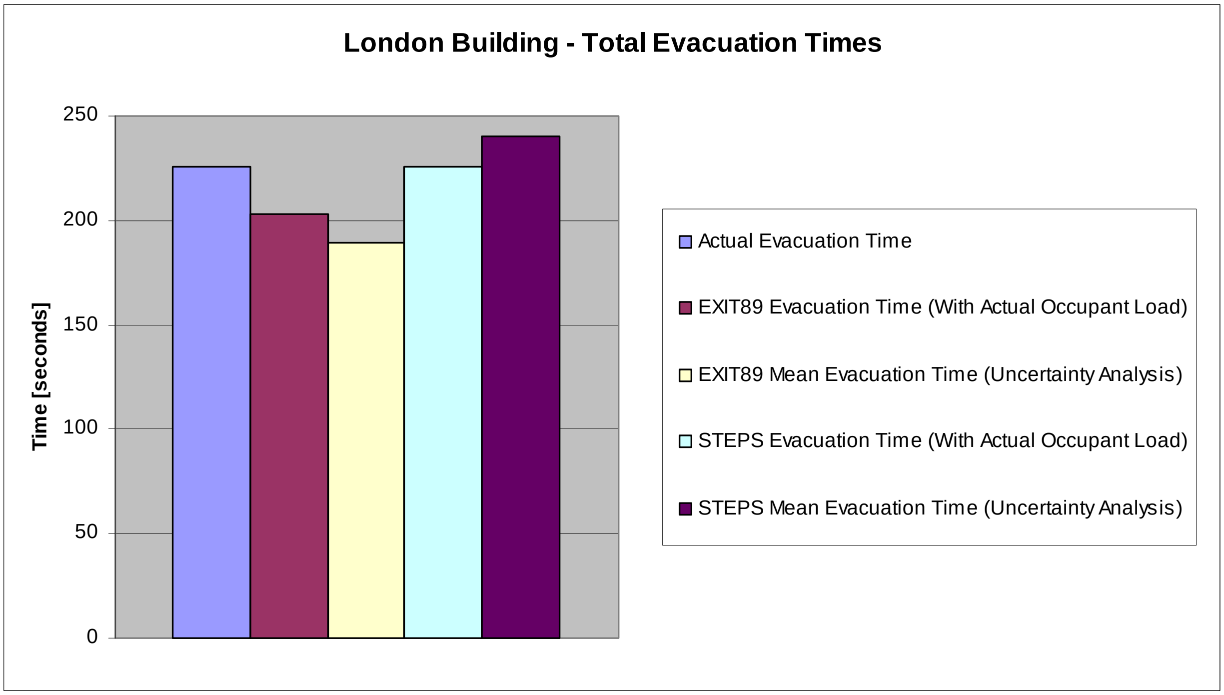
C2. LONDON BUILDING RESULTS

The London Building was modeled with both STEPS and EXIT89. Each model was first run using the known occupant loads from the evacuation data, then was run using the method of uncertainty analysis shown in Annex A.

C2.1 Total Evacuation Time

The actual total evacuation time for the London Building evacuation was 226 seconds (3.75 minutes). Given prior knowledge of the occupant load in the building, the STEPS model predicted a total evacuation time of 226 seconds and the EXIT89 model predicted a total evacuation time of 203 seconds. When the models were re-run using the uncertainty analysis techniques and given no prior knowledge of the occupant load of the building, the average total evacuation time predicted by STEPS was 240 seconds and the average total evacuation time predicted by EXIT89 was 189 seconds.

Figure 23: Total Evacuation Times for London Building



C2.2 Correlation of Variables

After running the uncertainty analysis of the London Building with the STEPS and EXIT89 models, correlations were formed for the variables that were tested using the Monte Carlo Analysis in relation to their effect on the total evacuation time. The results of these correlations are shown in the figures below.

Figure 24: Correlation of STEPS Variables to Total Evacuation Time for London Building

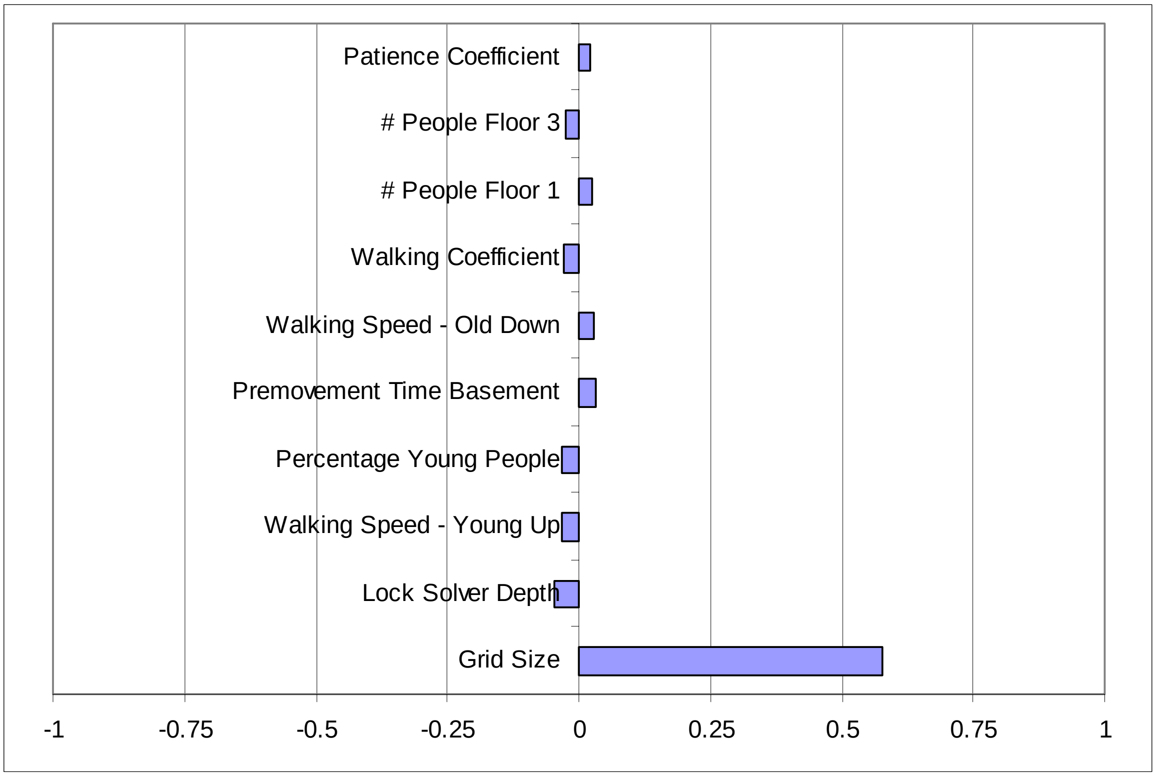
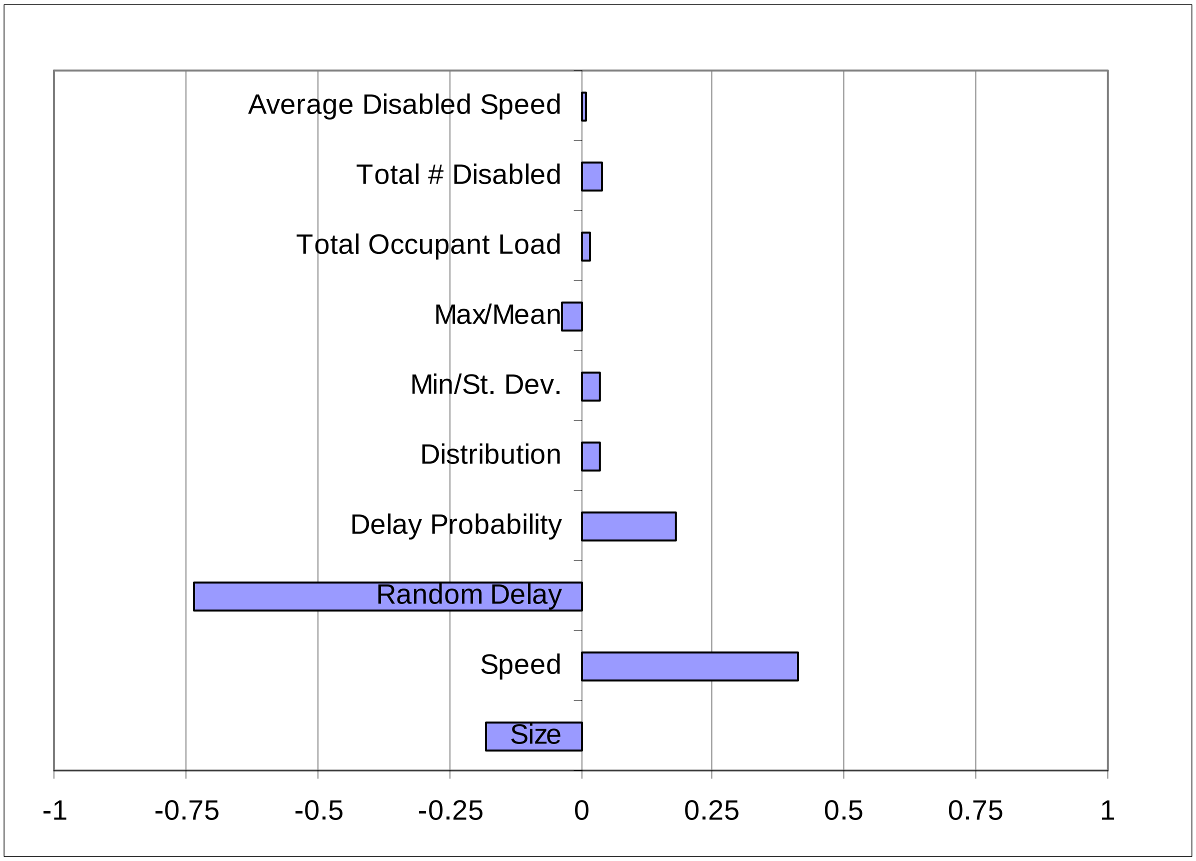


Figure 25: Correlation of EXIT89 Variables to Total Evacuation Time for London Building



According to these correlations, the STEPS grid size was variable with the largest impact on the STEPS-predicted total evacuation times, while the EXIT89-predicted total evacuation times were most effected by the random delay and speed of building occupants.

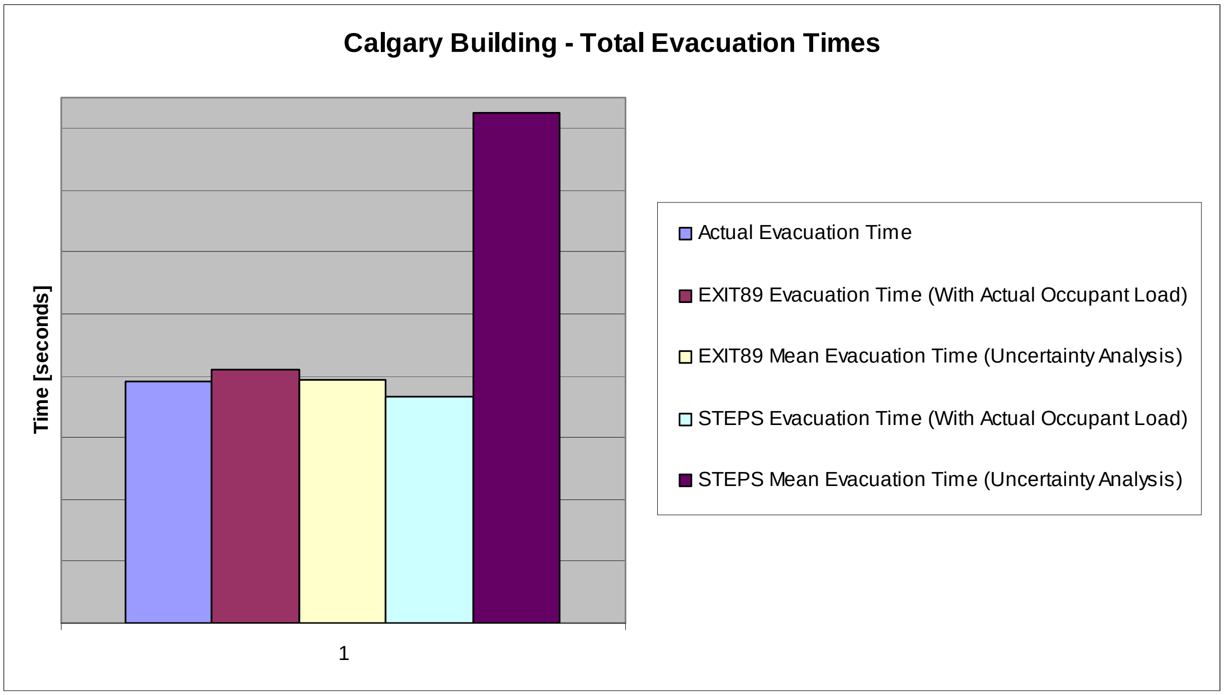
C3. CALGARY BUILDING RESULTS

The Calgary Building was modeled with both STEPS and EXIT89. Each model was first run using the known occupant loads from the evacuation data, then was run using the method of uncertainty analysis shown in Annex A.

C3.1 Total Evacuation Time

The actual total evacuation time for the Calgary Building evacuation was 780 seconds (13 minutes). Given prior knowledge of the occupant load in the building, the STEPS model predicted a total evacuation time of 731 seconds and the EXIT89 model predicted a total evacuation time of 822 seconds. When the models were re-run using the uncertainty analysis techniques and given no prior knowledge of the occupant load of the building, the average total evacuation time predicted by STEPS was 1649 seconds and the average total evacuation time predicted by EXIT89 was 787 seconds.

Figure 26: Total Evacuation Times for Calgary Building



C3.2 Correlation of Variables

After running the uncertainty analysis of the Calgary Building with the STEPS and EXIT89 models, correlations were formed for the variables that were tested using the Monte Carlo Analysis in relation to their effect on the total evacuation time. The results of these correlations are shown in the figures below.

Figure 27: Correlation of STEPS Variables to Total Evacuation Time for Calgary Building

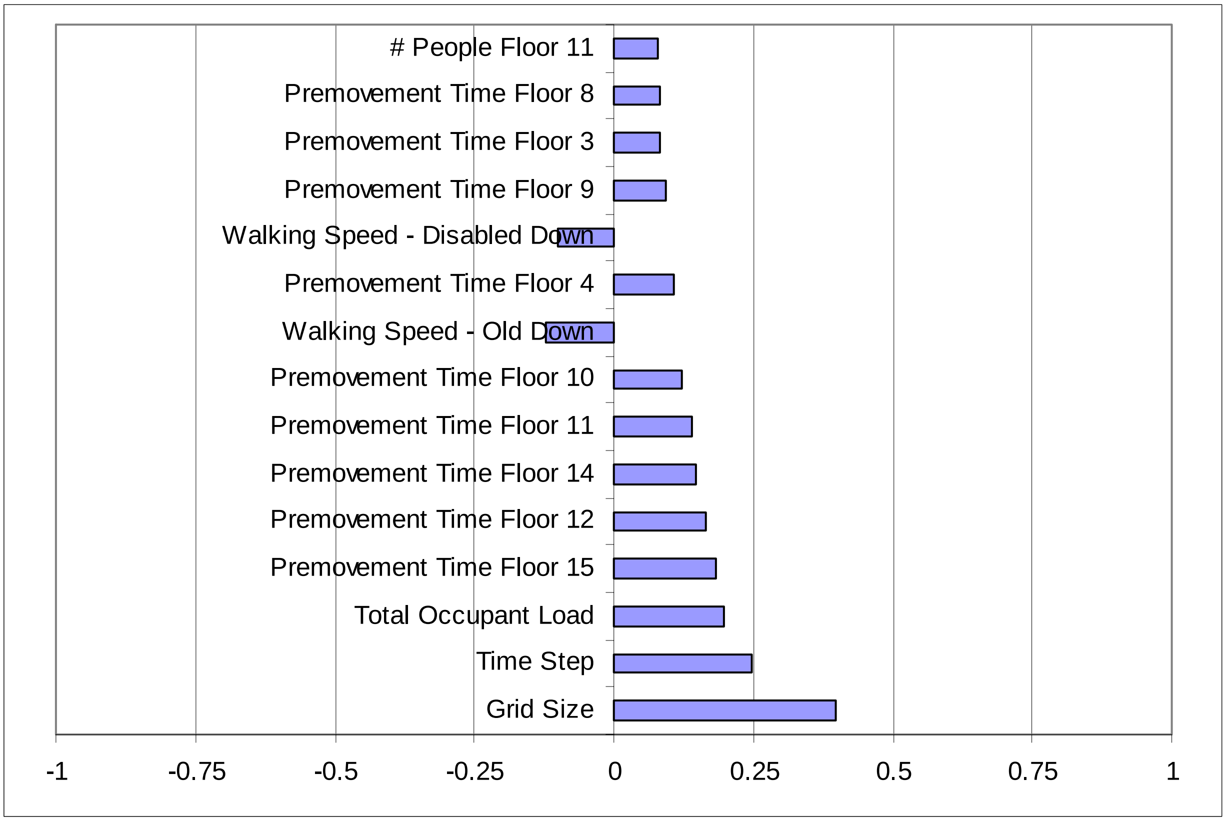
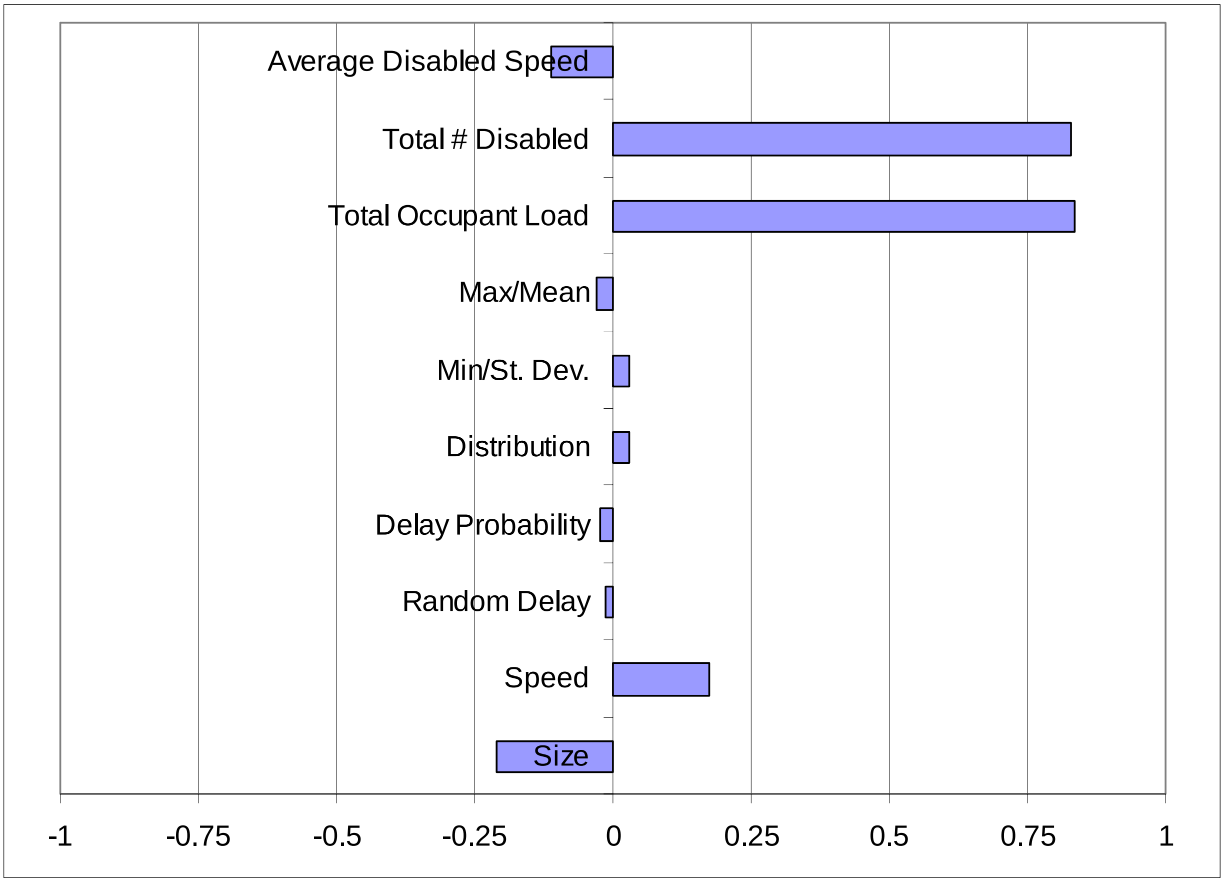


Figure 28: Correlation of EXIT89 Variables to Total Evacuation Time for Calgary Building



According to these correlations, the STEPS grid size was variable with the largest impact on the STEPS-predicted total evacuation times followed by the time-step, total occupant load, and pre-movement times. The EXIT89-predicted total evacuation times were most effected by the total number of disabled occupants in the building, and the total occupant load of the building.

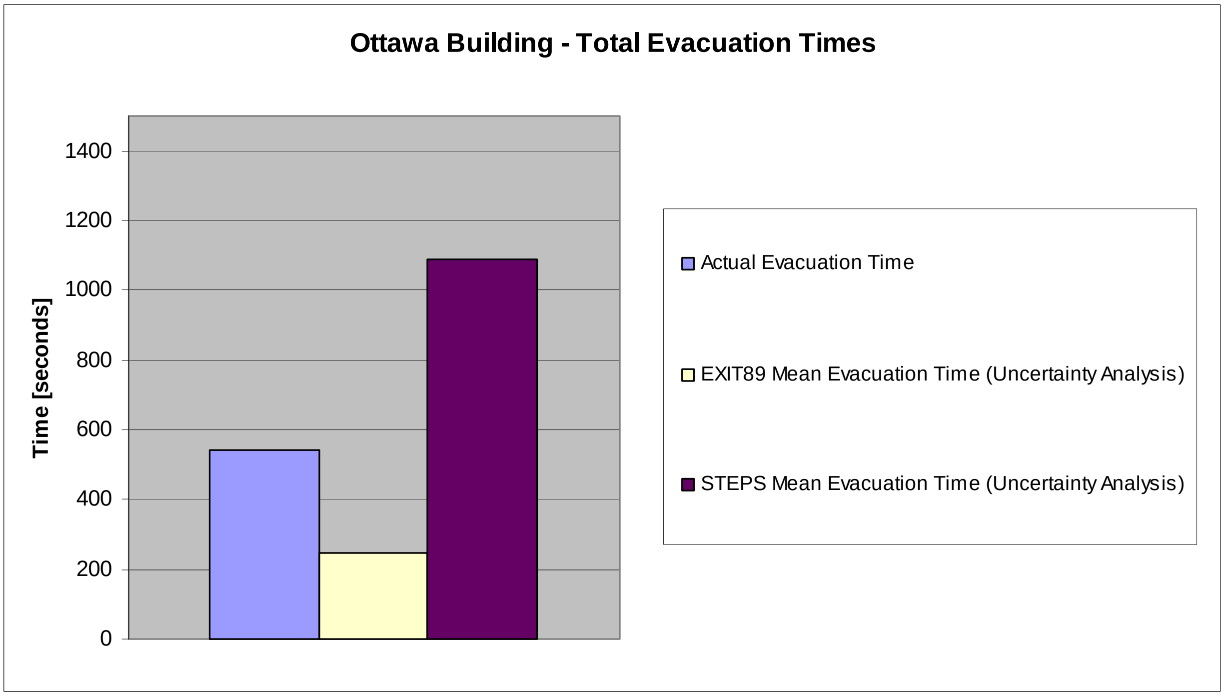
C4. OTTAWA BUILDING RESULTS

The Ottawa Building was modeled with both STEPS and EXIT89. Each model was run as a blind-test using the method of uncertainty analysis shown in Annex A. These models were not run with prior knowledge of the building occupants.

C4.1 Total Evacuation Time

The actual total evacuation time for the Ottawa Building evacuation was 540 seconds (9 minutes. When the models were run as blind-tests using the uncertainty analysis techniques and given no prior knowledge of the occupant load of the building, the average total evacuation time predicted by STEPS was 1091 seconds and the average total evacuation time predicted by EXIT89 was 248 seconds.

Figure 29: Total Evacuation Times for Ottawa Building



C4.2 Correlation of Variables

After running the uncertainty analysis of the Ottawa Building with the STEPS and EXIT89 models, correlations were formed for the variables that were tested using the Monte Carlo Analysis in relation to their effect on the total evacuation time. The results of these correlations are shown in the figures below.

Figure 30: Correlation of STEPS Variables to Total Evacuation Time for Ottawa Building

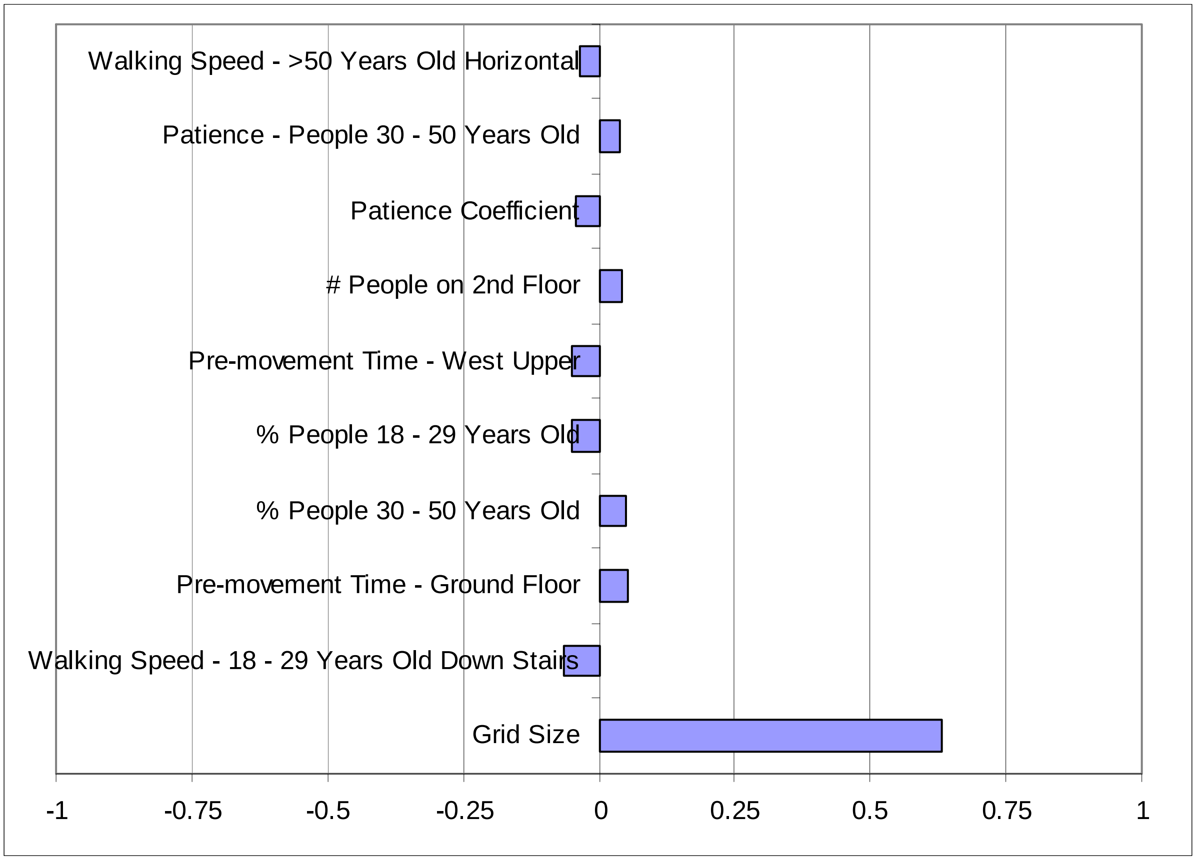
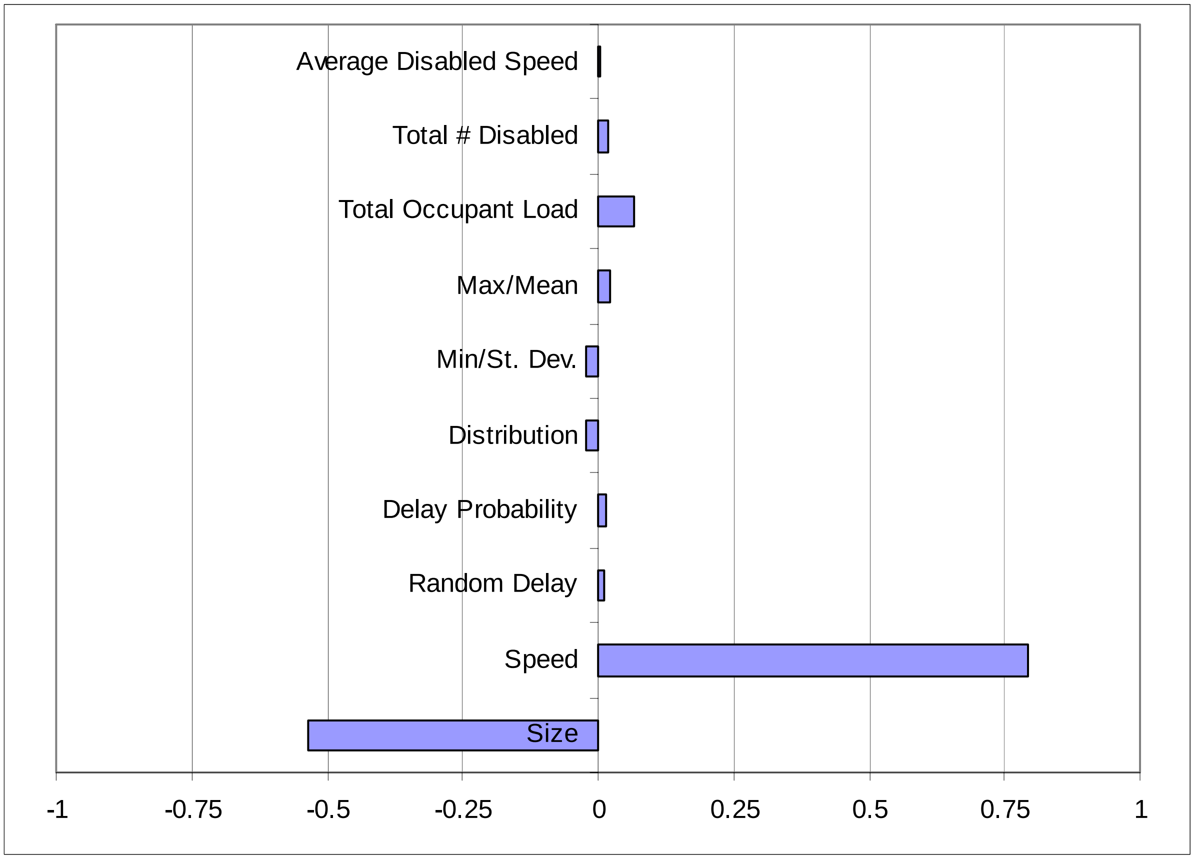


Figure 31: Correlation of EXIT89 Variables to Total Evacuation Time for Ottawa Building



According to these correlations, the STEPS grid size was again the variable with the largest impact on the STEPS-predicted total evacuation times. The EXIT89-predicted total evacuation times were most effected by the speed and size of the building occupants.

C5. CONCLUSIONS

After reviewing the data from EXIT89 and STEPS from the three analyses, some general conclusions can be drawn:

- Both EXIT89 and STEPS provide reasonably accurate total egress times for office and apartment buildings on the order of 6 to 14 stories in height.
- EXIT89 may under-predict the total evacuation time for a building if prior knowledge of the occupant load is not provided.
- STEPS may over-predict the total evacuation time for a building if prior knowledge of the occupant load is not provided.
- EXIT89 is sensitive to the occupant data that is provided. Varying the number of occupants, size of occupants, and speed of occupants will have a significant impact on the model results.
- STEPS is sensitive to grid-size. Changing the grid from 0.3 meters to 0.6 meters can have a significant impact on the results of the model. Efforts should be taken when using STEPS to use an appropriate grid size and to perform some sensitivity analysis.

There was sufficient variation from one scenario to another in the variables that exhibited significance that it would be difficult to eliminate the need to consider specific variables without future analyses that build off the information provided in this document. Until such analysis can be completed, the method of uncertainty analysis described in this document could be used to evaluate the significance of individual variables and to identify which variables are most significant for building evacuations on a case-by-case basis.

APPENDIX D

Paper Submitted to SFPE

The following paper was is published in the *Proceedings, 5th International Conference on Performance-Based Codes and Fire Safety Design Methods,* SFPE, Bethesda, MD, October 2004*

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

James Lord, Arup, USA[8]
Amanda Moore, Arup, USA
Brian Meacham, Arup, USA
Rita Fahy, NFPA, USA
Guylene Proulx, NRC/IRC, Canada

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, and 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*,[9] there is a 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[10] 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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[8] Author for correspondence.
[9] Fahy, R., "Available Data and Input into Models," *National Research Council Workshop to Identify Innovative Research Needs to Foster Improved Fire Safety in the United States, Session on Human Behavior*, 13 April 2002.
[10] Notarianni, K. "The Role of Uncertainty in Improving Fire Protection Regulation", PhD Dissertation, Carnegie Mellon University, May 2000.

OVERALL SCOPE OF RESEARCH PROGRAM

To begin addressing the above concerns, a three-year research program is underway, funded by a grant from the National Institute of Standards and Technology, Building and Fire Research Laboratory (Grant 60NANB2D0138), that aims to improve the predictive capabilities of egress models. The primary goals of this work are to:

- Understand sources of uncertainty and variability in egress models.
- 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.

In meeting the above goals, the following tasks have been developed:

- Collect data sets for use in and for verification of the predictive capabilities of egress models,
- Begin to identify sources, type, magnitude and importance of uncertainty and variability in data for egress models,
- Begin 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
- Begin 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).

YEAR 1 EFFORTS

The first year of the research program has been completed. The first year effort included selecting egress models for evaluation, collecting and analyzing data sets from previous evacuation and research work, assessing the egress models to determine dominant variables, sources, types, magnitudes and importance of uncertainty and variability, and how the models differ, assessing the above models against a data set and comparison of model results, identifying sources and type of uncertainty and variability in data (model inputs), and initial efforts to identify appropriate treatment of uncertainty and variability based on model specifics. For this effort, the egress models selected for analysis are STEPS (Simulation of Transient Evacuation and Pedestrian movementS)[11] and EXIT89[12].

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[11] Mott MacDonald, "STEPS – Simulation of Transient Evacuation and Pedestrian movements, Users Manual", 2004.

[12] Fahy, R. F., "EXIT 89 - An Evacuation Model for High-Rise Buildings -- Model Description and Example Applications," *Fire Safety Science-Proceedings of the Fourth International Symposium, International Association for Fire Safety Science*, 1994, pp. 657-668.

STEPS

The STEPS computer program implements an optimization evacuation model, including queuing, and has been used over the past five years on a wide range of projects, from mass transit stations,[13] to complex assembly spaces,[14] to high-rise buildings.[15] The model supports travel through a variety of egress routes as generated within the model for simulation by the modeler. With the ability to establish the various egress paths, different egress scenarios can be readily simulated to quantitatively differentiate between egress scenarios. The model begins with the establishment of people types and people groups. The people types contain the information about the travel speed of the person under various conditions. These conditions would typically be the travel speed on horizontal surfaces, while traveling up stairs, and while traveling down stairs. People groups are used so that different characteristics for certain groups of people can be used. For example if the population had a significant number of elderly or mobility impaired people, they could be represented with a slower travel speed.

Typically developed through the importing of CAD drawings, the geometry of the modeled space is added onto a plane over which egress will occur. The plane is broken into square grid cells typically ranging from 0.4 to 0.5 meters on a side. The geometric configurations for walls, partitions, columns and furnishings found on the drawing are interpreted by the STEPS model as blockages. Where blockages occur, the grid is marked as impassable and occupants cannot traverse those cells. For multi-level models, the addition of planes spanning from one level to another provides for the development of egress paths using stairs. From the grid cells generated as the interpretation of the CAD drawings, available grid cells that can be occupied by people are determined. Only one person can occupy a grid cell at a time. At each time step, the model calculates a "score" for each grid cell in relation to the exits for a particular plane. The occupant will move to a grid cell with a score lower than the presently occupied grid cell provided that the target grid cell is not already occupied. Scoring for the model is based on an algorithm that incorporates the time needed to reach a target, the time needed to queue at a target, and the patience of the building occupants[16]. A further discussion of the variables required for this algorithm is provided in the results section of this paper.

Along with geometric characteristics, people groups and exits are placed onto a plane to complete the modeling. The people groups placed on planes can be configured to randomly distribute people in the plane. The exits provide "goals" or "targets" for the people on the plane. The scoring, described above, is calculated in relation to the various exits available to the evacuee. The exits either provide a way for evacuees to leave the model (exit the building) or to move onto another plane (another floor). Exit routes that allow evacuees to leave the building would, for example, model an occupant leaving a floor, traversing the stairs, passing through a lobby, and leaving the building.

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[13] Hoffmann, N. and Henson, D., "Simulating Transient Evacuation and Pedestrian Movements in Stations," *Proceedings of the International Conference on Mass Transit*, International Technical Conferences, UK, 1997.

[14] Rhodes, N. and Hoffmann, N., "Fire Safety Engineering for the International Centre for Life, Newcastle-Upon-Tyne," *Proceedings of Interflam '99*, Interscience Communications, Ltd., London, UK, 1999, pp. 331-342.

[15] STEPS has been used for numerous high-rise evacuation simulations within Arup for buildings in the UK and the US. Various papers are in development for publication. Current client reports are confidential, but can be made available to reviewers upon request.

[16] Mott MacDonald, "STEPS – Simulation of Transient Evacuation and Pedestrian movements, Users Manual", 2004, pp. 163.

EXIT89

The EXIT89 program developed by Fahy was intended to model evacuation of a large building with the ability to track the path of each occupant[19]. The model uses traffic speeds dependent on flow densities as measured by Predtechenskii and Milinskii. The model can be used in conjunction with a zone model such as CFAST to incorporate the effects of fire and smoke spread on the occupants' evacuation behavior.

The model requires a network description of the structure, which includes the geometry of the compartments, openings between rooms, and the number of people located at each node of the building. The user must decide whether the occupants will evacuate at the first sign of fire or if they will delay some period of time. The decision process to evacuate or delay is implicitly handled as a time delay before the program begins to calculate the evacuation for a given occupant. The delay times are a user option and can be assigned to all occupants of a node or can be randomly assigned to individuals. Also considered in the model is whether the occupant will use the shortest route or nearest exit, or use a familiar route. To achieve this, the user must specify the appropriate route for an occupant to follow. Population and travel densities are based on body sizes, which are also user specified. Disabled occupants can be added, but are done by simply modifying the travel speed for that particular occupant and does not account for assistance from other occupants. By the developer's admission, the model is not capable of simulating behavioral considerations explicitly. Rather, certain considerations can be modeled implicitly by incorporating delays and modified occupant parameters. Essentially, the model calculates a flow of people from one node to the next (modifying the speed of movement according to population density and environmental conditions) until all occupants have exited the building. This assessment will build upon previous validation efforts,[4,17] resulting in more explicit understanding of sources of uncertainty and appropriate methods for treatment thereof.

STUDY METHODOLOGY AND YEAR 1 RESULTS

A five-phase process is being used to carry out the study, as detailed below. For the Year 1 efforts, Phases 3-5 focused on STEPS.

Phase 1: Construction of Base Models
Phase 2: Identification of Variables and Possible Values
Phase 3: Monte Carlo Analysis
Phase 4: Statistical Analysis of Computer Model Results
Phase 5: Identification of Significant Variables

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[17] Fahy, R. F., "EXIT89 - High-Rise Evacuation Model - Recent Enhancements and Example Applications," *Interflam 96 Conference, 7th Proceedings*, 1996, Cambridge, pp 1001-1005.

PHASE 1: CONSTRUCTION OF BASE MODELS

STEPS and EXIT89 were used to model a 6-story (plus basement) office building in London, Ontario (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.

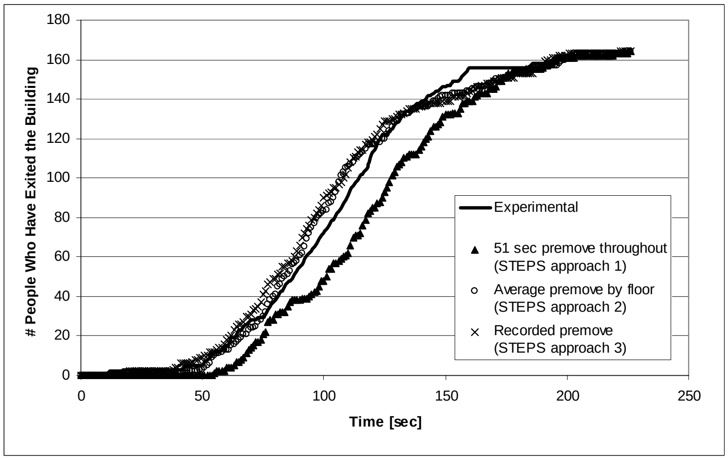

Figure 1: STEPS Model, Number of People Left in London Building Over Time, Experimental vs. Various Simulated Conditions

Based on these initial test simulations, Phases 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.

PHASE 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 evacuation 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.

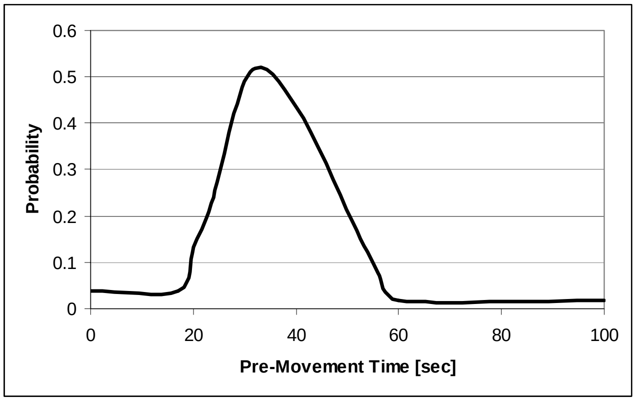

Figure 2: Sample Distribution Curve of Values for Pre-Movement Time (in seconds) for Occupants of Office Buildings. Formed from NRC "London Building" Data and Purser[18]

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 that is already available from different studies, but in varying formats. Some research has been done in the fields of risk management[19] and weather forecasting[20] 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.

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[18] Purser, D.A, "Quantification of Behaviour for Engineering Design Standards and Escape Time Calculations", *Human Behavior in Fire-Proceedings of the First International Symposium*, 31 August-2 Sept 1998.

[19] Clemen, R.T., Winkler, R.L, "Combining Probability Distributions from Experts in Risk Analysis", http://fisher.osu.edu/~butler_267/DAPapers/WP970009.pdf, October 22, 1997

[20] Clemen, R.T., Jones, S.K. & Winkler, R.L., "Aggregating forecasts: An empirical evaluation of some Bayesian methods", *Bayesian Statistics and Econometrics: Essays in Honor of Arnold Zellner*, 1996, pp. 3-13

Phase 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.

Phase 4: Statistical Analysis of Computer Model Results

The output from the 300 STEPS simulations were analyzed using a method described by Notarianni[21]. 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.

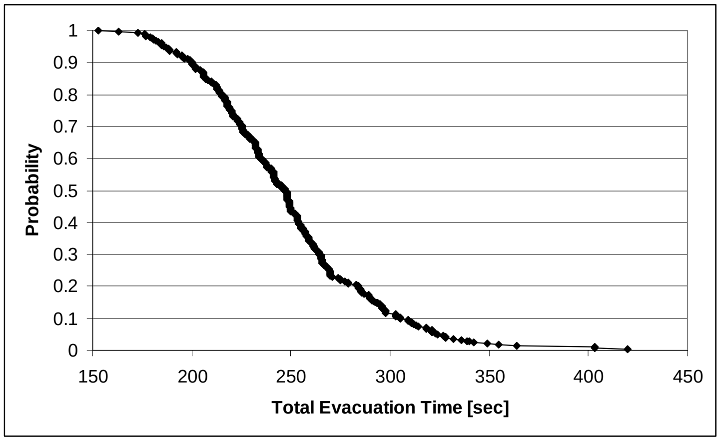

Figure 3: Cumulative Distribution Function of Total Evacuation Time

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.

PHASE 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 (CDFs) were formed for each of the tested variables, comparing different values of the variables with each other.

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[21] Notarianni, K. “The Role of Uncertainty in Improving Fire Protection Regulation”, PhD Dissertation, Carnegie Mellon University, May 2000.

Occupant Load

Figure 4 provides a CDF 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.

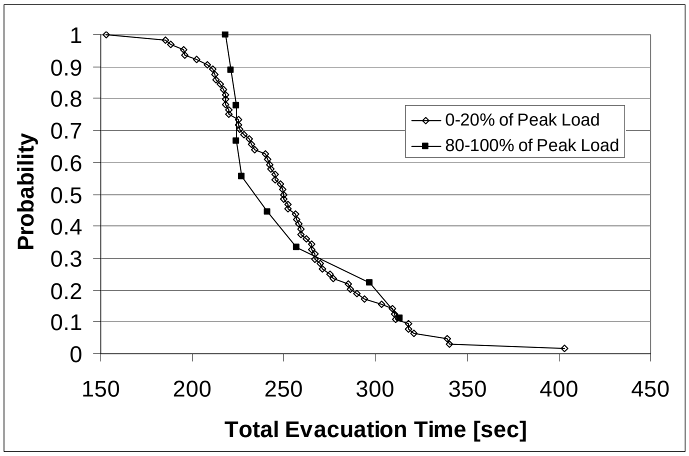


Figure 4: Cumulative Distribution Functions of Total Evacuation Time for Two Total Building Occupant Loads

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 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.

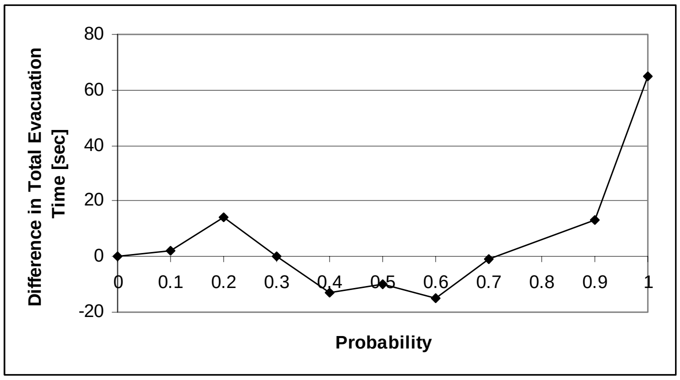
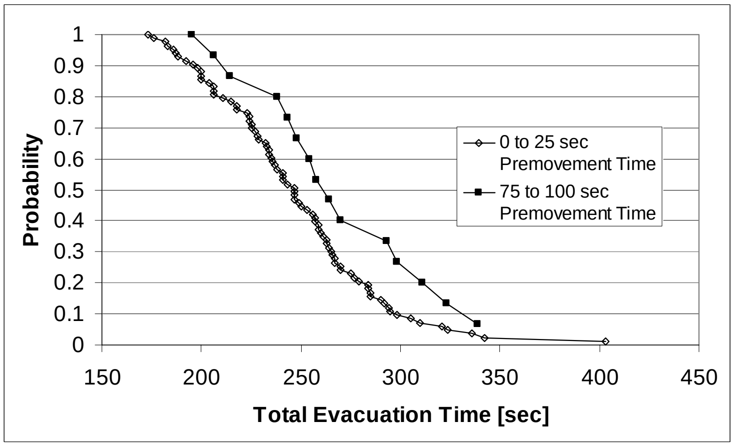


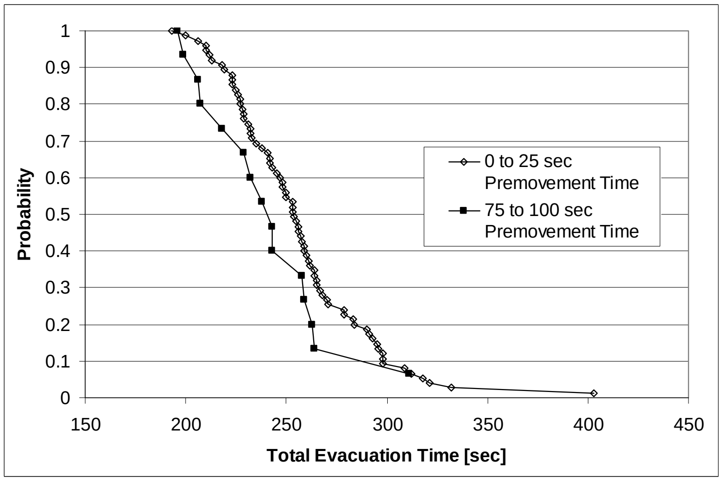
Figure 5: Sensitivity of Total Evacuation Time to Total Building Occupant Load

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 CDF 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.



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 CDF for the Floor 6 pre-movement times is provided in Figure 7 below.



Demographics & Walking Speed

The initial results of this study indicate that in buildings similar to the London building, demographics play a fairly insignificant role in the overall total evacuation time. This also correlates to occupant walking speed, which was related 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.

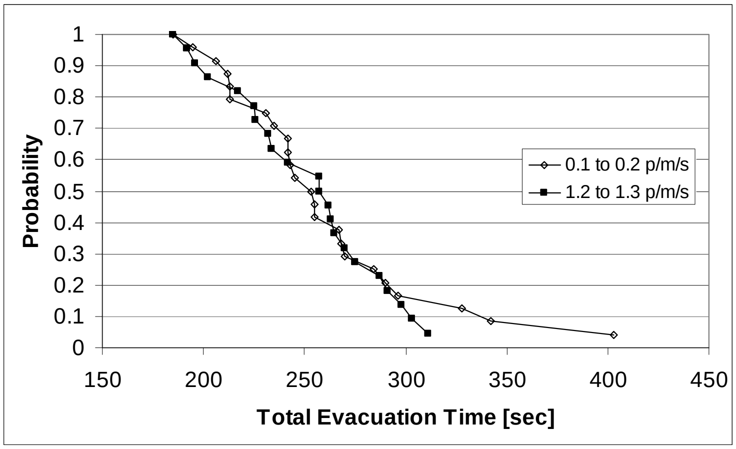


Figure 8: Cumulative Distribution Functions of Total Evacuation Time for Two Ranges of Door *Flow Rates*

Patience

STEPS allows a value to be assigned 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. This result may vary in buildings that have exits close together where there are more opportunities for occupants to choose between two nearby exits.

STEPS Coefficients

The STEPS software has three coefficients labeled "Patience Coefficient" (default value of 0.1), "Walking Coefficient" (default value of 1.0), and "Queuing 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 affect 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 Queuing coefficient. This graph was produced by subtracting the total evacuation times achieved with a low (0 to 0.1) queuing coefficient from those with a high (0.9 to 1.0) coefficient. The results indicate that the significance of the queuing coefficient was quite high at a probability near 0, but rapidly diminished as the probability approached 0.6.

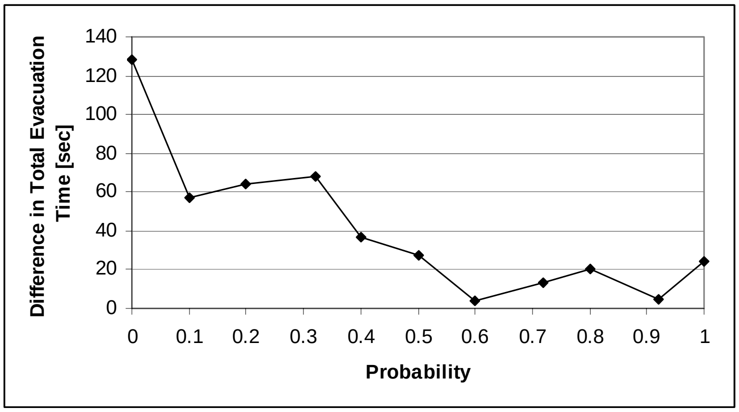
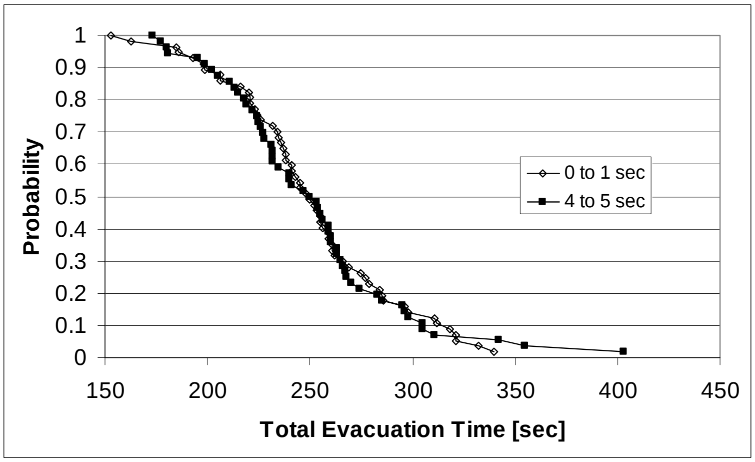
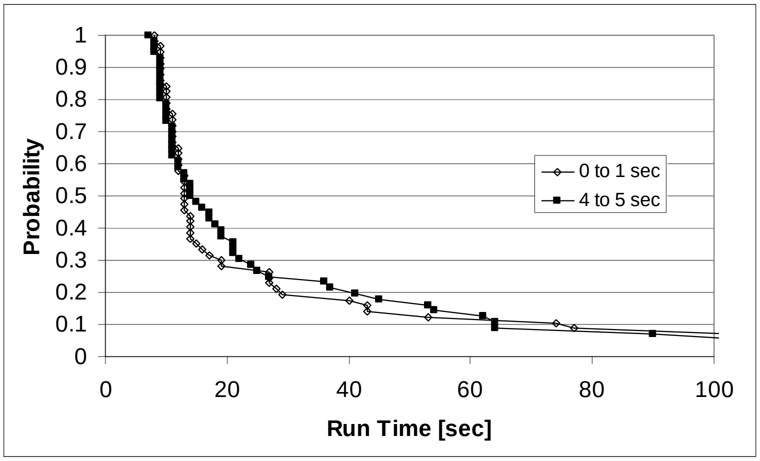


Figure 9: Sensitivity of Total Evacuation Time to Queuing Coefficient

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.





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 be 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[22] to computer egress modeling. This method uses a Monte Carlo technique 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, including:

- Occupant loads
- Pre-movement times
- Queuing 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 performed to investigate the significance of grid size on STEPS simulations, and the effect of larger numbers of simulations on the statistical analysis.

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[22] Notarianni, K. “The Role of Uncertainty in Improving Fire Protection Regulation”, PhD Dissertation, Carnegie Mellon University, May 2000.

APPENDIX E

Paper Submitted to Human Behavior Seminar

The following paper was is published in the *Proceedings, 3rd International Symposium on Human Behaviour in Fire*, Interscience Communications Ltd., September 2004, pp.419-430

INVESTIGATION OF UNCERTAINTY IN EGRESS MODELS AND DATA[23]

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ABSTRACT

The use of computational analysis to predict building egress during emergency situations has been steadily increasing in recent years. However, there is a general lack of data for use in computational egress models, and there are no benchmarks against which to test the predictive capability of the computational egress models. As a result, how well these models are able to predict a priori the time to egress a building is generally unknown, as are those variables that have the most significant impact on the predicted outcomes. To begin addressing the issues of evaluating the predictive capability of egress models, and the uncertainty and variability associated with the models and the available data, a three-year research effort is underway. The study methodology and preliminary results are presented.

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[23] This research is supported by a grant from the National Institute of Standards and Technology, Building and Fire Research Laboratory (Grant 60NANB2D0138). Any opinions, findings, conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of Arup, the National Fire Protection Association, the National Research Council, Canada, or the National Institute of Standards and Technology, Building and Fire Research Laboratory.
[24] Author for correspondence.
[25] Dr. Notarianni was the NIST/BFRL Program Manager for this research effort prior to her move to WPI.

INTRODUCTION

Accurate predictions of the time required to egress a building under various conditions are crucial to decisions regarding the acceptability of a building design. Accurate predictions of total time to egress require both robust models, i.e., models that capture the major factors of egress, as well as a large amount of good, reliable and readily available input data for the model, such as body sizes and walking speeds. Accurate predictions also require a methodology for expressing variability in factors such as occupant health, mobility, and location at the time of a fire event – parameters generally unknown prior to an event.

To help provide more accurate predictions of egress time, assessment of computational egress models to determine model structure, dominant variables, and sources, types, magnitudes and importance of uncertainty and variability is needed. Collection and analysis of data sets to support this computational modeling, especially for assessing emergency egress scenarios where data are extremely sparse and little is known about the validity of the data, is likewise essential. Ultimately, a methodology to quantify uncertainty and variability in both the input data and the predictions of the models must be developed and standardized.

These needs are well documented in the literature. Shields and Proulx,[26] for example, note shortcomings in the availability of data, in the current state of modeling, and in the application of current models. In their paper on creating a database for evacuation modeling, Fahy and Proulx[27] provide an extensive list of data needs, and conclude that "it is essential that engineers, designers and building officials have available to them accurate information upon which to base any assumptions of occupant time to start and movement speed that will be used in the evaluation of an engineered building design." Fahy[28] reiterated this concern at the *National Research Council Workshop to Identify Innovative Research Needs to Foster Improved Fire Safety in the United States*.

Previous work on uncertainty in fire-safety calculations has focused on the other side of the safety equation, i.e., prediction of the time to development of untenable conditions. Notarianni[29,30] and others[31,32,33] have discussed the importance of identifying and addressing uncertainty in data, models, and fire safety engineering analysis, as the failure to do so can lead to inappropriate use of data, misinterpretation of model output, and ultimately to misinformed decisions for life safety system design.

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[26] [26] Shields, T.J. and Proulx, G., "The Science of Human Behaviour: Past Research Endeavours, Current Developments and Fashioning a Research Agenda, *Proceedings of the International Association for Fire Safety Science, 6th International Symposium*, IAFSS, 2000, pp. 95-113.

[27] Fahy, R. and Proulx, G., "Toward Creating a Database on Delay Times to Start Evacuation and Walking Speeds for Use in Evacuation Modeling," *Proceedings of the Second International Symposium on Human Behavior in Fire*, Interscience Communications Limited, 2001, pp. 175-184.

[28] Fahy, R., "Available Data and Input into Models," *National Research Council Workshop to Identify Innovative Research Needs to Foster Improved Fire Safety in the United States, Session on Human Behavior*, 13 April 2002.

[29] Notarianni, K., *The Role of Uncertainty in improving Fire Protection Regulations,* PhD Dissertation, Carnegie Mellon University, May 2000.

[30] Notarianni, K.A., "Uncertainty," Section 5, Chapter 4, *SFPE Handbook of Fire Protection Engineering*, 3rd Edition, NFPA, Quincy, MA, pp. 5-40 – 5-64.

[31] Custer, R.L.P and Meacham, B.J., *Introduction to Performance-Based Fire Safety,* NFPA, Quincy, MA, 1997.

[32] Meacham, B.J., "Integrating Human Factors Issues Into Engineered Fire Safety Design," *Fire and Materials*, Vol. 23, Issue 6, 1999.

[33] Frantzich, H., *Uncertainty and Risk Analysis in Fire Safety Engineering*, Lund University, Report LUTVDG/(TVBB-1016), Lund, Sweden, 1998.

This work focuses on accurate predictions of time to egress so that complete information is available to the decision-makers.

OVERALL SCOPE OF RESEARCH PROGRAM

To begin addressing the issue of uncertainty and variability in egress data and in computational models for egress analysis, a three-year research began in September 2002 under a grant from the National Institute for Standards and Technology, Building and Fire Research Laboratory (Grant 60NANB2D0138), *Uncertainty in Egress Models and Data: Investigation of Dominant Parameters and Extent of Their Impact on Predicted Outcomes*. The primary goals of this work are to:

- Understand sources of uncertainty and variability in egress models.
- 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.

In meeting the above goals, the following tasks have been outlined:

- Collection of data sets for use in and for verification of the predictive capabilities of egress models,
- Documentation of the actual range of input variables used in egress models, and valid statistical representations of these variables
- Identification of sources, type, magnitude and importance of uncertainty and variability in data (input) for egress models, and
- Comparison of predictions of time to egress based on two egress models using a "blind" evacuation scenario (using a data set not used for the uncertainty analysis identified above).

The research plan follows generally the methodology proposed by Notarianni for use with any fire-safety calculation. The approach involves the following. Sensitivity analyses are conducted to identify the dominant input variables, i.e., those with the strongest correlation to, and thus the most potential to, change the outcome prediction. Collections of data sets are used to develop statistical representation of values of these dominant input variables to account for uncertainty and in some cases variability. In cases where sufficient data is not available, variables may be assigned broader ranges of potential values, which would account for their uncertainty, but would necessitate a greater number of simulations to complete the analysis. It is expected that some variables that show low statistical correlation may be set to best-guess or average values. After bounding the applicable variables, a Monte Carlo analysis will be applied to conduct a large number of predictions using the selected models. These simulations will be run, and their results will be analyzed to determine the level of uncertainty associated with each variable.

INITIAL EFFORTS

The first year of the research program, which has been completed, involved data gathering and preliminary assessment efforts. Efforts included:

- Selecting egress models for evaluation,
- Collecting and analyzing data sets from previous evacuation and research work,
- Assessing the egress models to determine dominant variables, sources, types, magnitudes and importance of uncertainty and variability, and how the models differ,
- Assessing the above models against a data set and comparison of model results,
- Identifying sources and type of uncertainty and variability in data (model inputs), and
- Initial efforts to identify appropriate treatment of uncertainty and variability based on model specifics.

For this effort, the egress models selected for analysis are STEPS (Simulation of Transient Evacuation and Pedestrian movementS)[34] and EXIT89.[35]

STEPS

The STEPS computer program implements an optimization evacuation model, including queuing, and has been used over the past five years on a wide range of projects, from mass transit stations,[36] to complex assembly spaces,[37] to high-rise buildings.[38] The model supports travel through a variety of egress routes as generated within the model for simulation by the modeler. With the ability to establish the various egress paths, different egress scenarios can be readily simulated to quantitatively differentiate between egress scenarios. The model begins with the establishment of people types and people groups. The people types contain the information about the travel speed of the person under various conditions. These conditions would typically be the travel speed on horizontal surfaces, while traveling up stairs, and while traveling down stairs. People groups are used so that different characteristics for certain groups of people can be used. For example if the population had a significant number of elderly or mobility impaired people, they could be represented with a slower travel speed. STEPS does not explicitly account for the actions of individuals assisting disabled persons, but it does have the ability to model groups of people that will search out each other before evacuating the building, and stay together throughout the simulation.

Typically developed through the importing of CAD drawings, the geometry of the modeled space is added onto a plane over which egress will occur. The plane is broken into square grid cells typically ranging from 0.4 to 0.5 meters on a side. The geometric configurations for walls, partitions, columns and furnishings found on the drawing are interpreted by the STEPS model as blockages. Where

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[34] Mott MacDonald, “STEPS – Simulation of Transient Evacuation and Pedestrian movements, Users Manual”, 2004.

[35] Fahy, R. F., "EXIT 89 - An Evacuation Model for High-Rise Buildings -- Model Description and Example Applications," *Fire Safety Science-Proceedings of the Fourth International Symposium, International Association for Fire Safety Science*, 1994, pp. 657-668.

[36] Hoffmann, N. and Henson, D., “Simulating Transient Evacuation and Pedestrian Movements in Stations,” *Proceedings of the International Conference on Mass Transit*, International Technical Conferences, UK, 1997.

[37] Rhodes, N. and Hoffmann, N., “Fire Safety Engineering for the International Centre for Life, Newcastle-Upon-Tyne,” *Proceedings of Interflam ’99*, Interscience Communications, Ltd., London, UK, 1999, pp. 331-342.

[38] STEPS has been used for numerous high-rise evacuation simulations within Arup for buildings in the UK and the US. Various papers are in development for publication. Current client reports are confidential, but can be made available to reviewers upon request.

blockages occur, the grid is marked as impassable and occupants cannot traverse those cells. For multi-level models, the addition of planes spanning from one level to another provides for the development of egress paths using stairs. From the grid cells generated as the interpretation of the CAD drawings, available grid cells that can be occupied by people are determined. Only one person can occupy a grid cell at a time. At each time step, the model calculates a "score" for each grid cell in relation to the exits for a particular plane. The occupant will move to a grid cell with a score lower than the presently occupied grid cell provided that the target grid cell is not already occupied. Scoring for the model is based on an algorithm that incorporates the time needed to reach a target, the time needed to queue at a target, and the patience of the building occupants.[39] A further discussion of the variables required for this algorithm is provided in the results section of this paper.

Along with geometric characteristics, people groups and exits are placed onto a plane to complete the modeling. The people groups placed on planes can be configured to randomly distribute people in the plane. The exits provide "goals" or "targets" for the people on the plane. The scoring, described above, is calculated in relation to the various exits available to the evacuee. The exits either provide a way for evacuees to leave the model (exit the building) or to move onto another plane (another floor). Exit routes that allow evacuees to leave the building would, for example, model an occupant leaving a floor, traversing the stairs, passing through a lobby, and leaving the building.

STEPS has two functions that are meant to model human behaviour. These are "patience", which drives how likely an occupant is to stand in a queue, and "families", which give the modeler the ability to specify that certain people will search out other people before leaving the building. Other than these two functions, the model does not simulate behavioral considerations explicitly. Rather, certain considerations can be modeled implicitly by incorporating delays and modified occupant parameters.

EXIT89

The EXIT89 program developed by Fahy[40] was intended to model evacuation of a large building with the ability to track the path of each occupant. The model uses traffic speeds dependent on flow densities as measured by Predtechenskii and Milinskii. The model can be used in conjunction with a zone model such as CFAST to incorporate the effects of fire and smoke spread on the occupants' evacuation behavior.

The model requires a network description of the structure, which includes the geometry of the compartments, openings between rooms, and the number of people located at each node of the building. The user must decide whether the occupants will evacuate at the first sign of fire or if they will delay some period of time. The decision process to evacuate or delay is implicitly handled as a time delay before the program begins to calculate the evacuation for a given occupant. The delay times are a user option and can be assigned to all occupants of a node or can be randomly assigned to individuals. Also considered in the model is whether the occupant will use the shortest route or nearest exit, or use a familiar route. To model the use of a familiar route, the user must specify the appropriate route for an occupant to follow; the shortest routes available are calculated by the model. Population and travel densities are based on body sizes, which are also user specified. Disabled occupants can be added, but are done by simply modifying the travel speed for that particular occupant and does not account for assistance from other occupants. The model does not simulate behavioral considerations explicitly. Rather, certain considerations can be modeled implicitly by incorporating delays and modified occupant parameters. Essentially, the model calculates a flow of people from one node to the next (modifying the

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[39] Mott MacDonald, "STEPS – Simulation of Transient Evacuation and Pedestrian movements, Users Manual", 2004, pp. 163.

[40] Fahy, R. F., *Development of an Evacuation Model for High-Rise Buildings, Volumes 1 and II*, Masters Thesis, School of the Built Environment Faculty of Engineering of the University of Ulster, December 1999.

speed of movement according to population density and environmental conditions) until all occupants have exited the building. This assessment will build upon previous validation efforts,[41] resulting in more explicit understanding of sources of uncertainty and appropriate methods for treatment thereof.

STUDY METHODOLOGY AND RESULTS TO DATE

As noted above, the research plan follows generally the methodology proposed by Notarianni. As used in this research program, a five-phase process is being used to carry out the study:

Phase 1: Construction of Base Models
Phase 2: Identification of Variables and Possible Values
Phase 3: Monte Carlo Analysis
Phase 4: Statistical Analysis of Computer Model Results
Phase 5: Identification of Significant Variables

PHASE 1: CONSTRUCTION OF BASE MODELS

STEPS and EXIT89 were used to model a 6-story (plus basement) office building in London, Ontario (the London building) and a 14-story apartment building in Calgary (the Calgary building), for which data was available from actual evacuations. 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.

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 who were present on each floor and their pre-movement times. 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.

STEPS also provided a good approximation of the travel time from the Calgary building. The actual evacuation time from the building was 790 seconds. Four initial STEPS simulations predicted total evacuation times of between 726 and 745 seconds. Simulation of the Calgary building with EXIT89 is ongoing.

PHASE 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 evacuation of the London and Calgary buildings. 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.

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[41] Fahy, R. F., "EXIT89 - High-Rise Evacuation Model - Recent Enhancements and Example Applications," *Interflam 96 Conference, 7th Proceedings*, 1996, Cambridge, pp 1001-1005.

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 1.

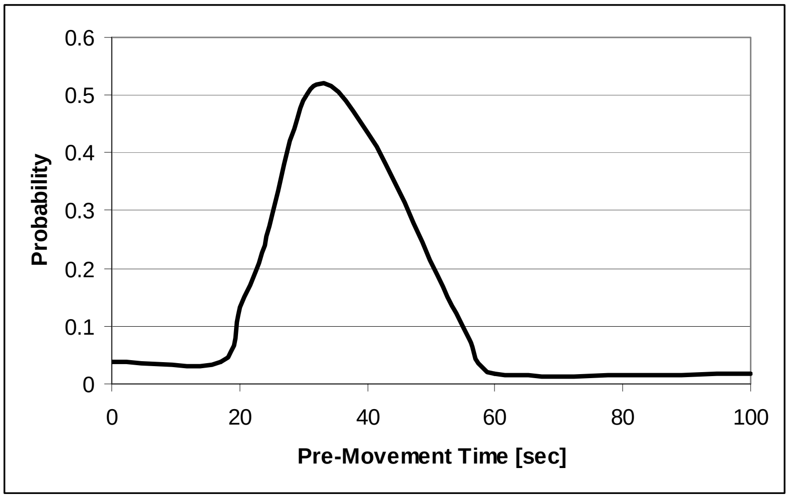

Figure 1: Sample Distribution Curve of Values for Pre-Movement Time (in seconds) for Occupants of Office Buildings. Formed from NRC "London Building" Data and Purser[42]

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 that is already available from different studies, but in varying formats. Some research has been done in the fields of risk management[43] and weather forecasting[44] 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 (which is different than the patience that is assigned to each type of person), 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. The effect of changing the grid size was tested during the Calgary building simulations, using grid sizes of 0.3m, 0.4m, 0.5m, and 0.6m.

Phase 3: Monte Carlo Analysis

For the efforts to date, Phases 3-5 have focused on STEPS. In Phase 3, 2000 STEPS input files were created and run using the Monte Carlo method for each of the buildings investigated. Variable values were randomly chosen from the distribution curves formed in Phase 2 of the analysis.

Phase 4: Statistical Analysis of Computer Model Results

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[42] Purser, D.A, "Quantification of Behaviour for Engineering Design Standards and Escape Time Calculations", *Human Behavior in Fire-Proceedings of the First International Symposium*, 31 August-2 Sept 1998.

[43] Clemen, R.T., Winkler, R.L, "Combining Probability Distributions from Experts in Risk Analysis", http://fisher.osu.edu/~butler_267/DAPapers/WP970009.pdf, October 22, 1997

[44] Clemen, R.T., Jones, S.K. & Winkler, R.L., "Aggregating forecasts: An empirical evaluation of some Bayesian methods", *Bayesian Statistics and Econometrics: Essays in Honor of Arnold Zellner*, 1996, pp. 3-13

The output from the STEPS simulations was analyzed using a method described by Notarianni[45]. A cumulative distribution function (CDF) was created to display the probabilities associated with an estimated evacuation time for the London building and for the Calgary building. This was accomplished by graphing each evacuation value against its rank, as displayed in Figure 2.

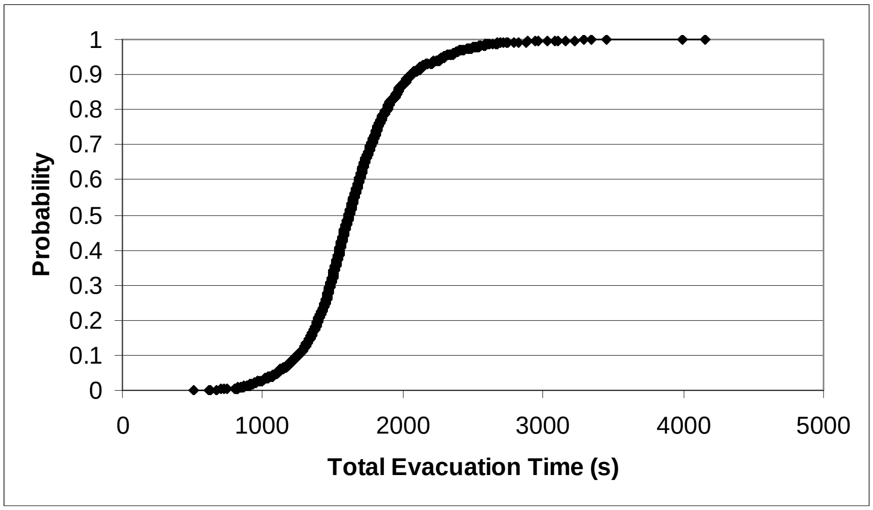

Figure 2: Cumulative Distribution Function of Total Evacuation Time (Calgary Building)

This graph provides the probabilities that are associated with a range of evacuation times. For example, according to this analysis, there is a 90% chance that it will take 2000 seconds or more to evacuate the London building. Therefore, if the acceptable level of uncertainty were 95%, it would be prudent to design fire/life safety systems for the building that could maintain tenable conditions for at least 2300 seconds.

PHASE 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 Phase 3. A sample of some analysis techniques is provided below, looking at the effect of varying occupant load on the total evacuation time from the Calgary building.

Sample Analysis - Occupant Load of Calgary Building

Figure 3 provides a CDF that reflects the effect of the total building occupant load on the total evacuation time for the Calgary building. The two series represent simulations with a low occupant load (0-25% of the maximum number of people simulated) and a high occupant load (75-100% of the maximum number of people simulated). This figure provides some insight into the effect of occupant load on total evacuation time. The general trend in the Calgary building, as one might expect, is that higher occupant loads result in higher total evacuation times from the building.

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[45] Notarianni, K. "The Role of Uncertainty in Improving Fire Protection Regulation", PhD Dissertation, Carnegie Mellon University, May 2000.

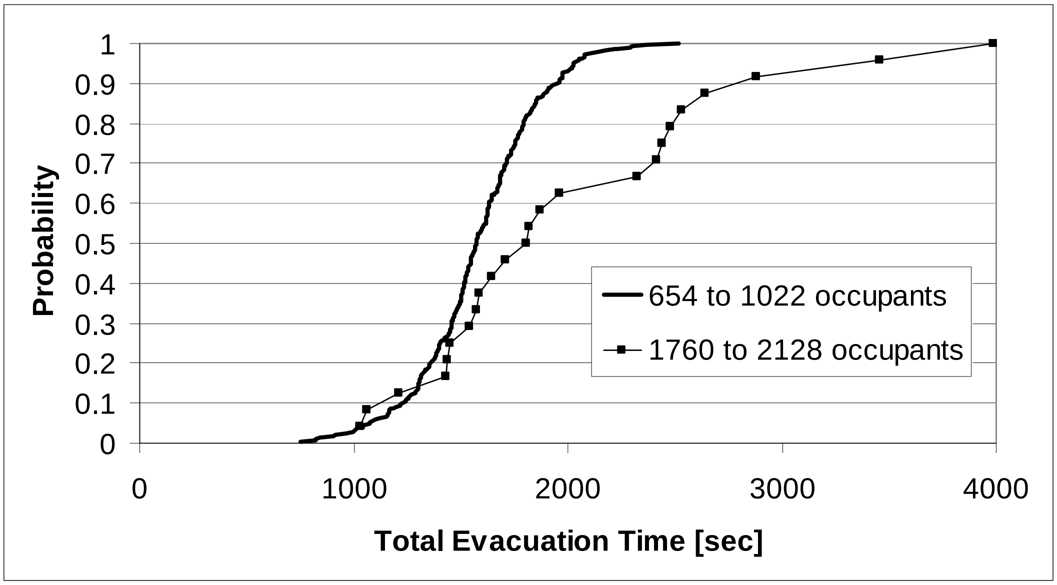

Figure 3: Cumulative Distribution Functions of Total Evacuation Time for Two Ranges of Total Building Occupant Loads (Calgary Building)

In addition, the graph in Figure 3 demonstrates that as we approach 90% to 100% certainty the effect of the occupant load on the total evacuation time for the Calgary building increases dramatically. An alternate method of displaying the data in Figure 3 is to graph the difference in the two series.

Figure 4 represents the difference in total evacuation times, subtracting the 0-25% of peak load (654 – 1022 occupants) series from the 75-100% of peak load (1760 to 2128 occupants) series. Figure 5 indicates that as the probability threshold increases, the effect of the occupant load on the total evacuation time increases rapidly. At the 95% certainty level, the difference between the low occupant load and the high occupant load in the Calgary building varied by almost 1500 seconds (25 minutes).

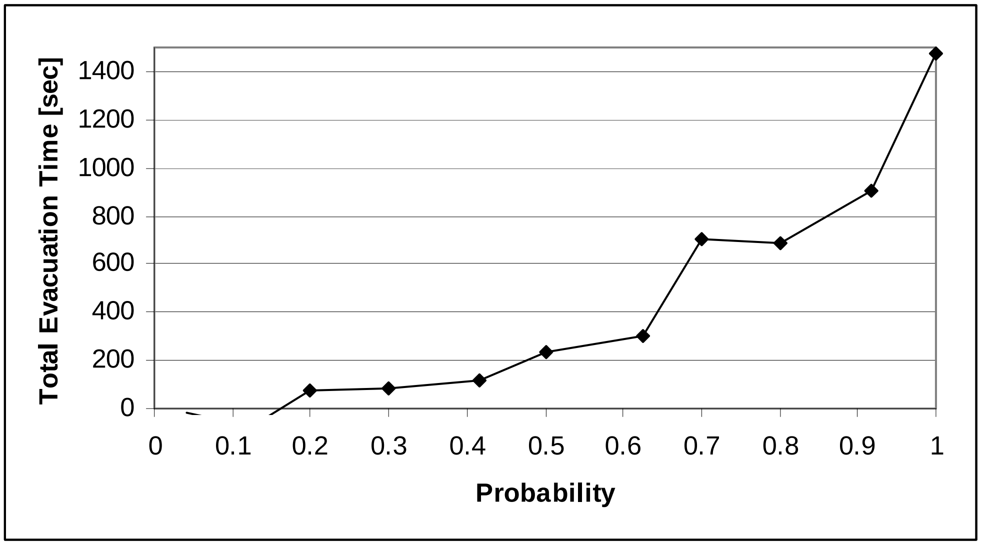

Figure 4: Sensitivity of Total Evacuation Time to Total Building Occupant Load

Evaluating Uncertainty Importance

In addition to the creation of CDFs, as shown above, useful information can be gained by evaluating the importance of each variable in relation to the total evacuation time (or any other quantity that is measured). Each variable's importance can be calculated on a scale from –1 to 1, where a correlation coefficient of 1 indicates a very strong direct correlation, 0 indicates no correlation, and –1 indicates a very strong inverse correlation.

The value of the correlation coefficient at which a variable becomes statistically significant can be calculated using the following equation:

$$t = \frac{c}{\sqrt{1-c^2}}\left(\sqrt{n-2}\right)$$

Where t is related to the confidence level, which is typically chosen as 95%[46], c is the statistical significance of the correlation coefficient, and n is the number of samples in the data set. For the London and Calgary buildings, both of which used sample sizes of 2,000, it was determined that correlation coefficients with an absolute value of 0.021 or less were statistically significant.

Table 1 provides the correlation coefficients that were calculated from the results of the London and Calgary building simulations. This table provides a partial list highlighting some of the more statistically significant variables.

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[46] Notarianni, K. "The Role of Uncertainty in Improving Fire Protection Regulation", PhD Dissertation, Carnegie Mellon University, May 2000.

In general, the individual variables showed less correlation to the total evacuation time in the London Building than in the Calgary building. Some variables correlated well to total evacuation time in the Calgary building, but not in the London building, suggesting that the importance of the variables in the egress models is tied to the geometry of the building. This hypothesis is somewhat enforced by the fact that the grid size, which was the one geometry-linked variable tested was the variable with the highest correlation coefficient. The effect of varying the grid size has not yet been tested for the London Building; this work will be completed as the study progresses.

Variable	**Correlation Coefficient**	
	Calgary Building	**London Building**
Grid Size	0.398	Not yet tested
Time Step	0.248	-0.034
Total Occupant Load	0.197	< 0.021 (not significant)
Pre-movement Time (top floor)	0.183	0.042
Walking Speed – Elderly Down Stairs	-0.121	-0.020
Walking Speed – Disabled Down Stairs	-0.099	Was not tested
Door Flow Rate	-0.052	-0.107
Number of People on Level 2	0.067	-0.046
Number of People in Basement	Not applicable	0.044
Patience of Elderly	< 0.021 (not significant)	-0.039
Queuing Coefficient	-0.026	-0.038
Randomness	0.056	-0.036

Table 1: Correlation Coefficients for Variables – Calgary Building and London Building

In some cases, increasing or decreasing the value of a variable might lengthen the total evacuation time in one building while having the opposite effect in the other. For example, the correlation coefficient for the time step was positive (0.248) in the Calgary building, indicating that an increase in time step correlated to an *increase* in total evacuation time; at the same time. The correlation coefficient for the time step in the London building was negative (-0.034) indicating that an increase in the time step would generally *decrease* the total evacuation time.

CONCLUSIONS

A study has been conducted to apply the method of Notarianni[47] to computer egress modeling. This method uses a Monte Carlo technique 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 and a 14-story apartment building in Calgary. A similar analysis is underway using the computer egress model “EXIT89”.

Preliminary findings appear to indicate that there is not necessarily a specific group of variables that is important for all building types. The significance of the variables seems to be case-specific and may be closely tied to the geometry of the building.

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[47] Notarianni, K. “The Role of Uncertainty in Improving Fire Protection Regulation”, PhD Dissertation, Carnegie Mellon University, May 2000.

Future work will involve the variation of grid size in the London building with the STEPS model, and completion of the method of analysis for both the Calgary building and the London building using EXIT89. Additional buildings will also be tested using this type of analysis to provide a large pool of data from which comparisons of variable importance can be made.