Testing the Robustness of Team Structures with Social Simulation[1]

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Abstract

Organizational structure design has been one of major topics in management, social science, operation research, etc. In this paper, we used a meta-matrix method and a simulation to test the robustness of team structures. We examined five top structures and five bottom structures form America's Army on-line game. Because we have prior knowledge about the robustness of the structures, we compare the performance measures from the simulations to the prior knowledge. According to our result, the performance measures can classify the top structures and the bottom structures. Furthermore, the classification based on the measures becomes clearer as simulation proceeds. After the simulation result analysis, we discuss possible improvements of this approach and future applications.

1. Introduction

Organizational structure and design have been the major topics in social science and management (Lin and Carley, 2003; Burton and Obel, 1998; Galbraith, 1977), and the structure is considered as one of the major factors of organization's performance. For example, network studies (Mayhew, 1980; Wellman 1988) think that organization's performance is determined by the structure of relations connecting agents in the organization. Also, contingency theorists (Woodward, 1965; Lupton, 1976; Burton and Obel, 1984) claim that organization's performance follows the fitness between organizational structure and task environment. Therefore, finding better organizational structures and testing the structures against various risks must be directly linked to enhancing the organization's performance.

Finding better organizational structures and testing them require adequate metrics and test methodologies, and the metrics and the methods should be able to detect the weaknesses of the structures and to predict their robustness under uncertainty or worst-case scenarios. However, static social network analysis might not serve this purpose well because it cannot simulate possible future threats and predict dynamically changing structures

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in the future. Instead of static social network analysis, we believe that social simulations can be used to examine the robustness of organizational structures. Because the social simulations are designed in the perspective of social contexts, the simulations are capable of modeling organizational structures. Furthermore, the simulations can model possible future threats and risks against structures by utilizing probabilities of each event. Therefore, in this paper, we will suggest a framework that tests the robustness of some organizational structures from a certain domain with a social simulation.

2. Previous research

To test the robustness of organizational structures, many researchers utilized social experiments in the real world. For example, Weber et al (Weber et al 2004) claims that organizational structures and codes influence an organization's performance greatly. Their paper presents experiments that they varied virtual software firm structures from centralized/hierarchical to decentralized/egalitarian and measured the performance of the two different kinds of firm structures. According to the paper, centralized/hierarchical firms develop codes more rapidly and decentralized/egalitarian firms assimilate new entrants more easily. Additionally, Bohte and Meier (Bohte and Meier 2001) studied how an organizational structure measure, or span of control, predicts performance in a large set of public organizations. Their research reveals that the span of control variable has the greatest impact on performance under moderately difficult task scenarios. Also, Jin and Levis (Jin and Levis 1990) experimented how two decision makers in different organizational structures, a parallel one and a hierarchical one, perform. The performance was measured in terms of decision makers' response time and accuracy. The experiment confirms that individual difference has more influence on performance in the parallel organization. On the other hand, the interactions in the hierarchical organization restricted the choices of the decision makers and coupled individual decisions with the decisions of other organization members. These research papers utilize real world social experiments, so we can see how researchers examined given organizational structures with possible future scenarios and how they measured the performance of the structures. Therefore, we will evaluate social network topologies with metrics from social network analysis communities.

On the contrary, there have been research papers measuring organizational structures in the social network analysis perspective and utilizing computer modeling techniques, not real world experiments. For instance, Lin and Carley (Lin and Carley, 1997) identify strong factors of organization's performance, and the organizational structure is one of them. In their paper, they setup a computer modeling of organization's performance based on an information processing and resource dependency. With the model, they compared the performance to various factors, time pressure, training, organizational complexity, environment complexity, which organizational theorists considered as important attributes of the performance. After the comparison they found out that the time pressure, training of agents, organizational complexity and organizational environments are strong factors. Another research paper written by Lin and Carley (Carley and Lin, 1995) shows the importance of organizational structures and their influence on the organization's performance. Specifically, the paper presents the role of organizational design in affecting organizational performance. To show the role of organizational design, they used a computer modeling, CORP, to examine the organizational structure and its performance under certain test conditions, such as operating in optimal conditions, operating under internal/external stress, etc. Their usages of computer modeling techniques for the investigation of organizational structures demonstrate that the social simulations can be an appropriate tool for measuring the robustness of organizational structures.

3. Dataset description

To utilize our simulation approach for testing the robustness of organizational structures, we need a set of organizational structures that are already known whether they are robust or not. If we have such a dataset with prior knowledge, we can compare the results from the simulation to the prior knowledge we have. For the purpose, we will use five winning communication structures and five losing structures from America's Army game (America's Army, 2006), which is an online multi-player first-person-shooting computer game. In our previous research, we analyzed the log record data (Moon et al, 2005) recorded off of 138 America's Army game servers over the course of 23 days. We discovered total 184,433 teams with more than 10 team members in the dataset, but we can reconstruct the networks and calculate the network measures for 152,907 teams due to some anomalies in the dataset. To order the selected teams in terms of their performance, we used the overall score that is a linear sum of various scores calculated by the game server and the survival ratios of the opponent team and the friendly team. After reordering the team based on the overall score, we selected the top 15,000 teams (1st ~ 15,000th team) as winning teams and the bottom 15,000 teams (137,908th ~ 152,907th team) as losing teams. From these selected teams, we extracted five representative Report-In (transmitting sender's current location) communication networks for both top team group and bottom team group. To make the representative communication networks, we 1) divided 15,000 teams into five clusters based on the various degree centralities and the network density of teams' communication networks, 2) averaged the centralities and the density of the clustered teams' networks, 3) generated an approximated social network for a cluster based on the averaged values. Therefore, we obtained five winning social network structures from the five clusters in the top team group, and five losing structures from the five clusters in the bottom team group. The resulted structures are shown in figure 1. Because we assume that the top clusters' networks are more robust than the bottom clusters', we can compare the results from our simulation to our prior knowledge of this dataset.

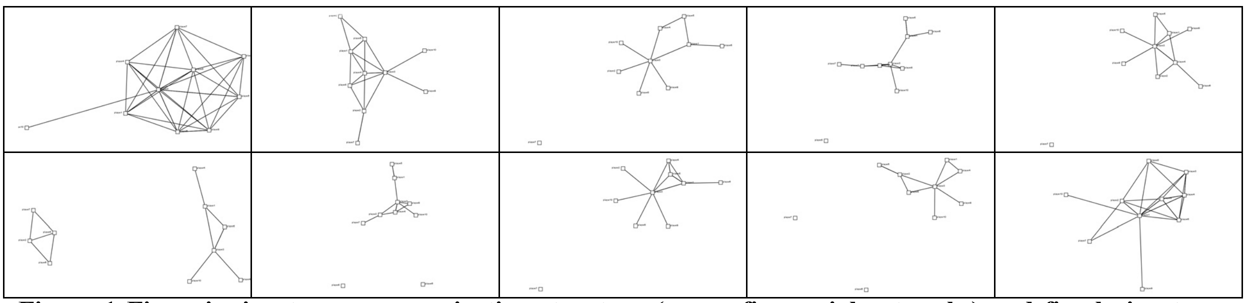

Figure 1 Five winning team communication structure (upper five social networks) and five losing team communication structure (lower five social networks). From left to right, the upper networks named Top 1, Top 2, …, Top 5, and Bottom 1, Bottom 2, …, Bottom 5 for the lower networks.

4. Method

Our evaluation of team networks with simulation involves three important features: extending team communication networks to meta-matrixes representing teams' whole structures, defining performance measures to score teams' robustness, and setting simulation procedures. We will discuss the three features in the following subsections.

4.1. Meta-matrix representing teams' whole structures

Carley (Carley, 2003) claims that traditional social network analysis has several limitations. For example, the traditional analysis does not handle multi-modal, multi-plex, and dynamically changing social networks. Furthermore, there is no way to represent agent, knowledge, resource and task at the same time with the traditional analysis method even though links and correlations between the different types of nodes are very common in the real world. Thus, she suggests using a meta-matrix representation for such a complex system. In our dataset, the team communication networks are typical agent-to-agent networks, but we believe that the players in the network are exchanging a piece of information through the links because the networks came from Report-In communications among team members. Also, the players are exchanging information because they have a set of tasks to accomplish in their perspective. With these assumptions, we can setup a meta-matrix for a team structure as shown in table 1. However, we do not have any information about relations among tasks and pieces of knowledge, so we randomly generated those networks with arbitrarily chosen density specification. Also, knowledge-to-knowledge network is not defined because there would be no obvious relation between two Report-In message contents.

Table 1 meta-matrix for a team structure. Except agent-to-agent network, the other networks are randomly generated with a network density setting.

	Agent (10 nodes)	Knowledge (7 nodes)	Task (5 nodes)
Agent	Team Report-In Comm. Network (came from the dataset)	Knowledge network (random network with density = 0.3)	Task network (random network with density = 0.7)
Knowledge		Undefined	Needs network (random network with density = 0.7)
Task			Temporal ordering (random network with density = 0.5)

4.2. Performance measures scoring the robustness of team structures

We used three performance measures, betweenness centralization, communication and personnel cost, to evaluate the team structures. First, betweenness centralization is a well-known social network measure for a single mode network data, so it may not fully utilize the above meta-matrix information. However, we included the measures to see how traditional social network analysis measure will evaluate the robustness of structures. The other two measures will fully use the meta-matrix information. Communication measures the communication need of agents to complete their assigned task. In other words, an agent's communication will approach one if the agent need frequent communication to finish his assigned tasks. Personnel cost scores the sum of an agent's contacts, knowledge and task, so personnel cost will represent the value of the agent in the organization. These three measures are calculated by Organization Risk Analyzer (Reminga and Carley, 2004), and the measure specification of ORA provides detailed formulas of the above measures.

4.3. Simulation procedure

After we setup the input and the performance measure for the simulation, we created a simulation procedure that creates a possible future threat event to team structures. By making the team structures go through threat events, we can see the changes of performance measures, and we analyze which structure is more steadfast and reliable to future threats. In the America's Army game, one of possible threats to the structures is the death of friendly players. Therefore, we will randomly choose one player in a team structure and isolate the player for each time step. In other words, each team structure will go through 10 time steps, and the structure will lose one player at a time. Finally, we will stop the simulation as soon as the team structure has only one player. Also, we will replicate the above simulation procedure for 1,000 times, and the output performance measures will be the averages of the 1,000 replications.

5. Result

Figure 2 shows the performance of the five top structures and the five bottom structure during the simulation. According to the figure, there are no big differences between the performance measures of the top team structures and the bottom team structures. Therefore, we may conclude that the simulation we setup was not able to detect the big differences between the top structures and the bottom structures. However, as we will discuss in

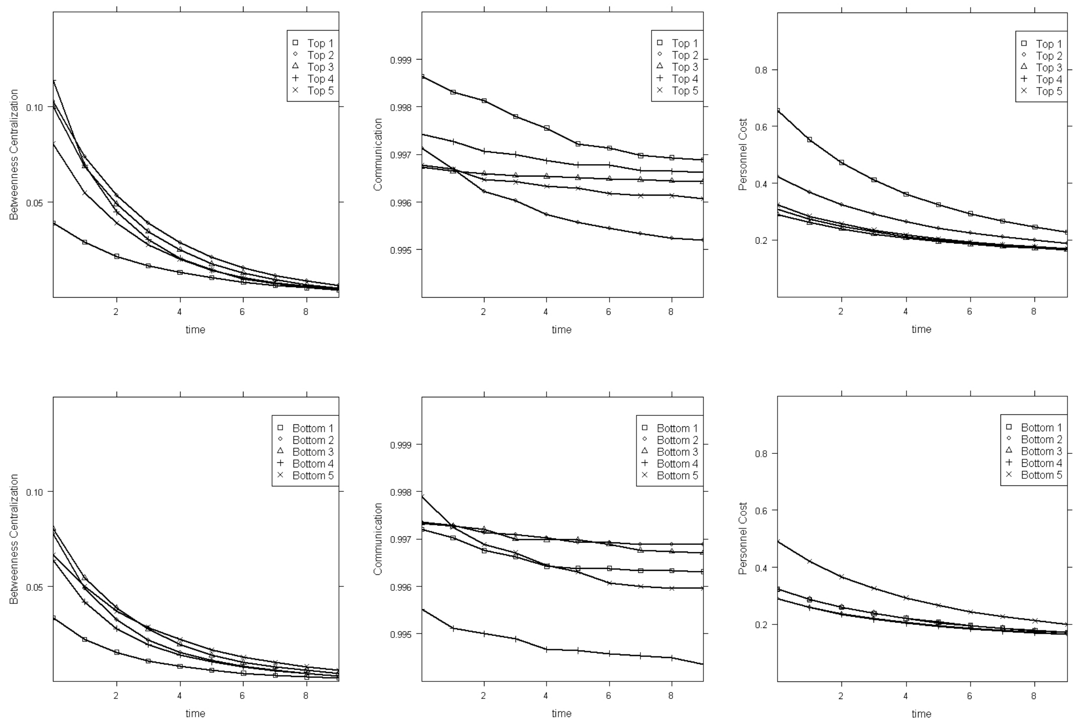

Figure 2 averaged performances from the simulations of five top team structures and five bottom team structures. The three graphs in the upper side are for top structures, and the three graphs in the bottom for the bottom structures.

the following part of this section, we probed three time points, time 0, time 5 and time 9, and we discovered that the simulation can classify the structures into the two different groups quite successfully though the classification is decided without huge differences between the measures of the tops and the bottoms.

In the figure, we can also see some general tendencies. For example, the performance of a structure decreases as the simulation proceeds. Surely, this is a natural reaction because the number of isolated players will increase as the simulation proceeds, and the isolated players must have pieces of information that are salient to perform tasks of others. Furthermore, the dense team structures such as Top 1 and Bottom 5 shows high performance at the beginning, and their performances deteriorate quite rapidly compared to the others. It means that these dense team structures may play well at the first time, but they are not robust against repeated casualties of team members.

Table 2 probed performance measures for the five tops and the five bottoms, probings are done at time 0, time 5 and time 9. The rows of the table are sorted in the descending order of the values of the structures. Therefore, the rows in the upper side are five structures with higher performance measures.

Time 0 Communication		Time 5 Communication		Time 9 Communication	
Bottom 1	0.998556	Bottom 1	0.9982	Bottom 1	0.998156
Bottom 5	0.998467	Bottom 3	0.9976	Bottom 3	0.997467
Top 1	0.998445	Bottom 5	0.997578	Bottom 5	0.9974
Bottom 3	0.997889	Bottom 2	0.997022	Top 1	0.996845
Top 4	0.997489	Top 1	0.996934	Bottom 2	0.9968
Top 2	0.997489	Top 4	0.996778	Bottom 4	0.9964
Bottom 2	0.997311	Top 3	0.996578	Top 4	0.996245
Bottom 4	0.997067	Bottom 4	0.996534	Top 3	0.996245
Top 5	0.997	Top 5	0.9964	Top 5	0.9962
Top 3	0.996778	Top 2	0.996378	Top 2	0.996178
Time 0 Personnel Cost		Time 5 Personnel Cost		Time 9 Personnel Cost	
Top 1	0.630805	Top 1	0.275676	Top 1	0.175662
Bottom 5	0.463815	Bottom 5	0.227287	Top 2	0.159196
Top 2	0.397518	Top 2	0.211278	Bottom 5	0.15762
Bottom 1	0.297487	Bottom 3	0.182174	Top 5	0.147725
Top 5	0.297182	Bottom 1	0.181288	Bottom 3	0.146293
Bottom 3	0.29684	Top 5	0.17989	Bottom 1	0.146021
Top 4	0.280425	Top 4	0.174261	Top 4	0.144145
Bottom 2	0.264525	Bottom 2	0.170221	Bottom 2	0.142621
Top 3	0.26419	Top 3	0.16626	Top 3	0.139729
Bottom 4	0.26332	Bottom 4	0.163582	Bottom 4	0.13465
Time 0 Betweenness		Time 5 Betweenness		Time 9 Betweenness	
Top 4	0.11389	Top 2	0.019257	Top 2	0.005562
Top 2	0.10277	Top 3	0.016359	Top 5	0.005087
Top 3	0.1	Bottom 3	0.015553	Top 3	0.004698
Top 5	0.08055	Top 5	0.015078	Bottom 3	0.004617
Bottom 3	0.08055	Top 4	0.014482	Top 4	0.004026
Bottom 2	0.07779	Bottom 5	0.0144	Bottom 5	0.003585
Bottom 5	0.06668	Bottom 2	0.011301	Bottom 2	0.00312
Bottom 4	0.06389	Bottom 4	0.009314	Top 1	0.002671
Top 1	0.0389	Top 1	0.008841	Bottom 4	0.002162
Bottom 1	0.03333	Bottom 1	0.005901	Bottom 1	0.001751

Table 2 shows the classification capability of the simulation and the measures we used. For instance, the communication measures at time 0 shows that three bottom structures and two top structures have higher communication. As the simulation progresses, the bottoms have higher communication degree and the tops are ranked in the lower places. Because the communication metric shows the necessity of the communication between team members to perform their assigned tasks, the lower communication will be desirable because members can do their job without going through numbers of communication. Thus, the tops have a tendency to be ranked in the lower place and the bottoms in the upper place, and we can see this ordering clearer as the simulation goes on. Additionally, we can see the same ordering tendency in personnel cost measure though it is not clear as communication measure. On the other hand, the betweenness centralization measure shows quite clear classification between the tops and the bottoms. Because the betweenness centralization only uses the information from the team communication network, it is understandable that the measure is sensitive to the initial dataset before its conversion to the meta-matrix. However, this leads that the conversion of the meta-matrix for this simulation can be enhanced by setting different network density or numbers of task, knowledge nodes, etc. Since, there may be some improvement in the classification by adding more information as a meta-matrix, so just having same classification power with the non meta-matrix measure is not good enough for meta-matrix measures. To summarize the above results, we can see that the simulation is effective in examining the robustness of the structures because the top structures and the bottom structures can be classified more clearly based on the performance measures as the simulation goes on. In other words, the performance measures start changing as simulation progresses, and the performance of a top/bottom structure will follow the rest of the performance measures of the same group.

6. Conclusion

Organizational structure design has been one of major topics in management, social science, operation research, etc. In this paper, we used a meta-matrix method and a simulation to test the robustness of team structures. For the dataset, we utilized five top structures and five bottom structures came from America's Army on-line game. Because we already know the performance of the structures, we can compare the performance measures from the simulations and the prior knowledge. According to our result, the performance measures can classify the top structures and the bottom structures. Furthermore, the classification based on the measures becomes clearer as simulation proceeds by isolating players one by one. This result suggests that the robustness of the team structures can be examined by the simulation procedure. We isolated players during the simulation to test the robustness, and the diversion between the tops and the bottoms get clearer. However, there are still no huge gaps between the measures of tops and bottoms. We conjecture that the reasons are 1) possible enhancements of conversion from team communication network to meta-matrixes, 2) small team structures, only 10 players to isolate. Though we can classify the team structures with slight differences, we demonstrated the usage of simulation as a mean to test the organizational structures, particularly in the perspective of robustness. We believe that this type of simulation usage can be scaled up and be used for designing command and control structures of military units, emergency room team communication design, security/control organization design of facilities, etc.

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