

Disaster Policy Optimization: A Simulation Based Approach

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Abstract

To help disaster response organizations improve the management of regional emergency assets and operations, we propose to interface an agent-based, discrete event simulator with a geographic information system and a rule base (describing standard policies and protocols for various disaster responses). The system architecture will enable modules to dynamically “talk” with each other by exchanging real-time data and making intelligent deductions. This integrated system is designed to accurately mimic the real-world disaster response scenarios. The system will be used to better assess how various configurations and operations of emergency resources might impact the effectiveness of responses to various large-scale incidents.

Keywords

Disaster management, agent-based simulation, discrete event simulation, geographic information system, rule-based system

1. Introduction

Disasters are one of the major barriers to the sustainable development of society. Recently, we have observed both large-scale natural and man-made disasters that have had great impacts on major cities. For example, the catastrophe caused by Hurricane Katrina in New Orleans in 2005 destroyed key aspects of that city including its assets, population and economy. Of the city’s 180,000 structures, 125,000 were flooded [1]; one year later New Orleans population has been reduced by nearly 60% according to New York Times [2]. The threat to lives is huge in densely populated urban areas where many structures, facilities and people are concentrated. For a large-scale disaster, even a small delay in responding can result in many more casualties and a huge loss of property. The mismanagement of Katrina responses cost more than \$100 billion and over 1,300 lives [3].

Disasters can be categorized into several major types: natural events, technological events, and human events [4]. Different disasters have distinct characteristics in terms of scale, complexity and treatment, so they require responders to act differently according to specific situations. How to respond to a disaster appropriately is a major challenge for emergency decision makers, e.g., incident managers.

While emergency commanders are well-trained personnel who have good knowledge of the responses to most kinds of disasters, to some extent, each one is an ad-hoc event that requires special treatment because unthinkable situations can emerge. For example, the September-11 terrorism attack in New York City is different from the Hurricane Katrina in New Orleans so the responses are different. Good disaster decisions are based upon a significant amount of information and knowledge of the event. However, because of the complexity of real-life events, knowledge and experience if combined with a limited capability for processing information are not sufficient for disaster management to precisely predict how future situations might arise and evolve. Decision makers could be

left far behind evolving events due to their limitations so that their decisions might actually delay the initiation of more appropriate responses. In contrast, a computer-based and seamlessly-integrated simulation, information sharing and decision making system could be used as a tool to comprehensively process information and make decisions on allocating current resources and dispatching first responders to treat the disaster in a proper way.

2. A Dynamic Simulation-based System

2.1 System Architecture and Work Flow

Discrete event simulation (DES) has been widely applied in modeling complex, large-scale systems and evaluating their performances. DES is preferred to other approaches (e.g., mathematical programming formulations) because it can fully capture the stochastic and dynamic nature of such systems. When a large-scale incident occurs, the scene could be extremely chaotic because of the excessive jams caused by both the responders and injured or panic people. It is extremely hard to model such a stochastic and dynamic system mathematically, but it is possible to simulate it with the operational rules and logic. Simulation can eliminate many of the assumptions needed for mathematical programming formulations and allow us to model the system more realistically. With simulation, we can obtain more accurate results which are critical for informed disaster decisions.

In this research, an automated computer system will be developed which incorporates an agent-based discrete event simulator, a geographic information system (GIS), a rule base, interactive databases, and other supporting components. The modules can intelligently “talk” with each other by exchanging real-time data and making deductions through embedded algorithms. This implementation will realize the idea of evolutionarily generating optimal or semi-optimal operational decisions based upon the progress of the events.

The simulation environment is a core component but not the only piece of the disaster decision support system. One challenge, also an innovation of this research, is the integration of the discrete event simulation with other real-time information systems to facilitate the synergic decision making process. Traditionally, simulation has been primarily a system evaluation tool, not used for making decisions in real time (or near real time). Our goal is to break this limitation and extend simulation for use as an evolutionary decision driver and optimizer. An evolutionary decision means the decision is not always static after it is made; it can be changed in order to optimize the overall performance as the time elapses and the event evolves. The proposed integrated system will work in an iterative way to reason out the proper decisions for disaster management. The system flow chart is depicted in Figure 1.

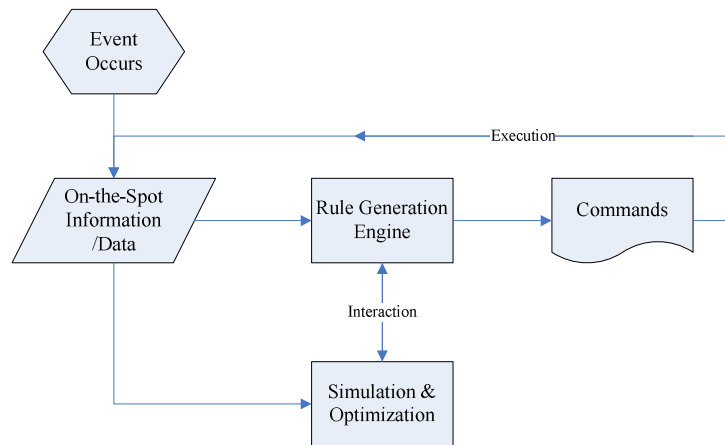


Figure 1: Dynamic, rule-driven simulation system flow chart

Figure 1 illustrates the basic work flow of the disaster decision support system. When an event occurs, certain on-the-spot data (e.g., number of victims, type of the event) are reported. The data quality affects the system’s performance significantly. The more credible the data input, the better the decisions made later. The data are then transmitted to the “Rule Generation Engine” and “Simulation and Optimization” module, respectively. The rule engine can initiate some basic, prompt responses to the disaster based upon the initial report of the event and send the response rules to the simulation. The simulator will be informed of updated data and operational rules which are generated as the system runs. Conversely, the simulation results will feedback to the rule generation module to assist

the engine in developing better decisions. It is believed that the rule-based system can develop better conclusions if it has more accurate and adequate information input [5]. Mathematical and statistical optimization techniques can also be incorporated into the simulation module to improve the performance of rules from the rule generation engine. For example, the rule-based system may make only general rules such as sending Emergency Medical Services (EMS) ambulances to the scene, but it will not specify the optimal rule parameters such as the number of ambulances that should be dispatched. In this sense, optimization can add specificity to the general rules, making them more operational. The interaction between the rule generation process and the simulation/optimization module is an essential function of the whole decision system and requires sufficient careful calibration before it is actually used for real problem solving. In this system, the simulation is not only a static system evaluator but also a dynamic decision driver. After several iterations, an operable plan will be produced by the rule engine, then justified and sent by the incident commanders, and executed by the emergency personnel to respond to the event. A new cycle of the system flow will start by updating the on-the-spot data.

2.2 Evolutionary Rule Generation Process

We propose to use a rule-based system (also called knowledge-based system) to simulate the decision making process for emergency responders and incident commanders. The system should be scalable and flexible to the change of rule sets in order to serve as a test bed for different types of incidents in the future. Normally, a rule-based system consists of a rule base with permanent data, a workspace or working memory with temporary data, and an inference engine. A user-friendly interface can be added to help decision makers interact with the system and improve the reasoning process [5]. The system architecture is depicted in Figure 2.

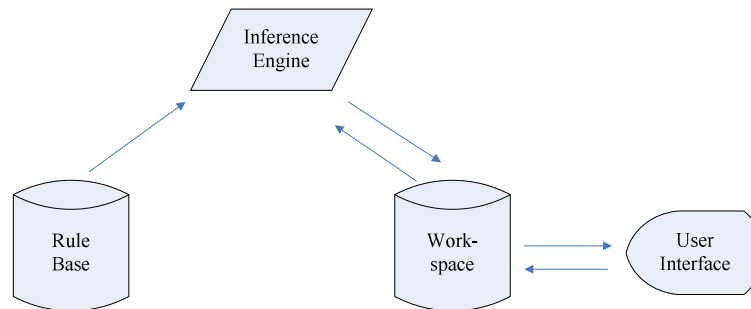


Figure 2: Rule-based system architecture

The knowledge used by first responders, incident managers and other decision makers is stored as pieces of rules in the rule base. More precise rules can cause the system to generate better outcomes. Rules will be in the format of Horn “what-if” clauses as follows:

IF some condition(s) THEN some action(s)

The clauses can be expanded by attaching attributes such as the probability of certain consequences if the plan is implemented. The workspace is a collection of databases that store the temporary fact data about the system. The data come from the simulation, rule bases and other integrated applications such as the geographic information system. The simulator, rule bases, GIS, and other components will update the databases “on the fly” as the event evolves. The inference engine determines how to pick and apply appropriate rules to the working memory and execute the rules. The execution of a rule may change the facts in the workspace immediately or after a while that would trigger other rules. In such an evolutionary manner, the time-dependent rules are generated and executed. The user interfaces can visualize the evolving situation and the decisions, and also facilitate human decision makers to interact with the system. Enabling the human experts to track the system’s progress can help them identify some unrealistic or defective rules and improve the disaster decision making process.

The rules generated by the system and the progressive situations depend on each other: a rule will be initiated by changing situations and the situation will be changed by new rules. If the simulated outcome is not favorable, we can adjust the simulation clock back for a time interval, say, one hour and apply a different rule until the overall outcome is satisfactory in the end. A sample dispatching rule set and its structure are as follows:

```
At 0:00, send <object(s)> from <base(s) ##>.  
At 1:00, send <object(s)> from <base(s) ##>.  
At 2:00, send <object(s)> from <base(s) ##>.  
... ..
```

In a more intelligent system, the rule updating interval can be flexible (update rules only when needed) instead of fixed.

3. Agent-based Discrete Event Modeling

The concept of agents has been used in the artificial intelligence (AI) field to model real-life intelligent entities. A computer agent is defined as an autonomously controlled entity that can perceive its own operations as well as the surrounding environment, compile predefined rules to make operational decisions, and act based on these decisions [6]. The agent-based model is a collection of such autonomous agents. It could best simulate complex, dynamic systems because their operations are highly analogous. Based on this rationale, we will incorporate the agent-based model into the discrete event simulator to simulate the behavior of the responders to the various disaster scenarios. The disaster responders can be regarded as rational agents that operate by rules towards a common goal and attempt to achieve the best outcomes for their actions. Every responder agent is capable of executing and changing its actions based upon its own status, that of other agents and/or the overall system, all of which are regulated by a set of action rules. In other words, the responders are instructed as to the next action to take and how to respond to the event by the commands or their own judgments authorized by the rules. The agent actions and interactions of an EMS ambulance are depicted in Figure 3.

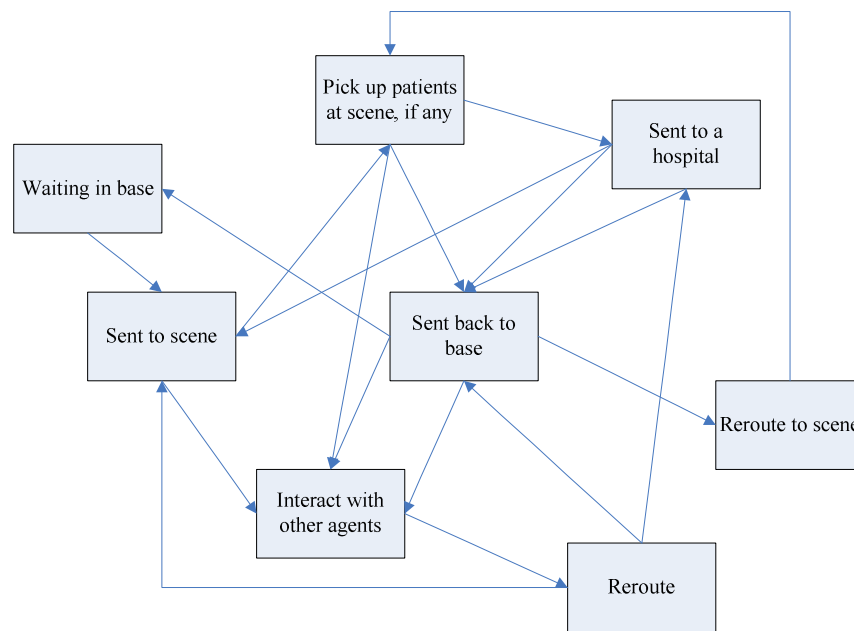


Figure 3: Agent actions and interactions of an EMS ambulance

The above illustrated ambulance agent's actions and interactions with other entities are defined by a set of ambulance dispatch and operation rules. Other responding agents such as emergency vehicles and evacuation vehicles will be built in a similar manner in the simulation system. The other emergency vehicles include fire trucks, police cars, HazMat trucks, etc.; the evacuation vehicles include helicopters, public buses and private-sector transits which can be temporarily recruited as victim transportation tools during emergency.

The responding vehicles are modeled as individual agents to facilitate their semi-autonomous decision making process during the simulation run, based upon a set of preset operational rules. A number of different types of moving agents built in the system. Different attributes and operational rules apply to various types of agents. For example, an ambulance needs to travel between the scene and hospitals back and forth, continuously transporting patients while a fire truck and the firefighters will stay at the scene to stabilize the situation. The agent's attributes

help define its operational status. To enable the dynamic status changes, all of the defining attributes should be parameterized to quantitative variables and maintained by databases. Some of the attribute values are fixed while many others are variable and updated as the simulated event evolves. The agents' status is critical information for decision makers to observe the behaviors and develop the responding plans.

Besides the designated vehicles, other relevant objects such as emergency assets (e.g., fire hydrants, medical suppliers) and city infrastructure (e.g., streets, bridges) are also tagged by their defining attributes. These objects are as important as the emergency vehicles in the process of decision making. Some of the object definitions are listed in Table 1.

Table 1: Sample of object definitions for agent-based model

Object	Attributes	Property	Values
Vehicle	Vehicle ID	Fixed, read-only	Integer ID
	Vehicle Type	Fixed, read-only	Integer ID
	Trip Start Node	Dynamic, simulation	Node ID
	Trip End Node	Dynamic, simulation	Node ID
	<i>Last Action</i>	Dynamic, simulation	Encoded integer
	<i>Current Action</i>	Dynamic, simulation	Encoded integer
	<i>Next Action</i>	Dynamic, simulation	Encoded integer
	Action Parameter	Dynamic, simulation	Integer
Queuing Priority	Fixed, or dynamic	Integer	
Street	Street ID	Fixed, read-only	Integer ID
	Connectivity	Fixed, read-only	Node ID
	Lane No	Fixed, read-only	Integer
	Speed Limit	Fixed, read-only	Integer
	Condition	Dynamic, GIS	Encoded integer
	Congestion	Dynamic, GIS, simul.	Floating-point

In the computer simulation system, all of the agents' attributes have to be encoded numerically as well as the discrete events because computers can only understand quantitative numbers. Whenever an agent performs actions, a simulation time delay will be imposed on that agent and its action attributes (defined in *italics* in Table 1) will be updated at the same time. In order to track the agent's behaviors, we need to encode all the possible actions into computer-readable numbers. Conversely, such codes can be easily decoded to provide more informative data to human decision makers. Some of the vehicle actions are encoded as shown in Table 2.

Table 2: Sample of vehicle action codes for agent-based model

Vehicle Agent	Numerical Codes	Action/Task Description
<i>N/A</i>	<i>0</i>	<i>Unknown or N/A</i>
EMS Ambulance	500	At base waiting for call
	501	At base called and processed (delay)
	502	Travel Base-Scene
	503	Travel Hosp-Scene
	504	Pick up LT at Scene
	505	Travel Scene-Hosp
	506	Drop off LT at Hospital
	507	Travel Scene-Base
	508	Hosp prepare after drop-off
	509	Travel Hosp-Base
Field Hospital	1400	At base waiting for call
	1401	At base called and processed
	1402	Travel Base-Spot
	1403	Stay at FH spot and operate.
	1404	Setup FH at spot.

The instructional rules and knowledge for the agents are coded in the format of “what-if” clause supported by the simulation. The programs can simulate human thought processes. When an entity finishes one action, it will “think” about what to do next so the computer programs will be executed to facilitate the “thinking” process, just like a human’s brain. With the modeling schemes described above, we can build each responding entity as a rational agent whose behaviors will be instructed by the integrated rules and applications.

4. Conclusions

We have presented an overview of a proposed dynamic simulation-based decision system to achieve the goal of making better decisions based on more realistic models for various disaster scenarios. In the system, the major, pertinent geography-related objects are stored in a GIS. These objects include structures, transportation routes, resources, population distribution, and so forth. In the core simulator, responders are built as moving entities whose actions are regulated by standard protocols or specific decision rules. Under normal conditions, the entities behave subject to the system constraints. In some emergent situations, say, disasters, they will be governed by additional ad-hoc rules and constraints. Such ad-hoc rules and constraints are determined dynamically by the commanders’ decisions, responders’ involvement, and other objects’ behaviors. Using a validated simulation system, the decision makers are able to predict the effects of various critical decisions before actually implementing them on the scene. The system can help detect inappropriate management early to avoid worsening the situation. In this approach, the responses are revised whenever necessary based on the simulation feedback as the event evolves. Traditionally, discrete event simulation is a tool for analyzing and evaluating a complex system’s operations. In this dynamic decision system, DES will be used in an innovative manner: it is essentially a decision driver.

The integrated system will have a large variety of applications. Its use by municipal governments to manage the urban large-scale disasters is the main focus of this research; it could also be applied in military base management and the broader homeland security arenas. It provides decision makers with an active laboratory to test policies, training, strategy and tactics in a simulated real-life decision scenario.

Acknowledgements

The authors would like to thank Office of the Provost at the University of Pittsburgh for the support provided to this research.

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