Timely assessment of disaster and emergency response networks in the aftermath of superstorm Sandy, 2012

Jungwon Yeo
School of Public Administration, University of Central Florida, Orlando, Florida, USA
Louise Comfort
Graduate School of Public and International Affairs, University of Pittsburgh, Pittsburgh, Pennsylvania, USA, and
Kyujin Jung
Department of Public Administration, Sungkyunkwan University, Seoul, Republic of Korea

Abstract

Purpose – The purpose of this paper is to elaborate pros and cons of two coding methods: the rapid network assessment (RNA) and the manual content analysis (MCA). In particular, it focuses on the applicability of a new rapid data extraction and utilization method, which can contribute to the timely coordination of disaster and emergency response operations.

Design/methodology/approach – Utilizing the data set of textual information on the Superstorm Sandy response in 2012, retrieved from the LexisNexis Academic news archive, the two coding methods, MCA and RNA, are subjected to social network analysis.

Findings – The analysis results indicate a significant level of similarity between the data collected using these two methods. The findings indicate that the RNA method could be effectively used to extract megabytes of electronic data, characterize the emerging disaster response network and suggest timely policy implications for managers and practitioners during actual emergency response operations and coordination processes.

Originality/value – Considering the growing needs for the timely assessment of real-time disaster response systems and the emerging doubts regarding the effectiveness of the RNA method, this study contributes to uncovering the potential of the RNA method to extract relevant data from the megabytes of digitally available information. Also this research illustrates the applicability of MCA for assessing real-time disaster response networks by comparing network analysis results from data sets built by both the RNA and the MCA.

Keywords Disaster response network analysis, Manual content analysis, Rapid network assessment, Superstorm sandy

Paper type Research paper

Introduction

Disaster and emergency management studies have employed social network analysis, which allows for superior understanding of the roles and functions of emergent disaster response systems (Jung et al., 2017; Yeo and Comfort, 2017; Kim et al., 2017; Kim and Hossain, 2013; Comfort et al., 2004, 2012; Kapucu et al., 2010; Provan and Kenis, 2007; Comfort and Haase, 2006; Comfort, 1994). Social network analysis supports operations of disaster response and recovery by identifying key agents and by highlighting any relationships, functional or
dysfunctional, among those agents (Kim and Hossain, 2013; Comfort et al., 2012; Kapucu et al., 2010). The analysis results help managers understand emergent disaster response systems and develop better strategies for managing disasters (Jung and Song, 2015; Comfort et al., 2012; Kapucu et al., 2010; Provan and Kenis, 2007; Comfort, 1994).

Studies of disaster response networks have utilized textual data from multiple sources, such as newspapers, magazines, situation reports, whitepapers and inquiry transcripts (Yeo and Comfort, 2017; Jung and Park, 2016; Kim and Hossain, 2013; Diesner, 2012; Pfeffer and Carley, 2012; Isett et al., 2011; Moynihan, 2009; Van Atteveldt, 2008; Comfort and Haase, 2006; Carley, 1993). Textual information has the advantage of providing a comparatively objective overview of events based on actual occurrences. It, thus, overcomes the retrospection and recollection bias prevalent in the results of traditional research tools, such as surveys, focus groups and interviews (Diesner, 2012; Pfeffer and Carley, 2012; Isett et al., 2011; Carley, 1993).

In particular, many disaster network scholars have recently become conscious of the utility of online textual information (Yeo et al., 2018; Kim and Hossain, 2013; Isett et al., 2011). Diverse online sources, such as news websites, cloud sources and social media platforms, provide an ample amount of real-time disaster information, which could enhance the understanding of emergent disaster response systems as well as support informed decision-making (Jung and Park, 2016; Kim and Hossain, 2013; Isett et al., 2011; Carley, 1993).

Despite the advantage, there is a certain challenge in the use of online information in disaster network studies, namely, the timely extraction of valid data. After the occurrence of a disaster, the volume of information available online expands exponentially. However, methods of traditional manual content analysis (MCA) coding cannot keep up with the amount of online information generated daily (Diesner, 2012; Pfeffer and Carley, 2012; Novak and Cañas, 2008). MCA coding usually requires a great deal of time and human resources as researchers must review all the textual information, screen the focusing events, and hand code relevant information in spreadsheets to build analyzable network data sets (Diesner, 2012; Novak and Cañas, 2008; Gephart, 1993; Carley, 1993). Given the nature of the coding process, MCA usually delays timely assessment of emerging disaster response coordination (Pfeffer and Carley, 2012; Carley, 1993).

In response to the limitations of MCA, computational sociology researchers (Morstatter et al., 2013; Martin et al., 2013; Diesner, 2012; Pfeffer and Carley, 2012; Tambayong and Carley, 2012; Mihalcea and Radev, 2011) have developed a simple method for rapid online data extraction, termed the rapid network assessment (RNA) coding method. Linking the coding of network data with modeling processes, RNA helps to promptly identify and assess emerging social networks from the massive volume of digital texts, improving time and cost efficiency in data collection (Diesner, 2012; Pfeffer and Carley, 2012; Martin et al., 2013).

Setting aside rapidity, the prominent advantage of RNA, the question remains whether the output generated by RNA would be comparable to that of MCA. However, there has been few comparison studies of RNA and MCA. With respect to the growing need for timely assessment of real-time disaster response systems yet emerging doubts regarding the comparability of the RNA to MCA, this study performs a cross comparison between two methods, examining similarities and differences of the findings from the data generated by RNA and MCA. The results will help to settle remaining questions around RNA by providing comprehensive information on the advantages and disadvantages of RNA relative to MCA of online information in assessing real-time disaster response networks.

In the following sections, this study describes the coding choices for RNA and MCA; provides background information on the research context, Superstorm Sandy; presents the detailed data-modeling processes of RNA and MCA; discusses findings; and concludes with a brief summary and policy implications.
Common and distinctive coding choice of RNA and MCA

In this section, we describe coding choices in both RNA and MCA. Network coding choices include units of observation and assumptions of nodes, links and identification of other attributes (Kim et al., 2017; Yeo and Comfort, 2017; Jung and Park, 2016; Diesner, 2012; Carley, 1993, 1994). Understanding this is important because such choices determine the content of data sets, as well as affecting the results of analysis and findings (Boréus and Bergström, 2017; Elo et al., 2014; Diesner, 2012; Carley, 1993, 1994). We first describe shared coding choices in both methods and then examine the distinctive coding choices in each method.

Common coding choices: identification of nodes and ties

Social network theory guides the essential coding choices of both RNA and MCA. In this theory, there are two fundamental concepts: node and tie. A node is a social entity, i.e., person, group, organizations, or nation, acting within an identified event (Wasserman and Faust, 1994). Ties are social relationships, occurring between any two nodes (Wasserman and Faust, 1994). The range or types of ties vary greatly, depending on the contents of communication, interactions, transactions, or affiliations. Guided by social network theory, both RNA and MCA identify entities and relationships between them in response to a given disaster situation.

Discrete coding choices: identification of nodes and ties

Specific coding choices are made in each method in the course of the identification of social entities and relationships in emerging disaster response networks (Zhavoronkov et al., 2017; Saldaña, 2015). In MCA, researchers first download and screen all available textual information, reading through all of it that is potentially relevant to identify node populations that have the same types of social entities. In addition, MCA defines the ties found among the nodes, using identification of the actual occurrences of actions, communications, interactions, or transactions, relative to disaster response. For example, let us say that researchers have identified three documents (Doc 1, Doc 2, and Doc 3 in Figure 1) that contain information about a disaster response. If the first document (Doc 1) indicates that organization A donated money to disaster relief organizations B and C, the researcher codes organization A as an initiating node and organizations B and C as organization A’s responding organizations (partners). At the same time, in document 2 (Doc 2 in Figure 1), the researchers identify that organization B sent water to other disaster relief organizations D and C. Here, the researcher codes the ties as outgoing from organization B to organizations D and C. Finally, if document 3 (Doc 3 in Figure 1) reports that organization D provided manpower to relief organizations C, E and F, the researchers code outgoing ties from organization D to organizations C, E and F. MCA add nodes incrementally and
links information. The structure of the network can be identified by the subsequent extension of the bilateral relationships across all nodes. The overarching network structure cannot therefore be comprehended until all the available textual information has been reviewed. Figure 1 illustrates the coding process for MCA.

By contrast, RNA first screens social entities from each available document, using pre-structured indices (Diesner, 2012; Pfeffer and Carley, 2012); then, two-mode networks are created between each document and the actors identified within that document (Diesner, 2012; Pfeffer and Carley, 2012). This step is based on the assumption of co-occurrence, which states all actors reported in the same document are connected to each other. RNA folds all two-mode networks of actors and documents into a one-mode actor-based network (Diesner, 2012; Martin et al., 2013; Pfeffer and Carley, 2012). For example, if organization A, B and C are screened in document 1 (Doc 1 in Figure 2), then RNA assumes that organizations A, B and C worked with each other. In the same way, organizations B, E and F from document 2 (Doc 2 in Figure 2) are also identified as partners. The relationships among actors in documents 3 and 4 (Docs 3 and 4 in Figure 2) are likewise identified. Each node’s extended linkages are automatically retrieved from the folding processes, and RNA identifies the overarching disaster response network in this way (Martin et al., 2013; Diesner, 2012; Pfeffer and Carley, 2012). Where RNA is utilized, node populations and relationships among nodes easily can be identified over a relatively short period due to its assumption of co-occurrence and its automated node screening and folding. Figure 2 illustrates RNA at work.

Background for Superstorm Sandy

Brief introduction to the disaster

In late October 2012, Tropical Storm Sandy formed in the southwestern Caribbean. By the time it made landfall in Jamaica on October 24, it had increased in intensity to form a Category 1 hurricane. The storm again increased in severity as it moved toward Cuba, making a second landfall as a Category 3 hurricane on October 25. It then turned north, moving slowly over the Atlantic Ocean toward the coast of New Jersey and New York, weakening to a post-tropical storm as it made a third landfall near Brigantine, New Jersey, on the US Atlantic Coast at around 8:00 p.m. on October 29, 2012. The storm was well tracked: the US National Weather Service continuously projected simulations of the direction and strength of the storm for three days before its third landfall. This allowed emergency services and the residents of coastal communities to make preparations for the storm.

At the same time, a major cold front was moving from the Midwest toward the East Coast. It collided with Tropical Storm Sandy’s warm front, creating Superstorm Sandy;
this event unleashed a cascade of damaging effects; these went rippling through coastal communities, disrupting business operations in at least five states: New York, New Jersey, Connecticut, Delaware and Maryland (Benfield Report, 2013). Superstorm Sandy then coincided with an unusually high tide in New York City, creating a storm surge of 14 feet (4.2 meters) on Manhattan Island. This unusual coincidence of meteorological events hit one of the most densely populated regions of the East Coast, with New York City and the coastal communities of New Jersey bearing the brunt of the storm. Public agencies, business organizations and households endured significant damage and upheaval from the severe impact of this rapidly changing set of extreme events.

The total economic losses caused by Superstorm Sandy in 2012 are estimated to have reached $72bn, including approximately $30bn of insured losses and roughly $7.2bn in payments made by the US National Flood Insurance Program (Benfield Report, 2013). Roughly 60m people, many of whom lost work or suffered damage to their homes and businesses, were directly affected by Sandy, across 24 states. The economic losses to New Jersey and New York alone were estimated to be $66bn. Sandy was thus second only to Hurricane Katrina in amount of losses generated by a disaster in the USA. The need to conduct rapid data collection, analysis and interactive exchanges of information among the communities, organizations and households affected by this unusually severe storm can be seen in the evidence of the reported losses, some of which could have been reduced by informed, coordinated action.

Why Superstorm Sandy?
Due to its size and impact, Superstorm Sandy received extensive coverage by the media, leading to a gigantic amount of textual information being produced by a wide range of sources even before Sandy’s formation as a hurricane or landfall on the US East Coast. If this written information had been organized and analyzed promptly, effectiveness of disaster response could have been increased and accelerated. Yet, using MCA, it was almost impossible to collect data from the exponentially increasing mass of textual information or to conduct timely analyses of response networks working in the most affected parts of New Jersey and New York.

Although the actual disaster has now passed, rendering the processing of the available information less urgent for actual disaster response, it remains necessary to identify and test methods of data extraction, thus preparing for future disasters and crises. The mass of textual information and documents produced during the response to Superstorm Sandy will serve to provide a good platform for understanding and testing the RNA’s efficacy.

Data and methodology
Sources of data
The news articles and other documents used for this study were downloaded from the news archive LexisNexis Academic (www.lexisnexis.com/hottopics/lnacademic/), using the search query (“Hurricane Sandy” or Superstorm Sandy or Sandy Hurricane) and (New York or New Jersey) on the platform LexisNexis Smartindexing. The period for the data includes the first three months following the incident, from October 24, 2012 to January 31, 2013, which covers the preparation period, landfall and post-disaster response and recovery in the state of New York and New Jersey. A total of 1,000 articles were exported from LexisNexis Academic. After redundant and duplicate articles were eliminated, we analyzed textual information from 541 distinct articles published by 223 distinct written news sources in English.

RNA coding
A researcher and a programmer conducted the RNA of the 541 articles. Utilizing the LexisNexis Smartindexing platform, which provides a set of pre-defined textual data,
the researcher obtained a first overview list of agents, including companies, organizations and individuals participating in disaster response. Agents and the articles where these agents were identified were coded into the two-mode network data set.

The researcher identified inconsistencies in the titles of the identified agents, because different references to or labels for the same agents could lead to the creation of false distinct nodes in the network analysis, thus distorting the results of analysis (Pfeffer and Carley, 2012). To resolve errors stemming from labeling inconsistency, a thesaurus was created to convert different references to the same agents into a standardized format (Pfeffer and Carley, 2012).

Using Java, the programmer also created text-mining software to identify missing information that had not been pre-indexed by the Smartindexing system. Using the rule of the English language that proper nouns must begin with a capital letter, and adding a comment to pass the titles initially identified by Smartindexing, the Java text-mining software extracted a supplemental list of agents from the 541 articles. The additional data were again cleaned and combined with the previous two-mode network data set. The RNA work overall, from text mining to data cleaning, and to the building of the two-mode network data set, took 60 hours (12 hours/day \times 5 days), from February 8 to February 12, 2013.

MCA coding process
Three researchers conducted MCA on the same 1,000 articles originally exported from the Smartindexing system. The articles were divided into two groups, based on the similarity of articles: 470 unique articles, and 530 articles with some duplicates. One researcher analyzed the unique set of 470 articles, and the other two researchers analyzed the set of 530 articles. Following standard coding choices for MCA, each researcher read each article thoroughly, identified nodes and ties, and hand-coded the information on a spreadsheet. For example, researchers identified actors based on their actual involvement in the response and relationships between actors based on explicit transactions occurring during the practice of disaster response. For each document, the researchers iteratively identified and coded dyadic relationships between two organizations, an (inter)action-initiating organization and a corresponding organization. Then, the researchers combined their coding sheets. In this way, a full roster of participating organizations and ties among the organizations that participated in Superstorm Sandy response was identified. At Last, the combined data set was reviewed and cleaned by all three researchers. Overall, MCA took nearly 480 hours (12 hours/day \times 40 days), from May 1 to June 30, 2013, to complete.

Data cleaning process
To create a valid comparison of the two data-coding methods, each data set from each coding method was cleaned and set into comparably equivalent formats (Grimmer and Stewart, 2013; Lewis et al., 2013). During the cleaning process, first, variations in the codes for the titles of some organizational agents were identified. This discrepancy in the data was cleaned through matching and recoding the titles the affected organizational agents. Second, discrepancies in codes representing individual agents were treated. The codes for RNA separated organizational from individual agents, according to the Smartindexing categorization of the identified agents. For example, if the US Congress was represented in one article and a specific congressional representative or senator was represented in another, Congress was coded as a unique organizational agent, and the name of the representative or senator was also coded as a unique individual agent. Using the code list generated using MCA, an individual who belonged to an organization was coded as an organizational agent. Reaching a consensus on the scaling down of the data units, it was decided that codes for individual agents in the RNA data set would be scaled up and that the titles of individual agents would be recoded with the titles of the organizations if those
agents belonged to any of the identified organizations or represented certain groups. However, titles were retained for individual agents that could not be categorized into any organizations or groups.

**Social network analysis**

Once the data sets had been authenticated through multiple reviews by several researchers regarding the data attributes and contents, social network analysis was conducted to compare the results of analysis from each data set that was collected using the different data-collection methods. ORA (Carley, 2001–2011), a software package for network analysis developed at the Center for Computational Analysis of Social and Organizational Systems, Carnegie Mellon University, was used to analyze the two data sets. The findings from social network analysis were reviewed to identify similarities and differences in the structural and compositional characteristics of each network, as identified by the respective data-coding methods. From these results, the distinctive value of each method was identified.

**Results**

**Network-level comparison**

Network analysis was conducted to examine the general patterns of structures and the characteristics of the networks that were identified using the different coding methods. First, descriptive analyses were calculated for the two static networks. In the RNA network, 639 agents were identified that responded to the disaster, of which 46 (7 percent) were isolates, i.e., independent actors that did not interact with any other agents during the disaster response; further, 2,884 unique dyads and monads were identified. In the MCA network, 617 agents were identified that responded to the disaster, of which 177 (29 percent) were identified as isolated agents; further, 556 distinctive links were constructed by the agents identified (Table I).

The density, distance, and fragmentation of the RNA and the MCA networks were then measured to determine in each network relationship patterns among agents (Table II).

As indicated by the results of descriptive analysis, the RNA network had greater density and connectedness owing to its higher number of links that that found in the MCA network. Furthermore, because the RNA network has well-interconnected agents, the average distance among them was much shorter than the average distance between agents in the MCA network. Because it had more isolated agents and found fewer links, the MCA network had much greater fragmentation and network-level values.

Each data set was graphically modeled to provide greater insight into the results of the above analysis. Figure 3 shows maps of the RNA and MCA static networks, including all agents.

| Table I. Static network descriptive analysis |
| Count, node | RNA | MCA |
| Link count | 2,884 | 556 |
| Isolate count | 46 | 177 |

| Table II. Static network structure analysis |
| Density | RNA | MCA |
| Average distance | 2.827 | 8.595 |
| Fragmentation | 0.343 | 0.768 |
| Network level | 6 | 24 |
Figure 4 gives only the core networks of the RNA and the MCA, excluding all isolated agents and groups. In both figures, the node of each agent node is colored according to its degree of centrality and its total number of direct links (where blueish = more, reddish = less), and they are sized according to their the betweenness centrality, i.e., the total number of shortest paths from all agents to all others that pass through a certain agent within the network (larger = more, smaller = fewer). Figures 3 and 4 reflect the differences between the RNA and MCA networks in terms of measures of network density, distance and fragmentation. The patterns (arrangement of node sizes and colors) for both core networks featured in Figure 4 show the structural similarities found between the networks produced by RNA and MCA.

To investigate the particular properties of the graph, centralization measures[5] were documented. The results, shown in Table III, support our claim about the overall structural
similarity between the networks produced by RNA and MCA. Even though there were actual
differences in absolute values for centralization measures, the centralization patterns in both
networks were similar. In both the RNA and MCA networks, the betweenness centralization
measures were the lowest, the degree centralization measures were slightly higher than the
betweenness centralization measures and the eigenvector centralization measures were the
highest of all. These results indicate that the structural advantages were distributed
among the agents within each network and that, overall, both networks’ agents were
connected to relatively central actors, and they shared resources or information with them
during disaster response.

Network-entity-level comparison
Analyses on the level of network entities were conducted to investigate whether the methods
of RNA and MCA congruently identified the agents participating in the Superstorm Sandy
response network. First, the percentage of agents in common in the networks, and the agents
that were distinct between them were determined. Among the agents in the RNA and MCA
networks, 371 (58 percent in the RNA network and 60 percent in the MCA network) were
found to be identical. In addition, 268 (42 percent) and 246 (40 percent) distinct, unshared
agents were identified in the RNA and MCA networks, respectively.

To determine the unique agents in each network more closely, the analysis of key
entities was conducted, using centrality measures, to examine whether the agents
had important positions in each network. The results of the analysis of key entities
indicated, also, discrepancies between the RNA and MCA in terms of the identification of
key agents with their structural roles and functions in the network of response to
Superstorm Sandy.

First, using a measure of degree centrality, the top 10 most-connected agents in each
network were identified: these were the agents that had a high degree centrality and an
immediate impact on many other agents in the disaster response they were involved in.
Despite differences in rank, seven out of ten agents were common to the RNA and MCA
networks; in addition, even though, within the top 10 most-connected agents, 6 were unique
to the top 10 of their respective system, they were all still agents that both the RNA network
and the MCA network had in common (Table IV).

<table>
<thead>
<tr>
<th>Rank</th>
<th>RNA</th>
<th>MCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>American Red Cross</td>
<td>American Red Cross</td>
</tr>
<tr>
<td>2</td>
<td>White House</td>
<td>Federal Emergency Management Agency</td>
</tr>
<tr>
<td>3</td>
<td>Federal Emergency Management Agency</td>
<td>Office of Governor of New Jersey</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>White House</td>
</tr>
<tr>
<td>5</td>
<td>Office of Governor of New Jersey</td>
<td>Congress</td>
</tr>
<tr>
<td>6</td>
<td>Office of Mayor of New York City</td>
<td>Office of Governor of New York</td>
</tr>
<tr>
<td>7</td>
<td>Congress</td>
<td>Office of Mayor of New York City</td>
</tr>
<tr>
<td>8</td>
<td>Office of Governor of New York</td>
<td></td>
</tr>
</tbody>
</table>
Second, using the betweenness centrality measure, the top 10 agents that were positioned to broker connections between groups were identified. These agents were the ones that could control or diffuse information among separate groups or individual agents. The results were similar to those for the analysis of the total degree centrality, regardless of the changes between the key agent lists. Seven out of ten agents were identified in common as the top gatekeeping agents. In addition, even though six agents within the top 10 gatekeeping agents for each of RNA and MCA, they were still identified as common agents in both the RNA network and the MCA networks (Table V).

Third, eigenvector centrality analysis was conducted to identify the key agents that had powerful neighbors. Through connections with powerful neighbors, agents that were eigenvector central could influence other nodes within the network. The results of analysis indicate that six common key agents enjoyed powerful neighbors; furthermore, four other agents in each network that were distinctive in terms of eigenvector central were found within the list of agents common to both the RNA and MCA networks (Table VI).

Finally, the top 10 emergent leaders in each network were examined. Emergent leaders are those that have many connections to other agents and are also engaged in multiple complex tasks requiring high levels of coordination (Carley, 2001–2011). The results of this analysis were identical to those for the top 10 most-connected agents; there were seven emergent leaders in common, with the other six emergent leaders that were not shared between the top 10s of the two networks being common to the RNA and MCA networks (Table VII).

**Conclusion**

This study investigated the RNA data-coding method. To test the method, the study compared the results of network analysis from two data sets, one developed using RNA and the other using MCA, using the same online textual information on the response to Superstorm Sandy.

<table>
<thead>
<tr>
<th>Rank</th>
<th>RNA</th>
<th>MCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>American Red Cross</td>
<td>Federal Emergency Management Agency</td>
</tr>
<tr>
<td>2</td>
<td>White House</td>
<td>Office of Governor of New York</td>
</tr>
<tr>
<td>3</td>
<td>Federal Emergency Management Agency</td>
<td>White House</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>Office of Mayor of New York City</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>Congress</td>
</tr>
<tr>
<td>6</td>
<td>Congress</td>
<td>Office of Governor of New Jersey</td>
</tr>
<tr>
<td>7</td>
<td>Office of Mayor of New York City</td>
<td>American Red Cross</td>
</tr>
<tr>
<td>8</td>
<td>Office of Governor of New Jersey</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Office of Governor of New York</td>
<td></td>
</tr>
</tbody>
</table>

Table V. Key entities of RNA network and MCA network according to betweenness centrality

<table>
<thead>
<tr>
<th>Rank</th>
<th>RNA</th>
<th>MCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>White House</td>
<td>Congress</td>
</tr>
<tr>
<td>2</td>
<td>Federal Emergency Management Agency</td>
<td>Office of Governor of New Jersey</td>
</tr>
<tr>
<td>3</td>
<td>Office of Governor of New Jersey</td>
<td>White House</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>Federal Emergency Management Agency</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Office of Governor of New York</td>
<td>The Wall Street Journal</td>
</tr>
<tr>
<td>7</td>
<td>Congress</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>The Wall Street Journal</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table VI. Key entities of RNA network and MCA network by eigenvector centrality
Two levels of analysis were conducted on each data set: network-level analyses to investigate the overall compositional and structural patterns of the Superstorm Sandy network produced from each data-coding method, and network-entity-level analyses to examine whether and how far there was congruence between the lists of key agents identified by RNA and MCA.

From these analyses, similarities and differences were identified. The results of network analysis for RNA and MCA showed significant similarities in the general overview of the response network of Superstorm Sandy in terms of the number of agent nodes (around 60 percent), global structural patterns among those agents (patterns among the centralization measures), and the majority of key agents (centrality measures). The similarities in the results of the analyses of the two methods, combined with the efficiency of RNA, indicate that it is a more efficient method than MCA for the rapid provision of information during the initial stages of disaster response. The RNA network provided a timely overview of rapidly emerging networks of disaster response and the locations of key agents that could have aided managers in actual emergency response operations in search of information that was practically organized.

Further, differences were found between the link counts of the two networks that affected the all values of network measurement. The disparities between the link counts produced in the two networks mainly emerge from the core coding choices, including assumptions of relationship identification. The assumption of the co-occurrence of RNA methods, which automatically endows all the agents identified in the same article with relationships among one another, may overestimate the number of relationships. Overrepresentations of the link counts would result in a continual overestimation of the values of the various network measures used to examine the overall health, effectiveness and efficiency of the RNA networks. Thus, network researchers may wish to consider developing and applying new methods or assumptions for RNA to overcome its tendency to overestimate nodes and ties, as well as the consequent errors in the results of analysis that this implies.

Given the relative advantages of RNA over MCA, it is impossible to definitively conclude that either method is superior to the other for conducting evaluative analyses of disaster response networks. However, we do recommend that flexible utilization of each method, or a mixture of methods, would be desirable, in accordance with the situation. For example, during the immediate phases of disaster relief and response, the key is collecting and distributing emerging information and key resources to where it is needed rather than identifying precise information on each individual actor within an arena. The convenience and rapidity of RNA may serve the situation better than the feature of MCA. RNA is an efficient method for grasping the overall structure of a system and key actors within a short period. Therefore, RNA may be efficient for the quick review of participating agents and resource flows through their relationships during initial disaster relief and response. On the other hand, for long-term preparation for future disasters, conducted during the recovery, mitigation and prevention phases, emergency managers may need data that have a greater

<table>
<thead>
<tr>
<th>Rank</th>
<th>RNA</th>
<th>MCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>American Red Cross</td>
<td>American Red Cross</td>
</tr>
<tr>
<td>2</td>
<td>White House</td>
<td>Federal Emergency Management Agency</td>
</tr>
<tr>
<td>3</td>
<td>Federal Emergency Management Agency</td>
<td>Office of Governor of New Jersey</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>White House</td>
</tr>
<tr>
<td>5</td>
<td>Office of Governor of New Jersey</td>
<td>Congress</td>
</tr>
<tr>
<td>6</td>
<td>Office of Mayor of New York City</td>
<td>Office of Governor of New York</td>
</tr>
<tr>
<td>7</td>
<td>Congress</td>
<td>Office of Mayor of New York City</td>
</tr>
<tr>
<td>8</td>
<td>Office of Governor of New York</td>
<td></td>
</tr>
</tbody>
</table>

Table VII. Key emergent leaders in the RNA and MCA networks
level of precision and accuracy to diagnose emergency management systems as a whole. In this context, rapidity of data accumulation is less relevant, but acquiring comprehensive and accurate data sets is the major concern. Therefore, researchers may strategically utilize either RNA or MCA, or they may take both approaches, to obtain information responding to the priorities of situations as they emerge and to assist the decision making of practitioners in the field of emergency and crisis management.

Notes
1. 4 hours/person × 3 persons.
2. Density = actual connections (links between nodes)/potential connections, potential connections = n(n – 1)/2, n = number of existing nodes.
3. Distance = 1/potential connections × (sum of shortest distance among any two nodes within a network, if one node cannot be reached by another node, the value of shortest distance between the two nodes is recorded as 0).
4. “Fragmentation = proportion of nodes in a network that is disconnected (Carley, 2001–2011).”
5. Centralization measures describe how tightly an overall connection of a network is organized around a particular focal point or how evenly nodes are sharing connections with other nodes within the network. Degree centralization is calculated based on the proportion of direct connections incident upon a central node within a network, and betweenness (i.e. the network is connected through certain nodes) and eigenvector centralization (i.e. the connectivity of the nodes depends on their neighboring or adjacent nodes) measures the proportion of connections of central nodes relative to the other nodes within the network.

References


For instructions on how to order reprints of this article, please visit our website: www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: permissions@emeraldinsight.com