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Modeling emergency medical response to a mass casualty incident using agent based simulation

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ABSTRACT

Emergency managers have to develop plans for responding to disasters within their jurisdiction. This includes coordinating multiple independent agencies participating in the response. While much of this is currently done by use of intuition and expert judgment, models can be used to test assumptions and examine the impact of policies and resource levels. The autonomous nature of responders as well as the rapidly changing information during a disaster suggests that agent based models can be especially suited for examining policy questions. In this work, we built an agent based model of a given urban area to simulate the emergency medical response to a mass casualty incident (MCI) in that area. The model was constructed from publicly available geographic information system and data regarding available response resources (such as ambulances, EMS personnel and hospital beds). Three different agent types are defined to model heterogeneous entities in the system. By simulating various response policies, the model can inform emergency responders on the requirements and response protocols for disaster response and build intuition and understanding in advance of facing actual incidents that are rare in the day-to-day operating experiences.

1. Introduction

Emergency managers are charged with planning, preparedness, response and mitigation for disasters within their jurisdiction. To do this well, managers must prepare plans in advance based on the resources available to them. Similarly, based on their plans, they can report to their jurisdictions that they have a resource shortfall. These plans and estimates for required resources are usually done by use of expert judgment and intuition and are then subject to acceptance by their jurisdictions. These can be augmented by the use of models to demonstrate the effects of different policy options or resources available by responders providing validity in the view of those who would approve any purchases or changes in policies.

Models are often used in enterprises for exploring various resource management policies. In particular, models are often used to explore policy options to react to non-forecasted disruptions. Applications include managing disruptions to commercial supply chains [1], reacting to disruptions in airline routes [2,3], selecting locations of military equipment for global deployment [4], and others. These models are used to test procedures, challenge assumptions and explore new ideas more efficiently and rapidly than experimenting with a real world system [5]. However, in the area of homeland security while the operations research community has developed techniques that could be applied to homeland security topics, Wright et al. find there are many rich opportunities still available [6].

In this work, we will describe an agent based simulation model of emergency response to a mass casualty incident in an urban area. This model is constructed using a foundation of available geographic information systems (GIS) data and resource information which facilitates building the model for any urban area where GIS and resources data are available. The model will then be used to evaluate a set of potential policies for emergency response. Finally, we describe ongoing work in using simulation models to evaluate options for policy makers.

2. Literature review of models on emergency response

2.1. Overview

Wright et al. [6] provide an overview of the use of models in homeland security, classifying them using the four phases of the disaster life cycle and the countermeasures and component support portfolios of the U.S. Department of Homeland Security

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(DHS). The phases of the disaster management life cycle are planning, prevention, preparedness and response. The countermeasures portfolios are chemical, biological, radiological, and high explosives. The component support portfolios of DHS are border and transportation security, critical infrastructure protection, cyber security, emergency preparedness and response, and threat analysis. Using their classifications, this work falls into the emergency preparedness and response portfolio and could be used for planning or preparedness by analyzing the effects of resource levels. It could also be used for response by testing a few preselected policy alternatives and the current resource levels to identify likely issues or identify critical resource needs.

One reason that models are important in disaster response is the relative scarcity of large-scale incidents compared to the day-to-day experience of hospital and emergency response managers. Models can be used to identify deficiencies in mass casualty incident response procedures that would not be apparent day-to-day practice prior to an actual incident.

2.2. Analytical models

Analytical models have been developed for Emergency, Preparedness and Response [6] for applications such as vehicle dispatching and routing [7], logistics coordination [8,9], evacuation planning [10], etc. Mathematical programming is generally used to find solutions to the optimization problems, such as maximal zone coverage or minimizing response time. Marianov and Revelle [11], Weaver and Church [12], and Toregas et al. [13] used set covering models while Badri et al. [14], Schilling et al. [15] and Revelle et al. [16] used goal programming methods. An early OR model for emergency medical service (EMS) deployment, the Hypercube Model was first introduced by Larson in 1974 [17]. In the Hypercube Model, the whole response system is modeled as an expanded, spatially distributed, multi-server queuing system. Since its introduction, the Hypercube Model has been used in other EMS base location studies [18–20].

2.3. Simulation models

In contrast to analytical mathematical programming or queuing models, simulation can be used to model individual entities, which allows researchers to analyze transient effects such as those occurring during the initial stages of a disaster event.

2.3.1. Discrete-event simulation (DES)

Discrete-event simulation (DES) is often used to model complex systems with interacting entities, which would include emergency response systems.

Shuman et al. [21] developed a discrete event simulator (RURALSIM) in the 1980s for designing and evaluating rural EMS systems. RURALSIM could generate multi-type and multi-severity distributed emergency incidents, which are then responded according to a set of pre-defined operational rules. A number of measures of effectiveness output by RURALSIM can provide decision makers more insights into the system evaluation. Several successful implementations of RURALSIM were reported in the states of Maine, Missouri, Oklahoma and Nebraska.

Goldberg et al. [22] built a comprehensive DES model to evaluate the emergency system performance in Tucson, AZ. The model simulates the response to emergency calls using a multi-server-queuing system. The model was extensively validated against the actual data and it was found that the zone structure is crucial to gaining valid simulation results, which restricts the flexible applications of the model.

DES models are also widely used to simulate operations in hospitals. Kolker [23] used discreet event simulation to establish a quantitative relationship between Emergency Department (ED) performance characteristics and the upper limits of patient length of stay (LOS). Boginski et al. [24] introduce a DES model built in Rockwell ARENA to study the process of patient flow through the hospital system and identify potential sources and locations of delays associated with equipment utilization.

2.3.2. Agent-based simulation (ABS)

An agent-based simulation (ABS) model contains a collection of autonomous agents which can perceive environment, exchange information, make operational decisions, and act based on these decisions [25–27].

Because of this, ABS models have been developed to model emergency responses. Carley et al. [28] developed a multi-agent simulation model (BioWar) to simulate biological and chemical attacks. BioWar incorporates several sub-models including agent-level disease, diagnosis, treatment, social networks, environmental and attack models into a single integrated model to investigate the impact of a bio-terrorism attack on a city. Narzisi et al. [29] developed PLAN-C to study the performance of populations under catastrophe scenarios. Their research provides particular insight into the dynamics that can emerge in this complex system.

Massaguer et al. [30] developed DrillSim, a multi-agent simulator with a purpose to provide an environment to test the effectiveness of IT solutions on the context of disaster response. Khalil et al. [31] compared DrillSim with other four Agent-based crisis response systems (DEFACTO, ALADDIN, RoboCup Rescue, and FireGrid). They analyzed the architecture and methodology of different systems, and identified features and limitations of systems based on crisis response domain requirements.

Schoenharl et al. [32] present an agent-based simulation model developed using Repast [33] as part of the Wireless Integrated Phone-based Emergency Response (WIPER) model. The objective of WIPER is to use a stream of cellular network activity to detect, classify and predict crisis events. The simulation models human activity, both in movement and cell phone activity, in an attempt to obtain better understanding of crisis events.

For hospital simulation, Zhu et al. [34] propose R-CAST-MED, an intelligent agent architecture built on Recognition-Primed Decision-making (RPD) and Shared Mental Models (SMMs), to alleviate the issues arising from ineffective information management in emergency medical services. Daknou et al. [35] studied applications of multi-agent systems for modeling emergency departments and proposed a tool to assist decision-making process for the care of patients at the emergency department.

In our work, we will build a model of emergency response that includes both pre-hospital care and transportation as well as emergency rooms. Through the use of agents we can model individual decision making based on the limited information available to different actors in the system and evaluate a set of policy alternatives that involve collecting and distributing information to decision makers within the system. By modeling some entities as proto-agents we can demonstrate how different entities can be modeled at different levels of fidelity based on their decision making requirements, combining decision making entities characteristic of ABS with less autonomous entities such as those characteristic of DES.

3. Methodology

The choice of models is dependent on the nature of the system and what aspects are considered critical. In emergency response, models have to explicitly consider the gathering of information and the change in the response policy that results as information is gathered. Because we need to model the effects of responders gathering information and decision makers adjusting the incident response plan in response to information collected and reported, we used agent-based simulation to model the effect of information gathering by decision makers as they adapt to their changing understanding of conditions on the ground.

ABS is characterized by the use of agents as the entities in the system. According to Mical and North [36] agents are identifiable, discrete individuals who are autonomous and self-directed. The behaviors and decision-making capability of agents are governed by a set of characteristics and rules. Agents are also social and situated, which means that they have the ability to interact with each other and explore their environment based on pre-defined protocols. An important characteristic of an agent is the ability to learn and adapt its behaviors based on experience.

For modeling emergency response, the characteristics of ABS lend themselves for modeling the actions of responders. In particular, in an emergency response, responders and their commanders begin with limited information about the incident and make decisions based on information they gather themselves or through communicating with other responders. Based on protocols and decisions made by incident commanders responders operate under a set of rules that can change as incident command gets new information. For example, in a mass casualty incident (MCI), there is an initial call to an emergency number that notifies responders that an incident occurs. The first units on the scene then provide situational awareness and begin triage of patients. As additional responders arrive casualties are triaged, information is collected and reported to incident command, and patients are evacuated to the appropriate hospitals. As information is reported and the scope of the incident becomes more apparent, incident commanders will adapt the response to the size and type of incident based on the resources available.

Because emergency response must deal with the problem of information gathering during the response with the structure of the response and responder decision dependent on the information gathered, agent based models are especially relevant to modeling emergency response to mass casualty incidents in ways that steady state models or discrete simulation models are not.

For these reasons, we have developed an agent based model to simulate the emergence response system using the Repast (an agent-based simulation toolkit [33]). We used readily available GIS data to build a transportation network along with data regarding ambulance and hospital locations and available capacity. The resulting model can be used to examine the effect of different response policies or resource levels on a response to a mass casualty incident.

4. ABS model for MCI response

4.1. General operations of MCI response

Mass casualty incidents (MCIs) refer to those large-scale disasters involving relatively large numbers of victims (affected people) with injuries at different severity levels. In a MCI response system, when an incident occurs and is reported, the incident command will assess the situation and dispatch responders to the disaster scene to perform triage, stabilization and evacuation.

Triage is the process of assessing a group of patients' situations and assigning appropriate medical resources for treatment [37], which is usually performed by the first arriving emergency medical technicians (EMTs). The first step of triage is to screen and classify injured victims into several categories (Black/Red/Yellow/Green) based on their severity levels [38,39].

As the next step, the on-site emergency medical services (EMS) personnel assess the patients' health conditions and determine the appropriate actions to take. For critical patients who suffer severe injury, the EMS responders treat and stabilize them and then evacuate them to appropriate medical facilities (hospitals). For those whose severity level is less critical, the EMS may just treat the patients at the scene and leave them for further medical care to be delivered by other support responders.

Evacuation is usually performed by ambulances traveling from their bases to the scene. When an ambulance arrives, the EMS will load the most critical patients and transport them to an appropriate hospital for more definitive treatment. An evacuation ambulance may travel back and forth between the scene and various hospitals multiple times, depending on management's decisions.

Although variations may be made in the details (rules) of EMS operations to fit the special needs in certain situations, the basic response principle is to stabilize the casualties at the scene and then transport them to medical facilities as soon as possible with a priority based on their severity.

A model that simulates the emergency medical response to a mass casualty incident in an urban area requires modeling casualties, EMT's performing triage, ambulances evacuating casualties to hospitals, hospitals that receive casualties and provide definitive care (care that results in improving the patient's condition for eventual discharge and end of treatment as opposed to stabilization), and an incident command that collects information and assigns casualties to hospitals based on the information available and the victim evacuation policy that is in place. The response system can be modeled by integrating three sub-models: the incident scene and patients, the actions of pre-hospital responders, and in-hospital processing.

4.2. Modeling entities as agents

In order to model the entities in the model as agents, we define three types of agents: Indicators, Performers and Commanders. Indicator agents are proto-agents without decision-making or information gathering abilities. Performer and Commander agents are full agents that can gather information and make decisions.

Indicator agents are entities that do not move through the system by themselves, but they can be moved through the system by other agents. Their state can change in accordance to specified rules and their state can be queried by other agents. In this system, casualties are modeled as Indicators.

Performer agents can move through the system according to their internal rules or instruction from Commanders. They also maintain a state that can be queried by commander agents. The triage EMTs, ambulances and sections of hospitals other than the emergency department are modeled as Performers.

Commander agents collect information from other agents and use this information to make decisions based on their decision making rules. They can direct Performer agents according to rules that depend on the state of the system as the Commander agent knows it. Incident command and hospital emergency departments are modeled as Commanders.

4.3. Sub-models

4.3.1. Incident site

The emergency medical response is comprised of the EMT's that perform on-scene triage at the incident site. As ambulances arrive, the first ambulance begins triage of casualties. Subsequent responders bring additional triage capacity as well as the ability to evacuate patients to hospitals throughout the region.

During triage, casualties are identified as being Red, Yellow, or Green (or Black, which means dead and no longer part of the model). In addition, at the time a patient is ready for transport by ambulance, it is determined if the patient requires care at a specialized hospital. While casualties are modeled as having a given RPM score (which is a relative measure of health) that incorporates respiratory rate, pulse rate, and best motor response [37] the other agents in the system are only aware of their triage designation.

4.3.1.1. On-site emergency medical technician (EMT). On-site EMTs are modeled by Performer agents, which are used to simulate the first arrived emergency medical technicians who perform on-site triage. They classify casualties into different groups by on their types (“General” or “Specialized”), and assigning a color designation (Red/Yellow/Green) to each casualty based on the triage result to indicate his/her injury severity. As ambulances arrive, triaged patients are loaded according to the policy in Section 4.3.2.1. By analysis of the data used in RURALSIM [21], we assume that the durations of both time required for triage and loading patients follow gamma-distributions. The scale and shape parameters are fitted from actual data collected by the City of Pittsburgh Emergency Medical Services.

4.3.1.2. Casualties. Casualties refer to the victims involved in the incident. For one specific incident, it is possible to observe multiple types of casualties with various injuries at different severity levels. For example, the possible injuries suffered in a bomb blast could include blunt, blast, and burnt trauma. And the casualties who were closer to the blast are usually injured more seriously than those far away. In order to appropriately address the variety of casualty, we model casualties using Indicators in our simulation model, and differentiate them by some pre-assigned attributes. Two major attributes of casualty used in the model are the “Casualty Type” and “RPM Score”. The Casualty Type is designed to indicate differences such as age, gender or injury type that determine whether or not casualties need to go to a specialized facility for definitive care. In this model, we define two basic casualty types – “General” and “Specialized”. The General type is assigned to adult casualties (indiscriminate gender), who suffer common injuries so that they can be admitted and treated by any hospital. In contrast, the Specialized type is used to represent the child/infant casualties since they have to be sent to a specialized children hospital to accept treatment. To any who wants a more practical model, it is easy to specify new concrete casualty types to handle more complex distinctions of casualties.

The other attribute, RPM, is used to specify the victim’s injury severity. A RPM score takes on integer values from 0 to 12, where smaller values correspond to severer injury and lower survival probability. The score is the sum of coded values for respiratory rate, pulse rate, and best motor response. According to Sacco et al. [37,40], RPM provides a good predictor of survival probability and can be easily obtained during the triage. Therefore, our model uses casualties’ RPM scores to determine their triage results. To be specific, the casualties with their RPM scores in 1–4 are triaged as “red”, RPM scores in 5–8 are “yellow”, and RPM scores in 9–12 are “green”.

Sacco et al. also provided evidence-based survival probability estimates for each RPM score through logistic regression, as well as deterioration rates which are estimated by experts for each RPM score through the Delphi method.

The logistic function used by Sacco et al. for estimating survival probability is

$$P_s = 1/\left(1+e^{-w}\right) \tag{1}$$

where P_s is the survival probability estimate. The parameter w is calculated using

$$w = w_0 + (w_1 \times \mathrm{RPM})$$

where w_0 and w_1 are weights that were determined by Sacco et al. through data analysis of injury survival rates.

The deterioration of RPM reflects such a fact, that is, without timely care or treatment, the health condition of a casualty could deteriorate continuously (especially for those injured seriously), which is called Casualty Degradation.

The consequence of degradation is the declining probability of survival of the casualty as the casualty waits for definitive care. For instance, a casualty with an initial RPM score of 12 may degrade to a RPM of 11 after 2 h (smaller RPM value corresponds to lower survival probability). Here we assume that the casualty received little or no treatment while awaiting transportation to a higher level of care.

We adopted Sacco’s Delphi estimates of casualty deterioration [37] as our casualty degradation model. Until the casualty reaches definitive care, the RPM deteriorates. The RPM score upon reaching the hospital determines the triage at the hospital. The RPM when the casualty reaches definitive care determines the survival probability for that casualty. While the RPM score and Sacco’s model were developed in an environment with advanced pre-hospital care, it could be possible to allow for advanced pre-hospital care to lead to a reduced rate of degradation, however we do not do so in this study as any effects of pre-hospital care would affect each policy in proportion to the performance of the policy when measured as time to definitive care and would not affect the identification of the best policy.

4.3.2. Pre-hospital sub-system

The pre-hospital sub-model involves ambulances and incident command. At the time the incident begins, ambulances that will be made available for the incident response are distributed in staging areas throughout the region. The first ambulance that arrives will initiate triage as described in Section 4.3.1. As subsequent ambulances arrive they bring patients to hospitals as directed by the incident command. The incident command decision on where to send a casualty is based on the results of triage as well as the current understanding of the state of the hospitals in the region (i.e. current utilization and other information that is communicated to incident command in accordance to the current policy used in the model, which could be one of the twelve alternative policies listed in Appendix 1).

4.3.2.1. Ambulance. Ambulances are responsible for casualty evacuation from the incident site to hospitals. They are also modeled by Performer agents, whose tasks include:

1. Stay-and-wait for orders from incident command;
2. Travel along a calculated shortest path to the disaster site;
3. Evacuate patients from the disaster site to hospitals.

In the beginning of the simulation, all ambulances are located at their initial staging areas (nodes). Upon receiving a “go-to-incident-site” order, each ambulance will calculate a shortest path (the one takes the least traveling time) from its staging node to the incident node, then set out and head to the incident node along the calculated path.

When an ambulance arrives at the incident site, it will begin to load casualties based on the following rules:

1. Triaged only: only triaged casualties can be loaded;
2. “Worst-first” pickup strategy: if there are casualties triaged differently available, an ambulance should load a red casualty first, then yellow, and then green;
3. Two passengers at most: one ambulance can take at most two casualties on each trip;

4. One red casualty per vehicle: once an ambulance loads a red casualty, the other casualty it takes can only be yellow or green;
5. Same type principle: on each trip an ambulance can only take casualties of the same type (general or specialized), determined by the first loaded casualty's type.
6. No waiting at incident site: an ambulance will be informed about available triaged casualties at that time immediately upon its arrival, then it has to make instant pickup decision and begin loading. Unless there are no triaged casualties at the scene, an ambulance is not allowed to wait at scene for next triaged casualty;
7. No replacement once loaded: once casualties are identified to load into an ambulance, there will be no change. For example, when an ambulance arrives, there are only two green casualties waiting for evacuation. According to the "No waiting at incident site" rule, the ambulance should begin to load them. Once the pickup decision was made, no change is allowed even if there is a red casualty is triaged while the ambulance is being loaded.

After casualties are loaded, the ambulance will request instructions from incident command about which hospital it should transport the casualties. Incident command will choose a target hospital following the current evacuation policies and provide the selected hospital to the ambulance.

In summary, Table 1 lists all possible states for a loaded ambulance.

4.3.2.2. Incident command. The incident command is modeled by a Commander agent, which is a full-function agent that can exchange information with other agents and make operation decisions.

Incident command can collect information from the incident site, ambulances and hospitals, so they know the status of the entire response system based on the dispatch policy in effect. Using the information provided by on-scene triage and hospitals in accordance with the current policy, incident command then assigns ambulances and casualties to specific hospitals when the ambulance picks up casualties.

4.3.3. *In-hospital sub-system*

Hospitals are the last stage of the response system, each evacuated casualty will be sent to a hospital for definitive care. There are two types of hospital in the system – specialized and regular hospitals. Specialized hospitals are defined as those that can provide the specific treatments required by specialized type of patients. A typical hospital is assumed to consist of the following medical units: emergency department (ED), intensive care unit (ICU), operating room (OR) and general wards (GW).

The size of each unit in each hospital represents the number of beds available for injured casualties, after accounting for on-going operations other than the MCI. The model will also track casualties in ambulances en route to the hospital. However, the hospital only reports to the incident command the information that is required for the policy being evaluated.

When a casualty arrives at the destination hospital, the casualty enters the emergency department, where the medical staff will perform triage. The casualty is then classified into one of two triage categories: Critical and Non-critical.

Critical casualties are those who may need resuscitation or urgent surgery. The critical patient will be moved to a bed in the emergency department and receive necessary care and diagnosis from an emergency medical specialist. Upon diagnosis, the specialist will make a decision whether or not an urgent surgery is needed. If no surgery needed, the casualty will be sent to a bed in either ICU (Intensive Care Unit) or GW (General Ward). Otherwise, the casualty will be moved to an operating room for surgery.

For the casualties who are diagnosed as non-critical during the arrival triage, they wait in a waiting room until is a bed available in the ED so that they can receive further examination from medical staff. The staff will then decide whether to admit the casualty into a general ward bed or be discharged.

If the casualty is to be admitted as an inpatient, a bed in the relevant ward is assigned. However, if the relevant ward is full, the casualty would be prevented from moving into a ward, which would cause a block in the emergency department.

It should be noted that for severe trauma casualties who need to be moved directly into an OR, a bed in a ward or an ICU typically must be found before admission to an OR is allowed. If there is no bed available, the critical casualty will be transferred to another hospital, which requires an ambulance and results in further delay before definitive care.

A brief chart of casualty flow in a hospital can be found in Fig. 1.

4.4. *Performance*

The performance measure for this model is mortality among the casualties. At the beginning of the incident, each casualty is randomly assigned an initial RPM score drawn from a distribution chosen to correspond to the incident being modeled. Over the course of the simulation, each casualty's RPM degrades according to the casualty degradation model in section Casualty degradation model. This continues until the casualty reaches definitive care (i.e. after the casualty has completed in-hospital triage and has been admitted to the OR, ICU, general ward or discharged). When the

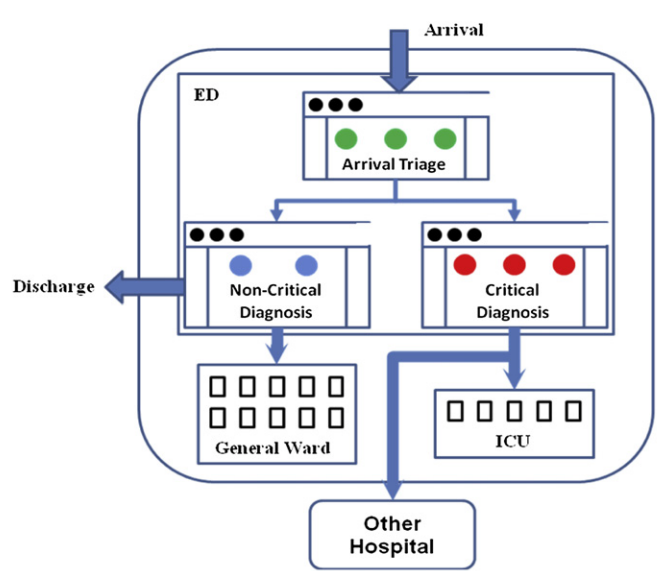

Fig. 1. Hospital process flow.

Table 1
Ambulance loading rules.

Patient(s) aboard	Comment
1 red	No same specialized type casualty with triaged yellow/green available when making pickup decision
1 red + 1 yellow/green	Two passengers are the same specialized type
2 yellow/green	Only when no red casualties are present. 2 green casualties would be loaded only when no yellow casualties are present.
1 yellow/green	Only when no red casualties are present and only a single yellow/green casualty of the given casualty type is available

casualty reaches definitive care, the casualty has a survival probability using the RPM and Eq. (1). The ultimate survival of the casualty is determined by comparing his/her survival probability at that time with a random number drawn from [0, 1]. The overall mortality of all the casualties is the mortality of that run of the simulation.

5. Case study

5.1. Evacuation policies

In this case study, we use this model to examine a set of alternative dispatch policies which govern the incident command's assignment of triaged casualties to hospitals. These dispatch policies (see Appendix 1) differ in the information made available and used by incident command to decide which hospital a given casualty should be sent to at the time the casualty is loaded on an ambulance. The alternative policies are then evaluated based on overall mortality.

As each transport ambulance reaches the scene, it picks up the next triaged casualty based on their triage priority as described in section Ambulance. Then, incident command provides the ambulance with its destination based on the characteristics of the patient(s) and the status of the hospitals using the dispatch policy in effect.

The policy chosen will impact the overall mortality in two ways. First, casualties need to reach definitive care in a timely manner. While distance to the hospital is a factor, casualties can also be delayed due to queuing inside the destination emergency room triage area. A hospital can also become full, where all beds are full, which will require that a casualty be transported to a hospital with room or ICU bed as needed.

We developed this model to examine a response to an improvised explosives device at the Pittsburgh D. L. Lawrence Convention Center during a major event. We then used the model to examine a range of different potential policies for assigning casualties to hospitals to identify a set of good policy options for a decision maker to choose for responding to this type of event.

5.2. Assumptions, constraints and parameter settings

For this study, we assume an Improvised Explosive Device (IED) explosion at the Pittsburgh D. L. Lawrence Convention Center in downtown Pittsburgh, PA, United States. There are 150 patients that require medical care. Casualties are of two types: children (specialized) and adults (general). Children have to be treated at one of two specialized hospitals: Children's Medical Center or Magee Women's Hospital. For each of the 15 total hospitals, we assume that there are 10 available beds in general wards and 5 beds in ICU in the beginning of the simulation. According to the observed pattern of injury severity from literature [41,42], we assume that the severity of each victim's injury is distributed according to a specified exponential distribution. While each victim has injuries that are modeled using Sacco's RPM score, within the model decisions are based on the information that has been collected by the agents. In order to represent a higher level of information obtained in a hospital setting, we chose to model the level of information available before evacuation to be the triage level (red/yellow/green), and the level of information available at the hospital to be the RPM score. After casualty are evacuated to the hospital, emergency room staff will perform in-hospital triage and decide if a casualty should be admitted or discharged by comparing his/her RPM to a pre-defined threshold; for those being admitted, another threshold value will be used to decide if they are in critical condition or not.

We assume that regionally there are 24 ambulances available to respond to the incident. The ambulances initially start in one of 6 bases which are distributed over the Pittsburgh region.

5.3. Transportation network construction

We generate the transportation network by using a simplified version of the Pittsburgh area road network as detailed in Zimmerman et al. [43]. We then identified 202 nodes which included the incident site, intersections of major roads, and locations of hospitals and ambulance staging areas. Then each resulting road segment is assigned a baseline speed which will be used to calculate the shortest path for ambulances.

5.4. Computational results

We simulate 12 different dispatching policies using our response model. Based on whether or not differentiating specialized hospitals from the general hospitals, the 12 policies can be classified into two groups. The policies in the first group (P-1 to P-6) do not reserve specialized hospitals for specialized casualties, and the policies in the second group (P-7 to P-12) reserve the capacity of specialized hospital for specialized patients based upon the number of observed specialized patients exceeding pre-defined thresholds.

These 12 policies differ on the information used in decision making. For examples, P-1 collects no information but just dispatches casualties randomly to the various hospitals. Starting from P-2, additional information is added into the decision criteria set. The decision criteria of P-2 include lengths of arrival waiting queues in hospital emergency departments, and distances from hospitals to the incident site. P-3, P-4 and P-5 adds other waiting queues, the number of patients currently en-route to the hospital and the available capacity in emergency departments into the decision criteria set, respectively. P-6 to P-12 adds the number of available beds in each hospital to the information criteria set.

Each policy was run for 300 replications. For each replication, 150 independent initial patient data (RPM scores) are sampled from the same exponential distribution with the rate parameter $\lambda = 0.4$. The results are shown in Fig. 2. For each policy, the box-and-whiskers plot identifies the mean, 25th and 75th percentiles, and outliers beyond the 1.5 $\times$ IQR (InterQuartile Range) of the lower/upper quartile of the mortality data obtained from the 300 replications.

In Fig. 2, the red dots connected by a dash line indicate the mean mortality for each of the different evacuation policies as labeled below the dot. From the figure, we can observe the following phenomena.

First, P-2 leads to the highest mortality, which is because P-2 only uses the distance and the length of arrival waiting queue at ED as its decision criteria to select the target hospital. However, since triage on arrival is relatively fast, injured casualties tend to be evacuated to those few hospitals nearest to the incident site. After the arrival triage, casualties may have to wait a long time in queues before receiving more definitive care. During this waiting period, the patients' conditions may continue to deteriorate. This is of particular concern for severe patients who may not survive (if they do not receive definitive care in a timely manner), which leads to a higher mortality for the incident.

Besides that, P-2 does not consider the available capacity of beds at each hospital when making decisions, so that it may send patients to a hospital without sufficient capacity to treat them. As a result, the excess patients will not receive a bed and will have to be sent to other hospitals, which makes the situation even worse.

Compared with P-2, P-3 obtains an improved performance because it considers all waiting queues instead of only arrival waiting queue, which reduces the negative effect due to patient congestion. For the same reason, P-4 improves upon P-3 by taking the currently en route patients at each hospital into consideration.

P-5 and P-6 differ from previous policies by using the available capacity of medical units as an additional decision criterion. This

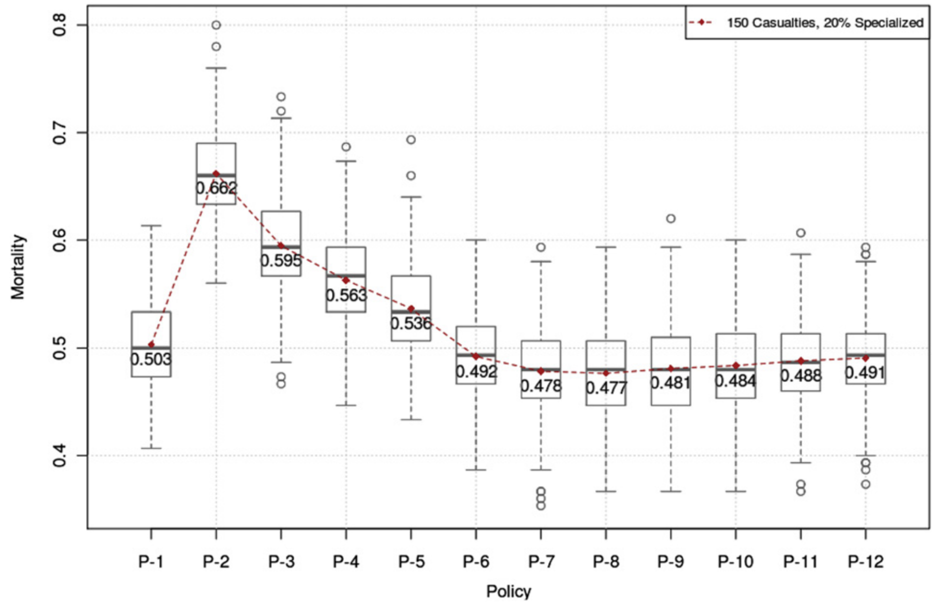

Fig. 2. Comparing dispatch policies.

helps to dispatch patients more reasonably to avoid a "no-beds-for-waiting-patients" situation from occurring, achieving even better results (lower mortality).

We note that the random dispatching policy (P-1) is a better than P-2, P-3, P-4 and P-5, but worse than P-6. The explanation for this interesting phenomenon is that P-1 balances the load of each hospital evenly, which happens to avoid long waiting times and situations where there are no beds for waiting patients who were already transported to the hospital, and therefore achieves a fairly good result despite longer transportation time. The comparisons between P-1 and P-2 through P-6 illustrate the possibility that decisions based on incomplete information may be worse than random selection, which suggests that only comprehensive information can support a good decision.

P-1 to P-6 do not reserve specialized hospitals for specialized casualties. In other words, while certain casualties should only be sent to a hospital with special facilities (e.g., burn patients require a burn unit), a more general type of injury can be treated at either a general type of hospital or a specialized one. However, the medical resources at specialized hospitals are relatively scarce since the number of specialized beds is substantially less than general hospital beds. For our Pittsburgh example case, two of the ten hospitals are assumed to have specialized beds available. Therefore, it may make sense to reserve some of the medical resources of specialized hospitals for those patients who really need it.

With this in mind, P-7 to P-12 reserve beds in specialized hospitals for specialized patients, and these policies are differentiated from each other by their threshold values (n_s), which marks when the Specialized-Hospital-Reserved policy should be triggered. For example, the zero-threshold of P-7 means the system implements the Specialized-Hospital-Reserved policy from the very beginning of the incident. For P-8 through P-12, the system implements the Specialized-Hospital-Reserved policy only after n_s specialized casualties are observed through triage, where n_s are sequentially increasing positive integer series with a constant step equal to 3.

In these results, we observe that while policy 8 has the lowest mortality (0.477 or 47.7%) policies 7–12 are all close. These policies are all of the form: check availability, check waiting queue (including patients en route), and reserve space at specialized hospitals when a threshold of specialized patients has been identified at the scene. These policies are significantly better than those that do not consider reserving specialized hospitals for specialized patients or accounting for the patients en route to the hospital. Therefore we propose that this is information that should be collected, tracked and reported in real time so that incident command can use these more effective policies in assigning patients to hospitals. P-7 through P-12 have the same structure, but with a different threshold for changing the status of the specialized hospitals from open to all patients to only open to patients that require specialized services (i.e. children). The threshold means that the specialized hospital does not have to change its status from open to close immediately at the beginning of an incident, but can wait until more information about the incident is obtained. When considering the correct threshold, a policy maker should consider if the improved performance is enough to justify the disruption that would occur through changing the day-to-day policy in smaller incidents. This may suggest repeating this study with a range of scenarios from small to large and understanding the relative frequency of various incident sizes in the area.

As a summary, we can see that different evacuation policies for MCI response lead to different impacts on mortality. The policies based on comprehensive information achieve better results than those utilizing partial information or no information. Considering that specialized casualties must be treated at specialized hospitals, it is necessary to strategically reserve some capacity of specialized hospitals for those casualties who really need it. That is, when an incident is determined to result in a threshold number of specialized casualties, a certain number of beds in specialized units should be made reserved in anticipation of more specialized casualties being identified. However, the cost of reserving these beds may be quite high.

6. Conclusions

We have developed an agent based simulation model for emergency medical response to a mass casualty incident in an urban area. The simulation model was constructed from GIS network data and data on response resources. Given this data, our simulation model is no longer location dependent and can be used to model any region (a city or a county) by simply replacing the source GIS data, which provides great flexibility to the model to simulate any urban area wherever GIS data are available. This model can also be used to evaluate other decisions such as the effect of increasing the number of ambulances or introducing additional hospital beds.

Use of this model can identify the limitations on current practice when facing scenarios that are rare in the day-to-day operating experiences of hospital and emergency response planners. In early conversations, one SME at a local hospital stated an expectation that all victims of an event of this scenario would go to that hospital. Simulations of Policy 2 demonstrate some of the weaknesses of that strategy and the delays in patients reaching definitive care that result from sending a preponderance of victims to any single facility until it is at capacity. By simulating various other policies, the model can inform discussion among regional emergency responders on the communications requirements and response protocols for disaster response in advance of an actual incident and build intuition and understanding that would otherwise only be gained through actually experiencing disasters.

From the analysis to the simulation results we can see that using only partial information may have no benefit or may even have a harmful impact on decision making instead (e.g., P-2 to P-5 versus P-1). In order to reduce mortality, the number of available beds at each hospital is an important piece of information to consider in decision making (e.g., P-6 to P-12 versus P-1). In addition, the result that P-1 achieves quite low mortality suggests that it is wise to utilize all available facility resources as much as possible in a MCI response, since it helps balance the load among hospitals and avoids unnecessary waiting and transferring for patients. Such a finding provides a useful guidance for emergency managers, especially when it is difficult to collect information under certain extreme conditions (e.g., after a severe earthquake). In summary, these experiments provide researchers with an important insight into the MCI response problem, and illustrate the importance of different impact factors on mortality. Hence, this provides a good foundation for the subsequent research on policy optimization by identifying the important factors that should be given priority.

Like all such models, there are limitations in interpretation. Currently, it only reports a single performance measure, mortality. In cases where there are more complex evaluation criteria, the model should be modified to report appropriate performance measures or combinations of performance measures. Second, it only reports quantitative results. Decision makers using this model should be aware of other factors that may impact decisions such as negotiated agreements or financial factors that should be considered in conjunction with the results of this model.

In addition, the abstraction of the casualty type is another limitation of the model. For simplification, we only defined two basic casualty types in this paper, which are “General” and “Specialized”. Although very simple, these two abstracted types provide us an effective way to depict the basic characteristics of different casualties. To anyone who wants the model to be more practical, it is very easy to derive various concrete sub-types based on those two abstracted types. For example, we could create a new casualty type called “Male Infant with Head Injury” as a sub-type of “Specialized”.

One area of future work is in the analysis of the simulation output. Agent based models are resource intensive and running all policies for a large number of runs to get good confidence intervals for policy performance is uneconomical. For finite sets of alternatives, ranking-and-selection methods can be used to identify a single best policy with an economy of model runs. However, what is needed in this case is to identify a set of good policies, where decision makers can be assured that any of these policies are good quantitatively, and they are free to choose between these policies based on other criteria. We plan on developing such methods for applications to models in policy studies like this one.

Contributions

Yu Wang implemented the model using the Repast agent-based simulation toolkit over the GIS network developed by Zimmerman et al. This includes defining, developing and implementing the Performer, Indicator and Commander agents described. He collated the facility and resource data for the areas the model was implemented in. He researched the injury and survival models and fit them to historical data for implementation in the model. He also performed the data analysis described in this paper. Louis Luangkesorn provided guidance and direction regarding the form of the model and the questions to be asked. He gave insight and references into emergency response practices. He took part in describing the behavior of agents and developing decision rules that are followed by the agents representing the responders. He also provided guidance in data analysis methodology of both input data and the simulation output. Larry Shuman provided guidance and insight into emergency response practices. He also provided guidance in data analysis of input data. He provided contacts for obtaining resource availability in the areas under study.

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Appendix 1. Evacuation policy alternatives

In this case study, we evaluate 12 different evacuation policies. These policies govern the incident command assignment of ambulances to hospitals at the time the ambulance has loaded triaged casualties at the incident site. The policies differ in the information required on the casualty and hospital status and thresholds for closing specialized hospitals.

Currently, twelve different evacuation policies (1–12) are implemented and employed to guide the casualty evacuation, the details are concluded in the tables below.

ID	*Policy-1*
Brief Description	Random Selection
Explanation in Detail	Select a hospital at random from all candidates
ID	*Policy-2*
Brief Description	Shortest Waiting Queue (only considering Arrival Queue)
Explanation in Detail	Select the nearest hospital (from the incident site) from a subset which involves those hospitals which have the shortest waiting queue of arrival patients at Emergency Department (ED). Procedures: 1. (Incident command receives a “where-to-go” inquiry from an ambulance); 2. Incident command checks the status of each hospital, identifies a subset which contains those hospital having shortest length of arrival waiting queue 3. If the subset consists of multiple hospitals having the same shortest length of arrival waiting queue, then select a nearest one from the subset as the target; otherwise simple select the one hospital with the shortest length.
ID	*Policy-3*
Brief Description	Shortest Waiting Queue (considering all waiting Queues)
Explanation in Detail	Select the nearest hospital from a subset which involves those hospitals which have the shortest length of total waiting queue, that is, the hospital should have the smallest number of waiting patients (including arrival waiting queue at ED, non-critical diagnosis waiting queue at ED, critical diagnosis waiting queue at ED, ICU waiting queue, and General Wards waiting queue)
ID	*Policy-4*
Brief Description	Shortest Waiting Queue (considering all waiting Queues + Expecting)
Explanation in Detail	Similar to Policy #2, but the number of scheduled coming patients will also be counted into the total waiting queue length (including arrival waiting queue at ED, non-critical diagnosis waiting queue at ED, critical diagnosis waiting queue at ED, ICU waiting queue, and General Wards waiting queue)
ID	*Policy-5*
Brief Description	Available First otherwise Shortest Waiting Queue
Explanation in Detail	First try to select the nearest hospital from a subset which involves those hospitals which have positive available ED capacity (which means the patient can get immediate treatment upon their arrival). The available ED capacity (AEDC) will be calculated as: AEDC = max{0, (# of Available ED Beds − # of scheduled coming patient)} If all hospitals' AEDC is 0, then using Policy-4 to select one hospital with the shortest waiting queue.
ID	*Policy-6*
Brief Description	Available Capacity AEDC otherwise Shortest Waiting Queue
Explanation in Detail	First identity hospitals with available ICU & GW beds, then using Policy-5 to select the target.
ID	*Policy-7*
Brief Description	Policy-6 in Specialized Reserved Mode
Explanation in Detail	An ambulance can only take the same type of patients (either all General or all Specialized), and will drop-off the patients loaded at hospital with corresponding type (general patients to general hospitals, specialized patients to specialized hospital). Other rules are the same as Policy-6
ID	*Policy-8 – Policy-12*
Brief Description	Policy-6 in First-Open-Then-Reserved-At-Threshold Mode
Explanation in Detail	In the beginning of simulation, the system is under All-Hospital-Open mode, which means that Policy-6 is using (an ambulance can take any patients and can go to any hospitals chosen by Policy-6). However, after a threshold number of Specialized type of patients (n_s) are observed, the system will then enter into Specialized-Hospital-Reserved mode (Policy-7), where: Policy-8: $n_s = 3$; Policy-9: $n_s = 6$; Policy-10: $n_s = 9$; Policy-11: $n_s = 12$; Policy-12: $n_s = 15$.

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