Impact of Individuals' Power on Organizational Learning: Agent-based Simulation Analysis

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Abstract: Any organization has a society of stakeholders in and around it who are interested in different aspects of the organization and actively contributing to organizational learning. These stakeholders are connected with each other through social ties and they are engaged in a continuous discussion with their socially connected neighbors to improve the organizational performance by sharing their individually learned innovative ideas. With the advancement of digital social media, this process has now been transferred onto electronic platforms, enabling faster sharing of ideas. However, due to the complexity of organization and conflicts in individuals' interests, idea sharing is not a smooth process. A common observation in smaller social groups is that some members have a better say than the others, which reflects how he or she is perceived in that particular society. In other words, those who are perceived positively in a given society, for example as sensible, credible, or intelligent, can influence others to adopt their opinions even if those opinions do not appear to be promising from the acceptor's viewpoint. This can be considered as one's informal power, which is normally called referent power or charisma rather than the formal positional power. In this research, we use an agent-based computational model to evaluate the impact of this informal power of individuals on the learning and innovation of the respective organization. Using the simulation results of our model, we show that such power dynamics let the organization to learn up to a particular performance level and stagnate in that level in the long run without reaching the maximum level possible under the current membership. We further discuss this result in relation with Michael Foucault's concept of 'Regimes of Truth'.

Key-Words: *Power, Organizational Learning, Social Learning, Agent-based Modeling, Regimes of Truth*

1. Introduction

Organizational learning, according to [3], is a multi-level process that begins with individual learning, that leads to group learning and that then leads to organizational learning. Advancements in social media technologies have opened up new ways for organizations to learn and innovate. As some researchers have pointed out, one way of increasing innovation capacity is by widening the framework of participation to a wider community [12] and developing places, which are called platforms for collaboration, for different stakeholders to come and work creatively [20]. There are some interesting discussions going on in online forums about the potential of social media to foster innovation by shifting all or part of the innovation process from R & D department to a larger crowd, which comprise of employees, experts, customers, etc. Social media play an important role in this context by enabling the exchanging and processing of innovative ideas of a wider community.

In practice, it is evident that organizations are increasingly using social media to create societies in and around them [5, 7, 10]. For example, a business organization would prefer to have a society of stakeholders as shown in figure 1 to co-create value in their business. These societies

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comprise of multiple individuals, or stakeholders having interest in different aspects of the same organization. More importantly, these individuals are continuously seeking to learn new ideas for improvements in aspects they are interested in and share them with those who are connected with them

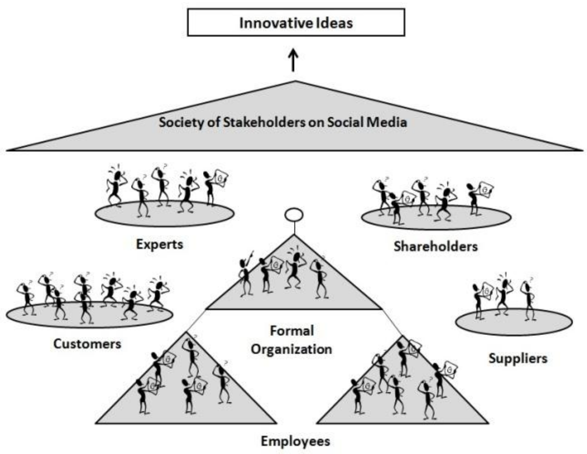

Figure 1: A business organization with socially connected stakeholders to co-create value

However, most organizations are inherently complex entities, which comprise of multiple interrelated aspects and a change in one aspect is more likely to occur unexpected changes in many other aspects. Further, no individual member can fully understand this complexity to propose an optimum solution, which satisfies all aspects of the organization [17]. Consequently, interests of the stakeholders who are interested in different organizational aspects are more likely to have conflicts with each other. Therefore, idea sharing is not a smooth process as it is commonly perceived in most organizational learning theories. An idea learned by an individual has to be accepted by the others in order to be propagated and become 'organizational' for implementation. One important factor in this context, which has been largely ignored though, is individuals' power to influence others to accept their opinions (i.e. ideas) [6, 8].

As far as learning in small societies is concerned, one important observation is that some individuals have a better say than the others, which reflects how he or she is perceived in that particular society. In other words, those who are perceived positively in a given society, for example as sensible, credible, intelligent, etc., can influence others to adopt their opinions even if those opinions do not appear to be promising from the acceptor's viewpoint. This can be considered as one's informal power (referent power or charisma [21]) rather than the formal positional power. The objective of this research is to evaluate the impact of this informal power of individuals on the innovative performance of the respective organization in social learning platforms made upon social media.

Taking the Agent-based Modeling approach [1, 25], we propose an agent-based computational model of a learning organization to study this phenomenon. The subsequent sections of this paper are ordered as below. We discuss the related research in section 2 and modeling details of the proposed agent-based model in section 3. In section 4, we discuss few experiments using our model and their results to draw conclusions. Section 5 contains the concluding remarks.

2. Related Research

As this is an interdisciplinary study, we discuss the related research in the literature of both organizational learning and computational organization theory.

2.1 Organizational Learning and Power

Over the past few decades, Organizational Learning has been studied from different perspectives [3, 4]. A comprehensive review on various organizational learning process models can be found in [6]. As we observe, a common characteristic of most of the organizational learning processes is that members learn individually, share what they learn with others and finally the new knowledge get stored in organizational processes, documents, etc. for the future use.

However, many researchers point out that sharing of individual knowledge is not taking place easily as power dynamics play a critical role in knowledge sharing process. According to [8], organizations are inherently political arenas and consequently, so are the processes of organizational learning. [6] presents a similar idea when discussing the process of corporation among multiple stakeholders with divergent and conflicting interests. Sharing the view of influence as an equivalent to power, they state that influence occurs when a stakeholder makes another actor behave in ways that he or she would not otherwise do.

However, power in organizations has been studied extensively over the past few decades [21, 22, 23]. According to [21], if the influence entails a radical departure from prior operations, then the uncertainty that emerges is likely to arouse emotional responses to influence attempts and factors such as trust, respect or liking may become important. Furthermore, [7] has introduced the term 'People Sensemaking' to denote the process of identifying an individual in a socially connected group as 'who he or she is', which is more likely to determine the referent power of that particular individual.

2.2 Social Learning

Social learning is a very vague and ambiguous term [11]. However, learning and sharing of ideas in multi-stakeholder societies concerned in this research can be better represented using social learning models. A highly appropriate model to this research, which is also based on organizational learning theories, has been introduced in [11]. According to that, to be called social learning, a process must: (1). demonstrate a change in understanding has taken place in the individuals involved; (2). demonstrate that this change goes beyond and becomes situated within wider social units or communities of practice and; (3). occur through social interactions and processes between actors within a social network.

2.3 Computational Modeling of Complex Organizations

According to [14], computational models of complex systems such as teams, task forces and organizations can be used to reason about the behavior of those systems under diverse conditions. Also known as computer simulation, it involves representing a model as a computer program. Complex systems, as stated in [15], by their very nature resist analysis by decomposition. Alternatively, to take a computational modeling approach means not having to assign an objective to an organization and instead modeling the agents that comprise it with explicit attention to how decisions are made and how the interaction of these decisions produces organizational output [9]. It enables to work with a vast parameter space [24] and avoid issues with mathematical modeling arising from non-linear relationships, which are very common in natural processes [25].

2.4 The NK Model

As a technique for computational modeling of complex organizations, the use of NK model has been discussed in [9] and [16]. Even though it has its origin in the Biology field, the NK model has been introduced to the organizational modeling field by Dan Levinthal in 1997 [16]. In this perspective, the primary task of the organization is to constantly search for and adopt routines that improve (not necessarily maximize) its performance. The NK Model has two main parts namely, the NK Landscape and the agents that continuously search the landscape. This is seen as typically taking the form of managers of various departments independently searching for better routines [9].

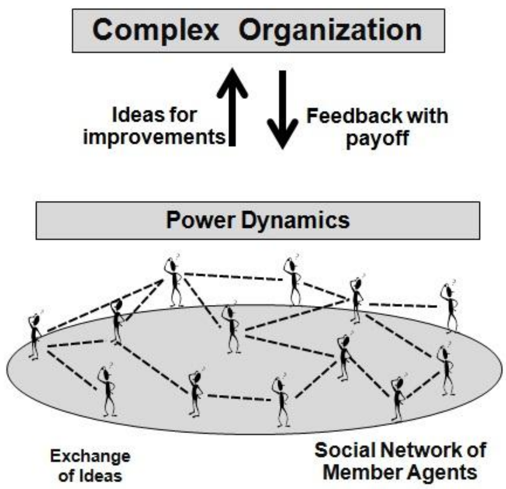

Figure 2: An overview of the proposed model

The two main parameters of the NK Model, N and K, represent the number of functions (or aspects) that comprise the organization (N) and the number of dependency relationships that each function (or aspect) has with other functions (or aspects) (K). There are set number of states for individual functions and different combinations of these individual states make the state space or the search space of the organization. Each function and the associated dependencies make individual search spaces, which determine individual payoff values. Each such individual state is associated with a payoff value, which is usually selected randomly. The pay off of the organization at a given state is determined by the average payoff of all individual functions' payoffs. Apart from many organizational models that uses NK model introduced in [9] and [6], a model that uses the NK Model to analyze organizational deviation and KAIZEN activities has been explained in [17].

3. The Proposed Agent-based Model

We propose our agent-based model based on the foundations laid by the related research discussed in the previous section. Figure 2 provides an overview of the proposed model. As shown in Figure 2, stakeholder agents are connected by a social network using which they exchange new ideas. However, power dynamics among agents act as a filter to those ideas, enabling only few of them to reach the organizational level for implementation.

3.1 Modeling the Search Landscape of the Organization

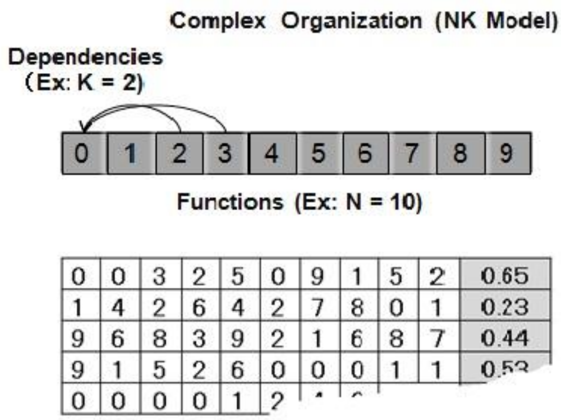

Figure 3: Representation of Complex Organization using NK Model

According to the guidelines given in the NK model, Figure 3 shows the representation of the search landscape of an organization with N (Ex: =10) functions and K (Ex: =2) relationships. In our model, N and K are two parameters, which can be changed as required.

Furthermore, each function can take D number of integer values ranging from 0 to (D-1), which determines different states that each function can be at. N number of functions with D possible states for each function results a search space of D^N states. Each state is associated with a particular payoff value, which determines the organizational performance at the given state. The table in Figure 3 shows few of such states of an organization with N = 10 functions and their associated payoff values. The payoff value corresponds to a particular state is determined by the average of the payoffs of all individual stakeholders. The next sub-section explains how to determine individual utilities.

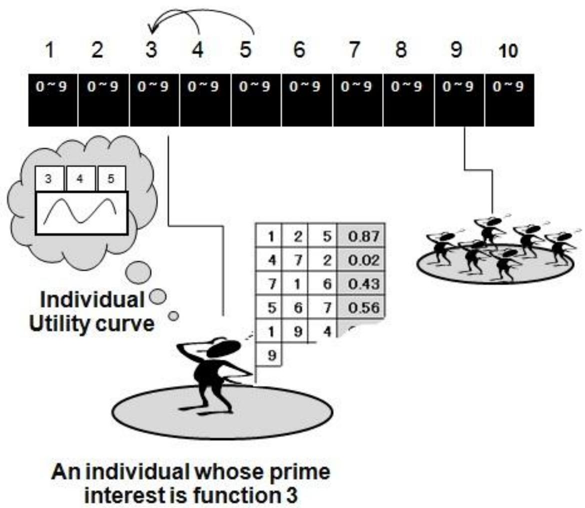

Figure 4: Representation of Individuals' Search Space

3.2 Individual Search Spaces and Payoffs

As shown in the overview in Figure 1, there is a society of stakeholders around the complex organization. In our model, each stakeholder (agent) has a prime interest on one function (or aspect) of the organization. But, since each function depends on K number of other functions, this gives (K + 1) dimensions for each individuals to evaluate. In other words, there is a (K + 1) dimensional search space with $D^{(K+1)}$ states for each individuals to search for new ideas to improve the organizational performance. For example, the agent in Figure

4 has his prime interest in function 3 but since K = 2, he has a 3 dimensional state space with D^3 states.

Each state has an associated payoff value drawn from a uniform random number series and the payoff values of the entire state space makes the agent's individual utility curve or the landscape. Each function has a randomly assigned number of agents whose prime interest is that particular function and each such agent has a unique utility curve. This results in a population of stakeholder agents with diverse interests, in which power dynamics are more likely to occur.

3.3 Modeling Individuals' Informal Power and Decision Rules

Since the number of dimensions in the individual search space is controlled by K, when K < N - 1, individual agents cannot understand all the dimensions of the organization. Furthermore, since each agent has a unique payoff function, even within same dimensions, two agents may hold completely different viewpoints. This complies with the fact that none of the agents can fully understand the organizational complexity and hence the outcome of their actions at the organizational level. Due to this reason, learned fact or a new idea of one agent, which appear to be good from that agent's viewpoint, may appear to be bad to another agent. This is a typical conflicting scenario common in any organization. However, since none of the agent knows the organizational level outcome of the new learning, there is an uncertainty, due to which the second agent may tend to conform to the new learning of the first agent, based on his informal power (referent or charismatic).

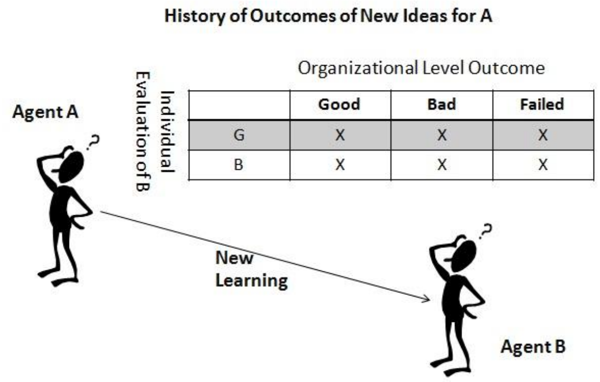

Figure 5: Agents' decision criteria based on their perception about other agents

In our model, agents decide whether to accept or not someone's new idea based on their perception about that particular agent. Each agent maintains a history of past learning outcomes, as shown in Figure 5, about each of those with whom they are connected. Agents evaluate new ideas of other agents as 'G' (good) or 'B' (bad) according to their individual utility functions. However, the agents cannot know the actual outcome of that idea using their individual utility function. If the idea was accepted by sufficient number of agents and was implemented, they again evaluate the idea as 'Good' or 'Bad', based on the actual outcome of that idea. Furthermore, if the idea was failed to get acceptance of sufficient number of agents to get implemented within a certain time period, they evaluate it as 'Failed'. This criteria result in a table with six categories, as shown in Figure 5, in which the cells contain the number of new ideas fall into each category.

When an agent receives a new idea from another agent, he uses the table of historical records to evaluate the conditional probability of that new idea of being 'Good' at the organizational level. If P(Good/G) is the probability of being 'Good' at the organizational level when evaluated 'G' at the individual level and P(Good/B) is the probability of being 'Good' at the organizational level when evaluated 'B' at the individual level, using Bayes' theorem;

$$\mathrm{P(Good|G)} = \frac{\mathrm{P(G|Good) \times P(Good)}}{\mathrm{(P(G|Good) \times P(Good) + P(G|Bad) \times P(Bad) + P(G|Failed) \times P(Failed))}} \tag{1}$$

$$\mathrm{P(Good|B)} = \frac{\mathrm{P(B|Good) \times P(Good)}}{\mathrm{(P(B|Good) \times P(Good) + P(B|Bad) \times P(Bad) + P(B|Failed) \times P(Failed))}} \tag{2}$$

Initially, P(Good) = P(Bad) = P(Failed) = 1/3. This conditional probability reflects the perception of an agent about another neighboring agent and therefore, acts as a determinant of that neighboring agent's informal power. In other words, higher this probability, higher the belief that the given agents ideas are more likely to give better payoffs.

3.4 Modeling the Society of Individuals

Agents of our model are connected with each other by a social network. The type of the network is determined by a parameter, which can be changed to generate Regular, Random and Scale-free networks [26, 27] in the given society. In the regular network, all agents are connected to each other. In the random network, each two agents are connected based on a probability value. In the scale-free network, agents are connected using preferential attachment principle. That is, two agents are connected if there is a similarity in their interested organizational functions and if the target node has a higher degree of connections.

3.5 Description of the Simulator

The model is implemented using Java language and Repast Agent Development Toolkit [19]. Apart from the parameters N, K, D and the Network Type, there are three other important parameters in the parameter list called 'Acceptance Threshold', 'Agents per Function' and 'Vary Learning Likelihood'. 'Acceptance Threshold' determines the percentage of agents in the population that should accept a particular idea in order to implement it. 'Agents per Function' determines the maximum number of agents that each function has, whose prime interest is that particular function. This is a random integer value between 1 and the input value. 'Vary Learning Likelihood' takes a Boolean value and if set as 'True', the probability that a given agent learns at a given time period varies.

At each time step, agents search in their individual utility landscape for better ideas to improve the organizational performance. This is modeled as an evolutionary search using a Real Coded Genetic Algorithm (RCGA) [18]. Once they come up with a better idea, they share it with the agents with whom they are connected via the social network (neighbors). All shared ideas are stored in the working memory of the agent together with newly learned ideas of themselves.

In the next time step, agents evaluate all relevant ideas received in the previous time step based on their decision criteria. The relevance of an idea to a given agent is determined by the availability of one or more organizational aspects common in the interest of the said agent and the creator of the new idea. Each agent has a 'Candidate Idea', which means the current position he holds or in other words the idea he supports at present. If a new idea is found from the evaluation, which is more likely to give a better payoff (i.e. with a higher probability), agents replace their current candidate idea with the new one and pass the new candidate to their neighborhood.

While this process continues, the organization, which is also an agent, scans its members' candidate ideas at each time step. If the organization agent could find an idea spread across its membership beyond the 'Acceptance Threshold', it picks that idea to implement. Implementation of a new idea involves taking the average of the individual payoffs of all the agents for the new idea. If the new idea is irrelevant to a particular agent, its individual payoff is considered as zero.

The average payoff of the society is compared with the current utility (performance) of the organization and if it is found to be greater, the organization adopts the new idea permanently, changing its state. Otherwise, the organization stays at the current state. An idea which increased the organizational performance is considered 'Good' and 'Bad' otherwise by individual agents and they update their histories based on that. Furthermore, if an idea failed to be implemented after 10 time steps, the organization categorize it as 'Failed' and individuals change their histories accordingly.

4. Experiments and Discussions

4.1 Experimental Settings

A powerful individual, as explained before, is someone whose ideas manage to get the acceptance of most agents. Hence in the experiments, we selected the most accepted idea (i.e. the most spread idea) at each given time step out of all the ideas active in the society at that time. Once removing the duplicates, it gave a unique set of most accepted ideas within the period of 10000 time steps we executed each simulation. We identified the creators of those most accepted ideas and

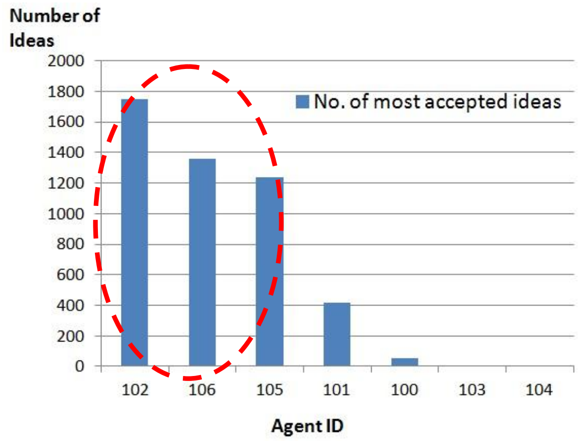

Figure 6: Number of most accepted ideas by each agent in the small group

took the frequency of most accepted ideas by each individual determining the ability of each individual to win the acceptance of others to their ideas. In other words, the agent with the highest number of most accepted ideas was considered as the most powerful agent. It is necessary to mention that we used an organization with N = 7 functions with 6 possible states, making the size of organizational state space equals to 6^7 (279600). Further, the dependency (K) was set to 3, making each function depending on the three subsequent functions.

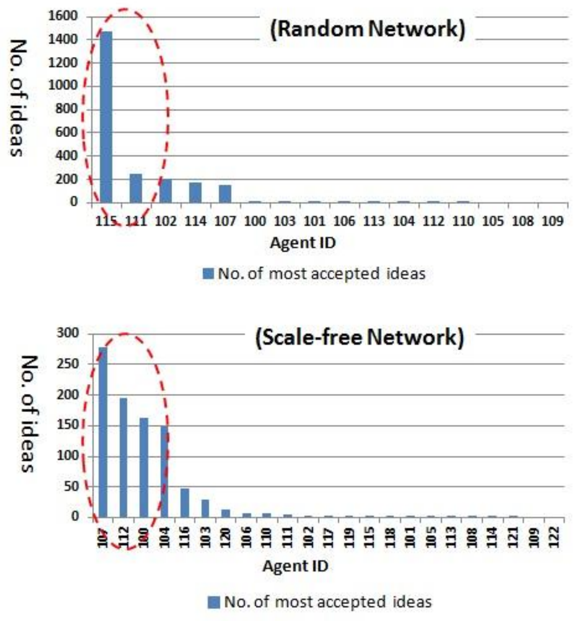

Figure 7: Number of most accepted ideas by each agent when the maximum number of agents per function is 5

4.2 Experiment 1: Simulating a Small Group of Agents

Our first experiment was to use our model to evaluate our initial observation that in small social groups, some individuals have a better say. We connected the society as a regular graph as in a small group it is more likely that everybody is connected with everybody. The figure 6 shows the results of the simulation. It is clearly visible that there is a significant power inequality in the group of seven agents with three agents, circled in red, having more power compared to the others. This indicates that our initial observation is valid.

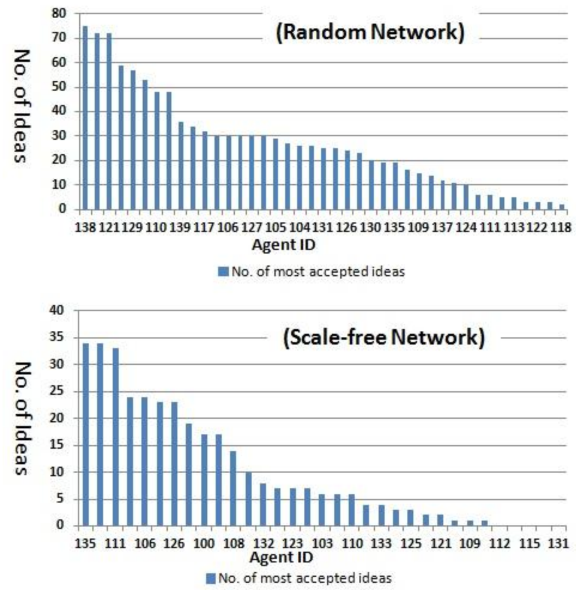

Figure 8: Number of most accepted ideas by each agent when the maximum number of agents per function is 10

4.3 Experiment 2: Evaluating larger groups

Our next experiment involved increasing the size of the society. We changed the parameter of maximum number of agents from 1 to 5 and 10 in two subsequent experiments and the number of agents in the society became approximately 20 and 40 respectively. Furthermore, we changed the structure of the social network to scale-free and random structures and obtained results separately because it is not reasonable to assume that everybody is connected with everybody in a larger group.

Figure 7 contains the results for both random and scale-free networks when the maximum number of agents per function is 5. Figure 8 shows the same results when the maximum number of agents per function is 10. It is evident in these graphs that the power inequalities still exist significantly. However, when the society gets larger, as can be seen in Figure 8, more people come up with new ideas, managing to get satisfactory acceptance.

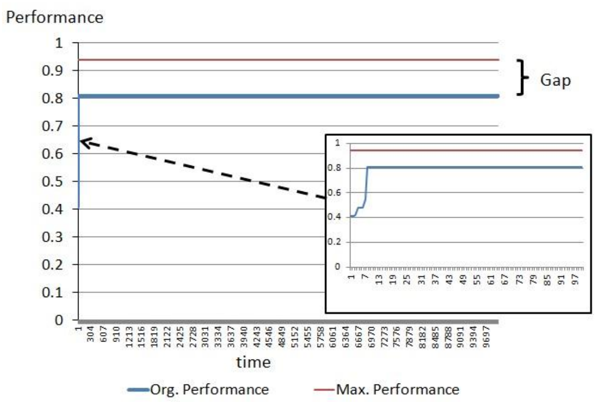

Figure 9: Organizational learning performance in Experiment 1: Maximum possible Vs. Actual

4.4 Impact of Power on Organizational Performance

Performance of the organization in experiment 1 is shown in Figure 9. Since the organizational utility is determined by the average of individual utilities, there is a maximum utility that the organization can reach under the given membership. This is shown in the 'Max. Performance' line in the graph.

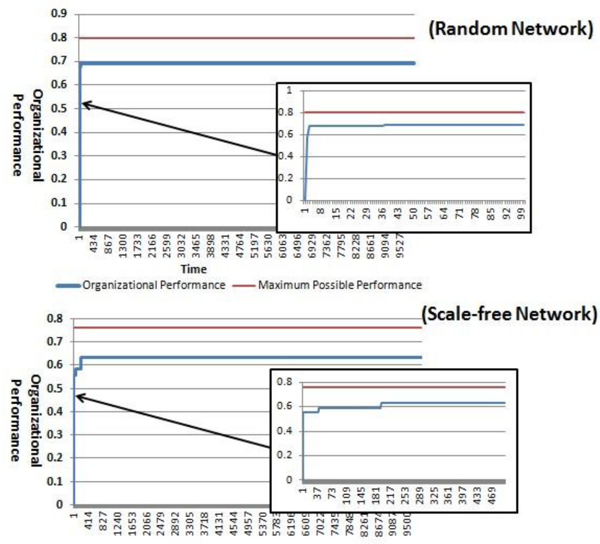

Figure 10: Organizational learning performance when the maximum number of agents per function was 5 in Experiment 2

However, it is interesting to infer that the organization is not capable of learning up to its maximum utility level, even in the long run. Furthermore, once reaching a particular level of utility, the organization stagnates at that utility level in the long run, without growing further. More interestingly, this is further evident in larger groups explained in experiment 2. Figure 10 shows the performance when the maximum number of agents per function is 5 and the Figure 11 shows the same when the maximum number of agents per function is 10. For all these experiments, the parameter value of 'Acceptance Threshold' was set to 0.24. However, the results did not change significantly even when experimented for different values of acceptance threshold.

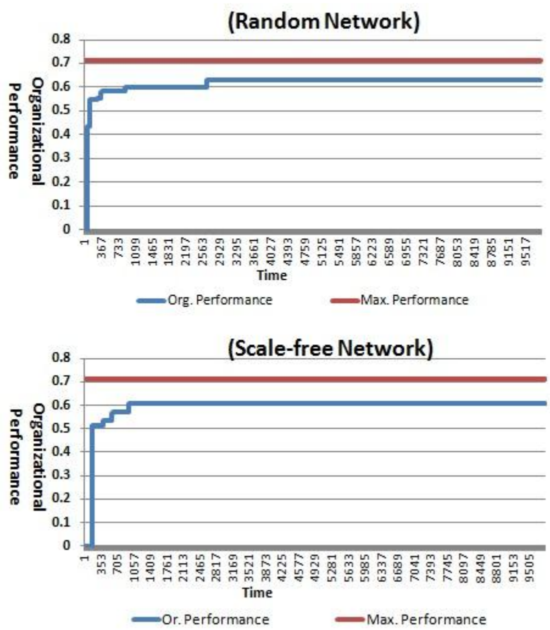

Figure 11: Organizational learning performance when maximum number of agents per function was 10 in Experiment 2

The existence of this gap enables this discussion to be directed towards the concept of 'Regimes of Truth' presented by the French philosopher Michael Foucault. According to Foucault, power and knowledge work together in each society through a 'regime of truth', which distinguishes the discourses that are accepted and function as truth and those that are not accepted and considered to be false [34]. As we interpret it here, there exists a group of individuals (a regime) who determines what is good and what is bad for the whole society. Such a regime acts as an adverse force, which obstructs the forward going (forward learning) of the society after a particular point.

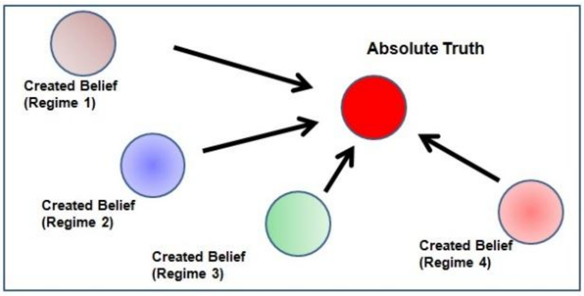

Figure 12: The difference between the created truths of different regimes of truth and the absolute truth

Consequently, the organization fails to identify the absolute truth or in other words the true maxima under the current membership. What they can reach under the given regime is just a created truth or near maxima, as shown in Figure 12, which is far from the true maxima. If the regime changes by, for example a paradigm shift or a radical innovation, the created maxima under the new regime might enhance the payoff than the previous regime but would be still far from the true maxima.

5. Conclusion

In this research, we modeled an agent-based learning organization as a social learning environment, in which socially connected stakeholder agents continuously learn new ideas for improvement and share with other stakeholders with whom they have social ties. Our objective was to evaluate the impact of individuals' informal power to influence others on the performance of the respective organization. Using the common observation in most social groups that some individuals have a better say than the others and theories on referent power and charisma, we modeled this informal power as a property arising from the way the person who holds it is perceived by his neighborhood.

From the results of the experiments, it was clear that few individuals control the learning of the whole society and the progress of the respective organization. It also revealed that the power inequality in the agent society obstructs organization to reach its full potential even in the long run, which complies with the idea of 'Regimes of Truth' presented by Michael Foucault. The validity of this model to accept these results can be evaluated on the grounds of the results of Experiment 1 as the results of that experiment complies with the initial observation that some people in a small society have a better say than the others.

As any other model, our model also has its own limitations. One major limitation is that it does not consider any organizational hierarchy. Even though there is an 'informal organization' in any organization based on social ties among its members, the formal hierarchy or the structure defines the formal positional power or the authority of individuals to make change decisions. The organization in this model lacks with this feature.

There is another significant limitation in our model from the computational resource view point. As the size of the organizational state space grows exponentially with parameters N, K and D, this study was compelled to narrow down the complexity of the organization as well as the size of the membership to a limited size as it can be handled by a single personal computer. The results would have been further interesting if it was possible to run few simulation runs for a much larger society of over 100 agents and also for a rather complex organization. However, since the parameter selection to obtain these results (i.e. N = 7, K = 3 and D = 6) provides an organizational search space with 279600 states, it is still possible to conclude that it is a fair enough complexity to draw these conclusions. The future plans of the research include (1) addressing the limitations mentioned above, (2) refining the model by grounding to different real world business and organizational applications and (3) improving the model to incorporate the formation of clusters in the social network to study the impact of group pressure on organizational performance .

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