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Simulation-based Decision Support System for Real-time Disaster Response Management

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Abstract

We have merged agent-based modeling, discrete event simulation, and geographical information systems (GIS) into one seamlessly integrated platform to simulate major disaster events in real time. One advantage of this hybrid architecture is the ability to assess the impact of agent rules on outcomes in disaster scenarios. A heuristic top-level framework has been developed to generate evolutionary, near-optimal dispatching decisions for the responders. The model considers multiple objectives and can dynamically drive the overall system towards a better performance over time. Because the users can interact with the simulation platform at a very high level linked to familiar interface features such as maps, it is accessible to end-users such as incident managers and decision makers with little simulation experience.

Keywords
Disaster management, emergency response, simulation optimization, decision support system, real-time decision making

1. Introduction
Effective decision support for disaster planning and response management requires simulation of a large number of time-varying factors and agents. These problem features render any purely analytical methods either ineffective or inefficient. Simulation is an attractive alternative approach to model the behavior of the large-scale stochastic systems. We have used agent-based discrete event simulation as a primary tool to model the first and secondary responses to catastrophic disasters. The integrated system includes comprehensive capabilities to simulate the responders' operations/actions and interactions with environmental factors such as weather patterns, traffic congestion and victim deterioration. The system has been "validated" by comparisons with historical data and review of results by experts. Although simulation is useful for modeling the expected behavior of complex operational systems, one must maintain the caveat that it is a prescriptive tool that may not necessarily be compatible with optimization procedures directly. One great advantage of our simulation system – called Dynamic Discrete Disaster Decision Support System (D^4S^2) – is the seamless integration of the simulation architecture with other components including a geographical information system (GIS) infrastructure data, user-friendly graphical interfaces and disaster information databases [1-4]. The computational flow in the system architecture is also based upon the recognition that disaster responses are an evolutionary decision process. The facts that decisions are influenced by events and implementation of decisions will alter subsequent events are implicit in the iterative and interactive updating of the data bases during the simulation, which effectively reset the initial conditions for the next decision iteration. We have also incorporated a Mixed Integer Program (MIP) model formulation (see section 3) to set initial conditions for local optimization of solutions, which greatly reduces computation time and resources.

2. Evolutionary Decision General Framework

Most large-scale systems and complex processes evolve over time frames ranging from hours to days to even longer periods. The response of agencies to catastrophic disaster is a typical example of a large-scale complex system because a major disaster normally involves a large number of victims, multiple response parties from each agency and multiple response agencies (governmental and non-governmental sectors). During the course of the event, no single decision path is universally applicable to all scenarios: new, unexpected conditions may arise for which previous response decisions must be modified. Figure 1 illustrates a basic simulation-based evolutionary decision process.

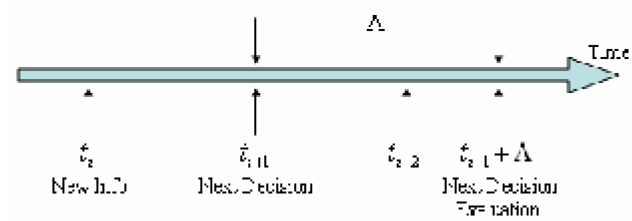

Figure 1: Evolutionary decision process

The evolutionary decision procedure is described as follows:

- At time t_i :
    - Deploy a new decision D_i which was made in the last iteration of the process. If $t = 0$ (start of the event), an experience-based expert decision D_0 is preferred because there is no time for detailed analysis. This decision must be valid for "all hazards," in the sense that it must (1) not exacerbate the situation directly (i.e., produce a deleterious outcome) and (2) not create deleterious bottlenecks or constraints on ensuing decisions.
    - Real-time, actual data of current time can be input as initial conditions for the first iteration of the decision process.
- During time $t_i \sim t_{i+1}$:
    - Run the simulator to the next decision point (simulation time) t_{i+1}. Store the simulation results of time t_{i+1} as SR_{i+1}.
    - Solve a closed-form Mixed Integer Program (MIP, see section 3 below) formulation which can approximate the simulation system to rapidly obtain a near-optimal solution $\widetilde{D}_{i+1}$ at time t_{i+1}. SR_{i+1} and/or earlier simulation results will be used to form the MIP model. The objectives are evaluated for time period $t_{i+1} \sim t_{i+1} + \Lambda$.
    - From $\widetilde{D}_{i+1}$, we perform simulation-based local searches to improve the solution. The best solution becomes D_{i+1}. The simulator runs from t_{i+1} to $t_{i+1} + \Lambda$ (simulation time) using SR_{i+1} as the initial conditions.
- At time t_{i+1} :
    - Deploy D_{i+1} and begin the next iteration.

3. Mixed-Integer Program (MIP) Formulation

The disaster response simulation system can represent the real system better than analytical models but at great expense in computation time. However, because disaster response decisions are normally extremely urgent, a time-consuming simulation process to search for optimal solution(s) is impractical and undesirable. An analytical MIP model has been developed to streamline the process of obtaining optimal solutions. The MIP model provides a rapid solution to guide the search into a promising neighborhood in the solution space. If initial search conditions are established by high-quality (near-optimal) initial solutions from the MIP formulation, only a few full simulation runs are needed for local optimization.

Solutions to complex decision problems often require a counterbalancing (or tradeoff) of multiple, partially incompatible objectives. For example, in our case, it is desirable to dispatch more emergency vehicles to the scene in order to increase the victim evacuation capacity. However, the introduction of too many vehicles into the response process (1) introduces significant congestion that can negatively impact access for other responders and the evaculation of casualties and (2) reduces the capacity to respond to baseline demands for responses to events such as heart attacks and traffic accidents. In some multi-objective cases, all objectives can be quantified in the same units (e.g., monetary units for economic consequences) to determine the tradeoffs automatically. Otherwise, one must find a set of candidate solutions and let a human decide. Which solutions should we include in the candidate decision set? A solution is Pareto-optimal if there are no feasible solutions that are at least as good in every objective. The set of Pareto-optimal solutions is called the efficient frontier or the tradeoff curve. A solution is dominated if there is another solution better in one objective and at least as good in the rest. One approach to find Pareto-optimal points is to combine the objectives with some weights. If all weights are positive, the combined single-objective program would give a Pareto-optimal point, if an optimal solution exists [5]. The weights are normally decided by the expert model users after evaluating the relative importance of all the objectives.

First, we formulated a nonlinear mixed-integer program (NMIP), termed a D^4S^2-NMIP, by closely investigating the internal structure of the simulation model. The model has eight main objectives as listed below:

Obj1. Maximize scene evacuation of life-threatening victims
Obj2. Maximize scene evacuation of severe victims
Obj3. Maximize scene evacuation of moderate victims
Obj4. Minimize scene fatalities
Obj5. Minimize EMS normal response degradation
Obj6. Minimize penalty cost for calling mutual aid responders
Obj7. Minimize penalty cost for changing tasks
Obj8. Minimize dispatching distance (or time)

Note that all the objective values are evaluated for the time period of Λ defined in Figure 1.

Emergency response planning is basically an assignment problem. Emergency vehicles (e.g., ambulances) are modeled as agents in the simulation model (agent-based simulation). These agents are (1) advanced life support (ALS) ambulances, (2) basic life support (BLS) ambulances, and (3) fire trucks. We want to assign one of the three possible tasks to each of the agents: (1) responding to the disaster, (2) responding to normal incidents, and (3) responding to an external service area (for mutual aid partners). The model D^4S^2-NMIP is presented below.

$$\text{D}^4\text{S}^2\text{-NMIP} = \underset{X}{\text{Min.}} \quad \sum_j w_j \cdot Q_j(X)$$

Subject to:

$$\sum_k x_{ik} = 1 \quad \forall i \in N \tag{1}$$

$$x_{i3} = 0 \quad \forall i \notin S_{\text{MutAid}} \tag{2}$$

$$\sum_{i \in S_1 \cup S_2} x_{i1} \geq 1 \tag{3}$$

$$\sum_{i \in S_1 \cup S_2} x_{i2} \geq 1 \tag{4}$$

$$x_{ik} = \begin{cases} 1 & \text{if agent } i \text{ is assigned to response task } k \\ 0 & \text{otherwise} \end{cases}$$

Let N be the set of all n emergency vehicle agents in the system. All agents are divided into r subsets. Type i agents ($i \in \{1,2,...,r\}$) are included in subset S_i such that $S_i \subseteq N$, $\bigcup_i S_i = N$, and $S_i \cap S_j = \phi$, $\forall i, j \in \{1,2,...,r\}$. In our problem, there are three types (r = 3 subsets) of agents: $S_1 = \{\text{ALS ambulances}\}$, $S_2 = \{\text{BLS ambulances}\}$ and $S_3 = \{\text{Fire trucks}\}$.

The objective function aggregates several individual objectives Q_j by imposing positive weights w_j for each objective, based upon their relative importance. Note that all the objective weights should be positive in order to obtain Pareto-optimal solutions. Without loss of generality, we have minimized the aggregated objective function. If any individual objective Q_j needs to be maximized, the Q_j should be flipped sign to negative in order to keep the weight term w_j positive.

The decision variables x_{ij} are binary. They indicate the response assignment for each vehicle agent. Because the task responses are mutually exclusive and collectively exhaustive, the integrity constraint (1) is necessary. Further, given that the type 3 task is only for mutual aid vehicles, constraint (2) specifies that the in-area vehicles cannot be assigned to a type 3 task for this disaster. S_{MutAid} is the agent subset of all mutual aid vehicles that are available for the disaster responses. Constraints (3) and (4) preserve basic EMS coverage by specifying that at least one emergency medical services (EMS) unit, ether ALS or BLS, should respond to the major disaster event and the normal emergency events, respectively. The objective functions Q_j have formulated by carefully investigating the internal operations of the simulation model; space limitations preclude their inclusion in this paper.

4. Computational Experiment

A relatively small network with 20 nodes was designed as a pilot study to test the performance of the D^4S^2-NMIP simulation-based approach for disaster management planning. It is depicted in Figure 2. Although the network is small, both the simulation and optimization are fully functional.

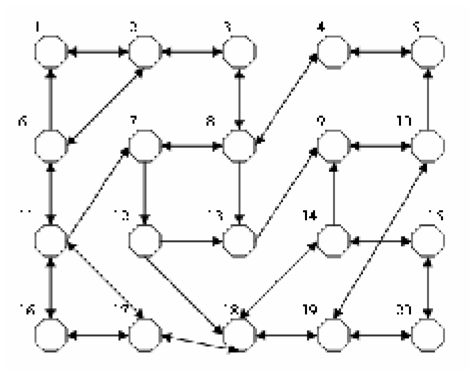

Figure 2: 20-node testing network

The network is completely connected (i.e., a vehicle at any one node can access to any other node through a finite path within the network). One-way streets are drawn as single-arrow connection lines; two-way streets are drawn as bidirectional arrows. Medical resources (e.g., hospitals, fire stations) are distributed on the network nodes and agent-based emergency vehicles can travel along the network from start nodes to destination nodes.

The simulation-based optimization procedure is implemented in VB.NET. The MIP model was generated and solved by the CPLEX Windows API with .Net. The simulation-related data were exchanged between the .Net program and Rockwell Arena simulation model through a database.

A specific disaster scenario was used to demonstrate the effectiveness of the evolutionary decision making procedure; 260 life-threatening, 346 severe, 223 moderate casualties occurred in an event at node #4. There were 120 deaths initially. The hospital and responder station information is listed in Table 1: there were four hospitals and 20 ALS, 8 BLS and 10 Fire responders available. The disaster decision support system generated decisions hourly until the scene was cleared.

The dynamic response solutions were compared with fixed solutions provided by the experts and/or protocols. Figure 4 compares the aggregate multi-objective value between the dynamic solutions obtained by the evolutionary decision procedure and the fixed expert decisions in the whole time series. For this minimization problem, the dynamic response solutions always obtained better overall performance.

It is hard to interpret the aggregate objective values because they do not have physical meanings. To better understand the dynamic solutions and their effectiveness, some key individual objectives are extracted in the following. Figure 5 shows the number of victims with life-threatening (LT) injuries at the scene as a function of time after the catastrophic event. With the dynamic solutions, LT patients can be cleared at the 11th hour, compared with about 19 hours using the fixed rule solutions.

Table 1: Hospital and responder stations

Hospital Info		**Responder Station Info**							
Location (Node)	*Capacity*	*Node*	*ALS#*	*BLS#*	*Fire#*	*Node*	*ALS#*	*BLS#*	*Fire#*
#1	Unlimited	#1	1			#11	1	1	
#2	Unlimited	#2	1		1	#13	1		3
#5	Moderate only	#4		1		#14	1		1
#17	Unlimited	#5	1	1		#15	3	1	
		#6		2		#16	2		
		#7	3			#17	1		3
		#8	1			#18		1	
		#9	1	1		#19	1		1
		#10	2		1				

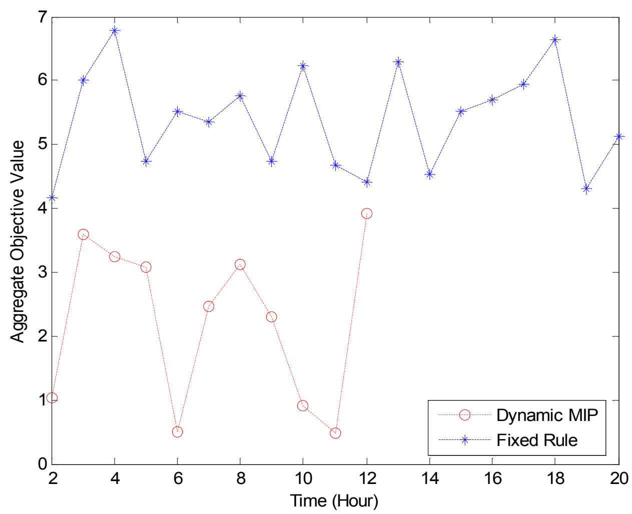

Figure 4: Comparison of aggregate objective value

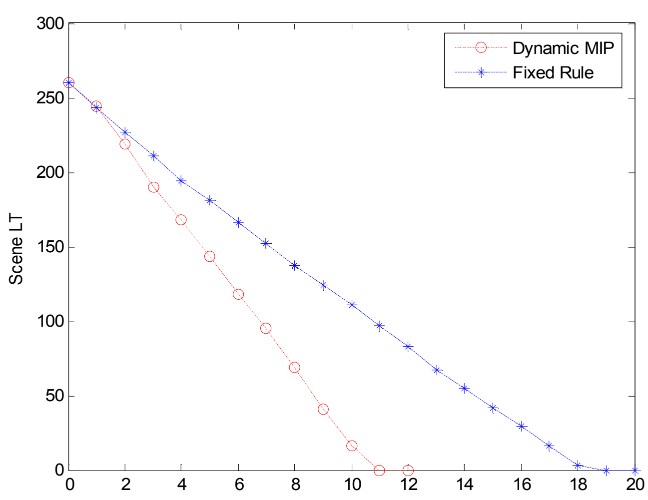

Figure 5: Comparison of scene life-threatening victim evacuation

The number of fatalities at the scene is another important measure of the response effectiveness. Figure 6 compares the numbers of fatalities between dynamic solutions and fixed solutions. Although the death rate for dynamic solutions is higher during the first nine hours after the response, there is a cumulative saving of five lives because the life-threatening victims are evacuated more rapidly. Further, although the fire responders can help treat/stabilize the severe victims, their appearance at the scene causes congestion that delays the EMS evacuation activity. Thus, the dynamic decision system dispatches the space-consuming fire trucks more conservatively to tradeoff rapid evacuation against an increased on-site deterioration rate of severely injured patients.

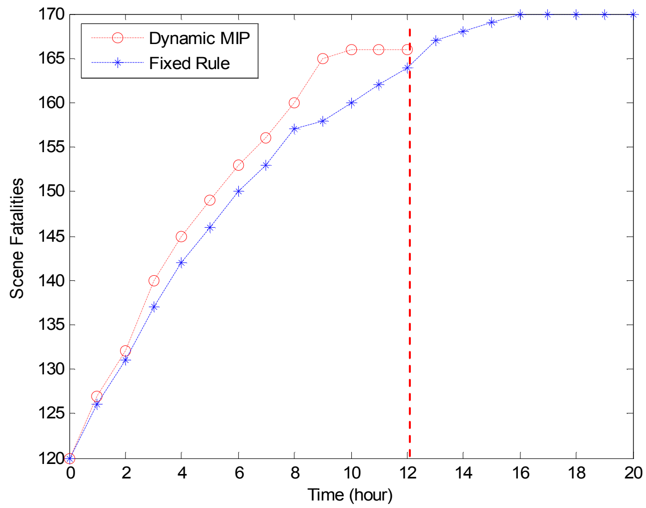

Figure 6: Comparison of scene fatalities

5. Conclusions

This paper briefly presents a simulation-based evolutionary decision making procedure and applies heuristic methods to solve a real-time disaster response management problem. The computational results from a pilot case study have shown the advantage of using the dynamic decision support system to obtain time-dependent solutions compared with fixed expert/rule decisions.

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