Emergency Response Planning for a Potential Sarin Gas Attack in Manhattan using Agent-based Models

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ABSTRACT

In this paper, we describe the agent-based modeling (ABM), simulation and analysis of a potential Sarin gas attack in the Port Authority Bus Terminal in the island of Manhattan in New York city, USA. The streets and subways of Manhattan have been modeled as a non-planar graph. The people at the terminal are modeled as agents initially moving randomly, but with a resultant drift velocity towards their destinations, e.g., work places. Upon exposure and illness, they choose to head to one of the hospitals they are aware of. A simple variant of the $LRTA^*$ algorithm for route computation is used to model a person's panic behavior. Information about hospital locations and current capacities are exchanged between adjacent persons, is broadcast by the hospital to persons within its premises and is also accessible to persons with some form of radio or cellular communication device. The hospital treats all persons reaching its premises and employs a triage policy to determine who deserves medical attention, in a situation of over-crowding or shortage of resources. On-Site Treatment units are assumed to arrive at the scene shortly after the event. In addition, there are several probabilistic parameters describing personality traits, hospital behavior choices, emergency responder actions and Sarin prognosis.

The modeling and simulation were carried out in Java RePast 3.1. The result of the interaction of these 1000+ agents is analyzed by repeated simulation and parameter sweeps. Some preliminary analyses are reported here, and lead us to conclude that simulation-based analysis can be successfully combined with other techniques to go hand in hand with traditional table-top exercises (as war-games) and can be used to develop, test, evaluate and refine public health policies governing catastrophe preparedness and emergency response.

Keywords

Agents, chemical terrorism, urban catastrophe, RePast, LRTA*

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1. INTRODUCTION

New York University's Center for Catastrophe Preparedness and Response (CCPR) was founded in the wake of the cataclysmic terrorist attacks on the World Trade Center in New York city. As part of its Large Scale Emergency Readiness (LaSER) project, mathematical models of the dynamics of urban catastrophes are being developed to improve preparedness and response capabilities. The need for emergency response planning has been reinforced by the recent string of natural calamities and controversies over the non-implementation of suggested plans (for example, see the Katrina disaster predicted and analyzed well-before the event [13]). It has been repeatedly observed that "disaster planning is only as good as the assumptions on which it is based" [4]. Conventional policy planning relies largely on war-gaming, where the potential disaster scenario is enacted as a table-top exercise, a computer simulation or an actual full-scale rehearsal using actual resources and players.

ABM for Disaster Management

Agent Based Modeling (ABM) is a recent technique that has seen an increasing number of applications in the last few years [2]. Even a simple agent-based model can exhibit complex emergent patterns of behavior and can provide useful information about the dynamic of a real-world system [6]. Multi-agent-based modeling is a relatively recent approach for simulating disasters, with its specific advantages in aiding planning efforts still open to discussion.

The first scenario we investigated was the 1998 food poisoning of a gathering of over 8000 people at a priest's coronation in Minas Gerais, Brazil leading to 16 fatalities [5]. Multi-agent modeling was explored for this problem by allowing simplistic hospital and person agents to interact on a 2-dimensional grid representing the Brazilian town [10]. Counter-intuitive and unanticipated behaviors emerged in the extremely parameter sensitive dynamics, immediately suggesting a potential use for such agent-simulation-based analysis of catastrophes. In this context, this paper provides a more thorough and practical example of how a large-scale urban catastrophe can be modeled, how real data about maps, subways and hospitals can be integrated, how person, hospital and first responder behavior can be modeled, and how simulations can be analyzed to yield tangible non-trivial inputs that a team of expert policy makers can utilize.

Specifically, we picked the nerve gas agent Sarin and the city of Manhattan to demonstrate our tools and techniques. Our choice was based on the literature available about a similar attack executed in Matsumoto in 1994 and in Tokyo in 1995 [11, 12, 7]. More importantly, by altering the parameters describing the conditions after the attack and the prognosis, the scenario can easily be extended to any nerve / chemical agent, bomb explosion or food poisoning involving a one-time exposure. Communicable diseases, radiological releases and events requiring evacuation or quarantine can also be modeled similarly, though they have more complex evolution.

2. WHY STUDY SARIN IN MANHATTAN?

2.1 Sarin and other Nerve Gas Agents

Sarin is an volatile odorless human-made chemical warfare agent classified as a nerve agent [12, 7].Nerve agents diffuse because of air currents, sink to lower areas and can penetrate clothing, skin, and mucous membranes in humans. Though Sarin presents only a short-lived threat because of quick evaporation, clothing exposed to Sarin vapor can release Sarin for several minutes after contact.

2.2 Sarin Attacks in Japan

The Aun Shinrikyo cult members initiated Sarin gas release in Matsumoto, Japan on June 27/28, 1994 leading to 7 deaths and injuring over 200.A larger scale attack was executed, less than a year later, on March 20, 1995. The location was a portion of the Tokyo subway system where three train lines intersected and the time was morning rush hour when the subway was extremely crowded with commuters. Following the attack, all commuters voluntarily evacuated the stations. Emergency Medical Services (EMS) were notified 14 minutes after the event. Police blocked free access to subway stations within an hour. The Japanese Self Defense Forces decontaminated subway stations and trains, and confirmed Sarin as the toxic-agent, three hours after the attack. This 1995 terrorist attack led to 12 fatalities and about 5,500 sickened people [11]. The kinds of questions that analyses can try to address become clear when some of the problems faced in this scenario are considered. These include: (1) overwhelming of communication system, (2) mis-classification and delayed characterization of attack agent, (3) secondary exposure, (4) shortage of hospital resources, (5) lack of mass casualty emergency response plan, (6) absence of centralized coordination, (7) overwhelming of medical transportation system.

2.3 Increased Preparedness in Manhattan

The sensational terrorist attack on the Twin Towers of the World Trade Center on November 11, 2001 has made New York city an accessible urban location for analyzing the problems with the Emergency Response system, warranting well-funded research programs to aid policy development and evaluation. Manhattan, a 20 square mile borough of New York city, is an island in the Hudson River accounting for 1.5 out of the 8 million residents and about 2.9 out of the 8.5 million daytime population. For many reasons, besides the fact that it has become a target of terrorist attacks, Manhattan poses many challenges, serving as an excellent testbed for verifying assumptions and refining policies about response to large-scale disasters in urban settings: namely, its geographical isolation, tremendous population density (e.g., a day-time population almost double that of the resident population), extensive public transportation system including subways, buses, trains and ferries, its almost vertical structure, its renowned linguistic, ethnic, and socioeconomic diversity, its asymmetric distribution of medical facilities, its proximity to nuclear and toxic-chemical facilities, its ports and airports as an international point of transit and entry, etc. (The model can be seen in *Figure* 2.3. The color code employed is: person – green(health=1.0), red (health=0.0); hospital/responder – unused (white), inactive (grey), available (blue), critical (pink), full (orange). The streets are black and the subways have the New York subway color codes.)

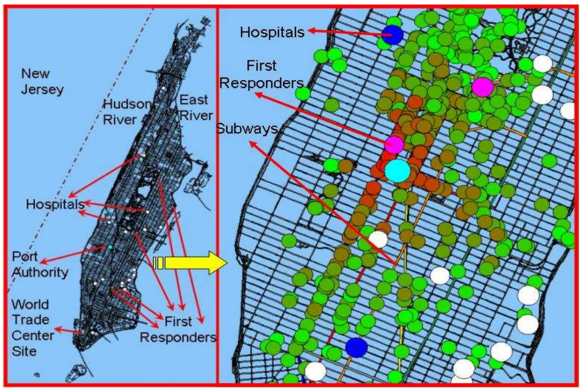

Figure 1: Snapshots of the Manhattan model

3. MODELING THE SARIN ATTACK

In this section, we describe the different aspects of our model, the sources of information, the assumptions, the computational approaches and algorithmic issues. Most behavior is probabilistic and most parameters are normalized and initialized uniformly in the range $(0, 1)$.

3.1 Manhattan: Topology and Transportation

We pick the 42nd Street Port Authority Bus Terminal,one block west of Times Square, as the site of Sarin attack. On a typical weekday, approximately 7,200 buses and about 200,000 people use the bus terminal leading to an average flux of over 133 people per minute.

3.1.1 Graph Representation of the Map

The GIS street map and the pictorial subway map of Manhattanwere obtained from publicly available data sources. The information was converted into a simple graph with 104,730 nodes (with 167 subway stops) under the following assumptions: (1) Each node represents a location (in real latitude-longitude) where the road curves or where there is a choice of edges to travel on; (2) Each edge represents a straight-line segment of any walkway or a subway; (3) All people and vehicles are constrained to move only along the edges of the graph; (4) The area between streets housing buildings and the area in parks which do not have walkways are deemed unusable for any kind of transportation, even in an emergency; (5) All edges are assumed to be bidirectional.

The intersection points were computed assuming that all roads, including fly-overs and bridges, intersect all roads that they cross, irrespective of altitude difference. The subway stops were approximated to the nearest node on the graph. The graph is non-planar because of the subway lines which are mostly underground in Manhattan. The locations of all major hospitals and some minor hospitals, in all 22 medical facilities, were also approximated to the nearest node on the graph.

3.1.2 Traffic Modeling

Average speed statistics that were available were integrated into a simple traffic model. The on-site treatment teams travel at a fixed speed initialized to a random value between 7 and 10 miles per hour. Subways have a fixed speed of 13 miles per hour. Each person has a maximum possible speed initialized to a random value between 6 and 9 miles per hour, consistent with average traffic speed in Midtown Manhattan. To account for congestion, effect of illhealth on mobility and other probabilistic effects, at each time instant, a person travels at an effective speed given by:

```
  if(U(0,1) < 1.0-health)
     effective speed = 0.0;
  else
     effective speed =
U(health * maximum speed / 2.0, maximum speed);
```

where $U(0,1)$ is a real random number generated uniformly in the range $(0,1)$. No congestion or road width is captured, so there is no enforced maximum number of people at a node or on an edge.

3.2 The People at Port Authority

A "Person" is the most fundamental agent in our multi-agent model. However, by-standers and the general population of Manhattan are assumed to play no role (not modeled); same is the case with people and organizations outside the isle of Manhattan.

3.2.1 Person's Parameters

Based on studies[9, 6] of factors influencing a person's response to a disaster scenario, the following attributes were chosen to be incorporated into our model: (1) *State:* headed to original destination or to a hospital; (2) *Facts:* current health level (H_l), currently admitted at a hospital or not, current amount of medication / treatment, access to a long-distance communication device, probability of the communication device working when the person tries to use it (information update rate); (3) *Knowledge:* location and current capacities of known hospitals and on-site treatment units, time of last-update of this information, tables of the $LRTA^*$ estimates for the known nodes, list of 100 most recently visited nodes; (4) *Personality:* degree of worry (W_l), level of obedience (O_l), perceived level of distress ($D = W_l \times (1 - H_l)$). The obedience parameter O_l captures the attitude of a person to follow the system's laws, in our case, just the decision when to head to a hospital. The worry parameter W_l instead represents the innate level of irrationality in the agent's behavior, and affects the following decisions: when to go to a hospital, when to get information from neighbors or via cell phone, how to select the hospital.

3.2.2 Rules of Behavior

The person's initial goal is to reach the original destination (e.g., home or place of work) from the initial location (which happens to be the Port Authority Bus Terminal). However, after exposure to Sarin, his/her health begins to deteriorate. At a certain health-level decided by environmental and personality factors, the person changes the destination state to a hospital:

```
if(U(0,1) < Obedience) {
   if (health < unsafe health level)
      Head to a hospital
}
else if (U(0,1) < distress level))
      Head to a hospital
}
```

where unsafe health level is the suggested health level when a person should head to a hospital.

At the beginning each person agent knows only a random number of hospitals and their absolute positions in the map (latitude and longitude), but this knowledge can be updated during the evolution of a simulation using the different communication channels (described in *Section* 3.5):

```
if (heading to a hospital && U(0,1) < distress level) {
      if (U(0,1) < information update rate)
         Get current hospital information via phone/radio
      else
         Talk to neighbors
}
```

The choice of hospital is then made based on the list of hospitals initially known, information about other hospital locations, on-site treatment facilities and their current capacities, and personality and environmental factors that affect information acquisition and usage.

```
if(U(0,1) < distress level) {
   Find nearest hospital
} else {
   Find nearest hospital in available mode
}
```

After being treated and cured at a medical facility, the person resumes moving towards his/her original destination.

3.2.3 $LRTA^*$ with Ignore-List for Route Finding

The Learning Real-Time ($LRTA^*$) algorithm proposed by Korf in 1990 [8]. $LRTA^*$ interleaves planning and execution in an on-line decision-making setting. As the planning time for each action executed by the agent is bounded (constant time), these algorithms can be used as control policies for autonomous agents, even in an unknown and/or non-stationary environment.

In our model, the person is trying to find the route to his original destination or to a hospital in an atmosphere of tension and panic. Thus, the rational $LRTA^*$ algorithm is inappropriate in its direct form. One common aspect of panic behavior is that people seldom come back to a previously visited node when an unexplored node is available. Extending this idea, the person-agent is modeled as maintaining an "ignore-list" of the last 100 nodes he/she visited, and uses the following algorithm:

1. *Action Selection* If all neighbors of the current node i are in the ignore list, pick one randomly.
2. Else:
   (a) *Look-Ahead* Calculate $f(j) = k(i,j) + h(j)$ for each neighbor j of the current node i that is not in the ignore-list. Here, $h(j)$ is the agent's current estimate of the minimal time-cost required to reach the goal node from j, and $k(i,j)$ is the link time-cost from i to j, which depends on the type of the link (road or subway) and its effective speed (subway or person speed).
   (b) *Update* Update the estimate of node i as follows:
   $$h(i) = max\{h(i), \min_{j \in Next(i)} f(j)\}$$

(c) *Action Selection* Move towards the neighbor j that has the minimum $f(j)$ value.

In other words, the only case when a person uses old learnt information is when they revisit a node they visited over a hundred nodes ago. The algorithmic characteristics of this "ignore-list" heuristic are being investigated separately.

3.3 The Medical Facilities in Manhattan

The hospital agent is a simple abstraction of any medical facility that can play a role at the time of a catastrophe. The hospital is a stationary agent which tries to allocate its resources in order to help persons requiring treatment. The major and minor hospitals (22 in all) have been included and the number of hospital beds was used as an indicator of the capacity of the hospital.

3.3.1 Hospital's Parameters

The attributes of a hospital that are included in our model are: (1) *State:* available, critical or full; (2) *Facts:* resource level (representing both recoverable resources like doctors, nurses and beds and irrecoverable resources like drugs and saline), reliability of communication device; (3) *Knowledge:* locations and current capacities of known hospitals; (4) *Triage Behavior:* health-level below which a person is considered critical, non-critical or dischargeable.

3.3.2 Rules of Behavior

As described in our Brazilian scenario [10], the hospital operates in three modes: "Available", "Critical" and "Full", depending on the current availability of resources. When a hospital's resource level drops below the *low* resource level ($\frac{1}{3}^{rd}$ of initial resources), its mode changes from available to critical. When a hospital's resource level drops below the *very low* resource level ($\frac{1}{10}^{th}$ of initial resources), its mode changes from critical to full.

The hospital mode directly influences the key decisions: whom to turn away, whom to treat and how much resources to allocate to a person requiring treatment. The medical parlance for this process is "triage", and research is actively being conducted to evaluate different triage policies appropriate to different scenarios (for example, see the Simple Triage and Rapid Treatment system [12]). The hospital's behavior at each time step is described by the following rules:

```
Treat all admitted patients
for all persons inside the hospital{
  if (health >= dischargeable health level)
      Discharge person
  else if(person is waiting for admission) {
          if(hospital is in available mode)
             Admit and treat the person
          else if(hospital is in critical mode &&
                 health < critical health level)
                 admit and treat the person
       }
  if (person is waiting &&
      health < critical health level)
       Add to critical list
  if (person is admitted &&
      health > non-critical health level)
       Add to non-critical list
}
Discharge non-critical patients, admit critically ill
```

3.4 On-Site Treatment Units

On-site treatment is provided by Major Emergency Response Vehicles (MERVs) which set up their units close to the site of action. The HazMat Team consists of experts trained in handling hazardous materials, who rescue people from the contaminated zone, collect samples for testing and eventually decontaminate the area. In our model, we group HazMat and MERVs into one unit – "on-site treatment providers". These small mobile hospitals are initially stationary and not helping anybody. When notified of the attack, they move towards the catastrophe site. Their properies may be summarized thus: (1) *Facts:* starting location, time of dispatch, reliability of on-board communication device; (2) *Behavior:* Exactly the same as a hospital in "critical" mode; (3) *Knowledge:* locations and current capacities of known hospitals.The model for which the statistics are reported in this paper has 5 on-site treatment providers. In a real situation, the first responders to the emergency typically consist of the Police and Fire department personnel. Ambulances arrive at the scene and transport sick people to the hospitals. No ambulance-like services are currently part of the model. The role of the police in cordoning the area and crowd management is implicit in that on-lookers and by-standers do not complicate the disaster management process in our model.

3.5 Communication Channels

Among the different types of information that are relevant to the Sarin exposure scenario, the following have been incorporated: hospital and first-responder locations, current capacities, and the suggested health level below which the person should rush to a hospital. In the model analyzed in this paper, only the information about the hospital and first responder locations and capacities are communicated dynamically. The channel of communication used for first responder activation is not modeled; only the time of availability of the information is controlled.

The communication channels available are: *one-to-one* communication between persons and any of the other three classes of agents adjacent to them, *one-to-many* communication from the hospital to all persons and first-responders within its premises, and *many-to-many* communication from the hospitals to all other hospitals, persons and first responders with access to a public telephone, radio or a mobile communication device. The role of media and the internet are not modeled. The effect of misinformation and rumors will also be incorporated into the model only in the future.

3.6 Sarin Gas Exposure

3.6.1 Time-course of Deterioration and Recovery

The time-course variation of the health level (with and without treatment) after the exposure is modeled using a 3-step probabilistic function depending on the person's current health level.

```
if (U(0,1) < health)
   health = health
      + U(0,  treatment + maximum untreated recovery);
else
   worsening = (health > dangerous health level)?
                  maximum worsening:
                   ((health > critical health level)?
                      maximum dangerous worsening:
                      maximum critical worsening))
health = health - U(0,(1 - treatment)*worsening);
```

Table 1: Exposure level and health level ranges

Exposure level	Health range	People Exposed
High (lethal injuries)	(0.0, 0.2]	5%
Intermediate (severe injuries)	(0.2, 0.5]	25%
Low (light injuries)	(0.5, 0.8]	35%
No symptoms	(0.8, 1.0)	35%

The exact values used are dangerous health level = 0.5, critical health level = 0.2, maximum worsening = $1.38 * 10^{-4}$ per minute, maximum dangerous worsening = $4.16 * 10^{-4}$ per minute and maximum critical worsening = $6.95 * 10^{-4}$ per minute.

3.6.2 *Level of Exposure*

Based on diffusion effects, air-currents, rate of breathing and amount of time exposed to Sarin, the amount of Sarin inhaled by a person ("acquired dose") at a certain distance from the source can be estimated. Based on this dosage, a certain health response results (based on traditional "dose-response curves" in toxicology). Unfortunately, it is impossible to estimate the nature, intensity and location of an attack (even within the Port Authority Bus Terminal). Further, time of day, number of people, temperature and air currents all play a role. More importantly, there is no clear-cut data on the rate of health degradation after exposure to a certain dosage. This is significant, as the ultimate aim of the modeling is to see how the time taken by the first responders to initiate treatment compares with the time taken by the Sarin poisoning to result in death. Reasonable estimates for the rate of health deterioration were arrived at in consultation with experts and related literature [12, 7].Table 1 shows the four main classes of exposure that have been modeled, the corresponding ranges of initialization for the health level and the percentage of people initialized to that category. These values try to capture the general situation of previously documented events[11],where only a small fraction of the affected population suffered fatal injuries.

One key assumption in our model is that there is no secondary exposure, i.e., first responders and hospital staff are not affected by treating Sarin-exposed patients.

3.6.3 *Chances of Survival*

The actual survival chances under optimistic and pessimistic conditions that result from the assumptions of our model are depicted in *Figure* 2. People with fatal and severe injuries can survive if they are treated on site or if they are transported to a nearby hospital. People with light injuries and those showing no symptoms will always recover eventually, but in this case, the damage to organs and the time to recover are the correct metrics of effectiveness of the emergency response. However, in this paper, we focus only on the number of deaths. As the survival-chances curve shows, only people with health less than 0.5 can ever die. However, all persons factor in, as they decide how information percolates and how resources are distributed.

4. ANALYSIS OF SIMULATIONS

The model has been implemented in the Java version of RePast 3.1[3], a popular and versatile toolkit for multi-agent modeling. In the results described below, the following additional assumptions were made: (1) The simulation is performed only for the first 3000 minutes (= 2 days and 2 hours). The assumption is that people who survive the first two days are not likely to die. Further, by this time resources from the outside the island of Manhattan will become available and the scenario is beyond the scope of our current model; (2) Neither a first-responder nor a hospital can help a person if the person does not ask for treatment ("head to a hospital" mode); (3) None of the behavior parameters change during a simulation. Learning behavior is supported only for the route finding algorithm. Knowledge acquisition and communication deal only with hospital / responder information.

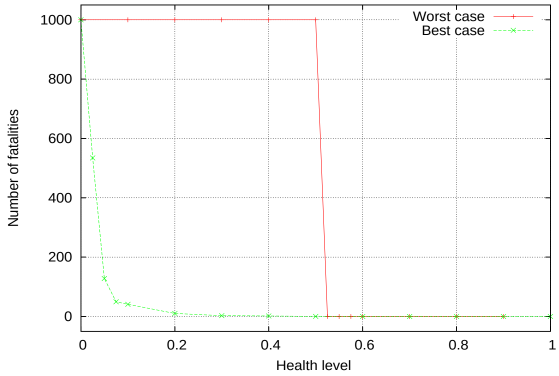

Figure 2: Sarin: Treatment and Survival Chances

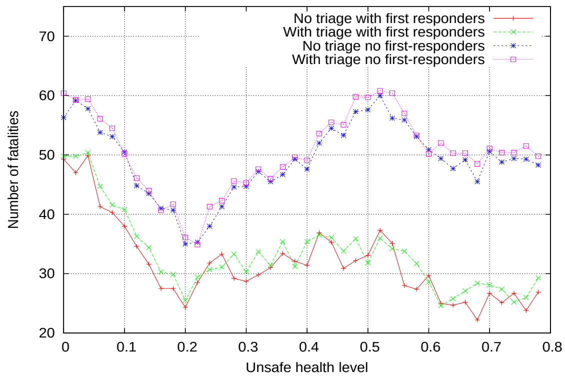

Figure 3: Persons heading to a hospital with and without first responders units (number of first responders = 5, first-resonder's dischargeable health level = 0.5, hospital's dischargeable health level = 0.8, responder alert time = 15 minutes).

Unless stated otherwise, all plots involve 1,000 people, 22 hospitals, 5 on-site responder teams. Every point that is plotted is the average of 10 runs, and all plots start with identical initializations. All plots without responders start at a slightly different initial state (with identical stochastic properties). When the number of responders is varied (*Fig.* 7), each run corresponds to a different initialization.

4.1 People Behavior

4.1.1 *Unsafe Health Level*

A critical disaster management question is: When should a person experiencing symptoms go to a hospital? Consider the scenario when there are no first responder units. In

Figure 3, the influence of the health-level at which a person decides to go to a hospital (called "unsafe health level") on the number of deaths is visualized. This plot suggests that person should decide to go to a hospital when his or her health approaches 0.2.

This unexpectedly low optimum value reflects a skewed health scale and can be explained thus. From *Figure* 2 we observe that if $healthlevel > 0.1$, almost 95% of the people will recover fully with treatment, while if $healthlevel > 0.5$, 100% of them will recover even without any treatment. When the unsafe health level is too low (< 0.2), people have been instructed to wait so much that their condition turns fatal (60 out of 1000 people die). The second factor affecting the optimum value for heading to a hospital is the distribution of people across the different classes of injuries. As seen in *Table* 1, a cut-off of 0.2 ensures that only the people who experienced lethal injuries (50/1000) go to a hospital. The moment this cut-off if increased, to say 0.5, crowding effects hamper emergency response as another 250 severely injured persons also rush to the hospitals. This situation is exacerbated by the fact that health level governs mobility, and hence healthier people are expected to reach a hospital earlier than sicker people. This is because people who do not require much emergency treatment end up consuming a share of the available resources, which would have been better spent on the sicker people already at the hospital or on persons who are still on their way to the hospital. Clearly, the presence of ambulances would alter the situation as the lethally injured persons would actually move faster than persons of all other classes. The drop in death rate after 0.6 can be attributed to the fact that these people would have recovered by themselves on the way to the hospital and hence may have not applied any pressure on the hospital resources. The optimum value turns out to be around 0.2, when the number of deaths (35) is almost halved.

The number of deaths due to crowding is dramatically mitigated if there are on-site treatment units, as seen in *Figure* 3. It is to be recalled that from the point of view of a person, an on-site treatment unit is equivalent to a hospital in "critical" mode. Note that the number of deaths due to people heading to a hospital earlier than necessary is less as most of these very sick people are now treated on-site and hence are no longer dependent on the resources of a hospital. When a person's health level is greater than the unsafe health level, in addition to not heading to a hospital, the person refuses treatment even from an on-site treatment provider. Though this assumption is unrealistic when the person's health is less than 0.2 or so, it is plotted for completeness.

4.1.2 Worry and Obedience

Two significant personality parameters that affect disaster-time behavior of a person are the innate degree of worry and obedience (see *Section* 3.2.2). These population parameters can be controlled by education, awareness and training before an event, and also by employing law enforcement officers during the emergency response.

Obedient persons do not head to a hospital when their health level is above what is considered unsafe, while disobedient persons will go based on their perceived level of distress. In order to understand their influence on the global system behavior, a set of simualtions have been done varing both O_l and W_l in the range [0.1] and assuming that first

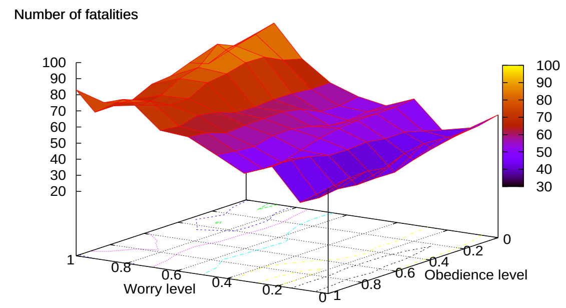

Figure 4: Obedient or not? Worried or not? (hospital's dischargeable health level $= 0.8$**).**

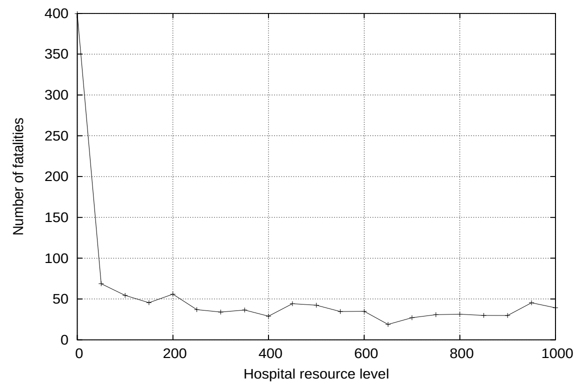

Figure 5: The effect of having more resources

responders are not active. *Figure* 4 shows the results of their mutual interaction.

By our definition of obedience and worry, disobedient worrying persons will head to the nearest hospital too early, thus crowding the most critical resource. At the other extreme, obedient people who are not worried choose to go to a hospital only when they are really sick, and also distribute themselves between the different hospitals; only when they become critically ill do they go to the nearest hospital irrespective of its mode. Disobedient people who are not worried do not worsen the situation because they will still get hospital information and choose to go to one only when necessary (based on level of illhealth).

4.2 Hospital Behavior

4.2.1 Resource Requirements

The meaning of the "resource" parameter is clarified in *Figure* 5. The thought experiment that lead to this plot was: When there is only one hospital, and the sarin attack occurs immediately adjacent to it, how much resources are necessary to save the 1000 affected people? As the plot shows, if the hospital has resources > 100.0, then no more than 50 deaths can result. A resource level > 200.0 can bring the number down between 40 or 20.

4.2.2 Optimal Dischargeable Health Level

The hospital's decision to discharge a patient is dictated

Figure 6: Hospital's patient-discharge behavior without first responders in action (Person's unsafe health level $= 0.2$).

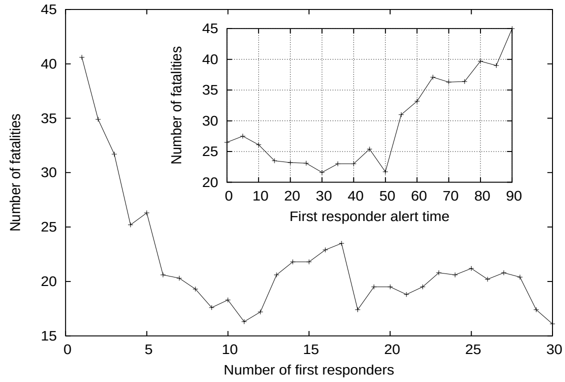

Figure 7: Number of first reponders and their alert time (first-resonder's dischargeable health level $=$ 0.5, hospital's dischargeable health level $= 0.8$, person's unsafe health level $= 0.4$).

by its estimate of whether the patient can recover using just medication (and rest) as opposed to requiring continuous monitoring. In our model, the hospital discharges persons whose health level is greater than "dischargeable health level". In *Figure* 6, the relationship of this decision with the number of deaths is plotted, and is seen to follow the same pattern as the "unsafe health level". When the dischargeable health level is too low, the person dies after being discharged prematurely. When it is too high, the person is given more medical attention than necessary and effectively decreases the chances of survival of sicker persons.

It is not immediately clear why the death-rate drops when the dischargeable health level is greater than 0.6. One possible explanation is that a person so discharged always recovers fully, whereas a fraction of the people discharged earlier return for treatment, possibly to a different hospital. The peak near 0.0 of 50 deaths is less than the peak near 0.6 of 65 deaths. This is because the hospital in reality is not entirely refusing treatment to persons with health level greater than dischargeable health level: (1) Since health is less than unsafe health level, the person reaches hospital and wants treatment; (2) The hospital treats the person; (3) The hospital finds that the person's health is greater than the dischargeable health level, so it discharges him/her. Steps (1)–(3) repeatedly happen until the person's health becomes greater than the unsafe health level, at which point he/she "accepts" the hospital's decision to discharge him/her and resumes moving towards his/her original destination. Also, unpredictable behaviors can result when the linear ordering of the parameters ($0 <$ critical health level $<$ non-critical health level $<$ dischargeable health level < 1) is violated.

The behaviors with and without triage not being very different may be related to the fact that hospitals broadcast their mode irrespective of whether they are enforcing triage policies or not. Persons use this mode information to choose the hospital. Only the persons experiencing a lot of distress (innate worry combined with health level) head to the nearest hospital even if it is supposed to be operating in the critical or full mode. Since we are counting only the number of deaths and since the very sick people go to the nearest hospital irrespective of triage enforcement, only the difference in the behavior of the hospital affects the result. However, in the critical mode, the hospital admits all persons with health level less than the critical health level (=0.25). Thus the difference are minimal when the triage is enforced and the hospital is in the critical or available mode. The difference would have been noticeable had the hospitals been small or had the the number of people been more; then the hospitals would have moved to "full" mode.

4.3 Role of First Responders

The role of the on-site treatment responders is patent in the plot of their number versus the number of deaths in *Figure* 7. The curve seems to flatten out at around 25 deaths requiring no more than 6 such teams. Clearly, the greater the number of dying people that can be saved, the more the number of first responder teams needed.

4.4 Significance of Communication

4.4.1 Getting Current Hospital Information

To understand the importance of communication channels using which people can get current information about location of first responder units, hospitals and their capacities, we modeled the scenario where every person has a communication device. We then controlled the rate of information update. This captures the ease with which cell phone calls can be made, the congested nature of the network, the fact that nobody may be able to respond to the information query, etc. When cell phones are not working and people get information from taxi radios or public phone booths, it is equivalent to setting the information update rate to be very low. This interaction is plotted in *Figure* 8.

As observed in the Brazilian scenario analysis[10] also, the death rate declines when more people have hospital information. However, this death-rate rises with too much information, as people are very likely to crowd at the nearest hospital. This prevents proper resource allocation and may also force many persons to visit a second hospital after having travelled to one.

4.4.2 Contacting the First Responders

The success of the on-site treatment responders is dependent on how soon after the event they get alerted, as shown in the inset plot of *Figure* 7. As a result of our parameter choice, we see that the net number of fatalities is stable

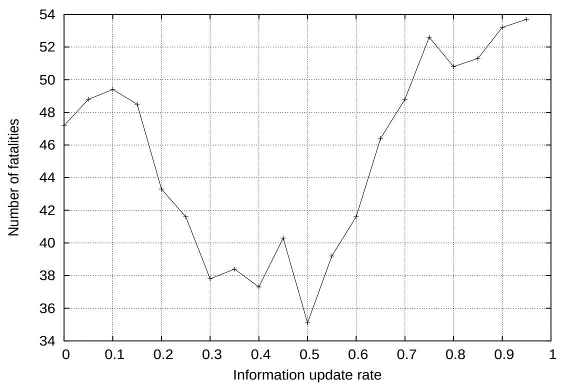

Figure 8: Importance of persons comunication (person's unsafe health level $= 0.2$).

(~ 25), as long as the first responders arrive within 50 minutes of the attack. The fluctuations could be due to the fact that the persons are themselves moving and need to be able to locate the first-responder.

5. DISCUSSION

Several important emergency response issues, such as when to head to a hospital, when to discharge a person, number of on-site treatment units necessary, the importance of public awareness and law enforcement, the role of responder size and activation time, and the diffusion of information about hospitals and capacities, were amenable to analysis by repeated simulation. ABM shows tremendous potential as a simulation-based tool for aiding disaster management policy refinement and evaluation.

The "Sarin in Manhattan" model in itself can be extended by addressing the assumptions discussed earlier. On the computational side, better knowledge and belief-state representation are necessary to simplify and generalize the communication mechanisms. Further, this will lead to simpler encoding of learning behavior and all parameters, including personality states, should be able to evolve with experience. We modified the simple $LRTA^*$ algorithm to take into account the memory of recently visited nodes to approximate real human behavior. This model needs to be refined and more personality and learnt parameters need to enter this model. The role of a centralized navigation system [14] in managing disaster-time traffic and routing also warrants investigation. Another aspect that is missing in our model is the information about routes and location of subway stops. These should be better communicated, and information booths (like sign-boards) should be incorporated into the model.

To improve the ultimate utility of the tool, we need to devise a uniform way of describing different catastrophic scenarios. Further, a conventional AUML-based description of agent behavior needs to be the input for the system. Some of the specific scenarios we hope to model in the near future include food-poisoning, mobile radioactive cloud, communicable diseases, natural disasters leading to resource damage in addition to disease, and events requiring evacuation or quarantine. On the theoretical side, we would like to automate the process of policy evaluation and comparison, and optimal parameter value estimation. We are also investigating representations of plans so that multi-objective optimization via genetic programming can be used to design new emergency response strategies. To address cultural and racial differences in response to catastrophes, game-theoretic behavior modeling and analysis is being surveyed [1].

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