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Interfacing Building Response with Human Behavior Under Seismic Events

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Interfacing Building Response with Human Behavior Under Seismic Events

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SUMMARY
The goal of this paper is to model the interaction of humans with their built environment during and immediately following a natural disaster. The study uses finite element simulations to evaluate the response of buildings under input ground motions and agent-based dynamic modeling to model the subsequent evacuation of building occupants in the study area immediately following the seismic event. The structural model directly captures building damage and collapse, as well as floor accelerations and displacements to determine nonstructural damage, injuries and fatalities. The goal of this research is to make connections between building damage and occupant injuries, with geographic automata as the information handler for the agent-based platform. This research demonstrates that human behavior and evacuation patterns can be evaluated in the context of realistic structural and nonstructural damage assessments, and that prior knowledge of evacuation patterns is critical for adequate preparedness of cities to severe earthquakes.

Keywords: building evacuation, damage analysis, agent-based modeling

1. INTRODUCTION

This paper describes the development of a tool to assess evacuation from a typical commercial building after a seismic event, and a proposed connection of this model to a city level evacuation model. The proposed model integrates finite-element modeling of structural behavior, probabilistic modeling of non-structural damage and injury, and agent-based modeling of human evacuation behavior. Therefore, the effect of post-earthquake damage and injuries on overall evacuation of the system can be analyzed. Preliminary results are provided for a four-story office building in the Los Angeles region subject to the ground motions of the 1994 Northridge earthquake. Three scenarios are modeled for the building: evacuation of agents from an undamaged structure (as a baseline to which other scenarios may be compared), evacuation of healthy agents from a damaged structure, and evacuation of injured agents from a damaged structure. This single-building evacuation model can feed into regional post-disaster models to inform emergency planners and other local authorities who need vulnerability information about the infrastructure they manage.

2. EXISTING MODELING METHODS

The model described in this paper combines nonlinear dynamic analysis of buildings and agent-based modeling of human movement in an emergency. This combination can develop a more accurate evacuation model that integrates physical damage to a building with human behavior. This section provides an overview of some of the methods by which evacuation and structural damage have previously been modeled, as well as a brief summary of the fundamentals of agent-based modeling.

2.1. Existing Evacuation Models

One focus of this work is on modeling human movement throughout a damaged structure after a major seismic event. While a number of quantitative models have been developed for normal conditions

(Muramatsu et. al 1999; Willis 2004), rigorous treatment of panic and the effect of injury are less common. Early work in the area was performed mostly in the context of social physiology (Kelly et.al 1965). This has contributed to the level of complexity at these situations and to a lack of quantitative data. Therefore, mathematical models that simulate empirically observed human behavior are important to better understand the nonlinear dynamic interaction of humans in an emergency event, especially in a compromised physical setting. Henderson (1971) applied principles of fluid and gas flows to human movement in an evacuation. They applied the Maxwell-Boltzman equations under the assumption that particles are statistically independent, and then derived the probability density for the speed of each individual. They also conducted tests on real crowds. The recent advancements of computational power and software tools have led to a surge of proposed evacuation simulations that have been implemented by several research groups (Pelechano et.al 2005; Treuille et.al 2006). This work can be generalized into four main categories: cellular automata, agent-based modeling, social-force modeling, and analogy to fluid-flow modeling. Helbing et al. (2000) used an innovative social-force model to predict evacuation behavior in both normal and emergency conditions. Lakoba et al. (2005) modified and extended the model by Helbing et al. to account for situations with a very low population density or even an isolated individual. They also reported that these modifications prevented the overlap of people in the model. Burstedde et al. (2001) used a cellular automation methodology to model 2D pedestrian dynamics. Their model is also applicable to emergency conditions. Helbing et al. (2000) also used image-processing techniques to analyze videos of crowd evacuation at a specific location to verify the fluid mechanics analogy that has been widely used. They argue that the movement of individuals might transition from laminar to turbulent flow under some circumstances, and irrespective of population density, the average local velocity never goes to zero.

2.2. Accounting for Structural Damage

An archetypical low-rise steel-frame building, extensively studied by others (Foley et al. 2008; Gupta and Krawinkler 2000), was used in this study. The analyzed structure represents a typical low rise seismic steel building in US. All prevailing requirements for gravity, wind, and seismic design were considered. It was designed for a typical office occupancy live load of 2.5 kPa. The floors were assumed to support a dead load of 4 kPa, which included a concrete-steel composite slab, steel decking, ceilings, flooring, fireproofing, mechanical, electrical, and plumbing systems and partitions (1 kPa). The study building is three stories tall, has a 6-bay by 4-bay footprint, and includes two staircases (shown in blue in Figure 1) on opposite corners of the building for vertical egress. As evidenced in the recent Canterbury earthquake (EERI 2011), strong ground shaking can severely damage and even collapse staircases, compromising key exit routes. Additionally, severe damage and local collapse of buildings can directly impact human safety, cause panic, and force occupants to search for new exit routes. In addition to the failure of load-bearing structural components, damage and collapse of non-structural components (e.g., partition walls, suspended ceilings, and overturned furniture or equipment) can injure occupants and directly impact evacuation time.

2.3. Agent-Based Modeling

Agent-based modeling (ABM) is a bottom up computational model, where the dynamic behavior of a system is captured by modeling the autonomous components of the system based on properties and rules that govern the behavior of these individual pieces or *agents*. The overall behavior of the system emerges from the individual responses of the agents. Agent behavior is typically goal-oriented and includes the capacity to learn and modify the rules of response. Agent-based modeling has several applications, including economics, traffic, epidemics, molecular dynamics, and evacuation. Zarboutis et al. (2004) have employed this technique in modeling a metro tunnel evacuation during a fire emergency. Pan et al. (2007) have adopted this methodology to model evacuation during emergencies such as layout design of an office building. Their model is capable of representing emergent behavior such as queuing and herding. There are a number of software tools available to implement this modeling approach, and Railsback et al. (2006) provides a comprehensive review of the literature.

3. METHODOLOGY

This section describes the development of each of the sub-models and overall framework that comprise the entire evacuation model. It includes descriptions of the non-linear finite element modeling used to describe structural behavior, heuristic estimation of population, probabilistic modeling of structural damage, and agent-based modeling of human behavior.

3.1. Structural Analysis

Non-linear dynamic finite element (FEM) analysis is employed to simulate the response of the study building. The original seismic design was modified by moving one of the moment resisting frames (red line in Figure 1) from the perimeter to the interior of the building; this was intentionally done to induce more severe structural damage and to impact horizontal and vertical means of egress. The structural model is subjected to a historic strong ground motion, the 1994 Northridge Earthquake.

A large strain, piecewise linear, *material model 24* from the LS-DYNA (Hallquist 2006) library was employed to represent large strain steel material behavior. *Model 24* operates on true stress and logarithmic strain measures, thus accounting for large strains. Hughes-Liu beam elements, with plasticity and large deformation capabilities, were utilized to model the steel frame of the model steel building. The Hughes-Liu formulation is incrementally objective (rigid body rotations do not generate strains). Thus, it is suitable for simulations characterized by large strains and displacements. It also includes finite transverse shear strains. Both beam and column elements are capable of exhibiting a variation of strains and their corresponding stresses through the section. Thus, the Hughes-Liu formulation was able to model yield propagation through the section. Material failure was controlled by the prescribed value of the effective plastic failure strain. The element was deleted, when the average effective plastic strain of nine integration points was greater than the critical, prescribed value.

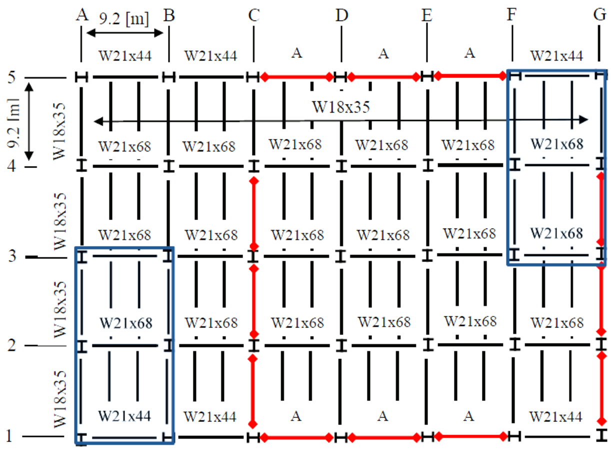

Figure 1. Building layout. Staircases are located in the south-west and north-east corners.

A lightly reinforced slab was employed in this study, and is represented by a 100 mm thick shell with the custom integration scheme. A steel material model was used for the bottom layer; whereas other layers were modeled using concrete material properties. An important structural element for the analysis of progressive collapse is the beam-column joint. Connections were represented with macro-models consisting of non-linear spring elements. The properties of the springs were calibrated against high-resolution finite element simulations (Lim and Krauthammer 2006). Spring representation is computationally efficient, yet it adequately captures the connection behavior. This approach is consistent with alternative macro-model methods (Khandelwal 2008; Sadek et al. 2011)

3.2. Non-Structural Analysis

The response of the structure allows for a straightforward damage analysis of both the structural and non-structural components. The response parameters from the FEM analysis, such as peak floor accelerations and interstory drift ratios, are directly used to estimate damage and collapse of structural components. However, non-structural damage cannot be captured directly from these simulations. Instead, fragility functions that describe the probability of reaching individual damage states for each building component are used to estimate damage and failure of these components. An overview of this damage analysis procedure is found in Mitrani-Reiser and Beck (2007).

3.2.1. Population Estimates

A reasonable estimate of the building's population must first be obtained to properly model the evacuation of the building and to capture the effect of building damage on human behavior. For this preliminary study, the population of the test structure is estimated according to provisions from ATC-13 (ATC 1985). These provisions predict the expected population of a structure per square foot as a function of occupancy type and the month, weekday, and time of day at which the earthquake occurs. It should be noted that these estimates are not dependent upon the region in which the earthquake occurs. To facilitate future estimation of building occupancy for a variety of building types and changes in timing of the earthquake, a graphical user interface was developed in MATLAB based on these provisions. For the building in this study, the population is estimated at 450.

3.2.2. Floor Plans

A floor plan representative of commercial facilities was developed for this study. Fire safety guidelines from Los Angeles and empirical data of office layouts were used to determine reasonable locations of glazing, partition walls, means of egress, and other non-structural elements. Layouts were developed for the ground floor and an upper-story floor. The latter layout is used to populate the nonstructural components of the remaining floor. Both furnished (i.e., desks, computers, etc.) and unfurnished versions of these plans were developed, but this preliminary study applies only the unfurnished version for the damage analysis. It should be noted that non-structural elements, such as wiring, piping, HVAC, etc., that are located behind ceilings and walls are assumed to have a consistent distribution over the entire structure. Unfurnished floor plans for all the stories are shown in Figure 2.

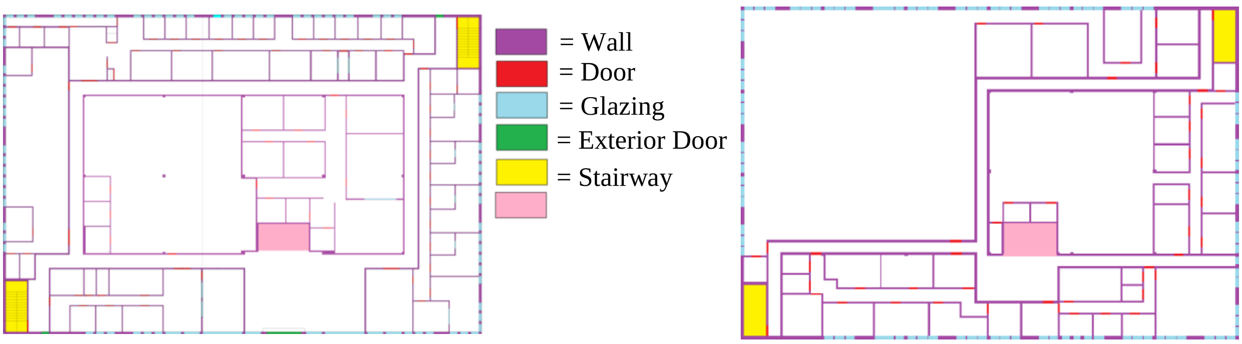

Figure 2: Floor plans of ground floor (left) and upper floors (right)

3.2.3. Fragility Functions

A fragility function describes the probability that a specific building component reaches or exceeds a specific damage state conditioned on a certain structural response parameter. Each damage state is typically correlated to a specific life safety level and/or repair effort. Examples of response parameters often used in fragility functions of building components include peak diaphragm acceleration (PDA), peak transient drift ratio (TD), residual interstory drift ratio (RID), and demand capacity ratio (DCR). The lognormal distribution is typically used to represent the fragility function of nonstructural component:

$$F_X(x) = \Phi\left(\frac{\ln(x/x_m)}{\beta}\right) \qquad (1)$$

where $\Phi(\cdot)$ is a standard normal CDF; x is a selected response parameter; and x_m and β are respectively the mean and logarithmic standard deviation capacity of the building component with respect to x. An example fragility function used in this study is plotted in , where the blue and red curves correspond to the probability of a glazing unit reaching or exceeding damage state one (i.e., cracking) or damage state two (i.e., fallout), respectively, for a given value of TD. The non-structural components considered in this preliminary study and the arguments of their fragility functions are shown in Table 1. The magnitudes of the corresponding response parameters are shown in Table 2.

Table 1: Fragility functions parameters for nonstructural components.

Assembly	Unit	Damage State	Response Parameter	x_m	β
Glazing	30 sf pane	Cracking	TD	0.040	0.36
	30 sf pane	Fallout	TD	0.046	0.33
Drywall partition	8'×8'	Visible damage	TD	0.0039	0.17
	8'×8'	Signif. damage	TD	0.0085	0.23
Acoustical Ceiling	One room	Collapse	PDA	$46/x_s$ [1]	0.80

Note: x_s = (ceiling length + width)/2, ft.; the result is in terms of gravity *g*.

Table 2: Key results from the structural analysis.

	1st floor	2nd floor	3rd floor	Roof
PDA (g)	0.9	1.7	2.9	3.4
TD	0.0308	0.0474	0.0346	N/A

3.2.4 Probabilistic Simulation of Damage States

The results from the FEM model and the fragility functions associated with each building component allow for the translation of structural response metrics to physical damage. The procedure is described using an example fragility function for glazing components. First, structural response values, which in this case are TD for each floor (shown as vertical lines in Figure 3) , are obtained from the FEM model. Then for each unit of glazing (30 sf pane) in the building, a random number is generated to represent the probability of its damage. This probability is extended horizontally across the plot of the fragility function (see dashed lines in Figure 3). The damage state of this unit is determined by the intersection of this horizontal line with the structural response values. For example, if U = 0.15 is sampled in one simulation for a unit of glazing on the first floor (see the horizontal black dashed line in Figure 3), then this component falls into the 'cracked' damage state because the intersection point between the black dash line and the vertical line of the 1st floor is between the blue curve (cracking) and the red curve (fallout). If the same random number is generated for glazing units on the 2nd and 3rd floors, these units would fall out because the intersection points fall below the red curve corresponding to the 'fallout' damage state. Now suppose for another unit of glazing the sampled random number U = 0.49 (see magenta dashed line in Figure 3). If this glazing unit is on the 1st or 2nd floors, it would experience no damage because they fall above the cracking fragility curve, but if it is on the 3rd floor, it would fall out.

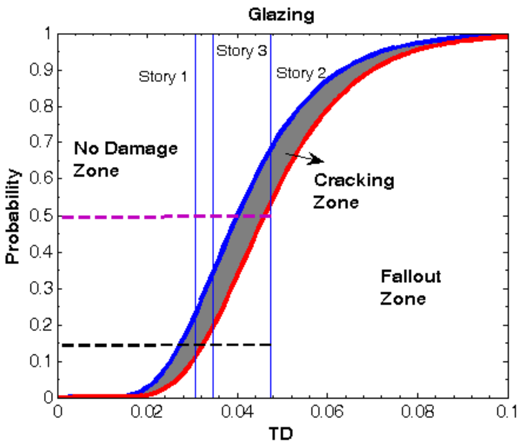

Figure 3: Example fragility curves for glazing units

A new random number is generated for each unit of the non-structural component, assuming that the damage states of individual units are uncorrelated. This step concludes once the damage states for all the components in the building have been established. The results from the structural and non-structural damage analyses completely describe the damage experienced by the study building under the impact of the scenario earthquake. The complete damage assessment is passed to the agent-based occupant model to study its impact on human safety (e.g., potential injuries and/or fatalities conditioned on building damage) and building evacuation. In this paper, the impact of uncertainties in the damage analysis is explored; future studies will include uncertainties in the hazard and the structural model.

3.3. Agent-Based Models

The final objective of this research is to understand, explain, and possibly forecast the evacuation of people from an urban area (i.e., Los Angeles) impacted by an earthquake, and the subsequent flow of people throughout buildings, the city, and into neighboring suburbs of the urban center. Ideally, the damage for each building in a region can be modeled using the structural and damage analyses steps described above. This information is then used as input for the agent-based model that describes the behavior of individuals, based on important social science considerations for evacuation behavior (Aguirre et al., 2011), in each facility and throughout the region of interest. The evacuation of individuals for the case study building is implemented in Netlogo program version 4.1.3. The agent-based model for a single facility consists of moving agents (people) and a stationery environment (physical office space). In this evacuation model, the moving agents interact with the stationary environment at each time step in pursuit of their goal, which is to evacuate the structure as quickly as possible. The results of each time step are used as the initial conditions for the following time step. The following sections explain the agent-based model in more detail.

3.3.1 Translation of Floor Plans and Damage to Agent-Based Models

The stationery environment (map) consists of a meshed grid (patches), and defines the coordinate system. Each patch in the model represents a 2-in. by 2-in. square, and contains information about the building component type (e.g., wall, hallway, furniture, etc.) physically present in that part of the building, as well as the story level. The accuracy of the location of each human or obstacle (damaged building component) in the horizontal plane is dependent on the spatial resolution of the mesh (i.e., size of the patches). Netlogo also allows for flexibility in the time scale, which is based on a tick counter where each tick is one unit of time; each tick in this model represents one second.

To effectively model evacuation of multi-story buildings, it is critical to accurately capture horizontal and vertical means of egress. The horizontal means of egress are unobstructed areas or passageways that lead the occupants from any point in the building to the vertical exit (i.e., stairway), a horizontal exit (i.e., into another building), or an outside exit (i.e., to a public way). The horizontal means of egress are represented by Netlogo patches (e.g., a patch designated as a door or a hallway), and are constrained by the floor plan for each story. The vertical means of egress are more challenging to track in Netlogo because agents move from one floor into a stairwell and then onto another floor. This model uses a vector space that allows the agents to interact and can track their locations in the building. The means of horizontal egress (e.g., width of unobstructed hallway) can be directly impacted by the earthquake damage. Therefore, evacuation results of damaged and undamaged states of the building are compared.

3.3.2 Casualties

In the single-building model, the probabilities of each agent being in a number of health states (i.e., healthy, suffering from minor or major injuries, or having suffered fatal injuries) can be specified by the user based on the damage state of the building; these probabilities are normalized within the model so they add to one. When each agent is created at the start of the simulation, that agent's health status is determined by generating a random number between zero and one. If the generated number is between 0 and X ,where X is the probability of a fatality, the agent is considered *dead*. If the generated number is between X and X+Y (where Y is the probability of major injury), the agent is designated as having *major injuries*. If the generated number is between X+Y and X+Y+Z (where Z is the probability of minor injuries), the agent has *minor injuries*. Otherwise, the agent is considered healthy. Healthy agents move at their full desired speed; agents that have minor injuries move at ¾ of the desired speed; agents with severe injuries move at $1/10$ of the desired speed; and dead agents do not move. If a healthy agent or an agent with minor injuries encounters an agent with major injuries, the healthier agent may choose to "rescue" the injured agent. The probability of this happening in any given encounter is again determined from user input. Under such circumstances, both agents move at half the speed of the healthier agent.

The probabilities for health states can be determined directly from the structural and damage analyses (Mitrani-Reiser and Beck 2007 and ATC-58 2012) when empirical data of fatality rates for specific building types are available. However, since fatality rates were not available for the study building, the initial probabilities for the agent's health states in the simulations were determined from the ATC-13 (ATC 1985) report on data for the estimation of earthquake loss in California. This report provides probabilities of major injuries, minor injuries, and fatalities conditioned on building damage states. The injury probabilities for the occupants in the test structure were modified to account for the alteration of the structural system; these modifications induce more damage and subsequently more complex dynamic human behavior in an evacuation. The probabilities of health states used in the damaged scenario are: 12% for minor injuries, 1.6% for major injuries, and 0.4% for fatal injuries. Note that these are an order of magnitude larger than those specified in ATC-13 for a steel moment-frame building subjected to the scenario earthquake.

3.3.3 Agent Navigation

It is assumed that most of occupants will follow exit signs in the building, and that their movement is analogous to fluid flow. The ground gradient is defined as a static field that describes the distance to the exits. The highest points on this gradient are the innermost exits, such as a door of an innermost room on the highest floor; the lowest points are the outmost exits, such as the main entrance or other gates on the 1st floor. For each agent, the physical damage is used as input to a perception module, which describes the agent's risk perception. This information ultimately feeds into the rational module that is central for agent decision making. Although the rational module of the agent follows simple rules, this module differs from agent to agent; this allows for heterogeneity in the model, which is not possible using systems dynamic modeling. Although it is assumed that a majority of occupants know the shortest path to an exit in the building from their current locations, some of them will not always choose this path. This could represent the individuals who are not regular occupants in the building.

Each agent is assigned a desired moving speed based on its age, gender and sampled health level after the earthquake. The agent moves to a neighboring patch based on the perceived risk from the environmental information (i.e., damage) and on the suggested behavior output from the rational module. In the rational module, the agent follows simple rules: (1) try to follow the static field, (2) avoid walking over other agents, and (3) avoid walking into walls and objects. The agent will execute the same procedure iteratively until it reaches its desired moving speed or cannot move any more.

3.3.4 Efficacy for Developing Probabilistic Distributions

Since the damage for a particular building component is uncertain for a given structural response, it is possible to run the evacuation model with different initial damage, which subsequently impacts the evacuation time. One method to assess the variability of the evacuation results is to run many Monte Carlo simulations. This methodology could also validate any observed emergent behaviors.

4. PRELIMINARY RESULTS

This section describes preliminary results of the evacuation model, which includes a detailed nonlinear dynamic analysis of a building, the subsequent damage and human injury/fatality estimation, and the resulting dynamic behavior of individuals attempting to evacuate under the realistic conditions expected from a seismic event. The results from this model show the power of combining engineering tools with human behavior research to better understand the dynamics of people immediately following a disaster when their decision-making is based on visual cues from their environment.

4.1. Structural Damage

This section describes the results of the FEM simulation of structure response to the 1994 Northridge earthquake. The input seismic motion resulted in the collapse of the first story slabs adjacent to the moment-resisting frame. The collapse is depicted in Figure 4. The weakened design (Figure 1) is not symmetric, and thus the seismic motions induced noticeable torsional twisting, which caused localized damage in the corners of the floor slabs. The south-west staircase failed on the second level. Building occupants were unable to exit the structure using this egress route (southwest). The other staircase (northeast) remained functional after the earthquake simulation and provided a viable alternative to the damaged staircase for occupants located in the western portion of the building. This highlights the importance of having egress redundancies in buildings. The building also experienced large displacements. The acceleration and displacement time histories are recorded at every *0.1 s* at multiple building locations. The peak accelerations and drifts are useful for the subsequent damage assessment. The maximum simulated inter-story drift is 4.8%, and the peak floor accelerations are 1.7 g (second-floor), 2.9 g (third-floor), and 3.4 g (roof-level).

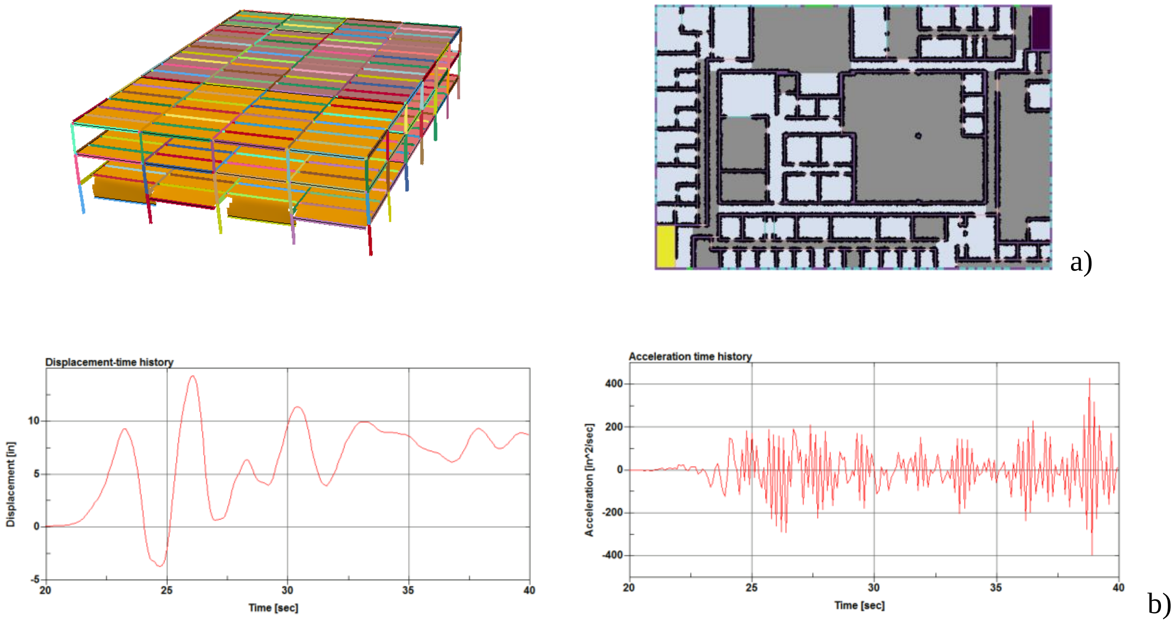

Figure 4. Example structural analysis results: a) seismic damage, b) acceleration and displacement time histories.

4.2. Non-Structural Damage

Figure 4a shows an example of the damaged floor plan used in the evacuation model. In the damaged area, the evacuees' speeds will decrease. For example, in the partition-wall-fallout area evacuees' speeds will decrease to 50% of their desired speeds, and in the acoustic-ceiling-damage area their speeds will decrease to 70% of their desired speeds. The reduction of desired speeds is based on expert judgement that mobility becomes disrupted in the damaged areas. It is also assumed that people are unable to enter the collapsed areas of the building. Future versions of this model will be improved with empirical data on evacuation through damaged spaces, corridors, and exits.

4.3. Agent-Based Evacuation

Three scenarios were chosen for the initial test of the agent-based model. In the first scenario, agents evacuate from an undamaged structure, as per a fire drill. This serves as a baseline to which other scenarios can be compared. In the second and third scenarios, the building is damaged according the structural and non-structure damage analyses, including the failure of the southwest staircase. The second scenario assumes all agents are unharmed, and are only impeded by the damage to the building. In the third scenario, the effect of human injuries is included. The agent based model was run 25 times for each scenario in this initial study.

For each run of the simulation under each scenario, the times at which agents evacuated were recorded. Sample time histories are shown in Figure 5. The average evacuation time for all 450 building occupants in the undamaged scenario was around 8 minutes. Hostikka et al. 2007 performed a fire disaster experiment in a four story office building, which found that the evacuation time for 139 people is around 6 minutes. Therefore, the simulation results are within an order of magnitude of empirically observed evacuation times.

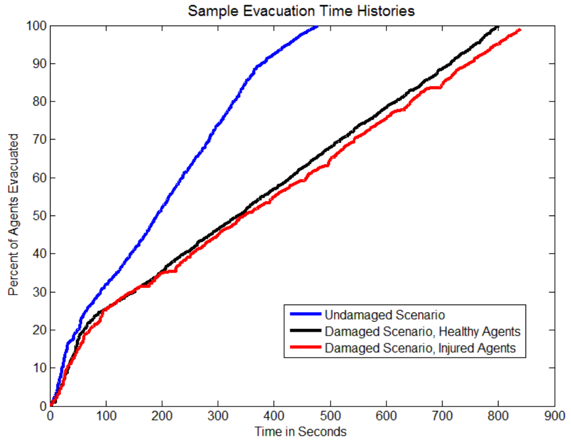

Figure 5: Sample time histories

As expected, the evacuation times were much longer for damaged scenarios than for the undamaged scenario, and slightly longer for the damaged scenario with injuries than for the damaged scenario without injuries. In all scenarios, the rate of evacuation was higher for first 20 to 50 seconds, during which time agents already close to the exits evacuated. The evacuation rate then remained fairly constant for until about 90% evacuation, as which point the rate of evacuation slowed down in the undamaged scenario only. The average evacuation times for all scenarios are presented in Table 3.

Table 3: Average Scenario Evacuation Times

Scenario	Undamaged	Damaged with Healthy Agents	Damaged with Injured Agents
Time to First Evacuation (seconds)	1.36	1.72	1.52
Time to 50% Evacuation (seconds)	186.7	331.1	350.7
Time to 100% Evacuation (seconds)	477.9	802.1	843.5*
Average Number of Deaths	N/A	N/A	2.1

* Note: This average excludes extra time added in some runs when one agent took much longer to evacuate than other agents. If this time is added in, the average 100% evacuation time becomes 906.2 seconds.

5. FUTURE WORK

Initial results indicate that this evacuation model provides reasonable estimates for evacuation times. Furthermore, it allows for the examination of the effect complex phenomena on evacuation trends. This tool can be applied to different structures and occupancies to model regional evacuation, which can then be connected to existing ABM models of healthcare systems, transportation, and other lifelines. From these integrated models, probabilistic functions of evacuation timing, injury rates, healthcare demand, and other types of disaster response can be developed. Such functions are crucial for healthcare providers, public health officials, and disaster managers, who must understand the expected human response to disasters to adequately prepare for them. This research is on-going, and future versions of the model will include more sophisticated and complex evacuation behaviors.

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