Available online at www.sciencedirect.com

Procedia - Social and Behavioral Sciences 00 (2019) 1–14

Procedia
Social and Behavioral Sciences

www.elsevier.com/locate/procedia

Conference on Agent-Based Modeling in Transportation Planning and Operations

Modeling Urban Transportation in the Aftermath of a Nuclear Disaster: The Role of Human Behavioral Responses

Abhijin Adiga[1], Madhav V. Marathe, Henning S. Mortveit, Sichao Wu, Samarth Swarup

Network Dynamics and Simulation Science Laboratory, Virginia Bioinformatics Institute, Virginia Tech, Blacksburg, VA 24061.
email:{abhijin,mmarathe,henning,sichao,swarup}@vbi.vt.edu

Abstract

This paper describes an integrated modeling environment for a large urban transportation system designed to capture human behaviors in the aftermath of an improvised nuclear device denotation. The integrated environment models the complex interplay of human behavior (under deteriorating health conditions) and infrastructural systems in the aftermath of such a hypothetical crisis. Prior work on this scenario has covered in detail physical and radiological effects of the blast, casualty estimates and impact on health, evacuation strategies, etc. assuming a static population distribution. Relatively few studies have accounted for how people respond to the event and the strong coupling that exists between the various infrastructural systems. This paper highlights the design aspects of the system concerning the transportation and behavior modules and their interactions. The transportation model incorporates dynamic network loading for auto and walk travel modes, group travel, crowd-following, as well as adjustments for *ambient traffic* to account for network loads caused by external agents. We present a collection of computational experiments offering insight into how different individual and collective behaviors of agents can affect evacuation times, route choices and health effects.

Selection and/or peer-review under responsibility of Chinese Overseas Transportation Association (COTA).

Keywords: Transportation, routing, constraints, sensitivity, stability, human behavior

1. Introduction

Large-scale natural and human-initiated disasters are a constant concern throughout the world. Over the past decade, planning and response to such contingencies have become key issues addressed by transportation research. Work in this area is to a great extent driven by the category of the disaster being studied which in turn determines other aspects such as the possibility of advanced warning, the extent of the damage as well as the level of uncertainty and fear that it evokes within the population. For example, a hurricane may affect a very large region while providing a long warning time. However, other events such as earthquakes and nuclear detonations provide no warning whatsoever. Modeling and simulation systems have been used to analyze the impact of such events on the population and transportation infrastructure under various evacuation strategies and restoration scenarios.

[1]Corresponding author. Tel: 540-231-1377.
Email address: abhijin@vbi.vt.edu

Here we focus on parts of a modeling environment employing disaggregated agent-based simulation methods to model the collective behavior after the detonation of a nuclear device in downtown Washington D.C. The population modeled in our study only captures those individuals located directly in the downtown area that was impacted which we refer to as the detailed study area, or DSA. Here, the entire system is composed of the following modules: human behavior, health, transportation, communication, electrical power, and infrastructure damage. An overview of the modeling environment is given in (Barrett et al., 2013), while the behavior, health and communication modules have been covered in (Parikh et al., 2013; Chandan et al., 2013). Here, we describe the transportation module and related aspects of the behavior module. We are interested in how the behavioral options of agents can affect route and mode choices as well as travel times which subsequently may influence health and network clearance time.

For the studied scenario, the prompt blast and radiation effects significantly damage the transportation system and cause power and communication failures. It impacts peoples' health which in turn impacts their behavior and mobility. Also modeled is the human reaction to this extreme event which includes behaviors such as panic, efforts to reach family members (household reconstitution), aid & assist, and attempts to evacuate. This in turn may lead to traffic congestion in certain routes, which may have an adverse impact on the health conditions due to continued radiation exposure and effects of blast. In (Parikh et al., 2013; Chandan et al., 2013), the impact of emergency broadcasts has been analyzed using this system. In (Adiga et al., 2012), a sensitivity analysis of the transportation module was performed with respect to ambient traffic density.

1.1. Related Work

During the last several decades, a number of computational models have been developed to analyze and evaluate emergency evacuation plans. Examples include NETVAC, DYNEV, MASSVAC, TEDSS, IMDAS, OREMS, CEMPS and so on; see (Pel et al., 2012) and references therein. Usually, these models assume that the traffic flow and the network characteristics are static, i.e. determined at the time of the impact. The network characteristics such as ambient traffic density and maximum travel speed may change substantially as a result of the crisis. Dynamic traffic management and control measures are introduced to incorporate these effects. For example, (Bish et al., 2013) studied the staging and routing strategies which attempt to manage travel demand in order to reduce or eliminate congestion, while (Kim & Shekhar, 2005) consider contraflow, or lane reversals, as a potential remedy to solve the tremendous congestion by increasing outbound evacuation route capacity. Some other dynamic simulation models integrate decision support systems. For instance, (Lindell & Perry, 2012) consider the processing of information derived from social and environmental cues. In addition, to simulate traffic conditions on a transportation network in case of evacuation, it is unavoidable to make assumptions on how travelers may behave. As a result, psycho-behavioral research techniques are also included in this types of situations, see (Parikh et al., 2013; Pel et al., 2012; Flötteröd et al., 2012; Lambert et al., 2012; Parlak et al., 2012) as examples. For an overview of research in evacuation modeling and simulation and current trends, see the recent survey by (Murray-Tuite & Wolshon, 2013) and the references therein.

After the 9/11 attack, considerable attention has been focused on plans for sheltering or evacuating the population of the U. S. national capital region in response to a human-initiated emergency such as a dirty bomb attack. A lot of researchers have conducted simulation experiments on such improvised nuclear disasters, and past studies have focused on physical and radiological effects of the blast, effect on human life based on static geographic distribution of population and evacuation policies and strategies (Buddemeier et al., 2011; Wein et al., 2010; Dombroski & Fischbeck, 2006; K., 2011; Homeland Security Council Interagency Policy Coordination Subcommittee, 2009). However, these studies ignore the effects of human behavior and response to the event. Some other simulation models endow agents with traits based on psychological models, though they have not included infrastructural aspects (Pelechano et al., 2005; Pelechano & Badler, 2006; Barrett et al., 2012). As a matter of fact, human behavior and various infrastructural systems are coupled, that is to say, damage to infrastructure such as buildings and roads influences population mobility and behavioral responses that could result in an increase in travel time. On the other hand, the impact of citizen's actions creates a load on infrastructural systems that can also lead to traffic congestion. To the best of our knowledge, few modeling efforts consider the strong coupling that exists between mass behavior and critical infrastructures such as transportation, communication and power.

1.2. Experiments and results

We considered the impact of three behavioral options (a) household reconstitution (HHR) with group travel (GT), (b) crowd-following (CF) behavior and (c) travel mode constraints. Household reconstitution means that the members of a household seeks to unite after initially being separated. Once reunited (fully or partially), members of the household may travel together as a group to accomplish their next goal. Crowd-following refers to the behavior where individuals or groups choose route segments involving roads with larger densities of pedestrians. In the travel mode choice experiments, we studied the effect of assigning different mode choices to agents. Two common metrics were used to quantify the impact of each of these behaviors: (1) the number of agents who evacuate the DSA, and (2) their health status as a function of time elapsed after the event.

Our computational experiments suggest that the HHR behavior can have a significant impact on route choices of agents and in turn, evacuation time and health. One main factor contributing to this outcome is that agents, especially in the absence of information, tend to stay longer in the DSA and even worse, move towards ground zero to unite with family members. Clearly, this action leads to more radiation exposure as well delay in evacuation. Our findings are consistent with those of (Chandan et al., 2013) where the same simulation system was used to study the effect of restoring communication rapidly, informing and instructing people about the event through emergency broadcasts.

In the CF experiment, we observed that increasing the inclination of agents to follow links with higher pedestrian densities, makes people take the less optimal route in terms of travel time and therefore longer evacuation times which matches intuition. Also, we observed that the greater the inclination, the higher the number of heavily loaded links. However, these are preliminary studies, and in future work it would be more meaningful to incorporate additional quantitative validation steps.

In the travel mode choice experiments, some agents were assigned more flexible mode choices than the existing ones and the effect on travel times and route assignments were observed.

Paper outline. In Section 2, we give a more careful outline of the scenario and the overall simulation model. This is followed by a detailed description of the transportation model in Section 3 covering the network construction, router and delay computations. Some more details of the human behavior module follow in Section 4. The computational experiments investigating the impact of household reconstitution behavior, group travel, crowd-following and mode choice with our findings are described in Section 5.

2. Overall System Description

2.1. Scenario

The scenario is based on the work of Buddemeier et al. (Buddemeier et al., 2011) and Wein et al. (Wein et al., 2010). A hypothetical nuclear detonation occurs at ground level on a working day at 11 a.m. in downtown Washington D.C. on the corner of 16th and K Street NW. The blast covers a circular area from ground zero and the radioactive fallout cloud spreads mainly eastward and east-by-northeastward. The simulation model focuses on the population inside the *detailed study area* (DSA) shown in Figure 1. The immediate effects of the blast include human casualties which occur due to burns, prompt radiation sickness, trauma from blast and falling structures and significant damage to infrastructure such as buildings, roads, communication and power systems. Even after these initial blast effects have tapered off, health conditions deteriorate and casualties occur due to fallout contamination and radiation sickness. The entire simulation model seeks to answer questions such as how human behavior and various policies affect the number of lives saved.

2.2. System Model

Synthetic population. A synthetic population of the Washington DC Metro Area is constructed based on the work of (Barrett et al., 2010) and (Beckman et al., 1996) with extensions to include transient populations (such as tourists or business travelers) and dorm students. It is created based on statistical samples and distributions of relevant demographic variables and contains information about home locations and daily activity patterns. The total size of the population in this region is over four million. In our simulations however, we limit our attention to the people in the DSA at the time of impact, a population of 730, 833 agents, see (Parikh et al., 2013).

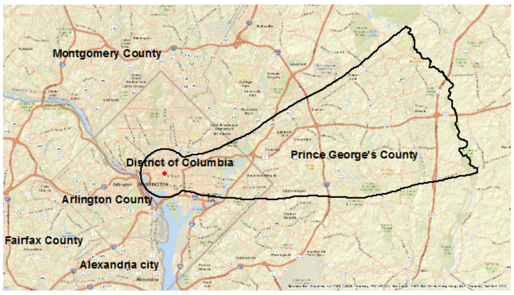


Fig. 1: The detailed study area (DSA) region which includes ground zero and the fallout path.

Overall system description. The system provides a highly detailed modeling environment to deal with the complex scenarios involving impact to infrastructures, individual behavior and recovery & restoration policies. The system is constructed from the following modules: human behavior, health, transportation, communication, infrastructure damage & restoration. Here, we briefly describe all the modules and how they interact with each other. Later, we will address the transportation and behavior modules in detail. Some of the significant interactions between the modules are illustrated in Figure 2.

Agents' actions are determined by the behavior model. There are several behavior options available such as household reconstitution, evacuation, seeking shelter inside a building to avoid radiation, and health-care seeking. Each option is associated with an action. For example, if the agent chooses household reconstitution, he or she may choose to make a call to ascertain the safety of the family member or try to reach the person's location, whereas a shelter-seeking behavior will prompt the agent to move to the nearest shelter location. To ascertain the health and family status for each agent, the behavior module takes input from the health and communication modules, while agents' actions affect the transportation and communication modules.

The health module takes into account not only the immediate effects of the blast, but also the cumulative radiation exposure to fallout cloud and injuries suffered while moving over the damaged landscape to assess the health. This means that the route taken and time delays impact the agent's health. Therefore, the health module takes input from the transportation module and in turn influences the behavior module. For more details of this model the reader is referred to (Parikh et al., 2013).

Agents who choose to travel for any of the reasons mentioned above are routed from their source to the destination by the transport module. Note that due to damage to roads, every such trip request may not be possible. The transport module uses a label constrained shortest path algorithm to route agents. Also implemented are features such as dynamic network loading, crowd following behavior and ambient traffic density which influence the route selection and travel time.

The communication module, which governs aspects of agents' communication capabilities and calling success, is covered in (Chandan et al., 2013). It also takes into consideration certain critical factors such as power availability in cell towers and the ability to make emergency broadcasts which can have a huge impact on the simulation outcomes.

Simulation procedure. The simulation process is a composition of the above described modules. The simulation proceeds in time steps or *iterations*. The first six iterations each correspond to 10 minutes of simulated time, that is, the first hour is simulated with a resolution of 10 minutes. Each of the remaining iterations cover 30 minutes. This is a data- and compute-intensive simulation system. The simulations were run on a large 60 node multi-core cluster. One complete run (around 125 iterations) takes about 35 hours and requires a few TB of space.

3. The transportation model

A general schematic of the transportation model is illustrated in Figure 3. There are two main aspects to the model: (a) The construction of the transportation network and (b) the routing of agents over the resulting network. The network is constructed in an offline process detailed in Section 3.1. It remains

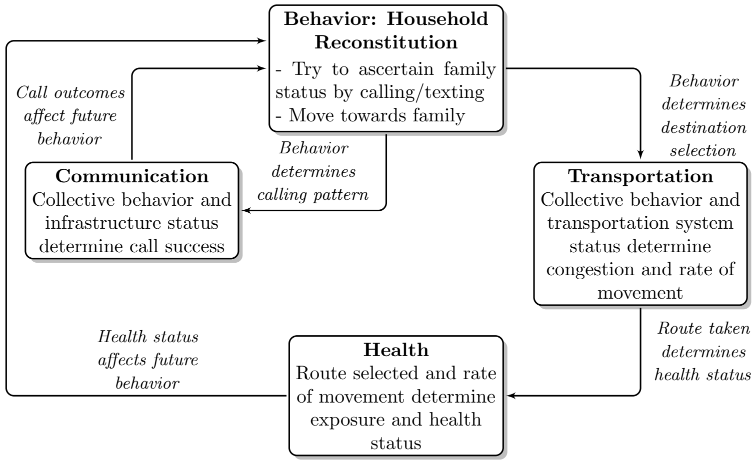


Fig. 2: A schematic of the overall simulation system with all the prominent modules and their primary interactions. (courtesy (Parikh et al., 2013)).

unchanged throughout the simulation except for delays on links which can be affected by dynamic loading. In each iteration the transportation module queries a database which keeps track of the current data for the agents. A *trip request* is constructed for each agent whose current location and desired destination are different. It is a triple specifying the source, the destination, and the travel mode. The source and destination are network nodes, and the travel mode specifies whether the agent has access to an automobile or not. The model permits group travel where an agent may follow a leader, in which case, the trip request for the agent will match that of the leader. Using the network and the delay information on each link, the router computes the route corresponding to the trip request. The route is specified as a path of nodes and links labeled by travel mode.

3.1. *The transportation network*

The transportation network is constructed in an offline process as a union of several networks. The networks included in this case were: (a) Road data (NAVTEQ) (b) Bus route data from the Washington Metropolitan Area Transit Authority (WMATA) and (c) Metro data (WMATA). From these three networks, we construct a synthetic network for walking by adding two links in either direction for each road link. Under normal circumstances, it may be unreasonable to permit walking on a highway, but for the scenario considered, allowing this seems like a fair assumption. We also include a bi-directional walk link between each WMATA bus/metro node to the nearest road node to allow for travel on all networks. We note that even though one may walk on any road link, the opposite is not necessarily true. The three networks above and the walk links are combined and this gives us the undamaged transportation network. The network has around 50,000 nodes and 230,000 links. At the end of this process, each network edge has the following key attributes: the physical distance between its end nodes, the mode of travel, and the speed limit of the link. In the case of an auto link, the speed limit is as given by NAVTEQ and for the walk links, the default speed is 3 miles/hour (mph). For all other links the speeds were estimated.

Modeling damage. The damage due to the blast is quantified using *displacement* and *rubble* data estimates provided to us by project collaborators. Here displacement measures the difference in ground level before and after the detonation while rubble measures the amount of debris present after this. The displacement d varies roughly in the range $-54m \leq d \leq 0.3m$. Based on the combined values of displacement and rubble, an affected link is either completely or partially damaged. The impact on travel speeds and link delays are specific to the mode of transportation (e.g., auto or walk) and the damage level modulates the mode-specific speed on the link. For example, the damage level impacts an auto link more than the corresponding walk link. If a link is sufficiently damaged, it cannot be used for any travel. We remark that the sensitivity analysis in this paper does not involve travel on bus or metro lines.

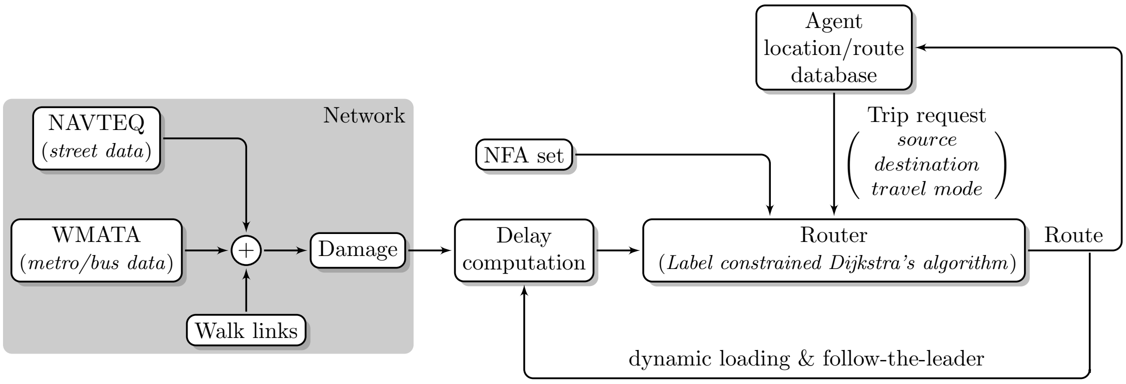


Fig. 3: The transportation model encompasses network construction, modeling damage due to impact of the detonation (left) and label constrained route construction over this network (right). The database is the interface between the transportation and other modules.

3.2. Routing

The route assigned to an agent depends not only on the link delays but also on what travel mode options are available. Also, we need to account for the fact that it is not easy to switch modes arbitrarily. To take these into consideration, the routing is based on a *regular language constrained shortest path algorithm*, see (Barrett et al., 2007). It is defined formally below.

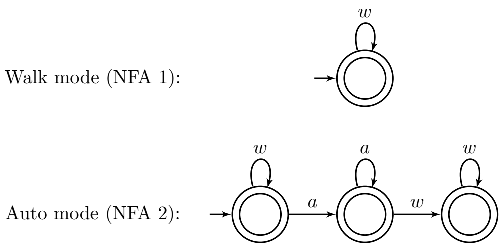
Regular-expression constrained route construction. Given an alphabet Σ (in our case, mode of travel on each link), the router takes as input (1) a network whose edges have weights or delays and are Σ-labeled, (2) a regular grammar $L \subseteq \Sigma^*$ and gives the shortest path between source and destination complying with the additional constraint that the word obtained by concatenating the labels of the path in their natural order belongs to L. The algorithm is an extension of the classical Dijkstra's algorithm on an appropriately defined product network.

Methodology. A trip request consists of the triple (source, destination, travel mode). The source and destination correspond to two nodes on the transportation network. In the current study there are two default modes (or regular grammars) for travel: auto and walk. These are not to be confused with labels on links. Assume that there is at least one route from the specified source to destination. If an agent requests a trip with "walk" mode, then the router assigns a route with only walk links. If the agent requests "auto" mode, the router can assign routes involving both auto and walk links. However, the following restriction is applied to the route assigned for this mode: The route links should follow the regular expression $w^*a^*w^*$ in their natural ordering from source to destination. This means for example, the routes (*waaaww*) or (*aaaaa*) are valid while (*waawa*) is not. This is under a fair assumption that in a trip, after abandoning or leaving an automobile, an agent will not have access to the same or a different automobile until he or she reaches the destination. These restrictions on routes are specified as *non-deterministic finite automata* (NFA) and are a part of the input to the router module. The NFAs corresponding to the travel modes described above are illustrated in Figure 4a. There are two other possible modes – bus and metro – that are not used because we assume that those services come to a halt inside the DSA region after the blast.

3.3. Computing link delay

As discussed in Section 3.1, the *free flow speed*, i.e. the speed in the absence of load, is set based on the the travel mode (auto or walk), speed limits and number of lanes. Additionally, the model incorporates dynamic link delays reflecting the current loads on the links and ambient traffic density. These features will be described in the remainder of the section.

Ambient traffic density. The *ambient traffic density* ρ accounts for the population (several million) of the DSA surrounding region that will be present on the transportation network inside the DSA. In our model, it corresponds to the background automobile traffic of individuals outside our synthetic population, and in the simulation it affects only the "auto" links. We assume that this density is a constant over the iterations.



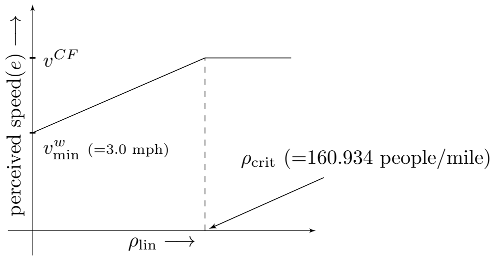


Fig. 4: Some important features concerning route selection and delays: (a) Travel modes assigned as NFA's to agents which determine the route assigned and (b) Effect of crowd-following phenomenon implemented as perceived increase in walking speed proportional to load (see (3.4)).

However, we use separate ρ-values for the links inside the DSA (ρ_{in}) and the links outside the DSA (ρ_{out}). The ambient density of a link e is denoted $\rho(e)$ and equals either ρ_{in} or ρ_{out}, respectively. Both ρ_{in} and ρ_{out} are between 0 and 1. We expect ρ_{in} to be smaller than ρ_{out} as most of the ambient traffic is expected to occur outside the DSA region.

3.3.1. Dynamic network loading

In the simulation process, loads on links are computed for each iteration and the load in the i^{th} iteration affects the delay in the $(i+1)^{\text{th}}$ iteration. The load impacts the walk and auto modes differently. In the auto mode, the load is used to model traffic congestion and therefore, greater the load, greater the delay. In the walk mode, it is used to model *crowd-following behavior*; higher the load on a link, greater is the propensity to choose that link. Denoting the load, length and free flow speed on the link e by $\lambda(e)$, $l(e)$ and $v(e)$, respectively, the delays taking into account the ambient traffic density and dynamic network loading is computed as follows:

Delay on an "auto" link. Let the free flow delay on a link e be denoted by $t_f(e) = l(e)/\text{speed}(e)$. The link is divided into cells, each of size equal to the average distance around an automobile of 7.5 meters as done in the TRANSIMS model (Barrett et al., 2001). Let cells(e) and lanes(e) denote the number of cells and number of lanes on e. The effective car count during the current iteration is computed as

$$\text{cars}(e) = \text{cells}(e) \times \rho(e) \times \text{lanes}(e) + \lambda(e) \times \frac{t_f(e)}{T_{\text{prev}}}, \tag{3.1}$$

where T_{prev} is the duration of the previous iteration. In the above equation, the first and second terms correspond to the ambient traffic density and dynamic network loading respectively. The factor $\frac{t_f(e)}{\text{T}_{\text{prev}}}$ denotes the fraction of time an automobile would have traveled on e during the previous iteration under free flow conditions. The effective background density is computed as:

$$\rho_{\text{eff}} = \frac{\text{cars}(e)}{\text{cells}(e) \times \text{lanes}(e)}\ . \tag{3.2}$$

Finally, the delay on the link is computed as

$$t(e) = \frac{t_f(e)}{1 - \rho_{\text{eff}}}\ . \tag{3.3}$$

3.3.2. Crowd-following behavior

It is well-observed that when faced with uncertainty people tend to follow the actions of others. Some of the explanations for this behavior are social proof, i.e. "if lot of people are doing the same thing, then, they must know something we don't", herding behavior (Pan, 2006) and sense of security. This phenomenon reaches extreme proportions in building evacuation when people blindly push through a narrow exit with devastating consequences. Hence, it has been a subject of extensive research. In our scenario, however, we assume that links always have enough capacity and therefore, increased density does not lead to increased delay for the walkers.

In our model we bias walking links with many travelers to capture the crowd-following phenomenon. We have minimal and perceived maximal walk speeds $v^w_{\min}$ and v^{CF}, respectively. On a walk link with no other travelers, an individual will walk with speed v^w_{min}. As the linear density of walkers increases, the walking speed is increased and is capped at v^{CF}. However, this only influences the choice of the route. Once a route is assigned, the delays are adjusted corresponding to the minimal walk speed $v^w_{\min}$. The detailed computation to determine the perceived delay on a walk link is done by first estimating the fraction $f(e)$ of time spent on the given link as

$$f(e) = \min\left\{1, \frac{l(e)}{v^w_{min} T_{prev}}\right\} ,$$

and then by determining the linear traveler density along the walk link as

$$\rho_{\text{lin}} = \frac{\lambda_e(t-1)}{l(e)} \times f(e) .$$

Here $\lambda_e(t-1)$ is the number of walkers on the link in the previous iteration. Next, the *perceived walking speed* is computed as

$$\text{perceived speed}(e) = v^w_{\min} + (v^{CF} - v^w_{\min}) \times \min\left\{1, \frac{\rho_{\text{lin}}}{\rho_{\text{crit}}}\right\} \tag{3.4}$$

where ρ_{crit} is the density parameter value at which maximal walking speed is realized; it is kept a constant equal to 160.934 people per mile in the system. This is illustrated in Figure 4b. Finally, the delay is determined as

$$t(e) = \frac{l(e)}{\text{perceived speed(e)}} . \tag{3.5}$$

4. The Behavior Model

The behavior model is responsible for selecting an action for each individual at each iteration. An action involves moving (a destination has to be specified) and calling (a callee has to be specified) and is selected in a two step process. First a high-level behavioral "option" is selected. Second, this option specifies action selection as a short program that takes into account the agent's state and the state of its environment. Six high-level behavioral options are modeled: *household reconstitution*, *evacuation*, *shelter-seeking*, *healthcare-seeking*, *panic*, and *aid & assist*.

Formally, the behavior model is specified as a decentralized Semi-Markov Decision Process (dec-SMDP) (Goldman & Zilberstein, 2004) using the framework of options (Sutton et al., 1999). We discuss this class of models below, though it should be noted that we are, at present, not doing any optimization. Thus, the individual agents are not trying to find *optimal* policies. They operate with fixed policies that embody our best guess, based on the literature, of how people might behave in the event of such a disaster.

A decentralized MDP is a multi-agent version of the standard MDP, where each agent observes a subset of the full state of the system. If the agents have a way of combining their observations (through communication, e.g.,), then the full state is available to them, and they can learn and plan in essentially the same way as in a standard MDP. However, this is not the case in our simulation.

Note that in these models, all actions are atomic, that is each action takes exactly one time step to execute, and each agent must make a decision at each time step which action to execute next. This is insufficient for specifying realistic high-level behavior. For example, we may want to specify that an agent looks for a family member until some other condition is met (he finds the family member, or gets a phone call from them, or he gets injured, etc.). To incorporate this level of description, we can include the notion of *options*, which are temporally abstracted actions. In particular, an option is specified by a triplet: $opt = \langle \pi : S \times A \to [0, 1], \beta : S^+ \to [0, 1], I \subseteq S \rangle$ (Sutton et al., 1999), where π is a single-agent policy which specifies a fixed policy to be followed until termination condition β is met. An option is available in a state s if $s \in I$. S and A are the sets of states and actions respectively. A decentralized *semi*-Markov Decision Process is a dec-MDP which includes options.

While the scale of the simulation is prohibitive for doing optimization using reinforcement learning in the standard way, it should be noted that we are keeping track of agent health, which provides a natural reward signal. A second desired outcome for an agent would be the safety of his/her family members. Thus, knowledge that household members are safe could be considered a component of a reward signal as well.

In order to specify our aforementioned six high-level behaviors as options, we have to specify their initiation conditions, the action selection mechanism for each option, and their termination conditions. Complete details are given elsewhere (Parikh et al., 2013). Here we present the initiation conditions, since those will form the basis of an experiment.

We use the decision tree shown in Figure 5 to choose between options for each agent. A small number of conditions are used to narrow down the set of applicable options, after which a probability distribution is specified over those options. It should be noted that, while the behaviors themselves are based on the literature (Guterbock et al., 2011; Lasker, 2004; Lasker et al., 2007; Liu et al., 2012; Perry & Lindell, 2003; Sherman et al., 2011), actual probabilities are hard to find, and are mostly set as best guesses by us. Some of the high-level assumptions embodied in this decision tree are:

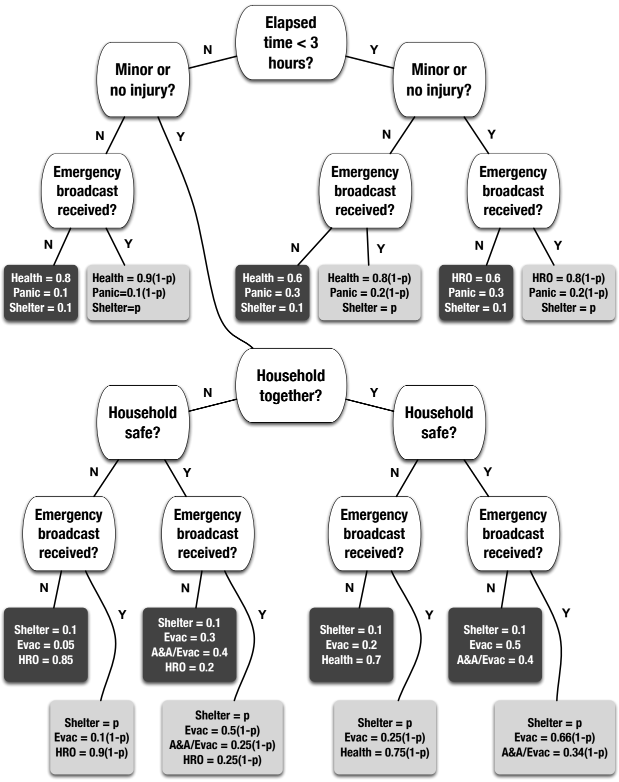


Fig. 5: The decision tree for choosing between high-level behavioral options in the baseline case, i.e., with household reconstitution and group travel on.

- Panic naturally subsides in ~3 hours.
- People who receive emergency broadcasts advising taking shelter are more likely to do so. We have made this number a parameter, p, though in the present work, we assume $p = 0.5$ throughout.
- People who are injured or otherwise in poor health (due to radiation exposure, e.g.,) are more likely to seek healthcare.

- People who aren't in poor health will try to seek out their household members (in person as well as through phone calls).

We also assume that people who find their family members travel together with them thereafter. Also, people who are aiding others (in the aid & assist behavioral option) transport them to the nearest healthcare centers. We refer to these two phenomena as "group travel".

In prior work on modeling this scenario, the focus has been on the relative benefit of sheltering vs. evacuation (Wein et al., 2010). While this is an important question, it doesn't take into account natural human inclinations to seek family members (Drabek & Boggs, 1968; Liu et al., 2012) and to assist others in distress (Perry & Lindell, 2003). The question we ask now is, what changes in outcomes happen due to these two behaviors? Our approach to this problem is to modify our simulation to turn off group travel. This leads to a modified decision tree, as shown in Figure 6.

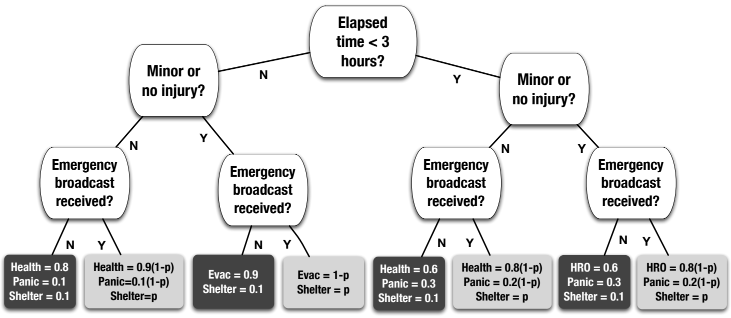


Fig. 6: The reduced decision tree for choosing between high-level behavioral options, obtained by turning off household reconstitution and group travel.

We conducted a simulation for each decision tree and Section 5.1 covers in detail the experiment setup and our inferences.

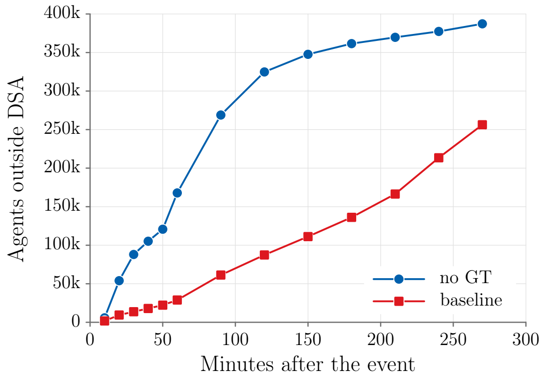
5. Experiments and results

We designed three experiments; (1) household reconstitution (HHR & GT), (2) crowd-following behavior (CF) and (3) travel mode choice, each intended to study the effect of a specific behavioral option on evacuation times and health of the population inside the DSA. For comparison we used a common baseline scenario which corresponds to HHR & GT enabled, the walking speed $v^{w}_{\min} = 3$mph, the crowd following bias $v^{CF} = 3$mph (see Figure 4b) and mode choices auto and walk which correspond to NFAs 1 & 2 respectively in Figure 4a. The assignment of modes depends on the agent's location. In the baseline case, if the agent is in the damaged area, then only walk mode is assigned and if outside the damaged area, with probability $p_1 = 0.4$ we assign walk mode and with remaining probability $p_2 = 0.6$, auto mode (where the indices correspond to NFA numbers).

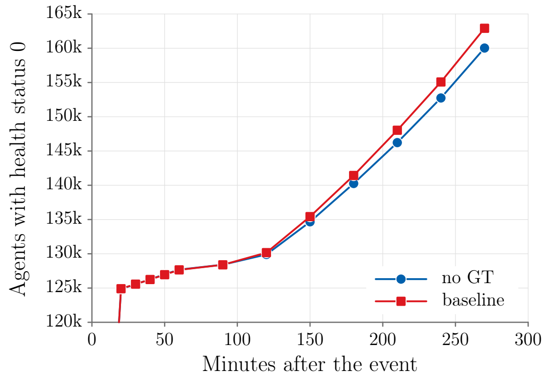
The parameters of communication, health and infrastructure damage modules are fixed throughout the experiments. We used the following common metrics for comparison: (1) The number of agents outside the DSA region and (2) the number of agents dead or average radiation exposure (of agents outside one-mile radius) at the end of each iteration. In addition, depending on the experiment, we also looked at distance traveled and distribution of load on links as was relevant to the experiment.

5.1. Household-reconstitution and group travel

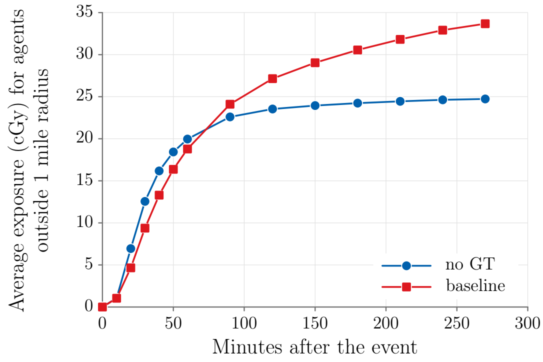
In this experiment, we compared two scenarios; with and without HHR & GT. The first case is the baseline scenario which corresponds to the first tree (Figure 5) while the latter corresponds to Figure 6. The results are shown in Figure 7. The primary observation from Figures 7a and 7c is that when HHR & GT are disabled, we obtain a much more optimistic estimate of the rate at which people evacuate the area and the health state of the agents respectively. It is easy to see that the two figures are related; the



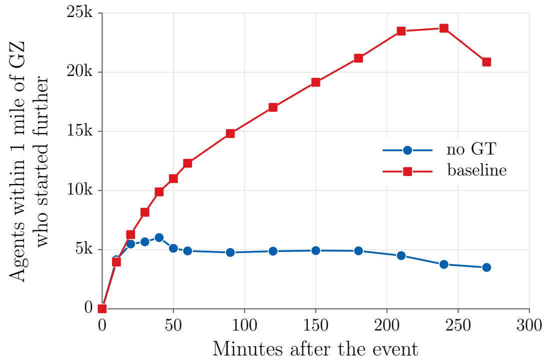
(a) Number evacuated.



(b) Number dead.



(c) Average exposure.



(d) Number who approached within 1 mile.

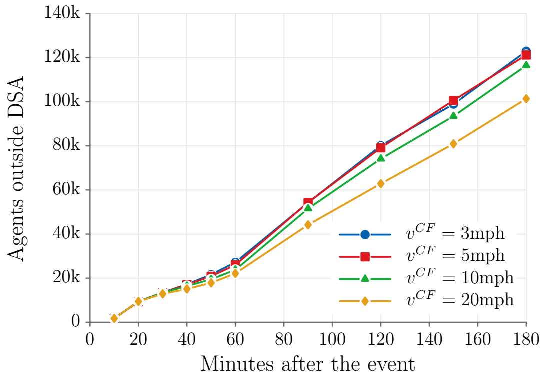
Fig. 7: Household reconstitution and Group travel experiments: A comparison of outcomes of simulations with and without the HHR & GT feature.

earlier the agents move out of the DSA, the lesser the exposure to radiation. Figure 7d throws more light on this outcome. It looks at how many agents who were initially outside of one-mile radius of ground zero approached within this area in each iteration. We see that, in the base case the numbers are significantly higher. Clearly, this implies that these agents are trying to approach their household members and therefore risking exposure and delayed exit out of the DSA.

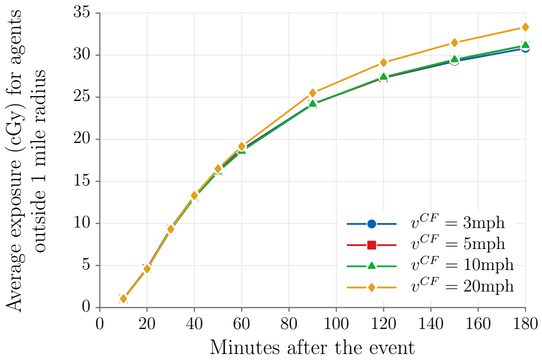
We seek to explain our findings by viewing our transport module as a selfish router. Let us for the time being ignore dynamic loading and crowd-following behavior. We note that without HHR & GT, agents are on their own and in this case their best response to the event is to move out of the DSA. In this scenario, the transportation module assigns to each agent the route with the least delay on the empty network. However, with these behaviors enabled, the aim of the agent is to still move out of the DSA, but subject to certain constraints. In this case, the transportation module allocates the best possible route on the empty network, but with the added constraint that the route must visit a particular node (which happens to be the location of a family member or a health care facility).

5.2. *Crowd-following behavior*

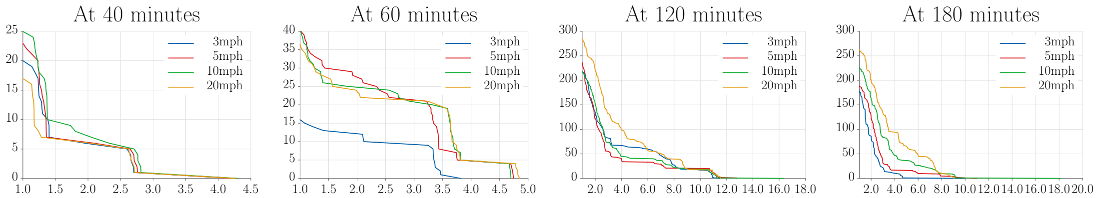
The modeling of crowd-following phenomenon for the walk mode was described in Section 3.3.2 and illustrated in Figure 4b. We considered four maximal perceived walking speeds v^{CF} = 3, 5, 10 and 20mph where 3mph corresponds to no CF. As in the previous experiments, we have plotted its effect on evacuation times and average exposure in Figures 8a and 8b respectively. In addition, we have also plotted a distribution of heavily loaded links at the end of particular iterations (or time steps) to show how the loads evolve with time in Figure 8c. The general trend is that higher the v^{CF}, greater is the number of highly loaded



(a) Number evacuated.



(b) Average radiation exposure.



(c) Load distribution at different time steps: The y-axis corresponds to number of links with load $\geqslant x \times 10^3$ value.

Fig. 8: Crowd-following behavior: a comparison of outcomes for different perceived speeds (v^{CF}).

links as well as the load on them. However, this is not true at all time steps and can be attributed to the fact that the mass movement evolves in different ways.

We note that in all our experiments, the agents were assigned shortest routes possible based on mode choice, network loads and background traffic conditions. This means that from an agent's perspective, the base case (v^{CF} =3mph) corresponds to the scenario where he/she is aware of the best possible route to the preferred destination. In the other cases, the agent prefers to take a route more traveled than the optimal one. Hence the increase in travel times. As noted earlier, these are preliminary results and require rigorous validation.

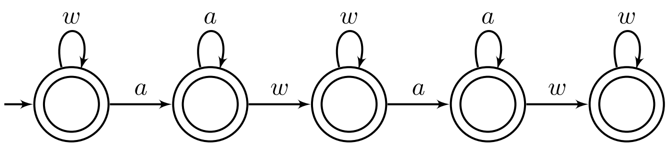
5.3. Travel mode constraints

In this section, we present results from an experiment involving one more mode choice, the "two-segment auto mode" specified by the third NFA in Figure 9a. If an agent is assigned this mode, it implies that in the particular trip, the agent may have an option of two automobiles in an assigned route. In our experiments, p_1 remains the same as in the base case. If the agent is outside the damaged area, then, with probability $0 < p_3 \leq 0.6$ we assign the two-segment auto mode and with the remaining probability ($p_2 = 0.6 - p_3$), we assign the auto mode. The results are in Figures 9b and 9c for $p_3 = 0.3, 0.6$; $p_3 = 0$ corresponds to base case. We note that there is not much difference in the outcomes and our simulations seem to be robust to reasonable changes in mode choice.

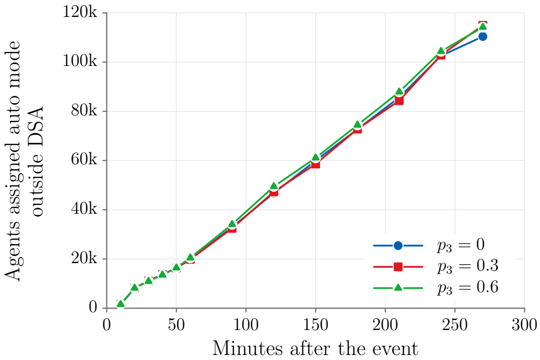
Acknowledgments We thank our external collaborators and members of the Network Dynamics and Simulation Science Laboratory (NDSSL) for their suggestions and comments. This work has been partially supported by the following grants: DTRA Grant HDTRA1-11-1-0016 NSF NetSE Grant CNS-1011769, NSF SDCI Grant OCI-1032677, NIH MIDAS Grant 2U01GM070694-09, and DTRA CNIMS Contract HDTRA1-11-D-0016-0010.

References

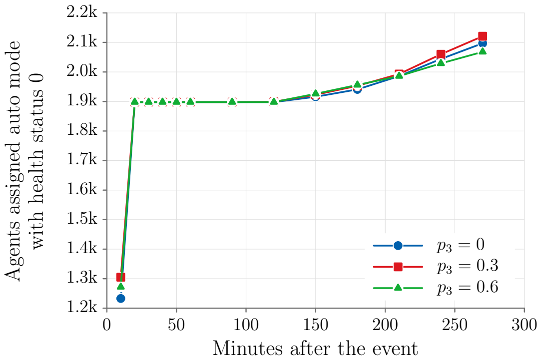
Adiga, A., Mortveit, H. S., & Wu, S. (2012). Route stability in large-scale transportation models. In *Workshop on Multiagent Interaction Networks, AAMAS'13*.



(a) Two-segment auto mode (NFA 3)



(b) Number evacuated.



(c) Number dead.

Fig. 9: Mode choice: A comparison of outcomes.

Barrett, C., Beckman, R., Berkbigler, K., Bisset, K., Bush, B., Campbell, K., Eubank, S., Henson, K., Hurford, J., Kubicek, D. et al. (2001). Transims: Transportation analysis simulation system. *Los Alamos National Laboratory Unclassified Report*, .

Barrett, C., Beckman, R., Channakeshava, K., Huang, F., Kumar, V., Marathe, A., Marathe, M., & Pei, G. (2010). Cascading failures in multiple infrastructures: From transportation to communication network. In *Critical Infrastructure (CRIS), 2010 5th International Conference on* (pp. 1–8). IEEE.

Barrett, C., Bisset, K., Chandan, S., Chen, J., Chungbaek, Y., Eubank, S., Evrenosoglu, Y., Lewis, B., Lum, K., Marathe, A. et al. (2013). Planning and response in the aftermath of a large crisis: an agent-based informatics framework. In R. Pasupathy, S.-H. Kim, R. H. A. Tolk, & M. E. Kuhl (Eds.), *Winter Simulation Conference*. WSC.

Barrett, C., Bisset, K., Jacob, R., Konjevod, G., Marathe, M. V., & Wagner, D. (2007). *Label constrained shortest path algorithms: An experimental evaluation using transportation networks*. Technical Report Technical report, Virginia Tech (USA), Arizona State University (USA), and Karlsruhe University (Germany).

Barrett, C., Channakeshava, K., Huang, F., Kim, J., Marathe, A., Marathe, M. V., Pei, G., Saha, S., Subbiah, B. S., & Vullikanti, A. K. S. (2012). Human initiated cascading failures in societal infrastructures. *PloS one*, *7*, e45406.

Beckman, R., Baggerly, K., & McKay, M. (1996). Creating synthetic baseline populations. *Transportation Research Part A: Policy and Practice*, *30*, 415–429.

Bish, D., Sherali, H., & Hobeika, A. (2013). Optimal evacuation planning using staging and routing. *Journal of the Operational Research Society*, .

Buddemeier, B. R., Valentine, J. E., Millage, K. K., & Brandt, L. D. (2011). *National Capital Region: Key Response Planning Factors for the Aftermath of Nuclear Terrorism*. Technical Report LLNL-TR-512111 Lawrence Livermore National Lab.

Chandan, S., Saha, S., Barrett, C., Eubank, S., Marathe, A., Marathe, M., Swarup, S., & Vullikanti, A. K. S. (2013). Modeling the interaction between emergency communications and behavior in the aftermath of a disaster. In *Social Computing, Behavioral-Cultural Modeling and Prediction* (pp. 476–485). Springer.

Dombroski, M. J., & Fischbeck, P. S. (2006). An integrated physical dispersion and behavioral response model for risk assessment of radiological dispersion device (RDD) events. *Risk Analysis*, *26*, 501–514. URL: `http://dx.doi.org/10.1111/j.1539-6924.2006.00742.x`. doi:`10.1111/j.1539-6924.2006.00742.x`.

Drabek, T. E., & Boggs, K. S. (1968). Families in disaster: reactions and relatives. *Journal of Marriage and the Family*, *30*, 443–451.

Flötteröd, G., Chen, Y., & Nagel, K. (2012). Behavioral calibration and analysis of a large-scale travel microsimulation. *Networks and Spatial Economics*, *12*, 481–502.

Goldman, C. V., & Zilberstein, S. (2004). Decentralized control of cooperative systems: Categorization and complexity analysis. *Journal of Artificial Intelligence Research*, *22*, 143–174.

Guterbock, T. M., Lambert, J. H., Bebel, R. A., & Parker, M. W. (2011). *NCR Behavioral Survey 2011: Work, School or Home? Issues in Sheltering in Place during an Emergency*. Technical Report Center for Survey Research, University of Virginia.

K., M. (2011). Modeling the effects of nuclear weapons in an urban setting. In *Radiation countermeasures symposium An AFRRI 50th Anniversary Event*.

Kim, S., & Shekhar, S. (2005). Contraflow network reconfiguration for evacuation planning: a summary of results. In *Proceedings of the 13th annual ACM international workshop on Geographic information systems* (pp. 250–259). ACM.

Lambert, J. H., Parlak, A. I., Zhou, Q., Miller, J. S., Fontaine, M. D., Guterbock, T. M., Clements, J. L., & Thekdi, S. A. (2012). Understanding and managing disaster evacuation on a transportation network. *Accident Analysis & Prevention*, .

Lasker, R. D. (2004). *Redefining Readiness: Terrorism Planning Through the Eyes of the Public*. Center for the Advancement of Collaborative Strategies in Health, New York Academy of Medicine. URL: http://books.google.com/books?id=dvfgGgAACAAJ.

Lasker, R. D., Hunter, N. D., & Francis, S. E. (2007). *With the Public's Knowledge, We Can Make Sheltering in Place Possible*. New York, NY: New York Academy of Medicine. URL: http://books.google.com/books?id=PUHQMwAACAAJ.

Lindell, M. K., & Perry, R. W. (2012). The protective action decision model: theoretical modifications and additional evidence. *Risk Analysis*, *32*, 616–632.

Liu, S., Murray-Tuite, P., & Schweitzer, L. (2012). Analysis of child pick-up during daily routines and for daytime no-notice evacuations. *Transportation Research Part A: Policy and Practice*, *46*, 48–67. URL: http://dx.doi.org/10.1016/j.tra.2011.09.003. doi:10.1016/j.tra.2011.09.003.

Murray-Tuite, P., & Wolshon, B. (2013). Evacuation transportation modeling: An overview of research, development, and practice. *Transportation Research Part C: Emerging Technologies*, *27*, 25–45.

Pan, X. (2006). *Computational modeling of human and social behaviors for emergency egress analysis*. Ph.D. thesis Stanford University.

Parikh, N., Swarup, S., Stretz, P. E., Rivers, C. M., Lewis, B. L., Marathe, M. V., Eubank, S. G., Barrett, C. L., Lum, K., & Chungbaek, Y. (2013). Modeling human behavior in the aftermath of a hypothetical improvised nuclear detonation. In *Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems* (pp. 949–956). International Foundation for Autonomous Agents and Multiagent Systems.

Parlak, A. I., Lambert, J. H., Guterbock, T. M., & Clements, J. L. (2012). Population behavioral scenarios influencing radiological disaster preparedness and planning. *Accident Analysis & Prevention*, *48*, 353–362.

Pel, A. J., Bliemer, M. C., & Hoogendoorn, S. P. (2012). A review on travel behaviour modelling in dynamic traffic simulation models for evacuations. *Transportation*, *39*, 97–123.

Pelechano, N., & Badler, N. I. (2006). Modeling crowd and trained leader behavior during building evacuation. *Computer Graphics and Applications, IEEE*, *26*, 80–86.

Pelechano, N., O'Brien, K., Silverman, B., & Badler, N. (2005). *Crowd simulation incorporating agent psychological models, roles and communication*. Technical Report DTIC Document.

Perry, R. W., & Lindell, M. K. (2003). Understanding citizen response to disasters with implications for terrorism. *Journal of Contingencies and Crisis Management*, *11*, 49–60.

Sherman, M. F., Peyrot, M., Magda, L. A., & Gershon, R. R. M. (2011). Modeling pre-evacuation delay by evacuees in World Trade Center towers 1 and 2 on September 11, 2001: A revisit using regression analysis. *Fire Safety Journal*, . URL: http://dx.doi.org/10.1016/j.firesaf.2011.07.001. doi:10.1016/j.firesaf.2011.07.001.

Homeland Security Council Interagency Policy Coordination Subcommittee (2009). *Planning guidance for response to a nuclear detonation*. Technical Report.

Sutton, R., Precup, D., & Singh, S. (1999). Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning. *Artificial Intelligence*, *112*, 181–211.

Wein, L. M., Choi, Y., & Denuit, S. (2010). Analyzing evacuation versus shelter-in-place strategies after a terrorist nuclear detonation. *Risk Analysis*, *30*, 1315–1327.