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Simulation Experiment of Disaster Response Organizational Structures With Alternative Optimization Techniques

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Abstract

Disaster response operations are critical for decreasing the devastating impacts that result in casualties and property damages. Since these operations require cooperation in dynamic and complex situations, the responding organizations require a solid organizational structure collectively. This article introduces computational designs and evaluations of alternative organizational structures for disaster responses to resolve the disconnections between resource demands and supplies. In particular, this research consists of (1) organizational structure designs with two optimization techniques, (2) agent-based simulations that virtually replicate disaster response contexts, and (3) social network analysis to interpret the relations between the structures and the performances from the network perspectives. We applied this approach to log records of Hurricane Katrina, and our evaluations suggest that alternative organizations would improve operation outcomes, that is, increase the successful resource delivery counts and reduce a number of organizational conflicts. This computational approach could be further utilized in designing and evaluating organizations under complex and dynamic situations.

Keywords

disaster response, dynamic network analysis, agent-based modeling and simulation, organizational structure optimization

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Introduction

Disasters such as earthquakes (Beavan, Fielding, Motagh, Samsonov, & Donnelly, 2011), hurricanes (Comfort, Oh, Ertan, & Scheinert, 2010), tsunami (Matanle, 2011), and massive landslides (Lee & Jung, 2011) call for well-organized responses to minimize the damage to our society. The damage is not limited to one facet of our society. Disasters affect our traffic infrastructure, health care services, communication lines, energy supply, shelters, and security (Tierney, Lindell, & Perry, 2001). Even if we respond to a single dimension, this single response depends upon full-spectrum supports. Getting food to evacuees, a single response, requires traffic routes for delivery, communication between providers and shelters, and more. To guarantee this general support, an organization needs authority over the multiple dimensions of our society. However, this idea is impractical in our society. Many societal infrastructures, resources, and information are managed by separate organizations to ensure technical specialization and task delegation. Under this decentralized structure, organizations should cooperate as a single body to respond to disasters effectively (Harrald, 2006).

Two approaches can improve cooperation among multiple entities specialized in different domains: the individual approach and the structural approach (Mayhew, 1980). The individual approach focuses on how to make an organization's internal structure and dynamics more cooperative with other organizations. The structural approach concentrates on designing a structure and dynamics among multiple organizations in the structure. In a disaster response, the distribution of resources and infrastructure demands interorganizational cooperation, which single organizations cannot achieve. A cooperative structure grows more important as more diverse organizations join with their different specializations.

Structures among social entities, including disaster response organizations, have evolved from hierarchies to networks (Simon, 1964; Weber, 1947). Traditionally, a tree-shaped hierarchy was enough to handle the complexity of organizational cooperation. Cooperation was limited to a simple subgroup of organizations, with no demands crossing group affiliations. However, disaster response makes a simple hierarchy impractical for several reasons. First, it is a collective response of organizations from multiple layers and multiple branches (Comfort et al., 2010), including federal, state, and local government branches, nongovernmental organizations (NGOs) and military units. It is impossible to organize these eclectic organizations in one hierarchy. Second, each disaster's characteristics require collaboration that crosses affiliations. Disaster scenes are often local areas not well known to federal organizations and NGOs. The local residents frequently require outside support from the government, military, and NGOs, which calls upon cooperation and structures supporting the flow of information to and from the local area (Schneider, 2005). Third, disaster response takes time and shifts its cooperation structure within that time. It starts the moment a disaster strikes and then response organizations arrive and leave dynamically (Comfort et al., 2010). This dynamism makes a hierarchy among organizations difficult. For these reasons, disaster response organizations instead collaborate in a network structure. That network grows complex by couplings among subgroups, changing demands of information and resources, and the dynamism of participations.

Designing the organizational network of the disaster response organizations is the major structural research question for improving the response. This question also arises in intelligence, military, management, and public policy. Diverse techniques have been used in seeking to answer it, including social network analysis (Wasserman & Faust, 1994), agent-based modeling and simulations (Bonabeau, 2002), and text analysis (Diesner & Carley, 2004). Previous research analyzes potential organizational networks in the domain with computational approaches. Many works evaluate the potential performance of typical structures like cellular, hierarchy, or scale free (Airoldi & Carley, 2005) with agent-based models and social network metrics to gauge information propagation speed, task accuracy, completeness (Moon & Carley, 2007), and so on. From these analyses, researchers provided alternative network structures with quantitative rationale.

This article describes two network design methods based upon optimization techniques and their application to disaster responses. Previous works used subject-matter expert knowledge, past records (Comfort et al., 2010), or a typical network structure (Carley & Lin, 1997) to provide sample organizational networks for analysis. Some heuristic approaches like simulated annealing (Davis, 1987) were also used.

This article contributes four major points to the organizational network design problem. First, it adds a deterministic network optimization technique using linear programming (LP) from the operations research field. More specifically, we identify similarities between the organizational design's structural issues and the multi-commodity network flow problem (MCNFP; Hu, 1963), so we modify and adapt the methodology to solve MCNFP in the operations research field to the organizational network design problem. Second, we found that network design has rarely used the genetic algorithm (Davis, 1987), so we add the particular heuristic that solves the resource delivery shortest path problem (RDSPP) to the methods of potential network generation. Third, in spite of a few previous works combining network design with network dynamics (Carley & Svoboda, 1996), we found that using network optimization and simulation models together still requires further application cases, and the disaster domain has not been studied in such a combined way. Fourth, we test this new approach to the disaster response scenario of Hurricane Katrina to which no one has applied an agent-based model. We applied both optimization methods to the simulation and found they have distinct characteristics and organizational performance.

Our work has a number of limitations. The first is the validation of our agent-based model, but given the shortage of real-world data sets, it would be impossible to empirically validate our simulation in the real world. To negotiate this limitation, we employed extensive statistical analyses on the results to verify statistical significance and robustness. The second limitation is the scope of the optimizations. We only optimized the communication structure of the organizations, not the resource demand and supply distributions. In the long term, these distributions should be the focus of optimization.

Previous Research

We surveyed previous research on the design of organizational structures with qualitative and quantitative approaches. After a general survey of structural designs, we concentrated on special applications to improving disaster response.

Organizational Structure Design

Since the 1950s, researchers have studied alternatives to the hierarchical tree structure (Guetzkow & Simon, 1955). The hierarchical perspective emphasized individual improvements, such as faster and accurate decision making, adaptation to an operating environment, and tighter control of an organization's members, which assumed elites in the organization as predictors of its performance. Naturally, this previous trend preferred more control by elites, and this led to the hierarchical structure. After the 1950s, researchers started treating an organization as more than a collection of individuals (Bittner, 1965; March & Simon, 1958; Simon, 1964): Once it is formed, the interactions among its agents (Carley & Newell, 1994; Eisenhardt, 1989; Perrow, 1986) make it something else, and the agents' status makes them something other than individuals. This structural perspective now informs structural design.

Herbert Simon performed some of the earliest work in this field by looking at diverse structures, such as all-channel, wheel, circle, and so on (Guetzkow & Simon, 1955). He quantitatively investigated the path length from one individual to another as a proxy measure for the organizational performance. This research is distinct from its predecessors in two ways. First, it changes the organizational management from ordering and controlling an individual to designing better coordination with their structure. Second, it extensively uses quantitative techniques to design, measure, and improve the organization because of its complex structure. In previous research, quantitative analyses mostly bolstered qualitative ideas, but now, quantitative approaches inspire new qualitative thoughts.

Quantitative analysis in organizational design has accelerated because of two major methodological advancements: social network analysis (Wasserman & Faust, 1994) and modeling and simulation analysis. Social network analysis investigates the various characteristics of social structures, mainly represented as a graph (White, Boorman, & Breiger, 1976). Social network analysis uses clustering algorithms such as Newman clustering to find a cohesive group (Newman, 2001) as well as property measures such as degree centrality to measure an entity's relative position in a structure (Friedkin, 1991).

In applying this analysis, researchers identify cohesive groups that might cover individual organizations from different branches and sectors. This heterogeneous group is not formally represented in the hierarchy, but it would still interact closely in a disaster. Social network analysis can also measure cognitive burdens and information flow in an organization (Carley & Lin, 1997). If a single organization has many subordinates—which would suggest many links from it to them—the hub organization may suffer from information overload in a disaster. Such difficulties would compromise its performance and call for reconfiguring it; for example, mid-class organizations may need to be reassigned to the hub organization.

The modeling and simulation analysis generates the expected situation virtually and walks through it with the models representing organizational operations and performances (Daly & Tolk, 2003; Macal & North, 2010). Although live experiments provide realistic results, they have several limitations. Mainly, they are difficult to execute many times because of their cost and running time, so the design and trial of organizational structures are difficult to iterate for many samples. Simulation models regenerate the situation by representing organization participants as computer models (Pew & Mavor, 1998). Due to the nature of the agency of organizations, agent-based modeling and simulation (Bonabeau, 2002) are frequently used. Agent-based models depict the individual process of perceiving the situation, deciding the agents' own choices about it on those choices and acting on it. For example, Soar (Laird, Newell, & Rosenbloom, 1987) is a modeling framework that simulates an agent's cognitive and decision-making processes. Plural Soar (Carley, Kjaer-Hansen, Newell, & Prietula, 1992) is a model to simulate a collection of agents, and this model simulates the organizational structure in the military domain. These simulations on organizational structures require a simulation setup, including the initial organizational structure to test and agent behavior parameters. Researchers focus on setting up the organizational structure because it is central to virtual experiments.

In early examples, researchers used hypothetical structures from diverse network topologies, such as cellular structure, scale-free structure, and core-periphery structure. After refining this approach, recent works experiment on structures from real-world case studies, such as a network-centric operation structure from the military (Moon & Carley, 2006), a cellular structure from a terrorist organization (Moon & Carley, 2007), and an information flow network after mergers and acquisitions (Frantz & Carley, 2013). Recent studies also evaluate structures that are hypothetical but optimized. For example, Carley and Svoboda (1996) combined network analyses, agent-based models, and simulated annealing to show how to adapt an organizational structure to increase its task performance. Their experiment combines individual learning structure with structural learning and a dual-mode learning structure. This article's contribution lies in combining network analyses, simulation, and optimization techniques to the specific real-world scenario of disaster response in Hurricane Katrina, instead of hypothetical task performances.

Disaster Response Organizational Structure

Analysis of collaborative and networked operations is one of the most popular research topics in disaster response. Researchers analyze them at the individual, intraorganization, and interorganization levels. Here, the intraorganization level means the internal structure and dynamics of an organization, and the interorganization level is the structure and the dynamics between multiple organizations. Also, the operations receive qualitative evaluations; quantitative, yet static evaluations; and quantitative and dynamic evaluations.

Many crisis management practitioners and researchers start with a qualitative approach. For instance, Comfort (2007) systematically organized qualitative evaluations of organizations in crisis management. She assessed the handling of past crises from the perspectives of cognition, communication, collaboration, and control. In public administration fields, Waugh and Streib (2006) said collaboration is important to treat natural and man-made crises, so we need new leadership that derives its power from effective strategies and compelling vision.

Qualitative analyses often rely on support from quantitative analyses from real-world observations. Comfort, Oh, Ertan, and Scheinert (2010) strengthened their previous qualitative analyses with observations about the Katrina crisis management data set. They counted the communication messages and coordinated efforts from the field survey and found the rates of successful responses to various requests and communication bottlenecks. By statistically examining the real-world data, they qualitatively argued how to prepare organizations to behave resiliently. Bharosa, Lee, and Janssen (2010) said sharing information is important, so they investigated the strength of interactions at each level of community, agency, and individual using empirical analysis.

Finally, some researchers analyzed crisis management operations with modeling and simulation. Oh and Moon (2008) used an agent-based model to find a new organizational structure for effectively handling requests and responses. They varied the organization's structural parameters as well as its information process capacity. They concluded that introducing more links to a structure might not be a better solution than increased capacity because more links might channel more broadcasts of unnecessary information. Our previous research (Lee, Oh, & Moon, 2012) was another analysis using agent-based model and tried to explain how to manage organizations from the viewpoint of network-centric operation to drill-down the internal dynamics of organizational operations.

This article extends the dynamic analysis of crisis management studies by adding an optimization stage to the analysis. Although the majority of the previous research evaluates the response of organizational structure as a fixed structure, we redesign it and evaluate it in a dynamic context. We use social network analysis to find real-world implications for this virtual structure and its evaluation results, which are this study's qualitative findings.

Scenario and Data Set Description

Before we introduce our methodologies, we describe the scenario and data set used in our virtual experiments. Moreover, our methodology aims to be a general framework of organizational network designs, but it is bound to the scenario and data set's characteristics. Therefore, knowing the scenario and the data set will make our work more understandable. We worked from the disaster response communication logs during Hurricane Katrina in 2005. These logs come from the situation reports by the Louisiana Office of Homeland Security and Emergency Preparedness and were refined by the Center for Disaster Management at the University of Pittsburgh. These logs illustrate communicative links between organizations during a disaster response. Others have analyzed them qualitatively and quantitatively but only used them for a couple of simulation analyses so far. Descriptive statistics of the data set are found in Table 1 and Figures 1 and 2.From the data set, we recovered a multimodal and multiplex network structure. The network includes three node classes. The data set describes how disaster responses are

Table 1. Summary of Simulation From the Hurricane Katrina Data Set.

Category	Descriptive Statistics
Number of events	2,576
Collection period	August 27–September 6 (250 hr)
Involved organizations	169
Exchanged services and resources	123
Number of communication links	616
Number of status type	8

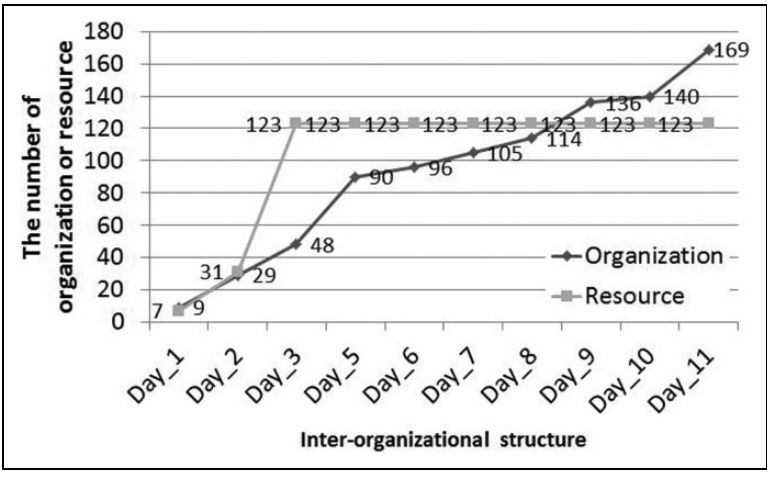

Figure 1. Number of involved organizations and delivered resources over period.

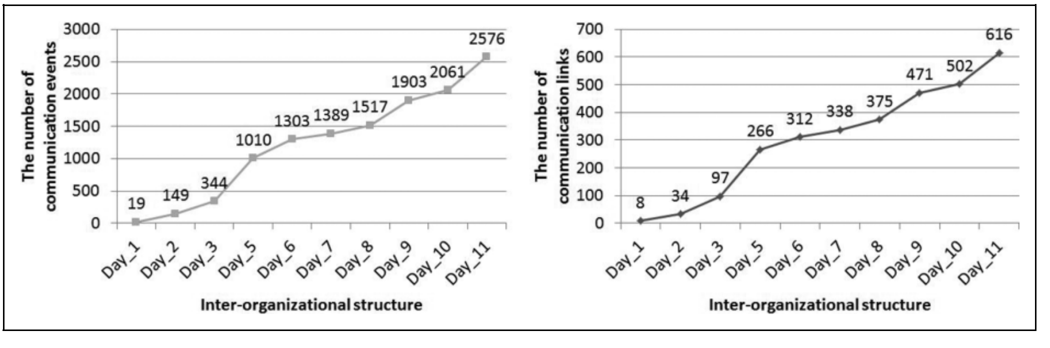

Figure 2. Descriptive statistic of data set. The number of communication events (left) and the number of communication links (right).

performed, such as a resource of an organization has been delivered to other organization, so the network consists of a set of organization nodes and a set of resource nodes. Moreover, we included one more node class called "message," which is not specified in the data set but modeled through our simulations. The message nodes represent all interactions exchanged among organizations in a simulation. The links of the network have six types of semantics: interorganizational structure, resource ownership, resource requirement, received message, sent message, and resource delivery message. Because many notations are defined and applied in this article, we summarized frequently used notations and their definitions in

Table 2. Meta-Network of the Hurricane Katrina Data Set.

	Organizations (*O*)	Resources (*R*)	Messages (*K*)
Organizations (O; 169 organizations)	Interorganizational Structure (*OO*; Density = 0.022)	Resource ownership (OR^S; density = 0.030) Resource requirement (OR^D; density = 0.051)	Received message (OK^S; density = 0.006) Sent message (OK^D; density = 0.006)
Resources (*R*; 123 resources)	–	Not used	Resource delivery message (RK; density = 0.008)
Messages (*K*; 2,576 messages)	–	–	Not used

the appendix section at the end of this article. These uncovered networks, using three types of node classes and six types of links, comprise a meta-network that represents the analyzed scenario. A meta-network (Carley & Krackhardt, 1999) is a systematic representation of a network with multiple node classes and link types. This particular meta-network setting (see Table 2) can be of further use in disaster response research if the research community shares the organizational view of this article. For example, Figure 7 represents a visualization of interorganizational structure from the data set.

Methodology

Our research consists of two major procedures: designing optimized organizational structures for a disaster response and evaluating the alternatives of organizational structures using agent-based models. Since our research applies two distinct approaches, we illustrate a research flow at the high level. Afterward, we explain the details of the design organizational structures and structures of the agent-based models.

Research Flow With Organizational Structure Design and Simulation Evaluation

Designing organizational structures should simultaneously consider structural properties and dynamics and operational context because they could be main factors for the performance of the organizational structure. Due to these concerns, designing ideas could be extracted from past records, expert knowledge, numerical network optimization, or heuristic methods. In evaluating the designed organizational structures, many methodologies could be applied compositely. For instance, social network analysis can identify and analyze the structural properties. On the other hand, simulations, particularly agent-based models, are better at generating and analyzing operational dynamics. In our research, we designed organizational structures using optimization techniques and evaluated the optimized organizational structures using agent-based modeling and simulation and social network analysis methods.

Figure 3 illustrates our research flow combining optimization techniques, agent-based simulation, and social network analysis in the design and evaluation phases. In the data set, there are communication logs that contain (1) which organization sent requests for resources and (2) which organization answered back to the requested organization. Based on the information from the communication logs, we have developed an organizational structure. For example, if organization "A" sent a request and organizations "B" and "C" answered, there are two links between organizations "A" and "B" and between organizations "A" and "C." Adapting the identical approach to organization resource, organization message, and resource message structures, we could represent the data set to a meta-network form. Then, we optimize it through two methodologies: (1) an LP to solve the MCNFP and (2) the genetic algorithm to solve the RDSPP. With the resultants of optimization,

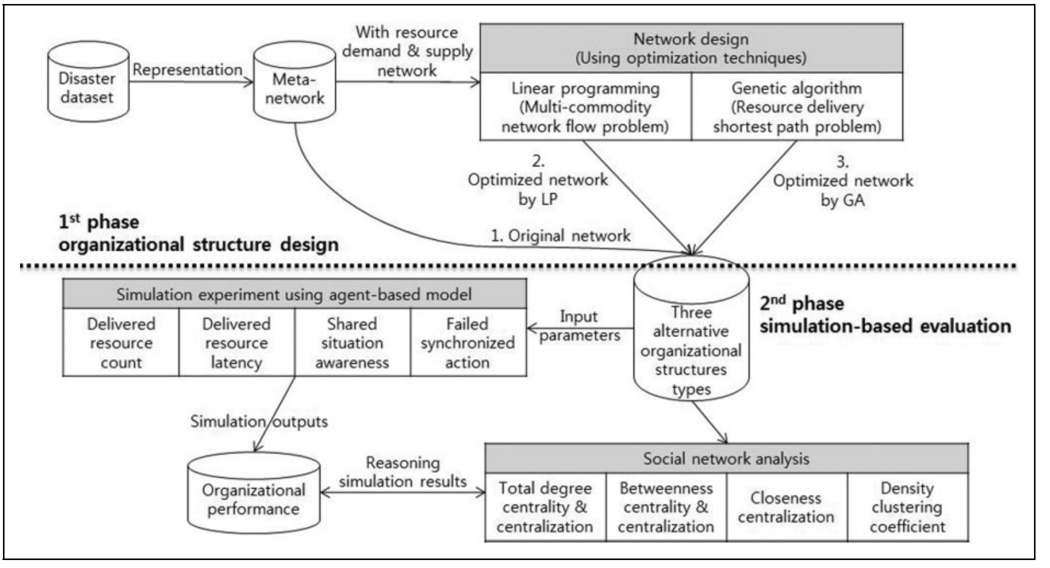

Figure 3. Research flow chart.

we evaluated three types of organizational structures: (1) the network from the original Hurricane Katrina scenario, (2) the network from the MCNFP approach, and (3) the network from the RDSPP approach. The evaluation has been performed with the results of virtual experiments based on agent-based modeling methods. In particular, for the quantitative analysis, we have devised the following four aspects of performance measures: delivered resource counts, delivered resource latency, shared situation awareness, and failed synchronized action. We also employed social network analysis to observe and interpret the relations between the structures and the performances.

Network Optimization for Designing Organizational Structures

For getting alternatives of organizational structure from the meta-network model, we developed two methods of designing organizational structures: MCNFP and RDSPP. In solving the problems, we optimized the interactions between disaster response organizations and not the resource distributions.

MCNFP formulation. MCNFP describes delivering multiple types of resources from one node to another one through an optimized network (Even, Itai, & Shamir, 1976). Figure 4 illustrates an example of MCNFP and its notations in the problem formulation. Generally, LP transforms MCNFP problems into optimization problems. The decision variables of LP are the delivered resource flows $OOR_{(i,\,j),\,r}$, the number of r_r delivered from o_i to o_j. The objective function of LP shows cost minimization in Equation 1. Following that, we devised four constraint functions from Equations 2–5. Equation 2 is a constraint of network edge capacity from a given data set. Equation 3 is a flow conservation constraint that means the number of transacted commodity from a node and the number of transacted commodities to the node are equal if the node is not source or sink of the transacted commodity. Equations 4 and 5 are demand satisfaction constraints that mean a gap between the number of transacted commodities from a node and the number of transacted commodities to the node showing the demand or supply of the transacted commodities in the node.

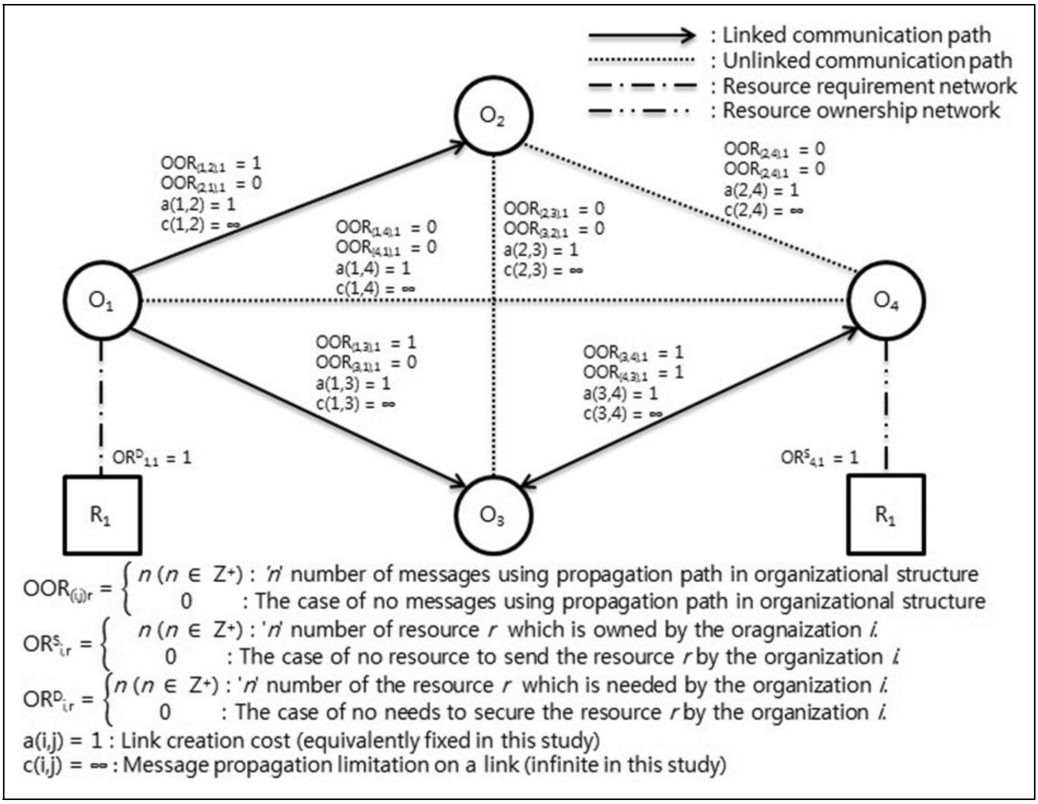

Figure 4. Illustration of Multi-Commodity Network Flow Problem (MCNFP) formulation.

Minimize

$$\sum_{(i,j)\in OO^E} \{a(i,j) \times \sum_{r\in R} OOR_{(i,j),r}\}, \tag{1}$$

subject to

$$\sum_{r\in R} OOR_{(i,j),r} \leq c(i,j) \text{ for all } (i,j) \in OO^E, \tag{2}$$

$$\sum_{j\in O} \{OOR_{(i,j),r} - OOR_{(j.i),r}\} = 0 \text{ for all } i \in O,\ r \in R \text{ when } OR^S_{i,r} = OR^D_{i,r} = 0, \tag{3}$$

$$\sum_{j\in O} OOR_{(i,j),r} = OR^D_{i,r} \text{ for all } i \in O,\ r \in R \text{ when } OR^D_{i,r} \neq 0, \tag{4}$$

$$\sum_{j\in O} OOR_{(j,i),r} = OR^S_{i,r} \text{ for all } i \in O,\ r \in R \text{ when } OR^S_{i,r} \neq 0, \tag{5}$$

where

$$a(i,j) = \text{weight value of } OO^E_{(i,j)};$$

$$c(i,j) = \text{capacity value of } OO^E_{(i,j)};$$

$$OOR_{(i,j),r} = \text{the number of } r_r \text{ using } OO^E_{(i,j)}.$$

Given the general MCNFP formulation in LP, we diverged from the original edge limitation constraint in three respects. First, the original MCNFP has network link capacity, but our problem would not assume such capacity because we modeled the coordination message transfer. Second, the original MCNFP does not have a network density constraint, but our problem requires the network density to regulate the complexity of organizational structure. To reflect the data set in the new formulation, we have defined the network density as the number of links that are extracted from the communication logs in the data set. Third, the original MCNFP assumes an optimal structure matching the supply and the demand perfectly, but our problem should consider that supplies of resources do not satisfy demand sometimes. These differences led us to reformulate the general MCNFP formulation as shown below.

Minimize

$$\alpha \times \sum_{(i,j)\in OO^E} \sum_{r\in R} \mathrm{OOR}_{(i,j),r} + (1-\alpha) \times \sum_{j\in O} \sum_{r\in R} \left| \left\{ \sum_{i\in O} \mathrm{OOR}_{(j,i),r} - \sum_{i\in O} \mathrm{OOR}_{(i,j),r} \right\} - \left\{ OR^D_{j,r} - OR^S_{j,r} \right\} \right|, \tag{6}$$

subject to

$$\sum_{r\in R} \mathrm{OOR}_{(i,j),r} \le M \times OO^E_{(i,j)} \text{ for all } i,j \in \mathrm{O}, \tag{7}$$

$$\sum_{(i,j)\in OO} OO^E_{(i,j)} = nLink, \tag{8}$$

where

1. $a(i,j) =$ Weight value of $\mathrm{OO}^{\mathrm{E}}_{(i,j)}$;
2. $nLink =$ Predefined number of communication links in OO;
3. $M =$ Sufficiently large number;
4. $OOR_{(i,j),k} =$ The number of $r_k$using $OO^E_{(i,j)}$.

From Equation 7, we could resolve the first difference. The capacity constraints are the same as Equation 2, but the only difference is the substitution for $c(i,j)$ by a sufficiently large number (M). By Equation 8, we could resolve the second difference. *nLink* is the number of communication links from the data set and equals to the edge limitation. Additionally, we set Equation 8 as a constraint of equality because if there is no equality in the constraint, then the LP solver finds an optimal solution as a maximum number of edges, which equals all full edges in the data set. This constraint enforces that a specific network density would generate the same number of links under any circumstances. Eventually, the network structure would be implemented as communication devices and personnel, so the number of links between the networks should be the same as in the evaluation stage.

Finally, turning Equation 3 into a part of the objective function in Equation 6 resolves the third difference. Equation 6 is a linear combination of the objective function of general formulation, Equation 1, and the constraints of Equations 3, 4, and 5. These LP objectives and constraints are illustrated in Figure 4. This linear combination led by the third difference results in introducing an additional parameter α. The parameter becomes a balancing ratio between matching demand to supply of resources and minimizing the network links. A decision variable is the same as the original formulation, $OOR_{(i,\ j),\ r}$, the delivered resource flow in organizational structure. We set a time limit, 16 hr, to get a solution from a solver for MCNFP and the solution gap is 7% of that.

RDSPP formulation. RDSPP describes delivering resources from one node to another through an optimized network. The genetic algorithm is one of the most useful heuristic search techniques (Kumar & Jani, 2010). In the mathematical formulations subsequently (Equations 9 and 10), *OO* represents organizational structure, OR^S is the resource distribution network across organizations, and OR^D is the resource demand network across organizations. The fitness function is one of the algorithm's most important factors, so we revised it to consider resource information. Most network problems use a strategy of shortest average distance, D_{OO} in our notations, but we were more concerned with the shortest delivery path to match resource demand and supply in Equation 9. We set a gene to a set of $OO^E{}_{(i,\ j)}$, which means whether the link from o_i to o_j exists or not, and we set D_{OO} to a matrix of shortest distances from a gene. Throughout this article, the fitness function in Equation 9 is defined as *RDSPP*. Equation 10 is a limitation constraint, *nLink*, the number of communication links in a network. Figure 5 is the illustration of RDSPP and its key notations. To solve RDSPP, we ran a genetic algorithm solver with 1,000 replications and a 100-solution set.

Minimize

$$\sum_{OO^E}\left\{D_{OO}{}^T\{\mathrm{OR^S}*\left(\mathrm{OR^D}\right)^T\}\right\}, \tag{9}$$

subject to

$$\sum_{(i,j)\in OO} OO^E_{(i,j)} = nLink, \tag{10}$$

where

1. D_{OO} = Matrix for distance value of OO constructed Floyd – Warshall algorithm(Floyd, 1962);
2. $nLink$ = Decided number of communication links in OO.

Agent-Based Model for Evaluating Organizational Structures

To evaluate the organizational structures from the optimization techniques, we developed an agent-based model simulating the coordination process under a disaster scenario. Particularly, the model were proposed in our previous research (Lee, Oh, & Moon, 2012). Our model is a simplified description of message propagations through an organizational structure, and the message is created when an organization demands a resource that it does not have. Once another organization which owns that resource receives the message, it will respond. This is a simplified process of single-resource delivery, simulated with multiple deliveries. We model the organizational structure into two layers. The first layer is the interorganizational structure which is the network structure among organizations. The second layer is the intraorganizational structure, which is an agent model corresponding to a single organization. The two layers are described in the following subsections.

Interorganizational structure. An interorganizational structure describes communication links among organizations (O), where a single organization (o) requests, broadcasts, and responds to messages (K) demanding resources (R) through links in the interorganizational structure. The two types are

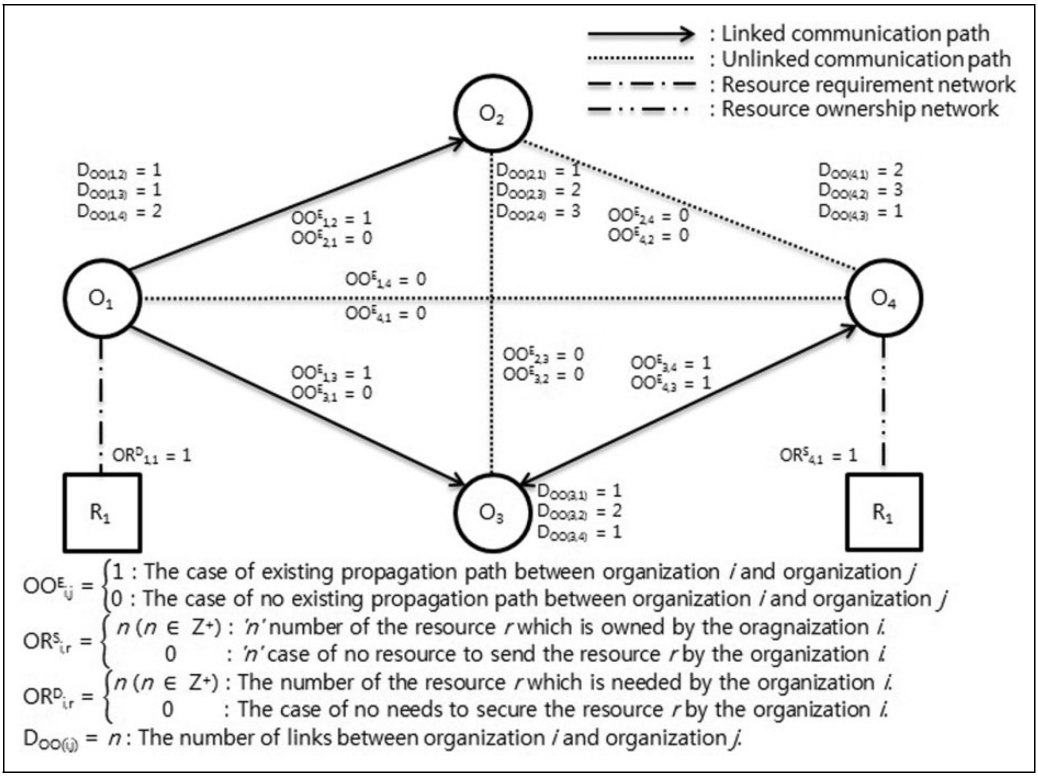

Figure 5. Illustration of resource delivery shortest path problem (RDSPP) formulation.

as follows: broadcast links for message broadcasts and response links for resource delivery. In this article, we assume the broadcast links are a directed network connecting pairs of organizations as defined in the data set and a message broadcasts through the interorganizational structure. The response links comprise a complete network of organizations. Figure 6 shows a conceptual interorganizational structure, with broadcast links as described in Figure 7 in the simulations using the original network. The network structure (*OO*) in the data set is subject to change in the interorganizational structure types: the original, the network design from MCNFP, and the network design from RDSPP.

Intraorganizational structure. An intraorganizational structure describes a single organization as an agent model and single node in the interorganizational structure. We hypothesized that each organization consists of a decision-making model and three information buffer models: request buffer, broadcast buffer, and response buffer. These submodels describe functional subgroups in a real-world disaster-response organization. The decision-making model corresponds to the decision-making units in the disaster-response organization where the key decisions are made, such as when to send a resource to other organizations. The request, broadcast, and response buffers correspond to field, communication, and response units, respectively. The field unit gathers the resource demands on the disaster and forwards them to the decision-making units using a message. The communication unit receives resource request messages from other organizations and delivers them to the decision-making units. Finally, the response unit, under the control of the decision-making units, responds to the requesting organization. Figure 8 captures these processes and structures. To describe our model formally, we used DEVS diagrams (Zeigler, Praehofer, & Kim, 2000).

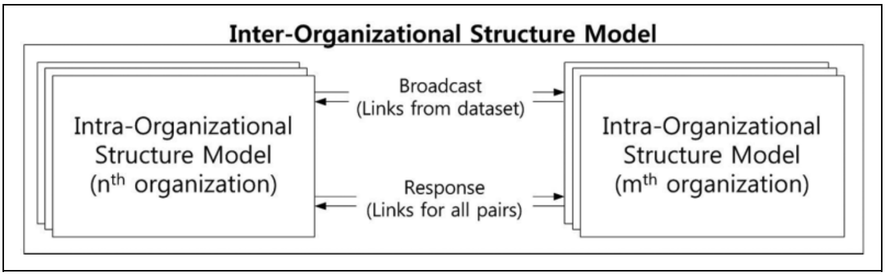

Figure 6. Model description of interorganizational structure model.

The decision-making model describes various decision operations: sending a message (K) that requests a resource (R), broadcasting a received message (K), and responding to a message (K) by providing a resource (R). We formally describe the decision-making process with meta-network notation in the section on Scenario and Data Set Description. When an organization (o_i) finds the needs of a resource (r_r) in a message (k_k) from the event buffer, the decision-making model checks whether o_i has r_r or not. If o_i has r_r, then the decision-making model does not broadcast or respond k_k because this request was solved internally. However, if o_i does not have r_r, the decision-making model decides to broadcast k_k to the linked organizations through the interorganizational structure (OO). When o_i takes k_k from the broadcast buffer, the decision-making model decides to respond and transfer r_r (when $OR^S_{i,j} > 0, OK^S_{i,k} = 1, \text{and } RK_{r,k} = 1$) or to broadcast k_k to other linked organizations (when $OR^S_{i,r} = 0, OK^S_{i,k} = 0, \text{or } RK_{r,k} = 0$). When o_i takes r_r for k_k from the response buffer, the decision-making model assumes that the message (k_k) is resolved. The DEVS diagram in Figure 9 illustrates this, adopting the extended representation of state transitions.

The request buffer collects internal information about requested relief resources ($RK_{r,j}$), which means this buffer describes the field unit that needs to secure a resource (R) at the disaster site. The broadcast buffer receives messages (K) transferred from other linked organizations (O). The response buffer collects the responded messages (K) with a delivered resource (R) from the other organizations (O). Though the objectives of the buffer models are different, behaviors of them are identical as seen in Figure 10.

Organizational Performance Criteria. To evaluate the effectiveness of interorganizational structure (OO), we devised four organizational performance measurements inspired by the network-centric operation doctrine from Alberts and Hayes (2003) and referred to our previous research (Lee, Oh, & Moon, 2012).

- *Delivered resource count* is the number of messages (K) counted when requested resources (R) are successfully delivered.
- *Delivered resource latency* is the average time delay from request time to response time of the message (K).
- *Shared situation awareness* is a ratio between the number of propagated request messages and the number of total request messages. We used an average shared situation awareness of organizations (O), by counting the number of messages propagated to a certain organization (Equation 11), dividing it by the total number of messages (Equation 12), and averaging results across organizations (Equation 13).

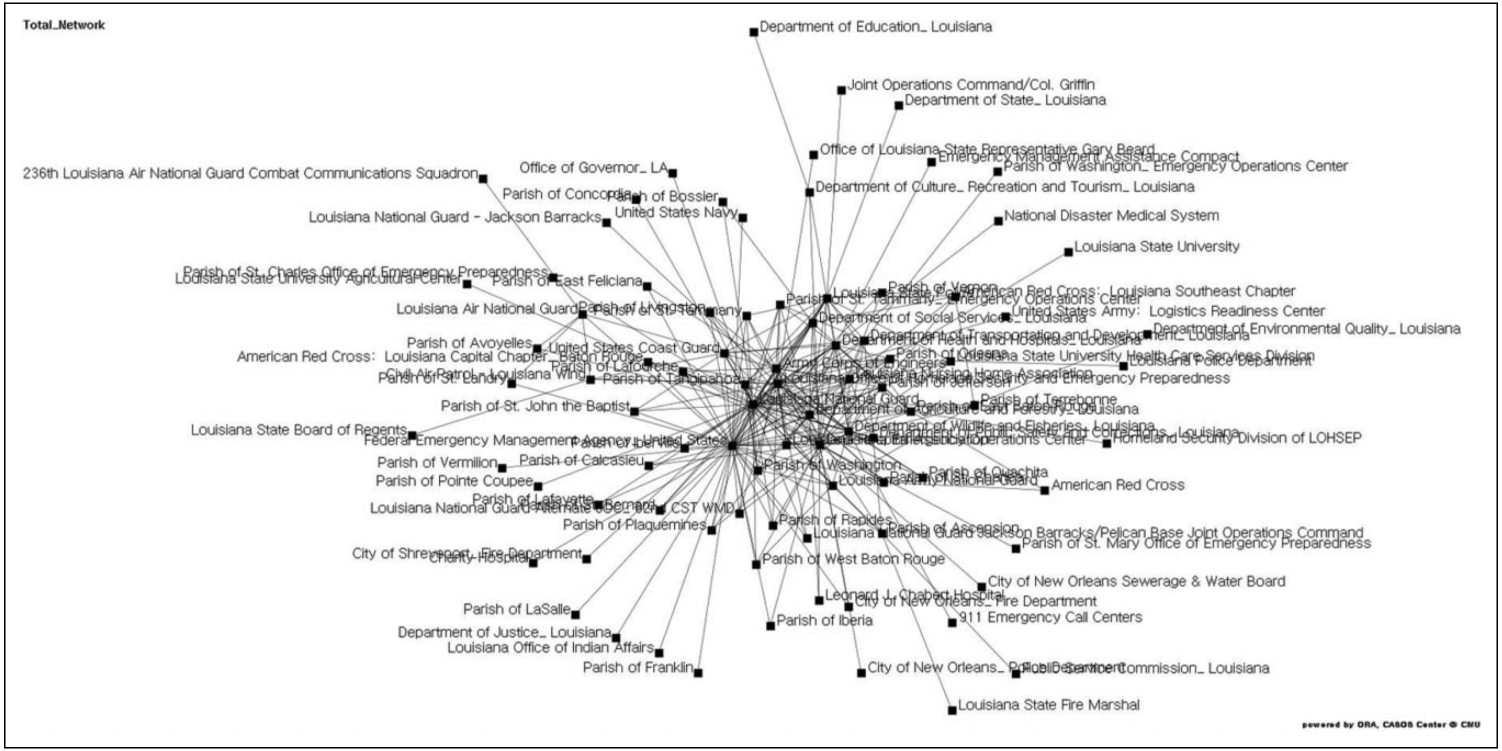

Figure 7. Visualized topology of the original network.

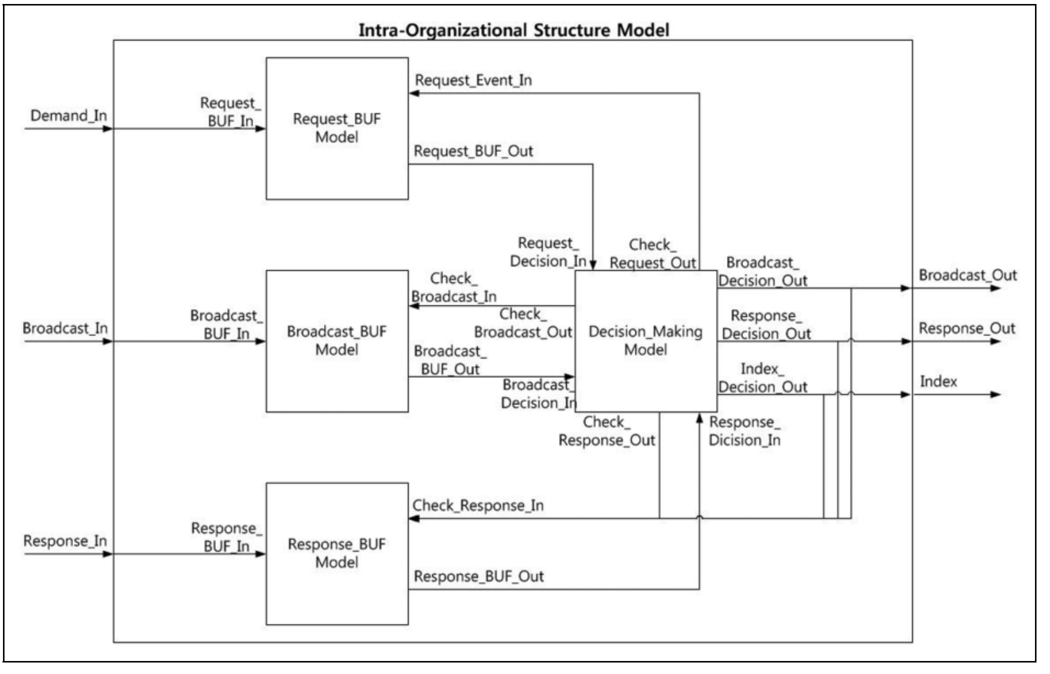

Figure 8. Model description of intraorganizational structure in the DEVS coupled diagram.

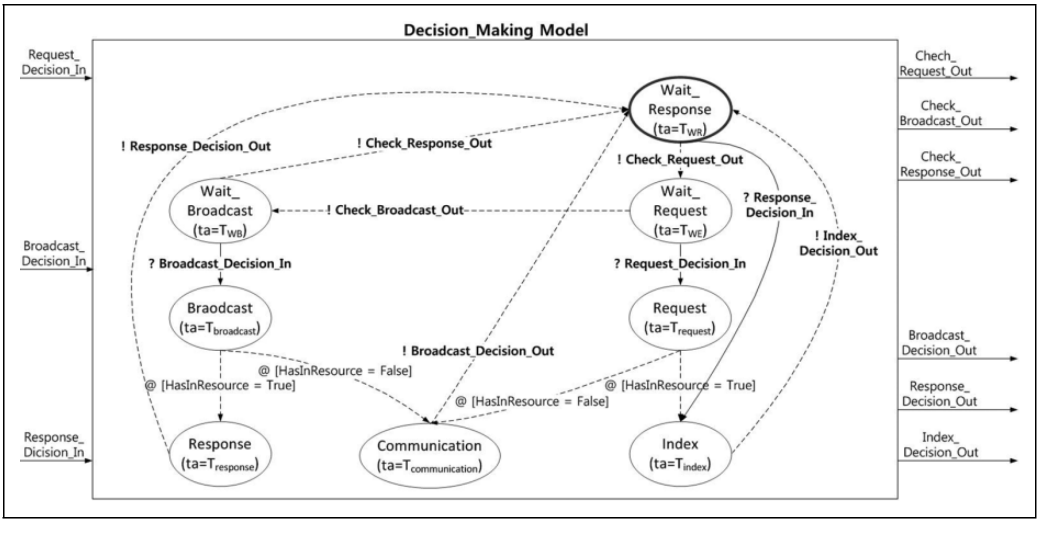

Figure 9. Operational behavior of decision-making model described in the DEVS atomic diagram.

$$OK_{i,k}^{B} = \begin{cases} 1, \textit{if } k_k \textit{ was in the broadcast buffer of } o_i \\ 0, \textit{ otherwise} \end{cases} \tag{11}$$

$$\mathrm{SSA}_i = \frac{\sum_{k \in K} OK_{i,k}^{B}}{\sum_{i \in O} \sum_{k \in K} OK_{i,k}^{B}} \tag{12}$$

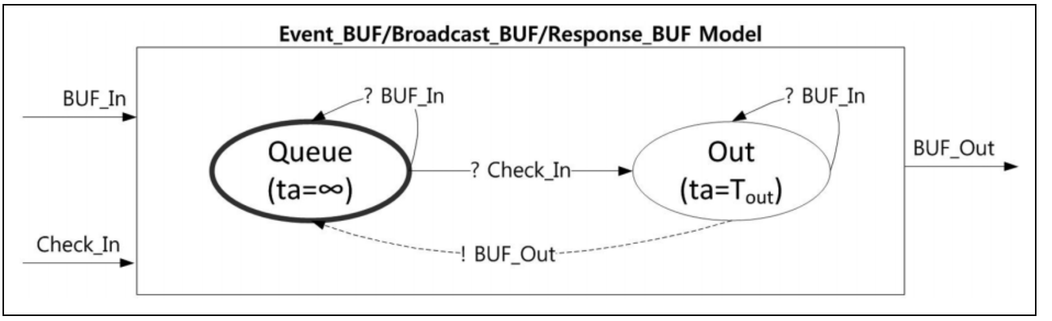

Figure 10. Operational behavior of buffer models described in the DEVS atomic diagram.

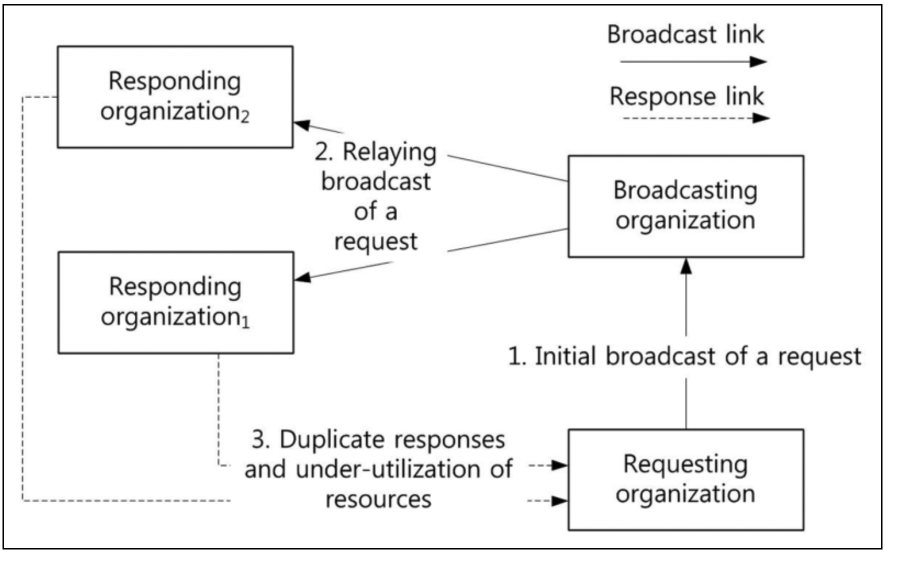

Figure 11. Illustrative description of failed synchronized action (FSA).

$$\text{SSA} = \frac{\sum_{i \in O} SSA_i}{|O|} \tag{13}$$

- *Failed synchronized action* is the number of conflicted deliveries of the requested resources. Conflicted deliveries occur when a message spread so widely that the requesting organization gets responses from multiple organizations. This causes underutilization of resources. Figure 11 illustrates the semantics of this measurement.

Summary of agent-based model. We summarized inputs, outputs, and auxiliary parameters for our agent-based model in Table 3. The input variables contain interorganizational structures (*OO*) from the original Hurricane Katrina data set, solution of MCNFP, and solution of RDSPP. Additionally, a simulation scenario of resource demands from the past records of Hurricane Katrina is used as input variables. In the experiments, each organization generates request events by time records of the scenario and forwards them to other connected organizations. Received organizations are operated as depicted in the section

Table 3. Parameter Table for Simulation Model of Disaster Management.

Type	Name	Value	Implication
Input	Network source (OO network)	Varied by virtual experiment settings	Generated organizational structure using various optimization techniques
	Simulation scenario of resource demands	Fixed from the past records	Resource demand records from organizations in the crisis period
Output	Delivered resource count (DRC)	Measured from simulations	Number of resources delivered as requested
	Delivered resource latency (DRL)	Measured from simulations	Time interval between a request and a response of a resource
	Shared situation awareness (SSA)	Measured from simulations	The ratio of shared broadcast messages across organization
	Failed synchronized action (FSA)	Measured from simulations	The count of duplicated responses and underutilization of resources
Parameters	T_{out} in buffer model	Default = 0.1	Buffer's delay time in responding to the decision-making model's message checking
	T_{WR}, T_{WB}, and T_{WE} in decision-making model	Default = 0.1	Decision-making model's delay time in message checking
	$T_{communication}$ in decision-making model	Default = 0.1	The λ value of the Poisson distribution for the decision-making model's delay time in broadcasting the message to linked organizations
	$T_{broadcast}$ and $T_{request}$ in decision-making model	Default = 1	The λ value of the Poisson distribution for the decision-making model's delay time in deciding whether a message should be re-broadcast or responded by itself
	$T_{response}$ in decision-making model	Default = 1	The λ value of the Poisson distribution for the decision-making model's delay time in transferring the resources for responses
	T_{index} in decision-making model	Default = 1	The λ value of the Poisson distribution for the decision-making model's delay time in finishing the delivery of the resources internally

Intraorganizational Structure. For processing received request messages, the resource state of the received organization is changed, which affects the next requests in the experiment. Based on these changes, for example, some organizations might succeed in securing requested resources, while other organizations might not. These interactions eventually cause varying performance measures in the experiments. Each experiment is executed until all request/answer events are processed. The resource requirement network (OR^D), which describes the relations between demanding organizations and demanded resources, is independent of the other networks in the meta-network, because the resource requirement information comes from the demanding organization at a disaster scene. The output measures are the four different aspects of organizational performances introduced in the section Organizational Performance Criteria. Finally, auxiliary parameters are a set of waiting time specifications for an agent's behaviors, which are indispensable for time advancing of agent-based models. Because this research is to investigate the effectiveness of network structures only, we have set the values of the parameters arbitrarily.

Results

Based upon the above methodologies, we designed and evaluated the interorganizational structure of disaster response organizations. First, we present the designed network structures from the optimization techniques. Second, we provide the virtual experiment setting and its simulation results. Finally, we investigate the designed networks' characteristics.

Design of Organizational Structures

We generated hypothetical interorganizational structures (*OO*) from the optimization techniques. First, we performed MCNFP optimization with the LP. This technique requires a coefficient (α) as explained in the section MCNFP Formulation, so we varied the coefficient as (1) $\alpha = .526$, which means a 1:0.9 combination, (2) $\alpha = .500$ which means a 1:1 combination, and (3) $\alpha = .476$ which means a 1:1.1 combination. The linear coefficient α indicates the importance of shortening message path lengths and satisfying the resource delivery requests. The coefficient becomes a single factor that configures the optimization objective in the LP. As α gets smaller, the LP emphasizes resource delivery rather than message propagation lengths. Second, in RDSPP optimization in the section RDSPP Formulation, we employed a genetic algorithm to design an optimized network. For solving MCNFP problem, we have implemented and optimized MCNFP problem using IBM ILOG CPLEX Optimization Studio V 5.5, and RDSPP problem and a genetic algorithm are implemented in JAVA SE 7.0 in an ad hoc manner. Furthermore, these works were performed on the following machine:

- CPU: Intel Core i7-2600 K 3.4 GHz;
- RAM: 8 GB;
- OS: Windows 7 64 bit.

Figure 12 shows the visualized topologies of organizational structures optimized by RDSPP and MCNFP, respectively. The topologies from MCNFP are similar to those of the original network in Figure 7, so its optimization results share some structural characteristics with the original network, especially high the concentration of links to hub organizations. On the other hand, RDSPP topology differs strongly from the original structure in the view of (1) less concentration of links to hub organizations and (2) more equal distributions of links between organizations. To further discuss these networks' structures, we need to see them perform in virtual experiments. Therefore, we next present the virtual experiment setting and its results.

Virtual Experiment Design

After optimizing organizational structures, we performed virtual experiments using the agent-based model introduced in the section Agent-Based Model for Evaluating Organizational Structures. Table 4 shows the combination of experimental cells in virtual experiment settings. Our research focuses on evaluating interorganizational structures (*OO*), so we differentiated the structures using original network from the data set and optimized organization structures, such as MCNFP and RDSPP. We have also varied the number of links on the organizational structures. As a default, we set up 266 links, the number of links in Day 5 in the Katrina data set, which is the first day that all major organizations and major resources are present in the data set. From that default setting, we experiment with changes in the number of links, presenting five levels of network density variations in Table 4. For example, in Table 4, a 0% level of network density means the same network density as the original network. As the network density increases (+10% and +20%) or decreases (−10% or −20%), the size of the organization structures network also randomly increases or decreases. Finally, we performed 30 replications for each cell and confirmed that the results provide meaningful confidence intervals with the given number of replications.

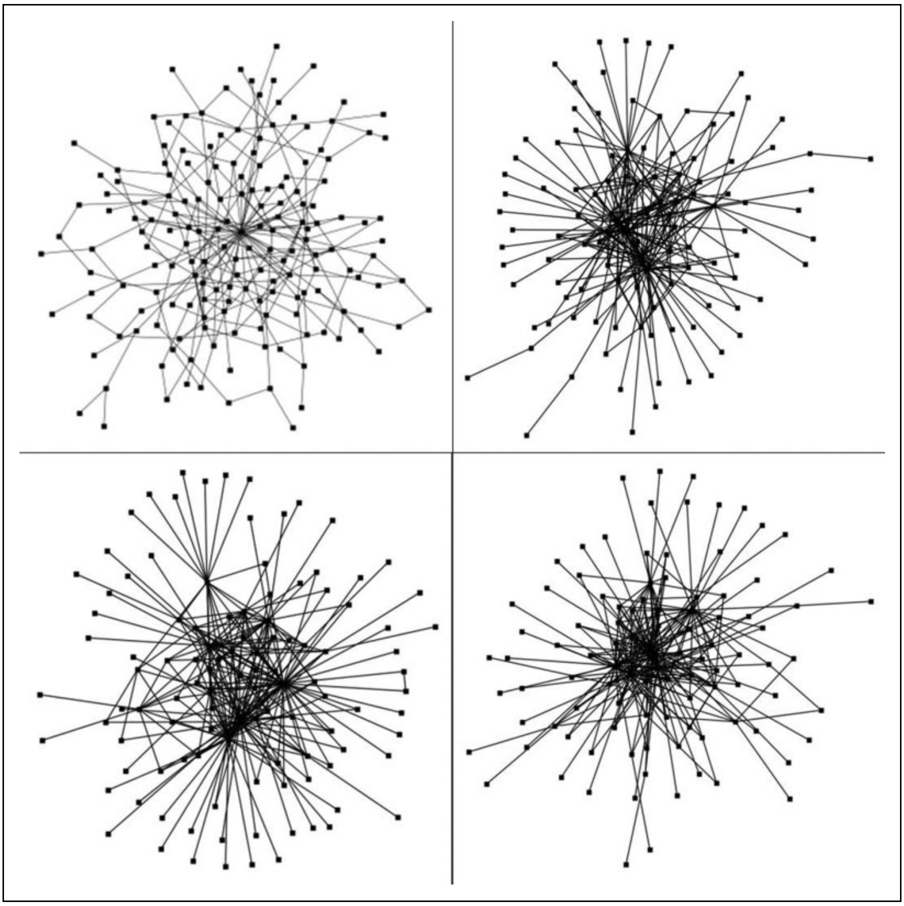

Figure 12. Visualized topologies. Top left, resource delivery shortest path problem (RDSPP); top right, Multi-Commodity Network Flow Problem (MCNFP; $\alpha = .526$); bottom left, MCNFP ($\alpha = .500$); and bottom right, MCNFP ($\alpha = .476$).

Table 4. Virtual Experimental Design for Disaster Management.

Variable	Value	Implication
Network source	Original, RDSPP, MCNFP ($\alpha = .526$), MCNFP ($\alpha = .5$), MCNFP ($\alpha = 0.476$) (Total 5 cases)	Method to generate C2 structure using various optimization techniques
Network density	0%, −20%, −10%, +10%, +20% (Total 5 cases)	Change of communication density
Total experiment cells	Total $5 \times 5 = 25$ cells	30 Replications for each cell (Total 750 simulation runs)

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.

Virtual Experiment Results

Figure 13 shows the results of the virtual experiment. Larger network density positively induces a higher delivered resource count and shared situation awareness. However, it also negatively heightens delivered resource latency and the higher failed synchronized action. The RDSPP-optimized

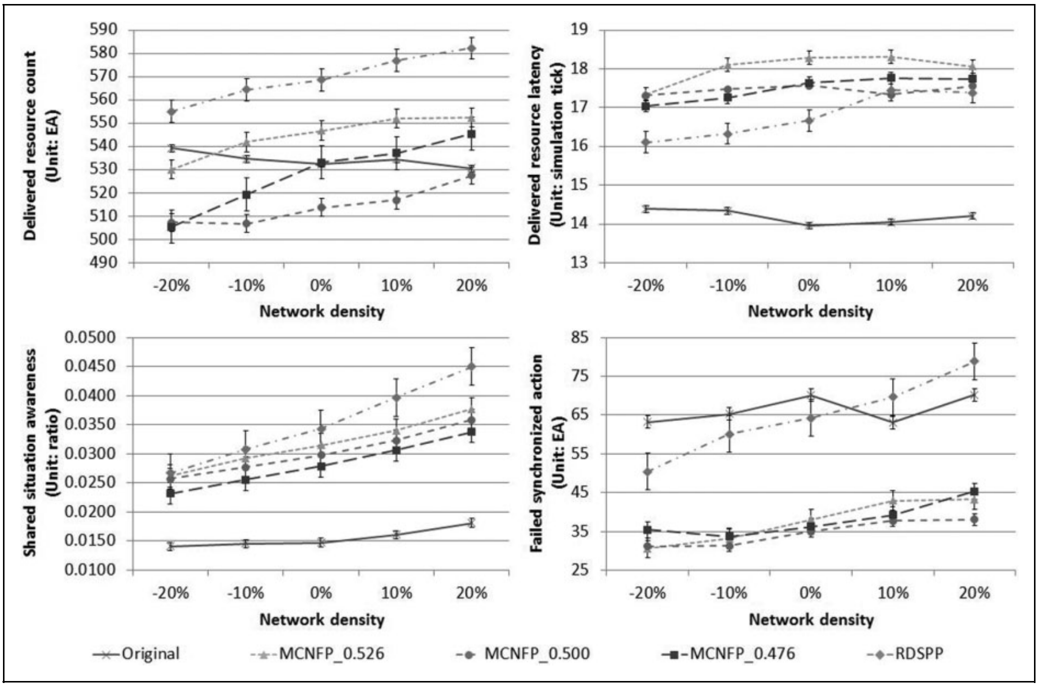

Figure 13. Results of virtual experiments. Top left, delivered resource count; Top right, delivered resource latency; bottom left, shared situation awareness; and Bottom right, failed synchronized action.

Table 5. The *t*-Value of Paired *t*-Test Results for Delivered Resource Count.

Row > Col	RDSPP	MCNFP (α = .526)	MCNFP (α = .500)	MCNFP (α = .476)
Original	−11.641	−5.625	10.840††	2.671††
RDSPP	—	8.097††	18.555††	13.699††
MCNFP (α = .526)		—	16.688††	7.846††
MCNFP (α = .500)			—	−6.228

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.
†*P* value < .05. ††*P* value < .01.

structure shows the best performance of delivered resource count and shared situation awareness, but MCNFP-optimized structures show the best performance of failed synchronized action.

To confirm the significance of the results, we performed a paired *t*-test for all pairs (Zimmerman, 1997). Tables 5, 6, and 7 confirm the statistical significance of the results for delivered resource count, delivered resource latency, and shared situation awareness. The results show RDSPP structure as the best structure. However, Table 8 confirms that MCNFP structures are best at reducing failed synchronized action.

After the statistical comparisons of organizational performances, we made meta-models for the above four measurements. The meta-model is a linear regression model of simulation results that analyzes the relationship between design parameters and responses. It implicitly represents the stochastic response of the simulation model as an explicit deterministic meta-model response function to support interpretation of the simulation results (Kleijnen & Sargent, 2000). Table 9 illustrates the standardized coefficients and adjusted R^2 of the meta-model. This meta-model provides an

Table 6. The *t*-Value of Paired *t*-Test Results for Delivered Resource Latency.

Row > Col	RDSPP	MCNFP (α = .526)	MCNFP (α = .500)	MCNFP (α = .476)
Original	−22.469	−38.758	−35.970	−33.763
RDSPP	—	−10.737	−5.859	−6.765
MCNFP (α = .526)		—	6.079††	5.256††
MCNFP (α = .500)			—	−0.389

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.
†*P* value < .05. ††*P* value < .01.

Table 7. The *t*-Value of Paired *t*-Test Results for Shared Situation Awareness.

Row > Col	RDSPP	MCNFP (α = .526)	MCNFP (α = .500)	MCNFP (α = .476)
Original	−38.786	−63.105	−65.337	−54.693
RDSPP	—	9.245††	12.674††	18.129††
MCNFP (α = .526)		—	7.485††	20.970††
MCNFP (α = .500)			—	12.244††

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.
†*P* value < .05. ††*P* value < .01.

Table 8. The *t*-Value of Paired *t*-Test Results for Failed Synchronized Action.

Row > Col	RDSPP	MCNFP (α = .526)	MCNFP (α = .500)	MCNFP (α = .476)
Original	0.798	14.708††	17.376††	15.461††
RDSPP	—	16.021††	14.742††	15.230††
MCNFP (α = .526)		—	2.026†	−0.279
MCNFP (α = .500)			—	−2.292

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.
†*P* value < .05. ††*P* value < .01.

interpretation between the major parameters of the potential organizational structure and the organizational performance. Therefore, we selected the presented parameters as independent variables specifically to analyze the performance changes, which are dependent variables, from the organizational restructuring. Also, it should be noted that the design of the meta-models are tightly linked to the virtual experimental design described in Table 4, where we describe our primary parameters of the organizational structures. The meta-models of the delivered resource count and shared situation awareness show the RDSPP structure increases the performance significantly and robustly. We verified significance with the scale of the standardized coefficient and robustness with the low *P* value. Similarly, the meta-model of failed synchronized action shows the MCNFP structures decreased the count significantly and robustly.

Organizational Structure Analysis

From the above-mentioned virtual experiments and analyses, it has been revealed that the organizational performance is strongly correlated to the method of the organizational restructuring and the resulting organizational structures. To quantitatively investigate the characteristics of the

Table 9. Regression for Sensitivity Analysis.

Dependent Variable			Delivered Resource Count	Delivered Resource Latency	Shared Situation Awareness	Failed Synchronized Action
Standardized coefficients	Network sources	RDSPP	0.683††	0.746††	1.018††	−0.042
		MCNFP (α = .526)	0.202†	1.098††	0.834††	−0.753††
		MCNFP (α = .500)	−0.384††	0.934††	0.656††	−0.832††
		MCNFP (α = .476)	−0.124	0.945††	0.653††	−0.748††
	Network density		0.346††	0.140††	0.414††	0.298††
Adjusted R^2			.901	.955	.885	.943

Note. MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.
†*P* value < .05. ††*P* value < .01.

Table 10. Twelve Categories of Organization Branch and Level.

Organization's Branch and Level (Number of Organization in the Original Network)		Source of Funding			
		Government (109)	Military (28)	NGO (19)	Private (13)
Level of jurisdiction	Federal (37)	FG (11)	FM (17)	FN (2)	FP (7)
	State (57)	SG (40)	SM (11)	SN (6)	SP (0)
	Local (75)	LG (58)	LM (0)	LN (11)	LP (6)

Note. NGO = nongovernmental organization; FG = federal government; SG = state government; LG = local government; FM = federal military; SM = state military; LM = local military; FN = federal NGO; SN = state NGO; LN = local NGO; FP = federal private; SP = state private; LP = local private.

organizational structure with higher performance, we applied social network analysis to the suggested organizational structures. Mainly, the analyses applied to the organizations are calculations of the centralization, which is the network-wide centrality, to see the key properties of the structure as a whole. Before we calculated the metrics, we observed the compositions of the nodes by the branches and the sources of their funding that may reveal the properties of the nodes in the network.

Prior to the calculation of the centralization, we classified 169 disaster response organizations into 12 categories based upon their level of jurisdiction and sources of funding, which are specified in the data set in Table 10. For example, federal private (FP) means an organization for which scale is as large as that of federal-level organizations and that is funded from private sources. Each organization is unique in its resource acquisition, demand, and positions on the interorganizational structures, but categorizing them helps the readers identify their node-level properties and the composition of their structure.

After identifying the node-level properties, the level of jurisdiction and the source of funding in this analysis, we used three measurements to find core organizations: degree centrality, betweenness centrality, and density clustering coefficient. Degree centrality is the number of links incident upon a node (Freeman, 1979). Betweenness centrality is the number of times a node is located on a shortest path between two other nodes (Freeman, 1977). The density clustering coefficient is the density of the node's ego network. Tables 11, 12, and 13 show the measurements from the five organizational structures. After measuring them with the three metrics, we selected the top 10 organizations for each measurement to see which organization played a major role and why. The RDSPP structure indicates high degrees of centrality, betweenness centrality, and clustering coefficient at the federal and local organizations, those at the hub and the edge in its authority. These indicate that the RDSPP structure, which showed a higher performance in resource delivery and shared situation awareness,

Table 11. Top 10 Organization's Characteristics of Organization Branch and Level Based Upon Degree Centrality.

	FG	FM	FN	FP	SG	SM	SN	SP	LG	LM	LN	LP
Original	1	1			6	1			1			
RDSPP	1	1		1	3	2	1				1	
MCNFP ($\alpha = .526$)	1	1			6	2						
MCNFP ($\alpha = .500$)	1	1			5	2			1			
MCNFP ($\alpha = .476$)	1	1			6	2						

Note. NGO = nongovernmental organization; FG = federal government; SG = state government; LG = local government; FM = federal military; SM = state military; LM = local military; FN = federal NGO; SN = state NGO; LN = local NGO; FP = federal private; SP = state private; LP = local private; MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.

Table 12. Top 10 Organization's Characteristics of Organization Branch and Level based Upon Betweenness Centrality.

	FG	FM	FN	FP	SG	SM	SN	SP	LG	LM	LN	LP
Original	1	2			4	2	1					
RDSPP	2	1		1	2	1	1		1		1	
MCNFP ($\alpha = .526$)	1	1			5	2			1			
MCNFP ($\alpha = .500$)	1	1			6	2						
MCNFP ($\alpha = .476$)	1	1			6	2						

Note. NGO = nongovernmental organization; FG = federal government; SG = state government; LG = local government; FM = federal military; SM = state military; LM = local military; FN = federal NGO; SN = state NGO; LN = local NGO; FP = federal private; SP = state private; LP = local private; MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.

Table 13. Top 10 Organization's Characteristics of Organization Branch and Level based Upon Density Clustering Coefficient.

	FG	FM	FN	FP	SG	SM	SN	SP	LG	LM	LN	LP
						2	1		7			
RDSPP	1	1		1	2	1	2		1			1
MCNFP ($\alpha = .526$)	1				1		1		6		1	
MCNFP ($\alpha = .500$)					2	1			5		2	
MCNFP ($\alpha = .476$)					1		1		7		1	

Note. NGO = nongovernmental organization; FG = federal government; SG = state government; LG = local government; FM = federal military; SM = state military; LM = local military; FN = federal NGO; SN = state NGO; LN = local NGO; FP = federal private; SP = state private; LP = local private; MCNFP = Multi-Commodity Network Flow Problem; RDSPP = resource delivery shortest path problem.

gives more communication emphasis at the hub and the edge organizations compared to the bridging organizations. On the other hand, the MCNFP structures, which were better at reducing the failed synchronized action, emphasize state-level organizations, those at the brokering and bridging positions. This social network analysis applied to the organizational structures suggest that, if the situation requires better performance in delivered resource counts and shared situation awareness, more network power to the federal and the local levels would be preferable. If the situation shows excessive double responses on the scene, more network concentration on the state-level organizations

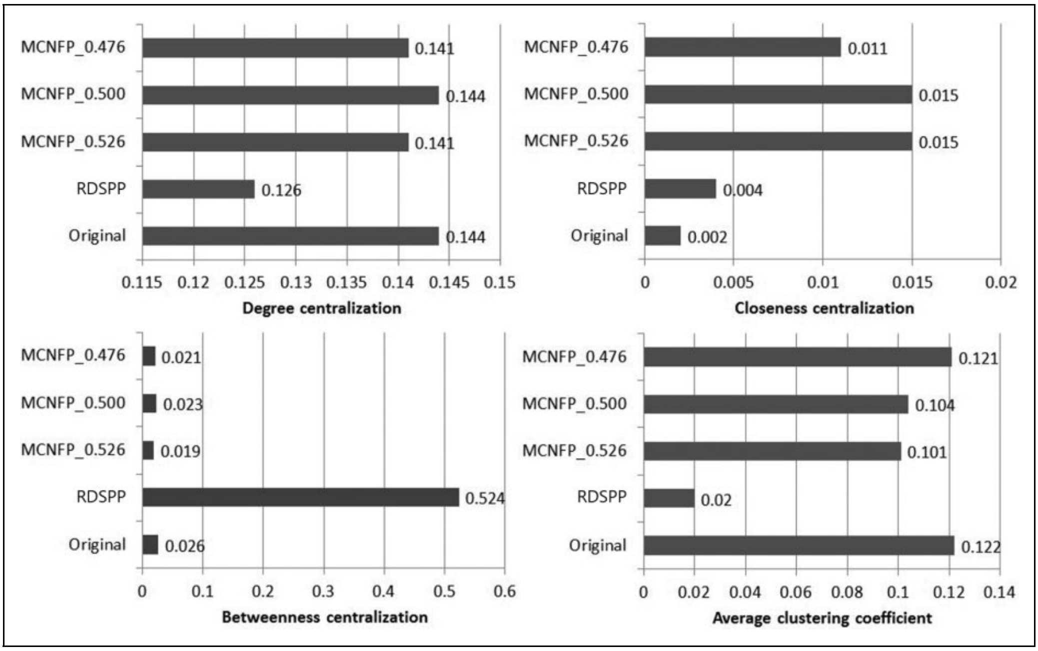

Figure 14. Results of social network analysis in network level.

would be preferable. The ultimate result of this research will depend on the reliability of virtual experiments and preferences of policy makers.

Although the previous social network analysis at the node level provides insights into connecting the individual organizations, the whole structure can be further analyzed by comparing network-level measurements: degree centralization, betweenness centralization, closeness centralization, and average clustering coefficients in this article. These are the extended versions of node-level measurements we used previously. Figure 14 shows the results from the network-level social network analyses. The RDSPP structure from the GA approach has far more betweenness centralization, which indicates that the organizations in RDSPP generally have higher betweenness values than the organizations in other structures. This result suggests that the organizations of RDSPP structure are more likely to be places on the information flow path, so the organizations would manage the information well and eventually reduce the excessive response on a certain request by sharing the load. On the contrary, the organizational structures from that MCNFP approach have a higher degree-based centralization, and this result points out that the organizations are generally more connected to other organizations, yet the increased connectivity does not improve the information sharing path. Such an implication, a higher degree centralization with less betweenness centralization, often occurs when the connectivity is particularly given to some selected nodes in the whole network, and such selected nodes in this case were the federal and the local organizations accounted for in Table 11.

Conclusion

Recently, we have seen many devastating disasters. As each passed, we saw reports of systematic failure and individual heroic efforts. Our question stems from this contrast. Each disaster response organization may try to improve its responses, but these individual efforts might fail collectively. Our research aims to mitigate this risk by optimizing individual interactions in dynamic situations. We employed two optimization techniques to quantitatively design a structure for reducing the risk.

Since disasters are dynamic, static social network analyses might not provide meaningful evaluations. Therefore, we created an agent-based model to replicate a dynamic situation and evaluate the optimized structure's response using four variables.

Although our findings do not differ from the standing argument in the organizational science community, we provide a systematic analysis approach to design and evaluate the organizational structures. Some of our results indicate that more networking strength at the hub (federal organizations) and at the edge (local organizations) would increase the response success, but the rest of the

Table 14. Description of Notations.

Notation	Description
O	A set of organizations
R	A set of resources and services
K	A set of message that is an interaction message among disaster response organizations
o_i	ith organization, $o_i \in O$, and i and j are indices of O
r_r	rth resource, $r_r \in R$, and r is index of R
k_k	kth message, $k_k \in K$, and k is index of K
OO	An adjacency matrix of the graph (<V, E>) representing a network of organizational structure, where $V = O$, $E = \{$communication links between O and $O\}$ (Dimension: $\|O\| \times \|O\|$ matrix)
OR^S	An adjacency matrix of the graph (<V, E>) representing the network of resource ownership relations, where $V = O \cup R$, $E = \{$ownership relations that which organization has a resource between O and $R\}$ (Dimension: $\|O\| \times \|R\|$ matrix)
OR^D	An adjacency matrix of the graph (<V, E>) representing the network of resource requirement relations, where $V = O \cup R$, $E = \{$requirement relations that which organization want to secure a resource between O and $R\}$ (Dimension: $\|O\| \times \|R\|$ matrix)
OK^S	An adjacency matrix of the graph (<V, E>) representing the network of received message relations, where $V = O \cup K$, $E = \{$sending relations that which organization send a message between O and $K\}$ (Dimension: $\|O\| \times \|K\|$ matrix)
OK^D	An adjacency matrix of the graph (<V, E>) representing network of sent message relations, where $V = O \cup K$, $E = \{$receiving relations that which organization receive a message between O and $K\}$ (Dimension: $\|O\|$ x $\|K\|$ matrix)
RK	An adjacency matrix of the graph (<V, E>) representing the network of resource delivery message relations, where $V = R \cup K$, $E = \{$relations that which resource is requested in a message between R and $K\}$ (Dimension: $\|R\| \times \|K\|$ matrix)
OO^E	A set of communication links between O and O, E in OO
$OO^E_{(i,j)}$	Whether a communication link between o_i and o_j exists or not ($T = 1$ or $F = 0$)
$OR^S_{i,r}$	The number of r_r which is owned by o_i
$OR^D_{i,r}$	The number of r_r which is requested by o_i
$OK^S_{i,k}$	Whether o_i receives k_k or not ($T = 1$ or $F = 0$)
$OK^D_{i,k}$	Whether o_i sends k_k or not ($T = 1$ or $F = 0$)
$RK_{r,k}$	Whether k_k is a message as message for requesting r_r or not ($T = 1$ or $F = 0$)
$OOR_{(i,j),r}$	The number of r_r using $OO_{(i,j)}$
$a(i,j)$	The weight of $OO_{(i,j)}$, i.e., link creation cost, link
$c(i,j)$	The limitation number of message propagation through $OO_{(i,j)}$

results suggest more networking strength at the brokers (state-level organizations) would decrease the response conflict between organizations. This dilemma is often found in the domains of corporate managements, military, intelligence, and other specialties. We think our contribution is the systematic analysis of the correlation between structural characteristics and organizational performances.

Appendix

Notations of Meta-Network and Optimization Techniques

This work strives to formally and specifically describe the given data set, the optimization techniques, and the simulation model. Hence, the description of our methodologies became complex, and this work uses many notations that require clear definitions. Table 14 is the enumeration of the notations and their definitions to support the reader's understanding of this article.

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