Coordination in Rapidly Evolving Disaster Response Systems: The Role of Information

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Coordination in Rapidly Evolving Disaster Response Systems

The Role of Information

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Assessing the changing dynamic between the demand that is placed on a community by cumulative exposure to hazards and the capacity of the community to mitigate or respond to that risk represents a central problem in estimating the community's resilience to disaster. The authors present an initial effort to simulate the dynamic between increasing demand and decreasing capacity in an actual disaster response system to determine the fragility of the system, or the point at which the system fails. The results show that access to core information enhances efficiency of response actions and increases coordination throughout the network of responding organizations.

Keywords: *disaster management; networks; fragility; core information; multiorganizational response*

POLICY PROBLEM

The shock of severe disaster in a major city creates a cascade of disruption among interdependent operating systems that shatters the existing functional capacity of the wider metropolitan region (Comfort, 1999; Quarantelli, 1998). Failure in one operational system triggers failure in other interdependent systems of electrical power, communications, transportation, water, gas, and sewage distribution. Under severe threat, the operational capacity of a complex region staggers under spreading dysfunction, compounding failure and creating new dangers for the population. For example, communications failure across

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conventional phone lines, cell phone systems, and overloaded radio channels following the 2001 World Trade Center (WTC) attacks in New York critically damaged the capacity of emergency response organizations in action and illustrated the vulnerability of interconnected metropolitan regions exposed to high risk (Seifert, 2002). Lack of resources, lack of coordination, and poor communication are recurring problems for organizational performance in disaster operations. However, these conditions are endemic to severely damaged disaster environments. Improving organizational performance in disaster environments means finding methods that overcome the potential risk posed by the initial conditions.

The amount of available resources alone does not explain organizational performance in disaster response operations. For example, availability of resources was not a limiting factor following the World Trade Center disaster of September 11, 2001. The Federal Emergency Management Agency (FEMA) granted $9.0 billion to disaster operations from the President's Disaster Relief Fund, the largest amount granted in disaster relief since FEMA was founded in 1979. Similarly, U.S. charities and public organizations received a flood of donations unlike any they had experienced before. Although it is difficult to tally precisely the total amount of funds received, 34 of the larger charities identified by the General Accounting Office (GAO) collected an estimated $2.4 billion after September 11, 2001 (GAO, 2002). A content analysis of news reports and official agency sources identified an evolving disaster response system of 456 public, private, and nonprofit organizations that engaged in response operations during the first 3 weeks (Comfort, 2002). Other sources identified more than 1,400 nonprofit organizations involved in recovery activities over a 6-month period (Kapucu, 2003). Yet, despite an abundance of material resources and voluntary personnel, many organizations and individuals needing assistance had difficulty in finding adequate support or services.

In disaster response and recovery operations, the ratio of demand for assistance to capacity to provide resources varies over time. In the initial stages of disaster, immediate demands involve actions to protect lives and provide assistance to injured persons. First-response organizations such as fire departments, emergency medical services, and police departments seek to meet urgent demands of disaster victims under tight time constraints. During the recovery period, issues of unemployment, sustainable business operations, housing, and medical care for victims and their families emerge that require long-term consideration. Households and community organizations need appropriate resources to meet different needs in the following distinct phases of disaster management: mitigation, preparedness, response, and recovery.

Theoretically, constructing a formal model to describe the dynamic relationship of demand to capacity in disaster operations is not easy. Different environments generate different types of demands that lead to the formation of different types of response patterns based on different levels of capacity in the system. These variable conditions increase the complexity of the model. Complexity theory, based on discrete dynamics, reveals the power of self-organization embedded in complex systems. The interactions among agents who participate in response operations form a disaster response system that reveals a spontaneous order. Agent-based simulation enables us to model those interactions and to study the dynamics of a complex system (Prietula, Carley, & Gasser, 1998). Agent-based simulation is a technique that models a system based on agents' behavior and their interaction. Whereas the initial definition of the system focuses on identifying the individual agents and their roles, the scope and order of the system emerges from the interactions among the participating agents. It is the interaction among the agents that defines the overall system properties. In this research, we test the applicability of a discrete dynamic modeling method, agent-based simulation, in a simulated disaster environment. We also emphasize the importance of identifying core information rather than the amount of information to be exchanged. Both social (Wasserman & Faust, 1994) and evolving network theories (Barabasi, 2002; Watts, 2003) are used to identify the structure of a disaster response network among organizations and the core information.

DISASTER RESPONSE AND FRAGILITY

MODEL

When a major disaster occurs, it threatens the potential collapse of the interconnected sociotechnical system that provides technical, social, economic, and cultural services to a specific region or community. The disaster threatens not only the destruction of technical infrastructure such as power lines, roads, and communication lines but also the social, organizational, and economic structures that support the daily operations of the community. The sociotechnical infrastructure in most communities is not a robust system but rather a fragile, interdependent system that is sensitive to shocks and disruptions. In such systems, disruption triggers unexpected consequences and cascading failure. The actual environment of disaster is extraordinarily complex. In this preliminary research, we make four basic assumptions regarding the disaster environment and the relationships among agents participating in the disaster response system. These assumptions allow us to reduce the complexity of the disaster environment and explore a simple model between demand and capacity in a dynamic environment.

First, we develop our model for a discrete geographical space and legal jurisdiction exposed to risk. In an actual disaster, geographic and jurisdictional boundaries are not necessarily congruent. In our model, we introduce geographical and jurisdictional regions within a two-dimensional space, which could be expanded. Second, the interaction among agents engaged in disaster response operations and the patterns of communication among their internal components and between the agents and other external systems create the dynamics of the response process. We assume that the demand flow of disaster response actions depends on the initial magnitude of disaster, the degree of cascade effect or interdependence among potential or actual damaged parts, and the capacity flow among the participating agents based on their initial conditions of resources, knowledge, skills, and equipment. The initial magnitude of disaster is measured by factors such as physical severity, geographic location, and preparedness for disaster. Assessing the initial magnitude of disaster is necessarily a preliminary effort in uncertain conditions, and this estimate is likely to be revised repeatedly as more accurate information becomes available. In the case of the WTC disaster, the number of dead was estimated at more than 10,000 on the first day but dropped to less than 3,000 as more specific information became available (Harrald, Ryan, & Comfort, 2003).

Estimating the cascade effect in any given disaster becomes a critical factor in assessing the demand for housing, sanitation, economic activities, telecommunication, psychological counseling, or other services. In routine operations, the components of the sociotechnical system are highly interconnected. If people need medical treatment, they may call 911 to ask for help and be transported to a hospital in an ambulance using the shortest route over city streets. However, if even a small part of this interdependent process malfunctions, it can cause serious disruption in performance. If the telephone lines are damaged, communication fails. If many people simultaneously switch their communication means from land telephone lines to wireless or cellular, cell phones will not work because the unexpected increase in the number of connections overloads the system. Assessing the interdependence among organizations and systems in disaster operations makes the analysis of actual events very complex. In this simulation, we limit the number of interactions among the agents to two steps.

Third, the degree of coordination developed among agents also affects disaster operations. Disaster may shatter the existing sociotechnical system, and rebuilding activities that reconnect components of the social and economic systems to the relevant technical systems through coordination are often more important than acquiring resources for the separate systems.

Finally, the type and quality of the initial disaster relief actions also affect the scope of demand over the period of recovery. Response to demand depends on the initial capacity of response agents, the inflow of additional resources from outside areas, and the burnout rate of personnel engaged in disaster operations, or the rate at which individuals drop out of service voluntarily. By definition, disaster is an unexpected event that exceeds the normal capacity of a community to respond to adverse events. Each of these indicators can be measured and included in a dynamic computational model.

Within the aforementioned framework, individuals seek ways to assist victims and lessen damage. Their behavior depends heavily on the type and amount of information available; the degree of planning and preparedness in place prior to the event; the specific time, location, and magnitude of the incident; and the existing organizational resources or constraints. In theory, if responders have perfect information, they find victims and assist them immediately. However, in practice, rescue agents do not know exactly who needs what kinds of help in which locations. Thus, we initiate the simulation in a state of high uncertainty and observe the pattern of changes in the interaction among the agents by increasing the amounts of information and rationality available to the agents.

To test the model, we developed a simulation platform using an agent-based approach to describe the relation between demand for assistance and a community's capacity to provide disaster services. Agent-based simulation is not only easy to model, using discrete spatial dynamics, but it is also expandable, allowing the developer to include various types of behavior. It produces a complex pattern of interactions among multiple agents and allows researchers to observe the emergence of patterns. The cooperation process (Axelrod, 1997), description of demand and supply functions (Epstein & Axtell, 1996), and other models of complex systems use this method (Flake, 1998; Gaylord & D'Andria, 1998; Langton, 1994).

To construct the model, we simplified the problem situation of a disaster environment as follows: First, we built a discrete two-dimensional, N by N, space that is divided by jurisdiction. The initial magnitude of the simulated disaster is annotated as C, and the number of damaged sites is N_d. We assign the initial demand to N_d randomly within the disaster space. The amount of resources required to meet demands at a damaged site is annotated as D^t_{ij}, which means that site ij requires the amount of D resources at time t.

Second, a cascade effect is introduced to increase the demand for disaster services, which in turn affects the capacity of the agents to reduce the demand. The relationship is formalized as $D^{t+1}_{ij} = (1 + r)\,(D^t_{ij} - S^t_{ij})$, where r is the growth rate of demand coming from the cascade effect, and S^t_{ij} is the supply of resources available to responding agents who are on site ij at time t. Demand does not increase infinitely. For instance, the cost of rescuing injured victims does not exceed the cost of human life. Thus, we set a constraint for the maximum demand level.

Third, each agent occupies one cell and moves around the space looking for damaged sites. When agents find damaged sites, they allocate their resource capacity to restore the site. Based on these assumptions, the capacity of the agent on the site ij at time t, S^t_{ij}, is defined as follows: $S^{t+1}_{ij} = (1 + R)\,(S^t_{ij} - D^t_{ij})$, where R is the growth rate of capacity coming from outside help.

Fourth, we follow the behavior rules for information search and movement defined by traditional agent-based simulation. We use the method attributed to von Neumann and used by others in the simulation of complex systems (Epstein & Axtell, 1996; Gaylord & D'Andria, 1998; Wolfram, 1994) for designating movement of the agents among their near neighbors in the system. The search method is heuristic and assumes high uncertainty. No command-and-control mechanism is used to control agents.

Finally, we introduce a weak type of voluntary coordination. We assume that the jurisdiction with the highest surplus capacity dispatches its agent to the location that has the greatest need or demand for services (Rawls, 1999). This process continues until either there are no surplus resources available or the demand is filled.

FINDINGS

The following graphs present a simplified version of demand and capacity over time, interpreting capacity as available resources. In practice, capacity includes a dimension of organizational learning, but for this initial model, we simplify the term *capacity* to mean available resources. The initial magnitude of disaster is given 1,000 units, which implies that the disaster requires 1,000 units of resources to relieve the damage at time $t = 1$. These demands are randomly allocated to 40% of the region. The agents only have a capacity of 30% of the initial demand at time $t = 1$. If agents determine the need and location of demand for damaged sites, they allocate their capacity for those sites and expend their resources but replenish their capacity at the rate $R = 0.02$ at the beginning of each time period. In the real world, the amount of time from the identification of demand to replenishing the agents' capacity after aid is given differs according to region, organizations, and disaster types. In this article, we assume 8 hours to be the unit of time for the simulation. The demand level decreases due to the agents' rescue activities but also increases due to the cascade effect, estimated at the rate of $r = 0.01$. The burnout rate of agents is given a value of 5. Thus, agents who expend all resources will take a break and reactivate 40 hours later.[1] Using these assumptions, the basic patterns of demand and capacity are shown in the following.

Figure 1 shows that the demand and capacity levels are changed by the agents' response activities after disaster. The graph could be divided into the following three periods: Phase I, Phase II, and Phase III. Phase I is the period from the starting point of disaster to the point where demand starts to decrease. In the initial period, from the first day to the sixth day, capacity gradually decreases as demand increases. This phenomenon occurs as agents expend their limited available resources to meet increasing demand from the event.

For example, during response operations following September 11, Health Care Financing Administration (HCFA) managers decided to send noncritical patients to nursing homes, thereby releasing beds for patients injured in the attacks. This strategy sought to alleviate crowding in area hospitals. If they allocated their finite resources for noncritical patients, they would not be able to help other people who had more serious medical needs. In actual events, response organizations may dispatch more resources than the victims actually need. If participating agencies do not conserve their resources but use all of them in the beginning stage of a disaster, there is a time lag to return their resources to the normal level. In Phase I, first-response operations are mobilized by

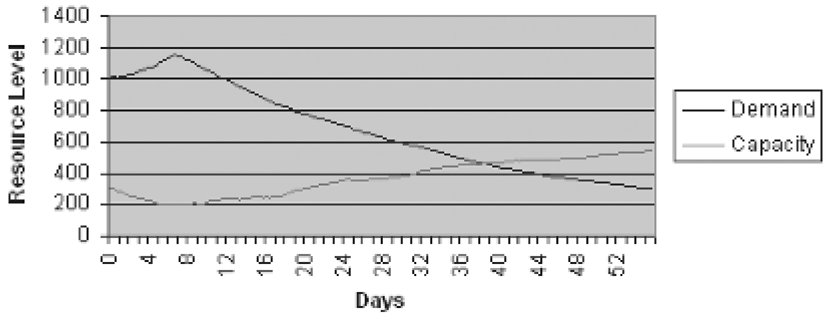

Figure 1: Demand and Capacity Changes Over Time
NOTE: We rescaled three units of simulation time, 24 hours, to 1 day in the figure.

organizations with legal responsibilities for protecting lives, property, and continuity of operations—police, fire, and emergency medical services—whereas informal groups of bystanders, family, and friends are often the immediate actors in the stricken area. This model considers only the actions of recognized response organizations in Phase I and assumes that these organizations are operating under the Incident Management System (Comfort, 1999).

Within our model, after a specific period of time, t = 39 days, capacity exceeds demand. Phase II is the period from the end of Phase I to the threshold point of change in the response system. At this stage, new resources enter disaster operations from outside the area, and other organizations join to help victims. The entrance of new organizations increases the difficulty of coordination in managing disaster response tasks as the operational relationships among first-response organizations and new organizations need to be defined. As response operations evolve, these interactions need to be redefined for each succeeding situation. New types of demand that are not anticipated in planned response procedures are likely to emerge, and respondents need to redefine the situation and assess their activities within their changed environment. Collective learning and action are essential to facilitate coordinated action.

Phase III represents the actions of disaster recovery and return to normal operations but has not had much attention in studies of disaster management. Contrary to common assumptions, resource scarcity is not the biggest problem in U.S. disasters. Rather, appropriate allocation of resources is more important in Phase III. Figure 2 shows the amount of funds raised and actually distributed by large charities following September 11, 2001.

Distribution of resources is a problem of coordination. Organizations may have resources, but they may not be distributed efficiently to people who need help. In some cases during the WTC operations, resources were distributed in a duplicative way; in other cases, victims and their families had difficulty in

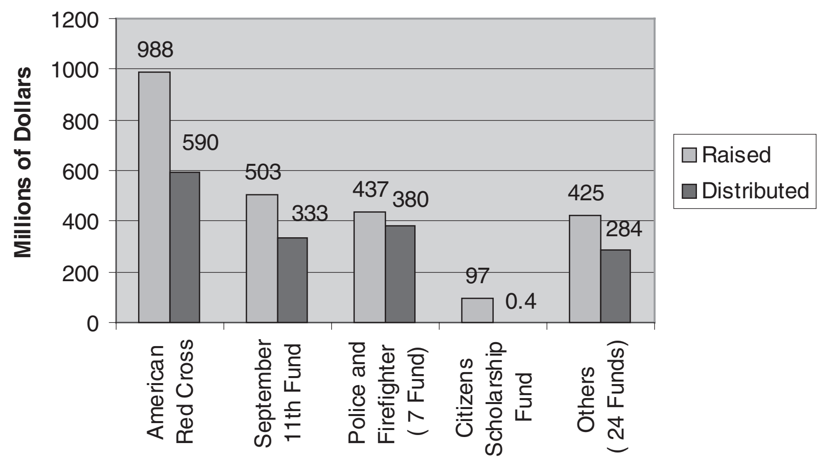

Figure 2: Amount of Funds Raised and Distributed by 34 Large Charities (General Accounting Office, 2002)

finding sources of assistance or applying for aid. Coordination in interorganizational activities is essential in Phase III.

The spatial size of the disaster area (*N*) also influences the demand and capacity flow. If the disaster affects a wide geographical area, it will require more time for recovery. To check this hypothesis, we increased the size of disaster area, *N*, and observed that the length of time required to terminate demand also increased. Here, we assume that one unit of geographical area = 1 km^2. Termination time is defined as the time when the demand level decreases to 10% of initial demand, and it is used in this model as a measure of the efficiency of response activities.

Figure 3 shows that as the size of the disaster area increases, the time needed to meet the demand also increases. If we divide the same spatial disaster area into multiple jurisdictions, it increases the efficiency of response activities. If relief teams affiliated with different jurisdictions have different command-and-control procedures, they may respond only to demands within their respective jurisdictions. We assume that each agent's activities are confined to his or her own region. We controlled the initial conditions such as scope of demand and capacity, area of disaster space, urgency of need, and divided the *N* by *N* disaster space according to the number of jurisdictions. Under a simulated disaster context, we calculated the termination time by increasing the number of jurisdictions participating in response operations (Figure 4).

ANOVA analysis shows that the number of jurisdictions influences the termination time (F = 169.9, p value = 0.0001). It implies a negative correlation between the number of jurisdictions and termination time. This finding suggests that the smaller jurisdictions, operating as self-organizing units, are more

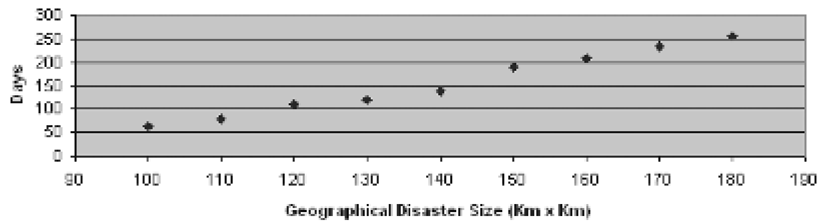

Figure 3: The Effect of Spatial Size on Duration of Disaster Response Activities
NOTE: We rescaled hours to days so that 1 day means three units of simulation time, 24 hours. The numbers on X-axis represent square km; for instance 140 means 140 km^2.

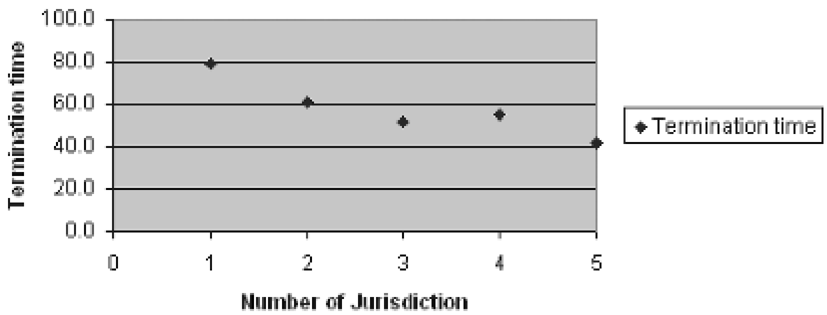

Figure 4: Duration of Disaster Response Operations by Number of Jurisdictions
NOTE: Like Figure 1 and Figure 3, we rescale three units of simulation time to a day.

effective in managing recovery operations than a single, centralized authority for the region.

Finally, an initial inquiry into the function of coordination was simulated by introducing a weak form of cooperation into the model. We sought to model spontaneous cooperation by introducing the following assumptions. Each jurisdiction has a different level of resources according to the size of its demand at each time phase of disaster operations. Some jurisdictions have surplus resources, whereas others lack resources in comparison to the size of their demands. The jurisdiction that has the highest amount of surplus resources will voluntarily dispatch agents to share its resources with the jurisdiction that has the lowest capacity in comparison to its demand. The amount of the shared resources does not exceed the amount of surplus.

The assumption we build into our model is that the dispatched agents do not directly reach the victims. They come from different jurisdictions and lack information regarding the specific needs and location of the victims. Therefore,

TABLE 1: Analysis of Difference in Mean Units of Search Time for Agents Responding to Demand, With and Without Coordination by Number of Jurisdictions

Number of Jurisdictions	*With Coordination*	*Without Coordination*	t *Statistic*	p *Value*
2	61.3	60.7	0.47	.64
3	52.7	51.7	0.59	.55
4	55.7	55.0	0.61	.54
5	41.3	41.7	–0.42	.68

they search for victims using von Neumann's search process of identifying critical targets through near neighbors. This assumption is similar to the strategies used by international search-and-rescue teams in response operations to major earthquake disasters (Comfort, 1999). Using these assumptions, the simulation results show that this form of spontaneous coordination has little effect on the efficiency of disaster response.

Controlling for the number of jurisdictions involved in disaster response activities, the model produced the results shown in Table 1.

The simple strategy of sharing resources without coordination for allocating the resources appropriately appears to have little effect on the efficiency of disaster response activities. This phenomenon can be attributed to the method by which the demand is distributed—we distribute demand by sampling from a uniform probability distribution. This results in the situation where all jurisdictions have a similar level of demand; hence there is no clear division between jurisdictions that have spare resources and those that have high demand. Conversely, if demand were distributed in clusters (a situation that would correspond more accurately to actual incidents), the influence of even simple voluntary coordination may be observed. These findings led us to explore factors of core information and timeliness as possible conditions that influence coordination and efficiency in disaster response more directly.

THE ROLE OF CORE INFORMATION IN DISASTER RESPONSE SYSTEMS

CORE INFORMATION

In the earlier section, we argued that cooperation without information is not sufficient to increase response effectiveness. This argument raises the following two basic questions: (a) What kind of information is critical in response operations, and (b) how is the core information shared among agents or organizations? In this section, we show the importance of identifying and exchanging core information by means of simulation, network theory, and assumptions based on empirical data.

A common assumption in disaster management is that lack of information is the basic factor in limiting the efficiency of response among organizations, and significant efforts are being made to improve this capacity. For example, the Pennsylvania Emergency Management Agency (PEMA) is responsible for collecting information and coordinating emergency response operations at the state level for all 67 counties. PEMA collects daily reports of emergencies occurring by county, which include incident date and time, response actions taken, response organizations notified, incident types, and date and time of closure. From the data analysis of PEMA Morning Reports[2] from June 1, 2003, to October 9, 2003 (Comfort, Ko, & Zagorecki, 2004), we find that the distribution of incidents falls in an exponential pattern not only for the number of incidents but also for the types of incidents.[3] Based on these results, we constructed a simulation platform implementing three different scenarios.

The first scenario represents the absence of information about time and severity available to emergency responders, in which agents search for cells that need assistance and expend their resources when they find a demand. This strategy is called *blind response*. The second scenario represents information available to agents based on time of demand, in which agents respond to demand on a first come, first served basis. This strategy is termed a *time-based response* and represents the general pattern of dispatching first responders immediately to emergency calls in practice.

In the third scenario, agents have access to information based on knowledge of time plus severity of the incident but where severity is the dominant factor in determining action and allocating resources. This strategy is called *severity-based response*. The three scenarios represent the relative importance of different strategies of action based on access to information regarding time and severity of the incident. These three scenarios are modeled with the following steps in an agent-based simulation.

This simulation framework is similar to the one previously discussed but differs in the following respects. First, we limited our second simulation to a single jurisdiction so that the possible influence of cooperation would not interfere with the results. Second, we introduced demand throughout the whole period of the simulation rather than introducing all of the demand at the beginning. These conditions created a situation where the responding agents are operating in a simulated world in which they are unable to predict where or what future demand will be. Therefore, they can build their action plans only on the basis of information available at a given time. To make our simulation more realistic, the distribution of demand over time was sampled from an exponential distribution based on an empirical analysis of the PEMA Morning Reports, June 1 through October 9, 2003. The severity of the incidents was sampled from a uniform distribution.

As the first step in the simulation, we created a sequence of incidents (defined by time and severity) that would happen in the simulated world. The responding agents do not have access to this information until an incident actually happens (at an earlier defined time). To model the influence of the information available to the responding agents, we learned that the amount of the information available to the agents should have been increased relative to the previous simulation setting. We achieved that effect by increasing the sight range of the responding agents. In our simulations we used the fixed range of metro distance 2, which is equivalent to the square 5 by 5 (with the agent in the middle).

To identify the importance of the various types of information in the process of emergency response, we designed three different frameworks according to which the agents acted. The frameworks were defined as follows:

- Blind response: In this strategy, agents randomly select one demand site from the list of those available in their range. This behavior is exactly the same as we used in the previous simulation.
- Time-based search: A responding agent in this framework always selects the demand site that appears earliest on the list of sites within the agent’s sight range. This framework corresponds to the strategy of first come, first served.
- Severity-based search: In this framework, an agent selects a site from the available demand sites that has the greatest severity. This selection also included knowledge of time.

Each of the three frameworks was placed in the same simulation setting and simulated multiple times to achieve meaningful results. For each simulation, we first created a series of incidents and assigned initial positions and amounts of resources for the responding agents. Then we used three copies of this setting to run simulations with the three different frameworks, ensuring that the initial conditions and the demand sequence were the same for each framework. This method allowed us to run what-if types of predictions.

We add one caveat regarding the interpretation of our findings. Because we placed a regrow ratio in our simulation (which corresponds to increasing the scope of the accident over time if the demand has not been adequately met), such a framework most likely magnifies the differences between the three frameworks. Even though our intent was to build a model for an emergency response system, the results of the simulation should not be interpreted literally. That is, it should not be assumed that the information on severity is more important than the information on time but rather that there is an additive effect when information is available to agents on both time and severity.

As a measure of the efficiency of response, we used average demand for the time unit over the whole period of the simulation. We adjusted the parameters of the simulation in such a way that the demand amount over time stayed on a flat level (with slight fluctuations). In other words, we wanted to have a system in which responding agents are constantly busy but the global situation is under their control. Each of the three frameworks was run multiple times to make the results statistically significant. The findings show that the combination of information on time plus information on severity represents the core information for emergency managers.

In Step 4, we repeated 300 simulations for each scenario to confirm the reliability of the results.

The most effective scenario will maintain lower average demands during the disaster response period. Table 2 shows the simulation results for each scenario.[4]

As observed, blind response in which agents have no information regarding time and severity is less effective than either time-based or severity-based response.[5] However, multiple comparisons of the three strategies using the Tukey-Kramer method[6] show that the difference between time-based response and severity-based response is not statistically significant, although the paired t test between time-based and severity-based response is statistically significant. These results indicate that blind search is the least effective strategy in comparison to the other two strategies. Furthermore, severity-based response that includes information on time of incident is at least equally or more effective than time-based response alone. In practice, first responders are dispatched immediately to an incident based on the time-based rule, first come, first served. However, if coordinating organizations have access to information regarding the severity of the incident in addition to time, the allocation of scarce resources is more efficient.

Reviewing the simulation results, it is apparent that the relatively small size of the map used for the simulation may influence the efficiency of the outcome. If agents have to search a wider area, it will likely affect their choice of desirable strategies and information. To test this possibility, we changed the map size to make the agents search in broader ranges for cells that have demand and reran the simulation. We increased the map size from 20 by 20 to 30 by 30, 40 by 40, and 50 by 50.

One noticeable change is that severity-based response is far more effective than the other two strategies over all ranges of sizes. In contrast, the blind search and time-based strategies do not show any differences in either the paired t test or multiple comparison results. The differences come from the risk of time-based response. If agents have to search wider ranges for demand, a time-based response strategy does not enable them to reallocate resources flexibly to newly emerging damage. Even if agents have sufficient resources to respond to other heavily damaged sites, they are usually locked in to a small area of damage.

The simulation results suggest two important conclusions. First, information contributes to increasing the efficiency of response activities. Using the two basic types of information, time and severity, yields far better results than blind response. However, the actual contribution of information depends on the situation. Even though knowledge of the time of occurrence for incidents provides valuable cues for response operations, these cues may misguide the agents' response under successive incidents within a wider geographic area. Thus, the essential factor in increasing coordination in disaster management is not only to

TABLE 2: Effectiveness of Response Actions by Type of Information Strategy

Scenario Type	λ = *0.14*	λ = *0.24*	λ = *0.34*	λ = *0.44*	λ = *0.54*	*Overall Sample*
Blind response	8.36	8.5	8.33	8.46	8.19	8.37
Time-based response	7.86	7.95	7.88	7.86	7.89	7.89
Severity-based response	7.67	7.64	7.62	7.62	7.68	7.65

provide information to response agents but also to identify the core information, including severity and time of incident, and share it with others.

SHARING INFORMATION THROUGH NETWORKS

Both empirical and theoretical research findings show that information flow is more efficient than initially recognized. The concept of "small-world" networks (Watts, 1999) assumes that the distance between any two nodes in large networks such as the World Wide Web or research collaboration networks can be traveled through a small average number of communication links compared to their network size. For instance, the World Wide Web network of 325,729 vertexes or nodes has an average distance of 11.2 links (Albert, Jeong, & Barabasi, 1999). The coauthorship network of MEDLINE, with approximately 1,520,251 vertexes, has an average distance of 4.91 nodes (Newman, 2000). The findings indicate that our world is small enough to reach any other anonymous person via a small number of other persons who are engaged in related activities (Milgram, 1967; Watts & Strogatz, 1998).

The original idea of a random network is modified by the small-world network (Watts & Strogatz, 1998) and the "scale-free" network (Barabasi & Albert, 1999; Dorogovtsev & Mendes, 2002; Newman, 2001). Whereas the small-world phenomenon identifies the smallest average distance among nodes in a large network, random graph theory has a weakness in explaining the clustering tendency and evolution of networks. In the real world, people tend to make linkages with each other not randomly but intentionally. For instance, if we know a person has many more friends than others, we may seek to establish a relationship with him rather than with a less popular person. Random graph theory does not describe this intentional behavior of networking.

Also, the degree distribution of complex networks follows an exponential distribution or power-law distribution, which is heavily skewed to the right and has a long right tail in contrast to the Poisson distribution.[7] Moreover, the clustering coefficient is greater than the random network model (Watts, 2003). The characteristics of small average distance, a high clustering coefficient, and formation of a gigantic connected component enable flexible information exchange. For example, on September 11, 2.3 million people visited FEMA's homepage (Seifert, 2002). FirstGov, Federal Bureau of Investigation, Department of Defense, and other agencies also provided information through a small-world network. An analysis of the e-mail exchange for one FEMA official in a key structural position for organizing relief activities following the 9/11 terrorist attacks shows that the average distance for the exchange of information in his communications network of 158 organizations is 2.04 nodes. This means that if an organization sends a message, it can reach any of the other 157 organizations in his network through 2.04 nodes (Comfort et al., 2003). This finding indicates that information is accumulated and delivered through a small-world network in crisis operations except under conditions of the physical destruction of the communications system.

The amount of information exchanged through telephone, wireless phone, satellite phone, mobile e-mail and paging devices, TV, radio, newspaper, and Internet is enormous, and finding effective means of exchanging core information among organizations with central responsibilities in disaster management is essential to improving regional capacity for disaster risk reduction. As scale-free networks show, the random failure of a network owing to disaster would be damaging only if it destroyed a significant number of high-degree nodes (Albert et al., 2000). The identification of small-world networks among organizations in a given geographic region exposed to disaster risk would represent a critical advance to improving capacity for interorganizational decision support in disaster management.

If complex networks transmit massive amounts of information, how is it possible to identify the core information? Core information is both structure and context dependent. The structural approach is to check the connectivity. Jurisdictions do not exchange information at the same rate and amount. The absence of certain key organizations will disconnect the whole network into partitioned subgraphs. One method is to check which node is a *cutpoint*, which means that deleting a specific node will increase the number of components in the graph. If we identify the cutpoints, we can analyze the activities and information exchange patterns of the actors. In her study of interorganizational coordination following the WTC attacks, Comfort (Harrald et al., 2003) adopted this approach and analyzed the information exchange patterns of FEMA with other organizations.

A second method is to check the *bridges*. This analogy has been used for both social networks and transportation networks. If certain edges of the network are destroyed, the network will divide into disconnected components. Thus, identifying which edges are bridges and which are *incident* nodes to the bridges will identify types of core information. When we use network analysis to identify the core information, we need to use multiple measures. For instance, Comfort (Harrald et al., 2003) identified the following six cutpoints in the network of organizations engaged in response operations following the WTC attacks: FEMA, Salvation Amy, Columbia University, Presbyterian Disaster Assistance

Newsgroup, YMCA, and Department of Housing and Urban Development. The bridge identified by the Lamda set includes the linkage among FEMA, American Red Cross, Church World Service, TxNPSC Coordination Team, Better Business Bureau, and New York City. Also, when we use the K-core analysis, the identified core organizations are FEMA, American Red Cross, Church World Service, Salvation Army, Catholic Charities US, New York State Emergency Management Agency, American Psychiatric Association Committee on Disaster, New York Community Trust, and Feed the Children. Because we are able to identify key actors, we also can examine the content of the messages exchanged to identify the core information. Here, caution must be taken to assess whether differences in results originated from sampling methods. Thus, this means of identifying the core information should be complemented by in-depth qualitative interviews and intersubjective interpretation of the data.

CONCLUSIONS AND FURTHER DISCUSSION

Based on our agent-based simulation, we developed a preliminary model of the dynamics of disaster response operations. We argue that different phases of disaster response require different types of information, equipment, and management skills. The efficiency of disaster response is influenced by the severity of disaster, type and amount of resources available, number of jurisdictions involved, and complexity of the response strategies. The results show that efficiency in disaster response has a negative relation to initial disaster severity and a positive relation to initial supply capacity. This is not surprising and confirms the intuitive judgment of any practicing emergency manager. The interesting finding is the positive relation between the number of jurisdictions involved and the efficiency of disaster response operations. This finding is counterintuitive to the general observation from practice that efficiency drops as the number of jurisdictions involved in response operations increases. The intervening factor appears to be identifying the critical nodes through which core information is exchanged; that is, verifying the small number of links that are used to communicate critical information under urgent conditions. The degree of change and the direction of influence in this process need to be studied further in a more fully developed simulation of this pattern.

Finally, we explored different strategies of seeking coordination among agents. We first introduced a weak strategy of self-organizing cooperation as an indicator of coordination. In this strategy, the jurisdiction with the largest surplus of resources assists the jurisdiction with the greatest need at each time step. The results show that this simplified strategy of resource sharing does not increase efficiency in comparison to a strategy of noncooperation. However, when we simulated different strategies of response based on types of information available to the agents, the factors of access, timeliness, and severity of incident demonstrated increasing efficiency in the agents' response.

These findings support the concept of small-world networks in which large networks of many vertices emerge that are interconnected by a relatively small number of communication links. This structural property enhances information flow. However, the coordination of core information among the connected nodes is critical.

This research represents an initial phase in the construction of a computational model of rapidly evolving disaster response systems. Further studies will build on findings suggested in this article. The structure and content of information exchange, communication, and timeliness in coordination processes will be further analyzed to explore the dynamics of evolving networks. Acknowledging its limitations, computational simulation nonetheless is an invaluable tool for analyzing the complex activities of disaster response. This simulation method can fill an important gap between qualitative and empirical studies of rapidly evolving response systems.

NOTES

1. The sensitivity of the parameter affects the level of demand and capacity, but it does not significantly change the pattern. Also we assume a unit of simulation time = 8 hours, but it could vary according to disaster types, organization types, and geographical characteristics.

2. Pennsylvania Emergency Management Agency, "Morning Reports Summary," June 1, 2000, through October 9, 2003, Harrisburg, PA.

3. The types of incidents are transportation, hazardous material, fire, utility failure, and explosive material.

4. The initial size of the two-dimension map was given as a 20 by 20 lattice.

5. The difference of means among three scenarios is statistically significant under the confidence level 95%.

6. We used SAS V.8e to perform Tukey-Kramer's multiple comparison.

7. Random graph theory predicts that the degree distribution will follow the Poisson distribution, which is a symmetric bell-shaped discrete distribution. Refer to Dorogovtsev and Mendes (2002) for a mathematical explanation.

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