Modeling Fragility in Rapidly Evolving Disaster Response Systems

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Abstract

Assessing the changing dynamic between the demand that is placed upon 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. This paper presents an initial effort to simulate the dynamic between increasing demand and decreasing capacity in an actual disaster response system to determine the point at which the system fails, or the fragility of the system.

Public organizations with legal responsibilities for the protection of human life and property, as well as private organizations responsible for managing utilities, communications, and transportation systems in metropolitan regions, are unable to monitor the interdependent effects of these critical infrastructure systems in real time. Further, they are not able to share information effectively about an emerging threat, nor can they communicate easily among different response organizations at different jurisdictions in a regional event. Modeling the fragility of sociotechnical response systems is critical to enabling metropolitan regions to manage their exposure to risk more efficiently and effectively.

To construct a theoretical model of this process, we observe the changing relationship between the demand for assistance and the capacity of the community to provide assistance. We include in our model measures of the magnitude of the disaster, the number of jurisdictions, and a simple type of cooperation to observe how these factors influence the efficiency of disaster operations. Information spreads quickly through inter-organizational or human networks. Stress in organizational performance arises when the amount of information surpasses human capacity to absorb and comprehend it, leading to failure in action. In complex disaster environments, failure in one component of an interdependent system triggers failure in other components, decreasing performance throughout the system and threatening potential collapse.

Based on the assessment of disaster operations as a dynamic process among interdependent organizations, we sought to build a computational model of the relationship between demand and capacity in an evolving disaster response system. We developed a simulation platform using Cellular Automata (Epstein *et al.*, 1996; Wolfram, 1994) to describe the pattern of interaction between demand and capacity. To formalize the interaction between organizations and information flow, we used evolving network theory which has been studied in the field of mathematics (Erdos *et al.*, 1960), computer science, and physics (Barabasi *et al.*, 1999; Newman, 2003).

We show that different phases of disaster response require different types of information and management skills. The efficiency of disaster response is affected by the initial magnitude of the disaster, the type and amount of resources available, the number of jurisdictions engaged, and the type of response strategies used. The results from the simulation confirm that efficiency has a negative correlation to initial disaster magnitude and a positive correlation to initial capacity. The number of jurisdictions involved in response operations is an independent variable influencing efficiency in disaster response, but the strength and direction of this influence requires further study. Also, sharing resources without specific information to improve coordination appears not to enhance efficiency in disaster response. Finally, we focus not on the amount of information that is available to practicing managers, but on strategies for access to core information that enhance the efficiency of information flow throughout the network of responding organizations. Network theory is used to identify the core information.

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Keywords: Disaster management, Networks, Fragility, Core information, Multi-organizational 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 population. For example, communications failure across 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 President's Disaster Relief fund (FEMA 2003), 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. While 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 non-profit organizations that engaged in response operations during the first three weeks (Comfort, 2002). Other sources identified over 1400 nonprofit organizations involved in recovery activities over a six-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 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 upon different levels of capacity in the system. These variable conditions increase the complexity of 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. In this paper, we test the applicability of a discrete dynamic modeling method, Cellular Automata (CA), in a simulated disaster environment.

Disaster Response and Fragility

1) 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 well-connected 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. 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 magnitude, geographic location, and preparedness for disaster. Assessing the initial magnitude of disaster is necessarily a preliminary effort in uncertain conditions, and the magnitude 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 ten thousand on the first day, but dropped to less than three thousand as more specific information became available (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 implications. 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 would overload 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 socio-technical 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 burn-out 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 above framework, individuals seek ways to assist victims and lessen damages. Their behavior depends heavily on the degree 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 don't 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 Cellular Automata (CA) to describe the relation between demand for assistance and a community's capacity to provide disaster services. CA 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. Christopher Langton's model of artificial life, John Conway's game of life, Axelrod's cooperation model and other models of complex systems use this method (Flake, 1998; Gaylord *et al.*, 1998; Axelrod, 1996, 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 which 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 available to meet demands from the damaged site is annotated as $D^t{}_{ij}$ which means the site ij requires the amount of D resource at time t.

Second, a cascade effect is introduced to increase the demand for disaster services, and the response actions, or capacity of the agents, reduces the demand size. The relationship is formalized as:

$D^{t+1}{}_{ij} = (1+r)(D^t{}_{ij} - S^t{}_{ij})$, where r is growth rate of demand coming from cascade effect, and $S^t{}_{ij}$ is the resource of supply 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 give a constraint to maximum demand level.

Third, each agent occupies one cell and moves around the space looking for damaged sites. When agents find the damaged sites, they allocate their 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.

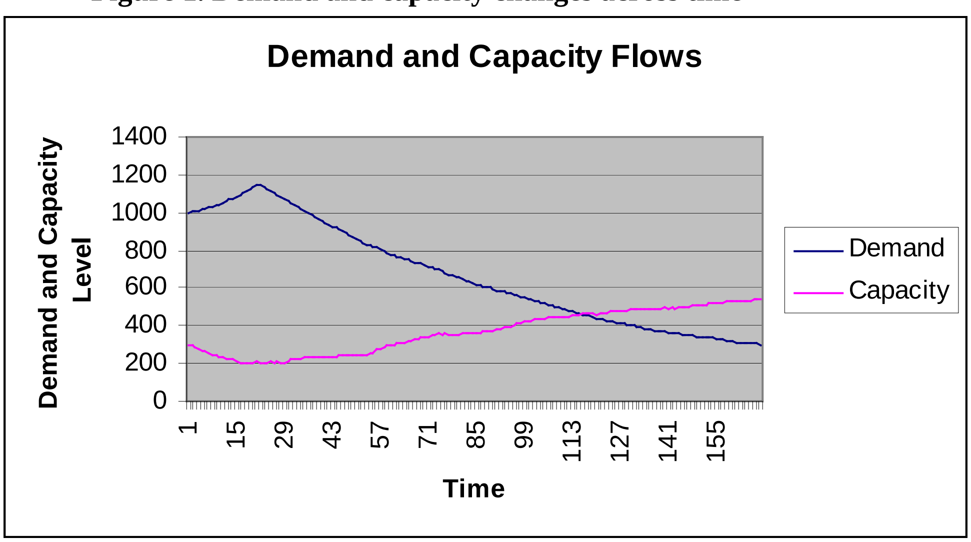
Fourth, we follow the behavior rules for information search and movement defined by traditional CA methods. We use the method for designating movement among near neighbors in the system attributed to Von Neumann and used by others in the simulation of complex systems (Epstein *et al.*, 1996; Gaylord *et al.*, 1998; Wolfram, 1994). 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 jurisdiction 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.

2) Findings

The graphs below present a simplified version of capacity, 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 1000 units, which implies that the disaster requires 1000 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. 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 burn-out rate of agents is given a value of 5. Thus, agents who expend all resources at t=i will not activate again until t=i+5[1]. Using this definition, the basic patterns of demand and capacity are shown below.

Figure 1. Demand and capacity changes across time



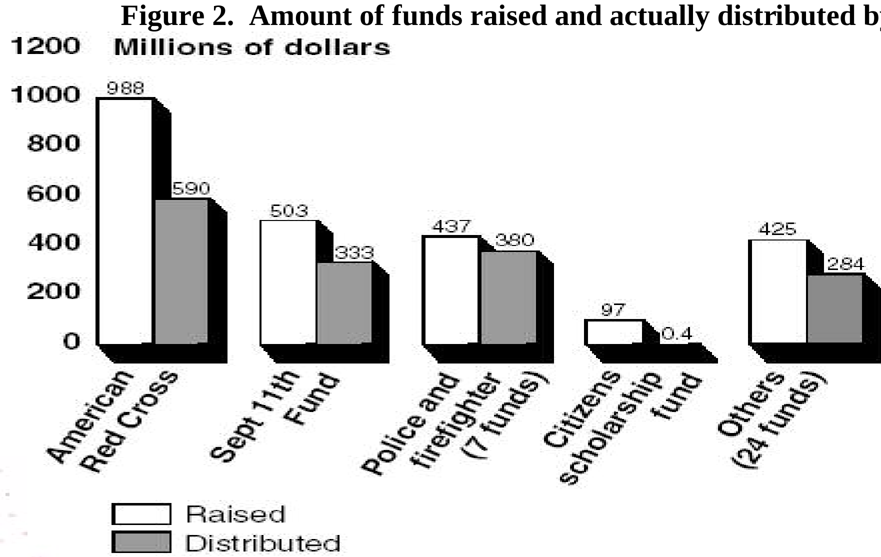
[1] Sensitivity of parameter affects the level of demand and capacity but it does not significantly change the pattern.

Figure 1 shows how the demand and capacity level is changed by the agents' response activities after disaster. The graph could be divided into 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, 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 administrators decided to send non-critical patients to nursing homes to alleviate crowding in area hospitals. If they allocated their resources for non-critical patients, they could not 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 and use all of them in the beginning stage, there is a time lag to return their resources to the normal level. In Phase I, first response operations are mobilized by organizations with legal responsibilities for protecting lives, property, and continuity of operations -- police, fire, and emergency medical services -- while informal groups of by-standers, 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 Command System (Comfort 1999).

Within our model, after a specific point, t=118 , 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 the disaster area from the outside 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; 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.

Figure 2. Amount of funds raised and actually distributed by 34 large charities

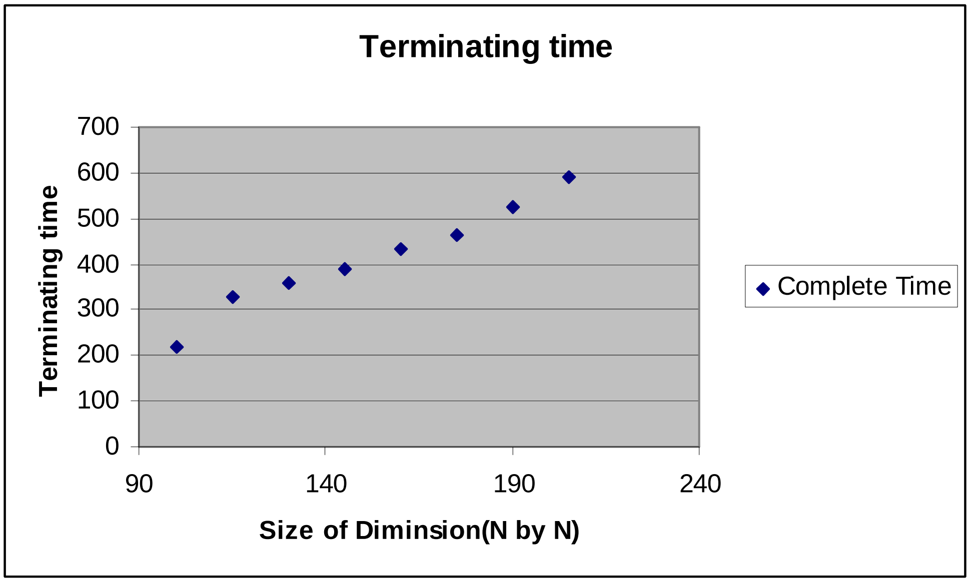


Source: GAO (2002), "SEPTEMBER 11-Interim Report on the Response of Charities," The U.S. General Accounting Office. p.13.

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 in the WTC operations, resources were distributed in a duplicative way; in other cases, victims and their families had difficulty in finding sources of assistance or applying for aid. Coordination in interorganizational activities is essential in Phase III

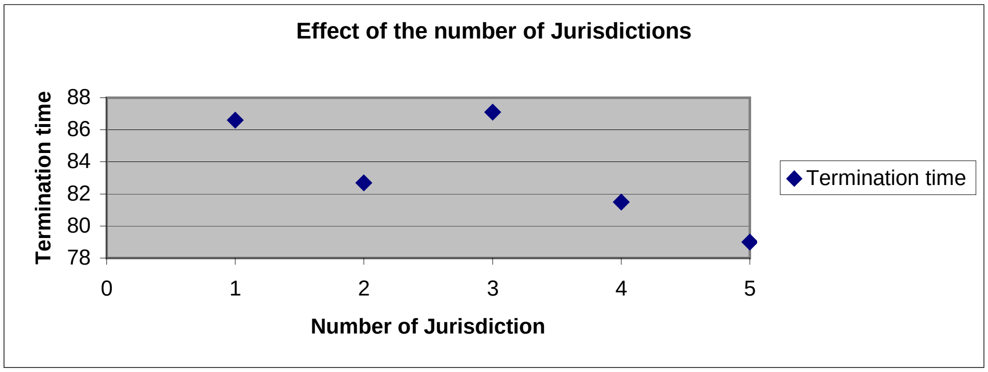
The spatial size of disaster (N) influences the demand and capacity flow. We increase the size of dimension, N, and observe that the termination time of demand decrease. Termination time is defined as the time when the demand level decreases to 10% of initial demand, and it is used in this model as a measure of the efficiency of response activities.

Figure 3. The effect of spatial size on duration of disaster response activities



The above figure shows that as the size of 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 control 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 calculate the termination time by increasing the number of jurisdictions participating in response operations.

Figure 4. The effect of Number of jurisdictions



ANOVA analysis shows that the number of jurisdictions influences the termination time (F=2.57, p-value=0.009). Although the evidence is not strong, it implies a negative correlation between the number of jurisdictions and termination time.

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, while 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, they search for victims using von Neumann's search process of identifying critical targets through near neighbors. Using these assumptions, the simulation results show that this form of spontaneous cooperation has little effect on the efficiency of disaster response. In further iterations of the model, we will explore factors of core information and timeliness as possible conditions that influence coordination and efficiency in disaster response.

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

Table 1. Statistical analysis result of sharing resource without coordination

Number of Jurisdictions	t-statistic	p-value
2	1.60	0.14
3	1.71	0.11
4	0.47	0.65
5	1.93	0.09

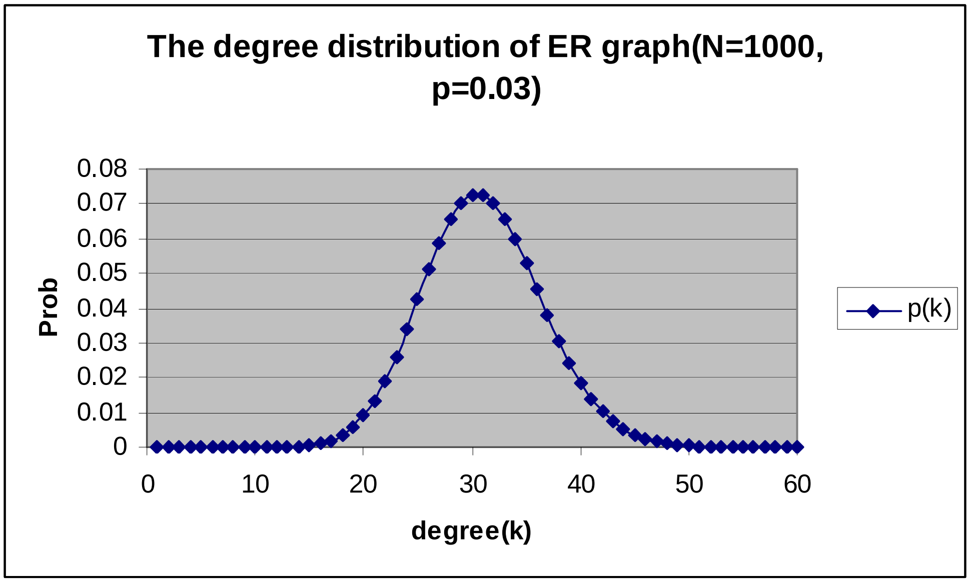
The simple strategy of sharing resources without coordination for allocating the resources appropriately appears to have little effect on the efficiency of disaster response activities. This phenomenon can be attributed to the method by which the demand is distributed – we distribute demand by sampling from a uniform probability distribution. This results in the situation where all the 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 cooperation may be observed.

The Role of Information

The general assumption in disaster management is that lack of information is the basic factor in limiting the efficiency of response among organizations. However, the critical factor appears to be the centrality of information to core disaster response activities, rather than simply the amount of information available to the participating agents. Network theory lends insight to this concept. Both empirical and theoretical research shows 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 *et al.*, 1999). The co-authorship 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 *et al.*, 1998). Random graph theories also provide evidence of efficient information flow. The random network of Erdős and Rényi (1960), usually called the ER network, is the pioneering model. Given a fixed number of edges, N, and probability, *p*, that each pair of edges is connected, the network, on average, will have pN(N-1)/2 edges.

The degree distribution follows binomial distribution, $P(k) = \binom{N-1}{k} p^k (1-p)^{N-1-k}$. If the N is large enough, the degree distribution will follow the Poisson distribution, $P(k) = e^{-\bar{k}} \bar{k}^k / k!$.

Figure 5. The degree of distribution of ER graph



We also calculate an average degree of distribution of vertices for the network. The average degree is $\bar{k} = p(N-1) \approx pN$, which implies the expected number of vertices with degree k is $E(X_k) = N * \binom{N-1}{k} p^k (1-p)^{N-1-k}$.

Also, we may calculate the point at which the network forms a clique. Percolation theory asserts that it is possible to identify the emergence of a giant connected component in dynamic networks (Peitgen, Jurgens and Saupe, 1992). The theory indicates that when a critical point, *Pc*, is reached, a giant cluster emerges within the entire network. The percolation threshold in a random graph is $p_c \cong 1/N$, that is, $\bar{k}_c \cong 1$. The findings of the ER network are modified by the "small world" network (Watts *et al.*, 1998), and the "scale-free" network (Barabasi *et al.*, 1999; Dorogovtsev *et al.*, 2002; Newman, 2001). The degree distribution of complex networks follows an exponential distribution or power-law distribution, which is heavily right skewed and has a long right tail in contrast to the Poisson distribution. Moreover, the clustering coefficient is greater than the ER 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 showsthat the average distance for the exchange of core 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 in an average of through 2.04 nodes. (Ko, Zagorecki, and Comfort 2003). This finding indicates that information is accumulated and delivered through a small world network, except under conditions of the physical destruction of the communications system.

The amount of information exchanged through telephone, wireless phone, satellite phone, a mobile e-mail and paging device, 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 interorganization 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. Comfort (2003) adopted this approach and analyzed the information exchange patterns of FEMA with other organizations. A second method is to check the *bridges*The 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 (2003) identified six cutpoints: FEMA, Salvation Amy, Columbia University, Presbyterian Disaster Assistance Newsgroup, YMCA, Department of Housing and Urban Development. The bridge identified by the *Lamda set* includes: the linkage among FEMA, ARC, Church

World Service, TxNPSC Coordination Team, Better Business Bureau, and NY. 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, Feed The Children. As we are able to identify key actors, we can examine the contents of 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 inter-subjective interpretation of the data.

The final issue in the model is the function of coordination. Our simulation shows that sharing resources using a simple form of cooperation based on a Rawlsian concept of justice as an indicator of coordination has little influence on the efficiency of disaster response operations. However, the conceptualization and formalization of coordination is still under study and observation in practice. We use simulation with empirical studies as a means to explore the possible combinations of information and strategies in practice (Flake, 1998; Rivkin, 2000).

Conclusions and Further Discussion

Based on our CA design, 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 magnitude 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 magnitude 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 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 non-cooperation. Other factors such as proximity, timeliness, and prior experience among agents may be more important in increasing efficiency than a Rawlsian theory of justice (Rawls, 1999) in resource sharing.

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. Thus, in the construction of a more advanced simulation model, it will be essential to determine what is the core information and to whom it is transmitted rather than simply assessing the amount of information that flows through the response system.

This research represents an initial phase in the construction of a computational model for a rapidly evolving disaster response system. Further studies will build on findings suggested in this paper. We will explore this model using different types and magnitudes of disaster, resources, internal and external communication patterns, and number of jurisdictions. We will also explore diverse types of coordination, based patterns observed in practice. Key variables of information exchange, communication, and timeliness in coordination processes will be 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.

Acknowledgments

I acknowledge, with thanks and appreciation, the leadership of John R. Harrald,, Principal Investigator, and the support of Julie Ryan, Co-Principal Investigator, in conducting the research on the National Science Foundation grant, CMS 0219953.

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