Power-law behavior in complex organizational communication networks during crisis

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Highlights

► We study power-law behavior of organizational email communication networks (ECN). ► We examine changes in ECN during crisis and non-crisis periods. ► We find that actors, who are prominent, become central during crisis. ► During crisis, ECN for each day as well as for each actor follow power law.
Power-law behavior in complex organizational communication networks during crisis

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ABSTRACT

Communication networks can be described as patterns of contacts which are created due to the flow of messages and information shared among participating actors. Contemporary organizations are now commonly viewed as dynamic systems of adaptation and evolution containing several parts, which interact with one another both in internal and in external environment. Although there is limited consensus among researchers on the precise definition of organizational crisis, there is evidence of a shared meaning: crisis produces individual crisis, crisis can be associated with positive or negative conditions, crises can be situations having been precipitated quickly or suddenly or situations that have developed over time and are predictable etc. In this research, we study the power-law behavior of an organizational email communication network during crisis from complexity perspective.

Power law simply describes that, the probability that a randomly selected node has k links (i.e. degree k) follows P(k) ~ k^−γ, where γ is the degree exponent. We used social network analysis tools and techniques to analyze the email communication dataset. We tested two propositions: (1) as organization goes through crisis, a few actors, who are prominent or more active, will become central, and (2) the daily communication network as well as the actors in the communication network exhibit power-law behavior. Our preliminary results support these two propositions. The outcome of this study may provide significant advancement in exploring organizational communication network behavior during crisis.

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1. Introduction

Communication networks are described as patterns of contacts which are created due to the flow of messages among the participating actors (or communicators). Messages include everything that can flow from one point of contact to another within and between the networks, including data, information, knowledge, image and symbol. These communication networks could take various forms, such as, personal contact networks, work related contact networks, strategic alliances among various firms, global network of organizations etc. [1].

Organizations are commonly viewed as dynamic systems of adaptation and evolution that contain several parts and these parts interact with each other and with the internal and external environment. In fact, this representation is such common that it has been described as a self-evident system by researchers[2]. This ‘self-evident’ representation of organizations also implicitly assumes that organizations are ‘complex systems’. Complex systems change inputs to outputs in a nonlinear way

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because their components interact with each other via a web of feedback loops. Complexity theory also suggests that some systems with many interactions and highly differentiated parts can produce surprisingly simple, predictable behavior, while others generate behavior that is impossible to forecast, though they feature simple laws and few participating actors [3]. Hence, complexity researchers argued that it is inappropriate for organizational scientists to settle prematurely into a normal science mindset, because organizations are inherently complex [3, 4]. Furthermore, organization theory and complex system theory deal with similar issues such as dynamic systems, adaptation, evolution in complex systems, emergence of new forms, naturally occurring patterns in systems etc.

In recent years, our understanding of complex networks has changed significantly due to the availability of ‘real-world’ networks coupled with the advances in the knowledge base of analytic techniques employed by social network researchers in areas as diverse as Physics and Biology, Mathematics and Sociology, Organizational science and Psychology. Interestingly, the most commonly cited link between these diverse areas of research is self-organizing behavior of complex system. Two of the most frequently mentioned properties of real-world complex systems are clustering behavior and the existence of scale-free network characteristics. Research indicates that most networks display a high degree of clustering and many scientific, technical and organizational network, ranging from biological network [5] to World wide web [6] have been found to be scale free. Scale-free network displays the characteristics of power-law distribution, which means that the probability that a randomly selected node has k links (i.e. degree k) follows \( P(k) \sim k^{-\gamma} \), where \( \gamma \) is the degree exponent and \( k \gg 1 \) [7].

In this paper, we analyze the changing organizational communications structure in order to investigate the patterns associated with final stages of an organizational crisis. In the next section, we discuss the relevance of studying organizations from communication network perspective and some relevant studies. Then, the power-law behavior of complex networks during crisis is discussed and a proposition is constructed based on the extant literature. After that, we discuss dataset and measures being used for our analysis. Results of the study are shown and discussed in the following section, followed by concluding remarks.

2. Communication network approach to study organization

Johnson [8] referred to organizational communication structure as the relatively stable configuration of communication relationships between entities within an organizational context. Relationships have always been the main focus of organizational communication within the communication structure. Relationships among various entities form an overall pattern that could form a gestalt of the total structure within an organizational context. Relationships are essentially linkages among people. Relationships link people from diverse backgrounds (e.g. departments, subgroups, teams, outsourced consultants etc.). These various types of relationships provide us with a better and more finely grained picture of organizational activities than do usual description of formal organizations. Organizations can, then, be assessed in terms of total number of linking activities, the linking activities which produce different numbers and kinds of subgroups, relational characteristics that link these subgroups, resulting (formal and informal) structures that evolve and dissolve etc.

In this research, we start with the premise that email networks constitute a useful proxy for the underlying communication networks within organizations. Tyler et al. [9] described email communication network as a tantalizing medium for research which offers a promising resource for tapping into the dynamics of information within organizations and for extracting the hidden patterns of collaboration. Gloor et al. [10] noted that analysis of email and other interaction logs of organizations will enable researchers to discern the structure of networks and identify core contributors. In their experiment, they analyzed the mailing list archives of three World Wide Web Consortium (W3C) working groups. They used several metrics developed in SNA research to compare the three W3C working groups: density, betweenness centrality, and group degree centrality. From the communication patterns, they were able to identify a group of leaders in the networks they analyzed. In this paper, we use centrality measures to identify the prominent actors in the Enron corpus and their correlation.

3. Power-law behavior in self-organizing complex system during organizational crisis

The presence of power-law behavior is observed in various types of complex systems, such as, in lung inflation system [11], in complex organizational communication network [12] as well as in metabolic networks [13]. It has also been noticed in nature, for example in the activity of sun, in the light from galaxies, in the flow of current through resistor, and in the flow of water through river [14]. Now-a-days, power-law behavior has been used for exploring complex environments by many researchers in diverse research areas and context [15–18].

Barabási and Albert [19] reported on the existence of high self-organizing characteristics in the large scale properties of complex networks based on their experiments on World Wide Web (WWW). They proposed that, independent of the system and the identity of its constituents, the probability \( P(k) \) that a vertex in the network interacts with k other vertices decays as a power law, following:

\[
P(k) \sim k^{-\gamma}
\]

where \( k \) is the degree \((1 < k < \infty)\) and \( \gamma \) is an exponent (typically \( 2 < \gamma < 3 \)).

Barabási and Albert [19] called this scale-free state, a feature unpredicted by all existing random network models. Random network models are often described by bell curves, whereas scale-free networks are described by power-law distributions. The following diagram shows the differences between these two types of distributions.
Fig. 1. Random network curve and scale-free network curve. The distribution of random networks shows bell curve. The power-law distribution of scale-free networks shows that most of the nodes have few links. Few nodes have a large number of links.

Fig. 2. Formation of a scale-free network. Adopted from [21].

From Fig. 1, we see that random networks have a characteristic scale, evidenced by average node and fixed by the peak of degree distribution. However, networks described by power-law distributions do not have any characteristic node, or scale. There is no single node which could be described as characteristic of all the nodes. Hence, Barabási and his research team described networks with power-law distribution as scale-free [20].

They proposed a model incorporating growth and preferential attachment, two key features of real-life networks, and showed that these features are associated with the power-law distribution properties observed in many real networks. The following figure (i.e., Fig. 2) demonstrates a formation of scale-free network, based on preferential attachment.

In the top-left column of first row, at $t = 1$, three nodes are connected to each other for the initial network. At $t = 2$, a new node is connected to the existing network. At $t = 3$, another node is connected to the network. Preferential attachment predicts that, in deciding which node to connect to, the new node will prefer the node which is more connected. Due to the phenomena of preferential attachment, a ‘rich-gets-richer’ network behavior is observed. It also implies that highly connected nodes acquire more links than those are less connected in a network, leading to the emergence of a few highly connected nodes which is referred to as hubs or highly prominent nodes [19,21].

To elaborate on the phenomena of preferential attachment, we introduce the sociological theory of self-interest theory. This theory postulates that people make decisions based on their own rational choices with a view of achieving maximum personal benefits. Homans [22] argued that when people face problems during the crisis period, they tend to examine all the possible solutions to the crisis and choose the one that appears to maximize their benefits. Simon [23] also described the term “bounded rationality” and argued that most of the people rarely have sufficient resources to explore all the possible alternatives. Instead, they satisfice (satisfy and suffice) rather than maximize. This also means that, they choose the first alternative that appears satisfactory rather than exploring multiple alternatives. Preferential attachment is one of such mechanisms where a new node prefers the prominent node(s) which is already more connected. These ‘more connected’ nodes or hubs play a vital role in shaping up the networks. From Fig. 2, we also see that the node size, proportional to the node’s degree (or number of links) illustrates the natural emergence of hubs as the largest nodes. The resulting degree distribution of the network follows the power law, described in Eq. (1) with exponent $\gamma = 3$.

One of the most frequently cited propositions in organization literature is related to the centralization of authority or constriction of control at the time of crisis. It has been observed that during the crisis period, organizations look to the leader for solutions [24]. Hamblin [25] initiated a laboratory investigation (consisting of 24 groups) of two hypotheses relating to leadership during crises. One of them was that leaders tend to have more influence during crisis than during non-crisis period and data from observational studies lend support to this hypothesis. Smart and Vertinsky [26] argued that during crisis period, decision making authority shifts to higher levels and there is also a reduction of persons participating in the decision making process. According to Staw et al. [27], when crisis (or threat) is observed in an organization, the importance of decisions increases and they are progressively made at the higher levels. As a poorly performing organization during the crisis period we also expect Enron communication networks to be more centralized. Argote et al. [28] also mentioned some
other reasons of centralization during crisis period which includes the motivation to increase control over the threatening situation and savings of valuable time which accrue from consulting less individuals in decision making process.

From the extant literature, regarding the power-law behavior of self-organizing complex network during organizational crisis period, we propose the following propositions.

**Proposition 1.** As organization goes through crisis, a few actors, who are prominent or more active, will become central.

**Proposition 2.** (a) Daily communication networks exhibit power-law behavior, and (b) Actors in the communication networks also exhibit power-law behavior.

### 4. Dataset and measure of communication networks

In May 2002, the US Federal Energy Regulatory Commission (FERC) publicly released a large set of email messages, the Enron corpus. The corpus contains 619,446 email messages belonging to 158 users over a period of 3.5 years. Shetty and Adibi [29] from University of Southern California created a MySQL database of this corpus. They also cleaned the database by removing a large number of duplicate emails, computer generated folders, junk data, invalid email addresses, blank messages etc. The resulting dataset contains 252,759 messages from 151 employees distributed in and around 3000 user defined folders. We use this modified dataset to perform our experiments. In the area of organizational science and social networking research, the Enron corpus is of great value because it allows the academic to conduct research on real-life organization over a number of years.

#### 4.1. Data cleaning

Since the process for creating MySQL database by using the Enron email corpus introduced by Shetty and Adibi [29] has been well documented, we decided to use this dataset. In extracting our required data we imposed some thresholds for our analyses.

- We considered the network of 151 employees only. It should be noted here that these 151 nodes are connected to more than 2500 other nodes, which includes both internal and external contacts.
- The email corpus includes email communications from 1997–2002. However, most of the active communications (many people communicated) occur between the years 2000–2001. We used the observation period of 131 days from July 2001 to December 2001 (excluding weekends and public holidays) for this experiment, as the major organizational crisis started to emerge during this period. For non-crisis period, we consider 126 days of email communication data from 1st July 2000 to 31 December 2000.
- We also concealed the names of the email communicators. We have given each employee an integer number and we refer to them by these numbers (e.g. Node 1, Node 2, Node 12, Node 58 etc.).

#### 4.2. Measure of communication networks

One of the important and primary uses of graph theory and network analysis is the identification of the most important actor(s) within a social network. Various researchers used words like 'importance' or 'prominence' to describe this important network measure. All such measures described and measured properties of 'actor location' in a social network. The social network literature has established definitions of many of these measures. These are based on degree, closeness, betweenness, information, and simply the differential status or rank of actors [30]. Prominent actors are described as extensively involved in relationships with others [30]. Knöke and Burt [31] also considered an actor to be prominent if the ties of the actor make the actor particularly visible compared to other actors within the network. Hence, the concept of degree centrality has been used to describe the prominence of an actor in our email communication networks. In particular, to describe scale-free network characteristics of our email communication network we used out-degree centrality measures which is defined by the following equation for an individual actor [30]:

\[
d(n_i) = \sum_j X_{ij}
\]

where, \(d(n_i)\) is the out-degree centrality for node or actor \(i\) and \(X\) refers to the adjacency matrix for network data.

Also, relationships are defined as communication linkages between the actors. Number of emails sent by the employees to the actors within their respective communication networks is used to quantify the out-degree centrality for all actors.

### 5. Results and discussions

In this section, we discuss the results obtained from the Enron data analyses and discuss the implications of the results in relation to our propositions. Before that, let us define four network terms that we used in our analyses to discuss the result findings.

(i) Daily network: the network was evolved, by means of email communications, amongst 151 employees for each day.
(ii) **Aggregated network:** this is the aggregation of daily networks. For crisis period, it consists of 131 daily networks; whereas, it consists of 126 daily networks for non-crisis period.

(iii) **Top-rank list:** list of actors who show most out-degree centralities in the daily networks or in the aggregated network.

(iv) **Centrality overlap:** this term was first defined by Braha and Bar-Yam [32]. In the process of comparing two top-rank lists of daily networks, an actor is said to be overlapped if it is found in both top-rank lists. When two daily top-rank lists are compared in overlapping, **centrality overlap** simply counts the number of actors that are located in both top-rank lists. For any two daily top-rank lists (say \(L_i\) and \(L_j\)) of size \(n\), it can be defined by the following equation:

\[
\text{Centrality}_{\text{Overlap}} = \sum_{i=1}^{n} \sum_{j=1}^{n} x \quad \text{where}, \quad x = \begin{cases} 
1 & \text{if } L_i = L_j \\
0 & \text{otherwise}
\end{cases}
\]  

\(\text{(3)}\)

where, \(L_i\) and \(L_j\) are the top-rank lists for day \(i\) and \(j\) \((i \neq j)\).

(v) **Mean centrality overlap:** it is the average number of ‘centrality overlap’ for each pair of daily networks [32]. We first add centrality overlaps for all possible pairs of daily networks. Then divide the summation by the total number of pairs of daily networks to measure mean of centrality overlap.

\[
\text{Mean of Centrality Overlap} = \frac{\sum \text{Centrality}_{\text{Overlap}}}{\text{Number of Pairs of Daily Network}}.
\]  

\(\text{(4)}\)

(vi) **Percentage of centrality overlap:** it is the ratio of ‘mean centrality overlap’ of daily networks and total number of actors in the network[32].

\[
\text{Percentage of Centrality Overlap} = \frac{\text{Mean of Centrality Overlap}}{\text{Number of Actors}}.
\]  

\(\text{(5)}\)

5.1. Actor centrality and prominence

To test the first proposition, we identify top-rank list of all the actors for each day. We, then, determined, for each pair of daily networks, the percentage of nodes that appear in both rank lists. We consider 131 and 126 daily networks for the year 2001 and 2000, respectively. Thus, we have a total of 8515 pairs \(\binom{131}{2} = \frac{131!}{(131-2)!2!}\) and 7875 pairs \(\binom{126}{2} = \frac{126!}{(126-2)!2!}\) for daily networks of 2001 and 2000.

We see from Table 1 that the **number of centrality overlaps** for the combination of any two daily networks increase with the size of the top-ranked list. Further, the increase of this centrality overlaps is significantly higher for crisis period (third column) than non-crisis period (second column). We represent this in Fig. 3. This centrality overlap statistics are free from the effects of the change in the number of emails and actors during crisis and non-crisis period as we have taken only top 10 actors to measure centrality overlaps.

All other measures in Table 1 (i.e. percentage of centrality overlap and mean of centrality overlap) increase with the increase of the size of top-ranking list. The higher centrality overlaps during crisis period indicates that same actors (or very similar actors with high out-degree centralities) are repeatedly listed in the top-rank positions as the organization was going through crisis. This result also demonstrates ‘rich-gets-richer’ phenomena as predicted by scale-free network theory.

Then, we checked the percentage of out-degree centralities of all daily networks showed by top ten actors of aggregated network in comparing to the overall out-degree centralities showed by all actors for both crisis and non-crisis periods (see Fig. 4). The average percentage of out-degree centralities by top ten actors are 49.91 and 60.92 for non-crisis and crisis period, respectively.

During crisis period, top 10 actors of the aggregated network exhibit around 60% of the out-degree centralities of 131 daily networks. The range is between 34.56 and 90.22. On the other hand, during non-crisis period, top 10 actors of the aggregated

### Table 1

Comparison of overlap statistics by the top-ranked actors during the crisis time (July–December 2001) and non-crisis time (July–December, 2000).

<table>
<thead>
<tr>
<th>Top-ranking list size</th>
<th>Number of centrality overlaps (July–December)</th>
<th>Percentage of centrality overlap (July–December)</th>
<th>Mean of centrality overlap (July–December)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2000</td>
<td>2001</td>
<td>2000</td>
</tr>
<tr>
<td>1</td>
<td>342</td>
<td>513</td>
<td>0.000288</td>
</tr>
<tr>
<td>2</td>
<td>918</td>
<td>1863</td>
<td>0.001567</td>
</tr>
<tr>
<td>3</td>
<td>2,313</td>
<td>3,998</td>
<td>0.003362</td>
</tr>
<tr>
<td>4</td>
<td>4844</td>
<td>6,825</td>
<td>0.005754</td>
</tr>
<tr>
<td>5</td>
<td>7,921</td>
<td>10,110</td>
<td>0.008502</td>
</tr>
<tr>
<td>6</td>
<td>11,264</td>
<td>13,816</td>
<td>0.011619</td>
</tr>
<tr>
<td>7</td>
<td>15,049</td>
<td>17,844</td>
<td>0.015006</td>
</tr>
<tr>
<td>8</td>
<td>18,909</td>
<td>22,140</td>
<td>0.018619</td>
</tr>
<tr>
<td>9</td>
<td>23,041</td>
<td>26,583</td>
<td>0.022355</td>
</tr>
<tr>
<td>10</td>
<td>27,297</td>
<td>31,083</td>
<td>0.026139</td>
</tr>
</tbody>
</table>

network exhibit around 50% of the out-degree centralities of 126 daily networks. The range is 28.57–76.07. This indicates, during crisis period the top 10 actors of the aggregated network shows higher percentage (around 10% more) of out-degree centrality than non-crisis period. These top ten actors have become more prominent actors during crisis period, having higher level of connectivity in the network which further reinforces the power-law distribution phenomena observed in the scale free emerging communication network of Enron during crisis period.

5.2. Daily network and individual actor’s network

To test the second proposition, we plot out-degree centralities of 151 actors for randomly selected dates of 21 August 2001 and 14 November 2001 (Fig. 5(a)–(b)). We also draw the corresponding log–log plot of out-degree centralities in Fig. 5(c)–(d).

From Fig. 5(c)–(d), we clearly see that the log–log plots of out-degree centralities follow power-law distribution as they produce straight lines. We then plot the log–log curve by considering all 131 daily networks together of crisis period. The resultant curve also follows power-law distribution as in Fig. 6(a). In addition to Fig. 5, this further confirms that all daily networks during crisis time follow power-law distribution.

After analyzing the daily network, we measure the out-degree centralities for each of the identified prominent actors of the crisis period. We found that most of the prominent actors exhibit time series that do not obey power law. Fig. 7 plots the graph of such out-degree centrality variations for a local hub node (Node 58). This node is found most of the times (85 times) in the top ten rank list. Out-degree centralities are high in general with low values in few occurrences.

From the Fig. 7, we find that the distribution for Node 58 does not follow the power-law characteristics as there are many high out-degree centralities on different days. However, we also found that a few nodes also exhibit highly fluctuating time series. One such node is Node 12. Fig. 8(a) demonstrates the fluctuating time series graph of the out-degree centrality for Node 12 during crisis period. This node was found once acting as a prominent hub within the crisis period of 131 days of the year 2001.

In Fig. 8(b), we also see that the log–log plot for the out-degree centrality of this node follows a power-law distribution. This implies that some of the actors became very prominent in the network over the time while some others became isolates, even though they became prominent for a short period of time. This phenomena can be explained by the fact that some people became prominent (higher out-degree centrality) as they might have been involved with a particular task for a certain period of time. But, when this task was accomplished they ceased, or greatly reduced email communications. Besides, as the organization was going through a period of crisis, we know that some of the employees were also leaving the organization. By summarizing the results of Figs. 5–8 we can conclude that the daily communication networks of Enron employees (included in the dataset) followed the power-law distribution. However, when we look at the network structure of individual prominent actor, we find that some of them follow power-law distribution whereas some others do not.

We also explore the out-degree centrality variation for daily networks during non-crisis period (July–December, 2000) and notice that they are similar to the graph as in Fig. 7. This indicates that during the non-crisis period, daily networks
Out-degree centralities of 151 actors at August 21, 2001
Out-degree centralities for 151 actors at November 14, 2001

Log-log plot for the date of 21/08/01
Log-log plot for the date of 14/11/01

Fig. 5. (a)–(b) Out-degree centralities of 151 actors for randomly selected dates of 21 August 2001 and 14 November 2001. (c)–(d) are the corresponding log-log plot of out-degree centralities (with exponents of $-2.47$ and $-2.51$ respectively).

Distribution of all email dataset: (a) for the crisis period which follows a power-law distribution (with an exponent of $-2.66$); (b) for non-crisis period that does not follow a power-law distribution.

Example of out-degree centrality variation for the node number 58 over the crisis period.

Fig. 6. Distribution of all email dataset: (a) for the crisis period which follows a power-law distribution (with an exponent of $-2.66$); (b) for non-crisis period that does not follow a power-law distribution. Further, we plot log–log curve by considering all 126 daily networks together for non-crisis period in Fig. 6(b). The resultant curve also does not follow a power-law distribution.

Fig. 7. Example of out-degree centrality variation for the local hub (Node 58). Distribution for this node does not follow a power-law distribution.
Fig. 8. (a) Example of fluctuating time series associated with the local hub (ID 12). (b) The log–log plot for the out-degree centrality distribution of this node follows a power-law distribution (with exponent of $-2.21$).

Table 2

<table>
<thead>
<tr>
<th>Node</th>
<th>Number of times having position in the daily top-rank list</th>
<th>Position in the top 10 ranking of aggregated network (Yes/No)</th>
</tr>
</thead>
<tbody>
<tr>
<td>58</td>
<td>85</td>
<td>Yes</td>
</tr>
<tr>
<td>21</td>
<td>74</td>
<td>Yes</td>
</tr>
<tr>
<td>90</td>
<td>69</td>
<td>Yes</td>
</tr>
<tr>
<td>52</td>
<td>62</td>
<td>Yes</td>
</tr>
<tr>
<td>95</td>
<td>61</td>
<td>Yes</td>
</tr>
<tr>
<td>81</td>
<td>50</td>
<td>Yes</td>
</tr>
<tr>
<td>27</td>
<td>50</td>
<td>Yes</td>
</tr>
<tr>
<td>80</td>
<td>49</td>
<td>Yes</td>
</tr>
<tr>
<td>89</td>
<td>41</td>
<td>Yes</td>
</tr>
<tr>
<td>142</td>
<td>34</td>
<td>No</td>
</tr>
</tbody>
</table>

We compared the positions (ranks) of the most prominent nodes in daily networks with their positions in aggregated network for crisis period. We did not find any significant deviation between them. Out of top 10 actors who are frequently located in the top-ranking list of size ten of daily networks, 9 (except Node 142, which is ranked 10th in the daily network based on the number of times it has position in the 131 daily top-rank lists) have also emerged as most prominent in the top-ranking list of aggregated network (Table 2).

The result in Table 2 implies that nodes are showing similar characteristics both in the daily and aggregated networks. Highly connected nodes in the daily networks have the similar role in the aggregated network. This result further confirms the power-law behavior of Enron communication networks during crisis.

We noticed significant differences in the number of emails sent by 151 Enron staff during crisis and non-crisis period. For each day, the number of emails sent by each actor are 1.52 and 0.89 in crisis and non-crisis period, respectively (30 081 versus 16 938 for total number of emails). The difference is high. Research about the crisis effect on organizational communication structure suggests that the amount of communication and number of communicators increase during crisis period [33]. Thus, it can be argued that the high difference in the amount of emails sent during crisis and non-crisis period for Enron communication network is due to its organizational crisis.

Studies on the investigation about Enron data revealed that during crisis period the network structure had become denser, more centralized and more connected [34], and more diverse with respect to established contacts and formal roles [35] compare to non-crisis period. Similar to these studies, the results from our first proposition demonstrated a significant difference with respect to the centralization of most prominent actors between crisis and non-crisis period.

Chapanond et al. [36] considered a single network for the total Enron dataset and examined the power-law property for the in-degree and out-degree centrality distributions of that network. They found that these two types of distributions do not obey a power law. We investigate the power-law behavior for the daily networks, and individual actor networks over time. Unlike the research of Chapanond et al. [36], we noticed that these two types of networks obey power-law behavior.

6. Conclusion

In this research, we studied two propositions and found strong support for Proposition 1, and weak support for second proposition. Our results from the experiments do not find any significant differences between the actor prominence in daily and aggregated networks of Enron. We also found that a few prominent actors become closer during crisis and daily communication networks and individual actor networks display power-law characteristics of scale-free network.

Wang and De Wilde [37] constructed and studied a simulation model for evolving networks by applying the idea of the evolution to the network by generating and deleting links within specific time intervals. In this study, we propose a novel approach to explore and compare organizational email networks during crisis and non-crisis periods. Using data from server log files, Ebel et al. [38] studied the topology of email networks and found that these networks exhibit a scale-free link distribution. For the Enron dataset, we also found scale-free distribution for crisis period data. However, the communication networks during non-crisis period do not follow scale-free distribution.

The findings of this study provide a valuable insight into a real-world organization during its crisis and non-crisis period. These results may be further used to develop dynamic models for organizational crisis which eventually lead to a better understanding of the underlying cause of organizational crisis. The methodological contributions of this study are worth noting. It builds on an emerging stream of structural research from complexity theory perspective that applies social network analysis to organizational email communication data in order to research important questions on organizational communication network. With the increasing popularity of complexity and self-organization research, widespread use of electronic communications, the increasing popularity of social network analysis and the growing sophistication of SNA tools, it is to be expected that we can develop deeper insights into a wide range of organizational phenomena.

References
