Evolving Multi-Agent Network Structure with Organizational Learning

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Abstract

Organizational structure changes over time due to various reasons, such as organizational learning, situation changes and personnel turnovers, etc. Estimating the structure changes will reflect organizational performance changes, emergent leaders, new key links, etc. This paper introduces a multi-agent model that simulates the organizational structure evolution over time. The simulated structure evolution will be driven by the organizational learning procedure that we devised. We perform virtual experiments with two distinct cases, an organization with the learning mechanism and the other one without learning. The performances of the two case organizations were examines under situation change assumptions. The organization with learning mechanism was better than the other when situation changes were predictable. We also scan the network topology changes over time, and we identified that the average distance among the nodes gets smaller as learning proceeds. This work is a preliminary effort to examine the effect of organizational learning and to formulate the evolution of organizational structures.

1. INTRODUCTION

Organizational structure [1] often changes and evolves. It reshapes itself to meet external constraints [2], group dynamic changes [3], organizational learning [4], etc. Due to the ever-changing nature of the organizational structure, anticipating its evolution is one of the key problems in the management of a corporate, a military command and control, a disaster management group, etc. By estimating the changes, we anticipate how the individuals in the organization will form their surrounding relations and what will be needed to facilitate the information diffusion and the responses to external changes.

In order to understand the structural evolution, we utilize a multi-agent model for the simulations of the evolution. The prediction of the evolution is not an easy task because we need realistic models, such as the complex system structure of an organization, individual agent behavior logics and external situation changes. In spite of these difficult modeling tasks, multi-agent models have shown its usefulness by representing the above factors to a certain extent [6, 7] and being utilized for theory building and policy making [5, 8]. Therefore, we setup a multi-agent model and perform a series of virtual experiments and a corresponding analysis to reveal an aspect of the structure evolution.

Thus, our purpose of this paper is modeling and simulating the evolution of an organizational structure under a set of assumptions. Because the assumptions define the agents' interaction mechanism, we can claim that this evolution is induced by micro-interactions among the agents in the organization. After the implementation of the simulation model, we observe some aspects of the evolution. First, we examine how the evolution affects the information diffusion in the organization. The evolution is not an optimization process, so the evolution with various parameters and situations can turn the structure into a well-functioning or an ill-functioning structure. Next, we analyze the evolved organizational structures to see the distinct characteristics and compare the evolved structure to the original one. From this structure analysis after evolution, we will have better understanding what may be a preferable or an avoidable course of structural evolution in a certain context.

2. PREVIOUS RESEARCH

Organizational learning and structure changes have been researched since 1950s [9]. While the early works show interesting human subject experiments, recent results are supported by multi-agent modeling and distributed artificial intelligence approaches. The two following sections review the traditional and qualitative works and the recent, quantitative and computational model-based works respectively.

2.1. Organizational learning and structure evolution

Bavelas [9] shows insightful analysis on organizational learning and structure. He drew several possible organizational structures with five individuals, and he analyzed the social distance, task completion rates and message transmit styles. We think this is a fundamental research to examine which organizational structure is better, how it changes and how the changing structure affects the performance. At a high level, we duplicate his research with a complex structure, a multi-agent simulation and detailed performance measures.

The paper by Zollo and Winter [10] is an intriguing qualitative research on organizational learning. Though they did not use any multi-agent models or human subject experiments, they formulated how organizational learning directs dynamic capabilities and the evolution of operating routines eventually. In our research, the operating routines are represented as a networked organizational structure and interactions on the network. Therefore, the evolution of operating routines in their paper will be modeled as a network evolution in our work.

Carley [11] wrote a paper clearly introducing the adoption of multi-agent modeling approach to the traditional organizational learning and adaptation. She used simulated annealing to adapt a given organizational structure to its context. In her paper, she argues that the members of a complex organization may not be able to find the optimal form of their organization, yet they still change their form and improve their performance. Finally, she went beyond just reporting the creation of models by investigating the nature of the adapted organizations from the viewpoints of social network analysis. She identifies that the evolved networks have fewer isolated agents and are less dense. We find that this analysis is a demonstration of using multi-agent models as a theory building tool, so we perform more detailed social network analysis on the evolved networks that our model produced.

2.2. Multi-agent network model for organizational structures

The introduction of the multi-agent modeling motivated the developments of multiple multi-agent models in management, organization behavior research, etc. For example, Terano et al [12] created a multi-agent model, TRURL, to simulate social interactions. This is a society model, rather than a team model, so it is different from our model in scale and modeling approach. Furthermore, it evolved the modeled societies by changing the parameters of models, not the society structure specifically. Therefore, this result is also different in the methods and the target of evolution of societies. However, we share the idea of using multi-agent model to simulate the changes of societies and evolving organizations based on social interactions.

Gaston, et al. [13] presented an interesting paper on organizational learning and network changes, and the paper was one of the papers that motivated this work. They used a simple agent-based model of team formation and tried to find an efficient team structure. They started simulations with a stylized network among agents and evolved the network over time. Also, they observed the performance changes according to the network adaptation. These are very similar to our work, and we believe that this procedure is insightful to see the relation among a multi-agent model, a dynamic team structure and performance. In this paper, we use formula based adaptation, unlike the rule based adaptation from Gaston, et al, and investigate the topologies of evolved networks that are not fully done in their paper.

Carley [14] introduced two multi-agent models, OrgaHead [15] and Construct [16], utilized for computational organization studies. She provides a series of virtual experiment results and demonstrates how these models can be used for social, organizational and policy analysis. For example, OrgaHead is a multi-agent model simulating behavior of agents and an organization as they learn, interact and perform their tasks. Also, Construct is a tool examining the co-evolution of social structure and culture, information diffusion, group assimilation, etc. Fundamentally, we take and expand the agent behavior mechanism of Construct. The expansion is done in the interaction regarding social network distances, but the initial mechanism, such as relative similarity and relative expertise, remains same. Therefore, our model presented in this paper may be considered as an expansion of Construct.

3. METHOD

The objective of this research is observing the evolution of an organizational structure through agent interactions. Therefore, we define a set of algorithms for agent interactions, organizational structure change and an output performance. The agent interactions are communications based on probability of interaction among agents. The probability of interaction is a probability model of how much two agents are likely to exchange a message, containing knowledge pieces, at the given time-point. After the interactions, the organization modifies its structure by changing the agent-to-agent network, and we regard that this modification is the organizational learning through communications. Finally, we calculate the degree of knowledge diffusion at a given time-tick.

3.1. Agent behavior

Agent behavior in our model consisted of a subset of Dynet [17] (a.k.a. Construct) and our social distance model introduced in this paper. The core Dynet agent behavior logic is the probability of interaction formula that drives agents to interact with a certain agent in the organization. In the formula, there are various variables, such as relative similarity, relative expertise, social distance, spatial proximity, socio-demographic, etc. Among the variables, we will adopt relative similarity and relative expertise model in this paper, and the other variables will not be used. On the other hand, our social distance model will substitute the social distance model in Dynet. The distance model in Dynet does not reflect the dynamic organizational structure change. In other words, the social distance value for a pair of agents would not change even though a simulation proceeds. This paper addresses the static social distance in Dynet.

$$RS_{ij} = \frac{\sum_{k=0}^{K} AK_{ik} AK_{jk}}{\sum_{k=0}^{K} AK_{ik}}, RE_{ij} = \frac{\sum_{k=0}^{K} AK_{jk}(1 - AK_{ik})}{\sum_{k=0}^{K} AK_{ik}} \tag{1}$$

$$AK = (\text{an adjacency network from Agents to Knowledge pieces in the organizational structure})$$

$$K = (\text{number of Knowledge pieces})$$

$$RS = (\text{relative similarity between two agents})$$

$$RE = (\text{relative expertise between two agents})$$

The two metrics, relative similarity and expertise, are calculated for every possible pair of agents. Relative similarity is the ratio of how much the target agent has the same knowledge pieces that the source agent has. On the contrary, relative expertise is the degree of how much the target agent has unknown knowledge pieces. These two metrics are originated from sociology. Homophily [18] means that two agents are likely to interact with if they share common knowledge or backgrounds, so the relative similarity on knowledge possession is a driver for this homophily phenomena. Also, expertise [19] is another factor for the selection. In our model, these two metrics are variables for deciding who to communicate with whom in the network. Formula 1 describes how the two metrics are calculated in our model. As we are using a networked organizational structure with agents and knowledge pieces, we can create a network (*AK*) between the agents and the knowledge pieces by linking an agent and a knowledge bit if the agent knows the knowledge. Then, the *AK* network can be the basis to calculate the values for the similarity and the expertise.

Unlike relative similarity and relative expertise originated from Dynet, there is one extended mechanism, social distance. The social distance between a pair of agents in Dynet is the number of social links on the shortest path connecting the two agents. However, this idea can be improved by changing some aspects. First, social distance by the number of social links does not track the agent interaction records and the organizational structure changes. It has been known that the interactions among members mold the organizational structure over time. Therefore, the model simulating the evolution of a structure should have feedbacks from the last agent interactions. Second, social distance can be modeled as a continuous value. Rather than a discrete model, a model of selecting interaction candidates will prefer a continuous social distance variable because it grants different priorities to agents for interactions at different social distances.

We extend the mechanism in two ways. One way is tracking the agent interaction records, which is closely related to the organizational learning. The other way is creating a continuous model for social distance based on the weighted organizational structure. Specifically, the model 1) updates edge weights over time by using Formula 2, 2) inverse the edge weights to turn them into the closeness value, 3) calculate the shortest distances from one agent to the other agents and 4) standardize the distances ranging from zero to one. Figure 1 describes the above procedure. The edge weight for the networked organization structure will be updated by Formula 2. Basically, the formula adds the incentive to interact with to the existing edge weights after interaction. The incentive value is the average number of exclusive knowledge for the two interacted agents, which means that the two agents have that amount of incentive for future interaction because the agents can gain unknown knowledge from future interactions.

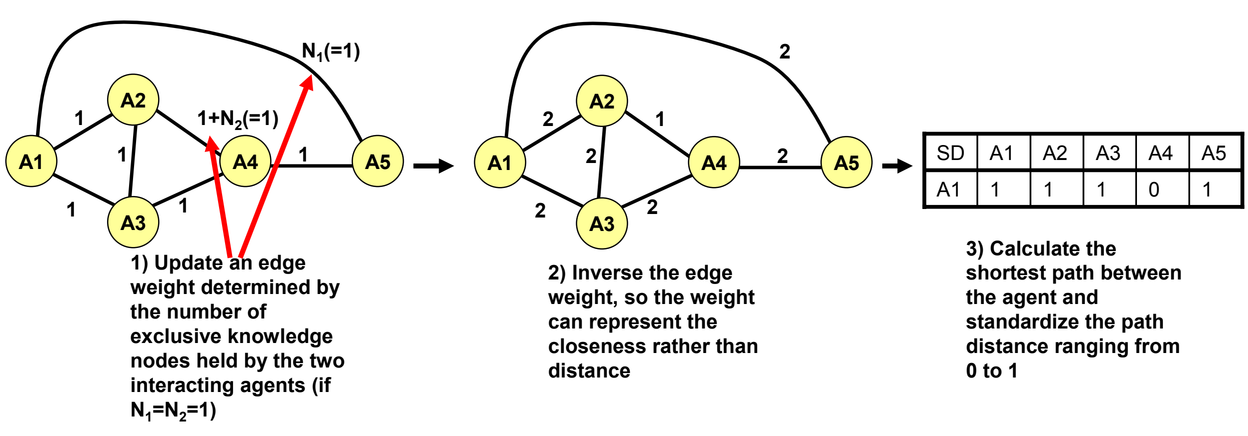

Figure 1. a diagram describing the network evolution after agent interactions

$$w^{a}_{(i,j)} = (\textit{weight on the link between i and j at time a})$$
$$incentive^{a}_{(i,j)} = (\textit{avg. number of exclusive knowledge between i and j}) \quad 2)$$
$$w^{a+1}_{(i,j)} = w^{a}_{(i,j)} + incentive^{a}_{(i,j)}$$

Thus, agents in this model will partly implement two existing interaction mechanisms, such as relative similarity and expertise, and one extended algorithm, social distance. The linear sum of these three factors, shown in Formula 3, is the probability of interaction between two agents, and an agent will pick an agent to interact with based on the probability. As a final point, it should be noted that the model is a stochastic model based on the probability, not a deterministic indicator. Therefore, one agent may choose an agent with low probability of interaction coincidently. However, this stochastic approach imitates real world human interactions in some sense because we usually choose and meet someone with high interaction probability, but we rarely end up interacting with agents with low interaction probability against our choice.

$$P_{ij} = w_1 RS_{ij} + w_2 RE_{ij} + w_2 SD_{ij} \quad 3)$$

3.2. Extracting the evolved organization structure

This model hypothesizes that only agent interactions induce the organizational structure changes. Therefore, we trace the agent interactions and apply the interaction result to the structure by updating the link weight. Eventually, the updated structure will affect social distances among agents and be a basis of the next structural change.

While the evolution of organizational structure follows the above rule, the evolved structure has many links with various degrees of weights. Though the links with low weight also come from agent interactions, the low weight links are not significant in the agent interaction mechanism compared to the links with high weights. For that reason, we generate an evolved network by cutting the links which is lower than a threshold. The threshold is set by the density of the original network. In other words, we accepted the links with high weight links and drop the rest of edges when the number of high weight links reached the number of links in the original network. This threshold strategy has pros and cons. First, it is one clear method of creating binary links out of a set of probabilistic links. Also, the usage of the original network density as the threshold may imply that the density is defined by the communication frequency of the organization, and the learning changes only the communication pairs without increasing or decreasing number of links. However, organizational learning may include the network density changes as well as the pair changes, and this threshold cut-off heuristic will not be able to catch the network density changes.

Table 1. network analysis measures used to examine the evolved network topologies

Name	Mearning
average distance	The average shortest path length between nodes, excluding infinite distances.
betweenness centralization	The Betweenness Centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v, the percentage that pass through v., The centralization is defined as the average of the centrality across the agents.
clustering coefficient	Measures the degree of clustering in a network by averaging the clustering coefficient of each node. The clustering coefficient of a node is the density of its ego network - the sub graph induced by
in-degree centralization	The In Degree Centrality of a node in a network is its normalized in-degree. The centralization is defined as the average of the centrality across the agents.
network levels	The Network Level of a square network is the maximum Node Level of its nodes.

3.3. Performance metrics

Finally, we need a measure to calculate the organizational performance. In this paper, we use the degree of knowledge diffusion. The knowledge diffusion (KD) stands for the degree of how much the agents in an organization exchanged knowledge that was exclusive to certain agents before simulation begins.

While the knowledge diffusion is used to gauge the performance of the organization, we use some social network analysis measures to examine the structure topology changes over time. The used social network measures are listed in Table 1. The calculation of the measures are done by Organization Risk Analyzer [20], and the detailed measure formula can be found in the software help file or general social network analysis papers [21].

$$KD = \frac{\sum_{i=0}^{k}\sum_{j=0}^{n} AK_{ij}}{kn}$$
$$n = (\text{num. of agents in a network at the time})$$
$$k = (\text{num. of knowledge bits})$$
$$\text{AK} = (\text{Adjacency matrix of Agent - Knowledge})$$

4. RESULT

The dataset used to test the introduced model is an organizational structure of a terrorist network from the U.S. Embassy bombing incident in Tanzania [22]. The network consists of 16 agents, 4 knowledge pieces, 4 resources and 5 tasks, and it is relatively small. We believe that the members of the network tried to complete the assigned tasks by communicating with other members to obtain their necessary knowledge and resource. Among the above nodes, the agent nodes will be the members of the organization, and the knowledge and the resource nodes will form the knowledge pieces that are diffused across the agents. Figure 2 is the visualization of the network.

To verify the knowledge diffusion across the network, we run a short simulation, with 100 time steps, and observe the knowledge diffusion curve of the two cases, one with and without the organizational learning procedure. Each case is repeated 100 times, and the result is the average of

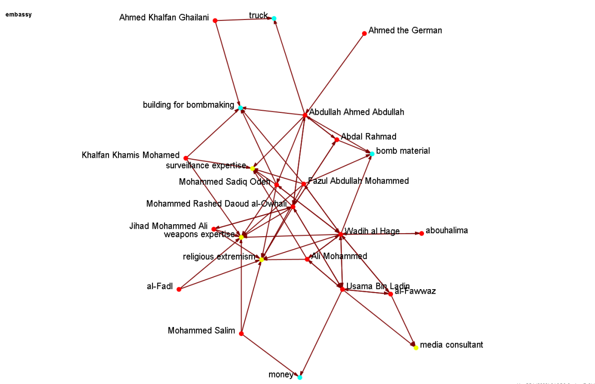

Figure 2. a test network visualization, 16 agents (4 isolates), 4 knowledge pieces and 4 resources

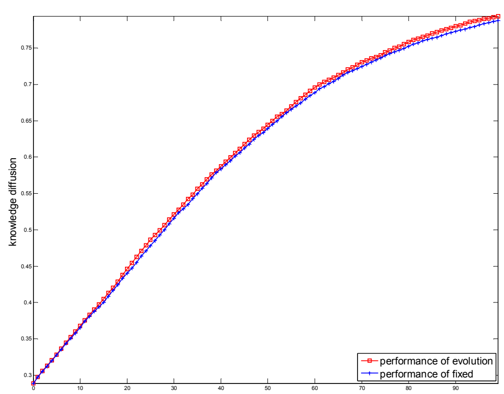

Figure 3. a knowledge diffusion curve from time 0 to time 100 without a knowledge invalidation event

the replications. The knowledge diffusion starts at 0.289 and increases as the agents exchange the knowledge with each other. It appears that the overall difference between the two is not great. However, we are able to see that the curve with learning is slightly better than the curve without learning. In the rest of this paper, we will show the deviation of the curve with learning from the one without learning, so the difference can be visualized better.

4.1. Dynamic environment change and structure adaptation

As the short experiment demonstrates the modeled organizational learning make the organization diffuse knowledge faster, we run a longer virtual experiment with dynamic environment changes. The introduced dynamic environment change is a knowledge invalidation event for every 100 time points. In other words, the diffused knowledge will be invalidated at the end of each period, and the members should learn the knowledge again through the evolved structures so far. Each invalidation in this experiment keeps the distribution of the knowledge pieces to the agents same as the original status.

Figure 4 is the result of the long experiment, 1000 time-step virtual experiments with nine knowledge invalidations. As you can see that the evolved structure shows higher knowledge diffusion rate compared to the structure without learning though there are few exceptions. The higher knowledge diffusion was observed mainly in the middle of the diffusion, and there is a brief under-performance event at the beginning of each period. Because the organization structure was adapted to the high diffusion rate status right before the knowledge invalidation, the structure briefly suffers from the over-fitting to that previous status immediately after the knowledge invalidation.

Furthermore, the learning does not always guarantee the increasing performance in spite of its continuing structure evolution. The interaction among agents is based on the probability of interaction, not a definite pointer or an indicator. Thus, if some agents chose to interact with agents with low probability of interaction accidentally, the organization may learn a bad structure, and its damaging consequence is shown at the fifth period in Figure 4.

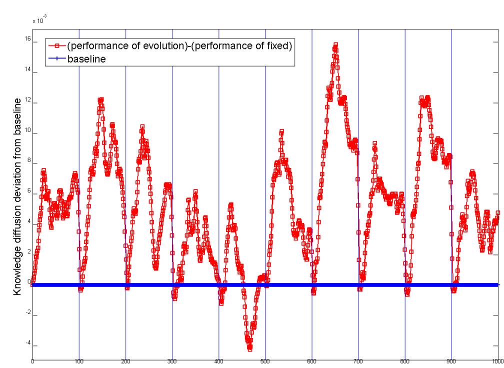

Figure 4. the deviation of knowledge diffusion of the organization with learning from the baseline. The experiment is done under constant knowledge invalidation

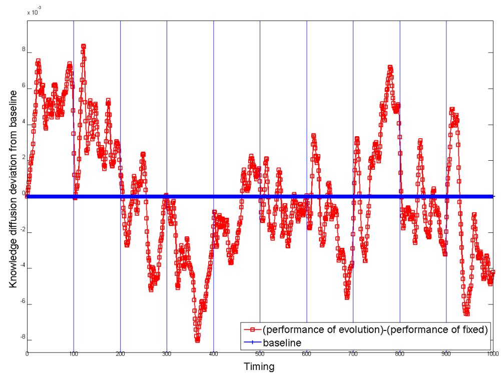

Figure 5. the deviation of knowledge diffusion of the organization with learning, the experiment is done under random knowledge invalidation

However, the organization will eventually choose a better organizational structure because the dynamic change itself is predictable and the learning mechanism will give incentives to better interactions and structures at the given changes.

While the previous experiment used the predictable dynamic environment changes, re-assigning the knowledge pieces to the agents who originally possessed the pieces, the next experiment invalidates the diffused knowledge and assigns the knowledge pieces to different agents who did not had the pieces when the experiment originally started. This represents the rapid and unexpected changes in the knowledge acquisition of an organization. Therefore, the adaptation of the organization structure to this changing environment will be different from the adaptation to the predictable environment changes.

As Figure 5 shows, the adaptation generates a more fluctuating diffusion curve compared to the curve in the previous experiment. Furthermore, we see there are several periods showing worse diffusion rate than the case without organizational learning. The organization changes its structure according to the incentive gained by the interactions. However, if the knowledge feed to this organization is different from the original feed, the adapted structure based on the knowledge diffusion incentive will not be efficient as expected because the knowledge incentive is also from the old knowledge feed. In other words, the given organizational learning will not increase the performance when the outside situation changes dynamically.

4.2. Network topology changes after learning

The performance differences induced by the existence of the organizational learning mechanism can be investigated deeper by examining the network topology changes over time. Figure 6 is a collection of graphs describing the course of the network topology measure changes over simulations. The stable line is the network measure of the organization structure without learning.

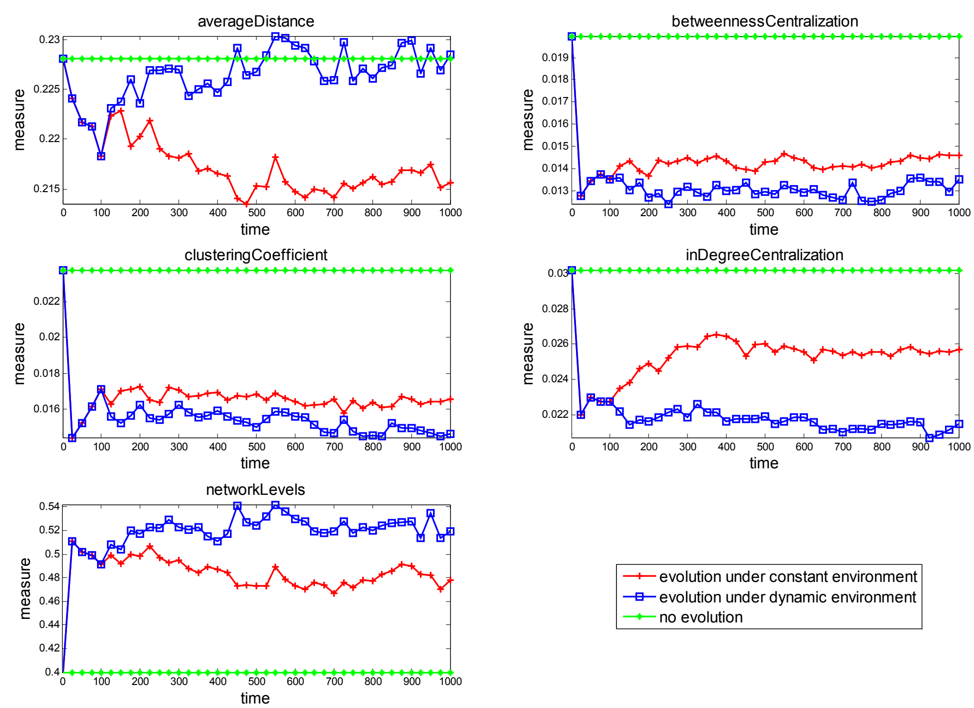

Figure 6. line charts displaying the network measure changes over time

Because there is no learning mechanism in the case, the organization structure never changes, neither do the measures. The other two lines show the network measure changes of the two previous experiments, one with predictable situation change and the other with permuted situation change.

Figure 6 indicates that there are interesting tendencies in the learning process. First, the initial learning effect can be seen in very early period, i.e. most of the measures deviate from the baseline before 100 time points. However, the oscillation, or the tuning of the organization structure, has been continued until the end of the simulation.

The figures also exhibit that the organizational learning under different situations results different adapted structures. For instance, the average distance of the learned structure under the constant situation change is lower than that of the structure under the permuted situation change. Moreover, the other network measures display different levels of plateaus where the two adapted structure reaches after the simulation period. Specifically, the lower centrality measures of the adapted structure under permuted situation change is an indicator that the learning under changing situations prohibits the centralization of the network structure, and its adaptation makes no clear emergence in the structure, rather the adaptation keeps or renders slightly its original structure. This can be seen in the average network visualization shown in Figure 7. The bottom of the figure presents three visualized network structure which shares a similar topology, a network with two cells, with the original network structure.

On the other hand, the organizational learning under constant situation change shows a clear directionality in the structure adaptation. The cellular network at the original status changes its topology to the core-periphery, or a star, network structure. We believe that the core agents of the evolved network have more knowledge pieces to share, and the communication incentive catches this skewed knowledge distribution and update the network by putting the agents at center positions.

Surely, organizational learning is different from organizational structure optimization. Therefore, the modeled learning mechanism may not find the most appropriate organizational structure for a given situation. However, if the situation change is predictable, i.e. daily basis routines, the learning over time gives a direction, how to change the organization structure to adapt the given predictable situation. On the contrary, the learning under unpredictable and random situation changes, i.e. dynamically changing combat situation, might fail to converge to a certain desirable topologies.

5. CONCLUSION

Anticipating the organization structure change is one of the important issues in management, disaster response and command and control structure research. The structure evolution may be driven by a number of factors, such as organizational learning, personnel changes, external situation changes, etc. In this paper, we model the organizational structure change under organizational learning. Our model is a multi-agent model based on a networked organizational structure and agent interactions on the network. The agent interaction and its corresponding incentive lead the structure change over time in the model.

Mainly, we setup and simulate three virtual experiment cases, an organization without learning, one with learning under constant situation change and one with learning under

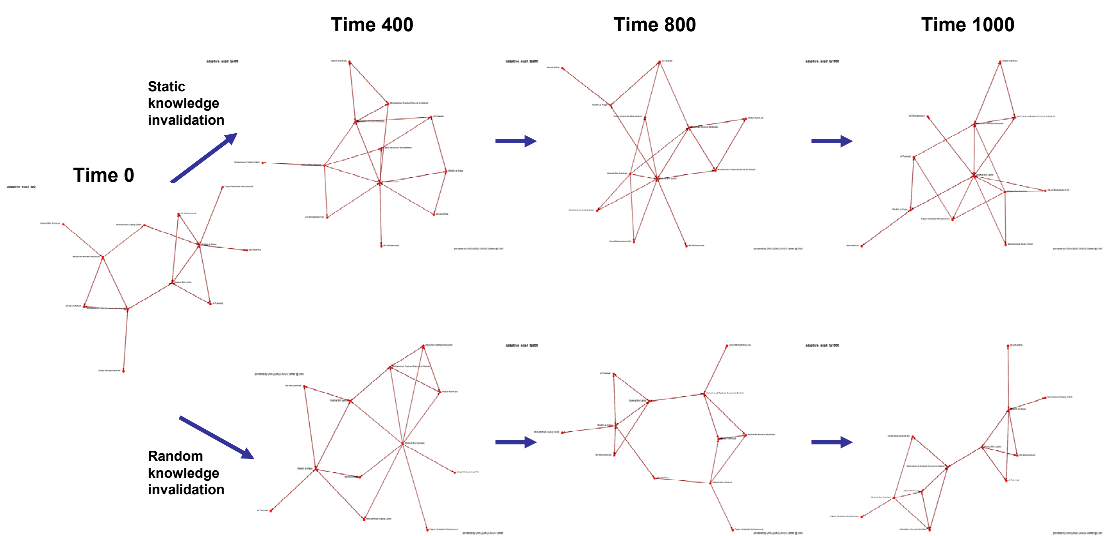

Figure 7. visualizations of adapted structures under two conditions, constant knowledge invalidation and random knowledge invalidation

random situation change. Our analysis suggests that the learning factor increases the performance over time under the constant situation updates, but the learning factor does not increase, even sometimes decrease, the performance if the situation erratically changes. This reflects the organizational learning that we designed is not an optimization procedure, and the learning can be facilitated under the predictable situation. On the other hand, the organizational learning under unpredictable situation may damage the performance.

This model is at its conceptual level in terms of virtual experiments, validation and complex modeling. It only demonstrates that the introduced organizational learning algorithm evolves network structure differently under different situations. On the other hand, it does not model various virtual experiment cases like personnel turn over or loss, link disconnections, task reassignments, etc. Furthermore, there should be a validation using some ground theories or live experiments with human subjects. Also, this organizational learning algorithm can be integrated into complex and realistic models, such as Dynet [17], for further usages.

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