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# How different connectivity patterns of individuals within an organization can speed up organizational learning

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**Abstract** Knowledge sharing within a cooperative organization is an important issue since the power of its outcome has been the principal source of competitive advantage over the competitors in the market. However, without a proper collective knowledge management, its utilization as a strategic weapon or competitive advantage becomes difficult and inefficient. From an organizational perspective, the most important aspect of knowledge management is to transfer knowledge. In this regards, organizations must adopt structures that allow them to create and transfer more knowledge. Organizational communication structure affects the nature of human interactions and information flow which in its own turn can lead to a competitive advantage in the knowledge economy. However, in addition to that, social relationships between individuals in an organization can also be utilized to produce positive returns. In this article we emphasize the role of individual structural importance within an organizational informal communication structure as a mechanism for knowledge flow and speeding up organizational learning. Our experimental results indicate the fact that structural position of individuals within their informal communication networks can help the network members to have a better access to ongoing information exchange processes in the organization. The results of our analyses also show that organizational learning through an informal communication network of people in the form of scale-free connectivity pattern is faster comparing to the small-world connectivity style.

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## 1 Introduction

A learning organization can be understood as a complex network in which individuals interact with each other, aiming at some global purpose. It can be considered as a peer-to-peer system (P2P) in which learning occurs during the interactions of individuals which are located in it. In a learning organization, collective knowledge of the individuals is needed in order for the organization to reach its over-all goals. When an organization becomes a learning organization [38], knowledge application is necessitated to help organizations to retain correct and valuable knowledge. If the workforces of an organization learn more quickly than the workforces of its competitors we can say that the company has a competitive advantage or edge over its rivals. Therefore, researchers and scientists try to understand the effective way of the knowledge collection and management in order to create value of its potentials and use it as a competitive advantage.

Knowledge management in an organization refers to the process of creating value from the organization's intangible assets [30]. In other words, it leverages the collective wisdom of the people by soliciting ideas and solutions for an organization. Organizational employees improve the chances of achieving organizational goals by utilization of all available resources as well as knowledge. Learn from the experiences of others who have been more effective in the similar or other areas, improve the quality and speed of problem solving. From an organizational perspective, the most important aspect of knowledge management is to transfer knowledge. Therefore, organizations must adopt structures that allow them to create and transfer more knowledge.

In this article we focus on a popular set of network metrics, mainly measures of centrality of individuals. Centrality measures help us to identify positions within the network, from where people have a better chance of accessing worthwhile information. We argue that centrality measures can be considered as strategic or expert type of knowledge transfer in an organization where the collective knowledge of the individuals is needed to accomplish the organizational goal, which is of critical importance to the whole organization. Despite the creation of new knowledge and process of learning at an individual level, organizational informal communication structure affects the nature of human interactions and information flow. We investigate and emphasize the role of individual structural importance within the communication structure of individuals as a mechanism for knowledge flow and organizational learning. Structural position of individuals in a network can help us to have a better access to ongoing information exchange processes in the organization. To address individual structural importance, two scenarios can be considered:

a) Asking for an information exchange from a person sitting in the bridging position of a small-world network with the hope that critical information might be accessible in this position;
b) Asking for an information exchange from a person with high eigenvector centrality value, the one who has more connection to the others or is connected to other important people in a scale-free network.

Therefore, by managing the information flow from such an individual structural importance, and exploiting the knowledge that peers managed to find, overall learning performance of the organization can be increased. To the best of our knowledge, not many researchers have investigated the effect of underlying structure of the informal communication networks of individuals on organizational learning and knowledge management so far [4, 6, 18]. Only a few researchers have used social network analysis as a methodology to measure information sharing within an organizational setting, peers, and supervisory supports [21]. Therefore, in this paper, we tackle this limitation and demonstrate how social network of people with different structures may contribute in organizational learning. In this regard, we test organizational learning performance under small-world [44] and scale-free [5] networks in which individuals utilize social influences of special entities in their networks for information exchange processes. We are interested to investigate whether a certain complex network topology would speed up organizational learning or not. We are also interested to check how information diffuses through individual structural importance within a communication network.

The rest of this paper is organized as follows. In section 2, we discuss related works and theoretical background on the topic. In section 3, we detail the model and its parameters. Experimental setup and results are presented in section 4 and 5 respectively. Finally we present our conclusion and discuss the future work in section 6.

## 2 Theoretical background

In the literature organizational structure is in the list of 11 critical success factors of knowledge management's successful implementation [1, 19]. Both formal communication (organizational structure) and informal communication network structures play an important role in information exchange [12, 20, 23]. The first step to create a complete system for knowledge transfer in the organization is to develop team knowledge modules to integrate knowledge resources. Developing team knowledge modules is based on the idea that in an organizational a task can be represented by a group of knowledgeable and expertise in that field. However, sometimes for making better decisions the tacit knowledge provided by other teams of knowledge are necessary. Having such a social experience is an important element in the organizational structure in the sense that it provides the team members a chance for knowledge exchange with other team members having the same area of interest or knowledge.

### 2.1 Organizational learning

With the development of science and technology and expansion of business areas, the business environment has become a challenging and competitive one. In such an environment, it is natural to see the changes in the sources of competitive advantage. The greatest competitive advantage in the new business survival paradigms is learning. Hence, the only way for an organization to overcome the uncertainty, complexity and dynamics in the business environment is to have competent and efficient workforces who are considered the organization's important assets and the foundation of wealth. Thus, organizations are more successful if they learn sooner and faster than their competitors. That is why the learning concept is growing rapidly and organizations employ it as a competitive advantage. In the organizational learning theory an organization is considered as an adaptive system which is able to sense changes from the environment and evolve to produce the desired outcome. Therefore, a learning organization actively create, store, transfer and use the knowledge for its adaptation to the changing environment. The topic of organizational learning was introduced around 1970 in Senge's most popular book “The Fifth Discipline” [39] which explores his vision of Systems Thinking and Learning Organizations. In the literature we can find various proposed models for facilitating organizational learning [3, 10, 25, 32, 36]. In this article we follow the March’s model in organizational learning. The detail description of the model is presented in section 3.

### 2.2 Organizational communication structure

The organizational communication structure can be defined as the combination of both formal communication and informal communication network structures. They both play an important role in information exchange. The organizational formal structure is important because it is an indicator of various roles, the hierarchy of these roles and also the distribution of power and authority within an organization. Regardless of the grouping criteria, finally we encounter a meaningful structure through which people communicate with each other. Within such a communication structure we can observe the collective learning which associates internal as well as external learning in the organization. The learning is the combination of Exploration and Exploitation processes. Knowledge exploitation happens through interpersonal learning (P2P interactions) and an organizational communication structure that certainly affect the possible range of solution space. We address these issues in more details in the following.

The interest in the classic problem of trade-off between exploration and exploitation in organizational learning grew in the 1990s, reflecting the importance and impact of this balancing act in an organization decision making [31, 33]. Similar to the recent researches [2, 13–15, 17, 22, 24, 29, 34, 40], Fang et al. [14] pointed to the classic problem of trade-off between exploration and exploitation in organizational learning. Individuals inside their model for achieving the organizational goal had the incentives to explore the environment by themselves or they could achieve that through social activities which can be regarded as exploitation. The following research question was investigated in that model: Does a semi-isolated subgroup structure which improves the balance of exploration and exploitation, leads to superior long-term learning performance outcomes? Their research results showed that modest amounts of cross-group linking are associated with higher equilibrium performance levels.

As it is pointed out in [41], the very first thing needed to create a learning organization is effective leadership which indicates the fact that individuals within an organization work on different levels and positions. Various empirical studies tried to identify the most important actors within the network and Centrality is one of the concepts that helps find people with the greatest structural importance [27]. The majority of centrality concepts such as degree, betweenness, eigenvector, closeness and other derivations of each mentioned centrality types were discussed in [16, 26, 37, 43, 45]. Betweenness centrality of a node determines the node’s position within a network and demonstrates its intermediary role for making connections to other groups. One of the common characteristics of people with high betweenness centrality is holding a powerful position from where they can have more influence on a network. Another particular form of node centrality in literature is called eigenvector centrality. Eigenvector centrality is an influence measure for a node which depends both on the number and quality of its connections. The existence of lateral connection is supported by the fact that two employees of the same organization who are at the same level of authority may have the tendency to create link with each other. The existence of such a link may represent the fact that both are as important as each other and both reliant on the other part for the whole work to be done properly.

In this article we consider two types of connectivity pattern among the learning individuals within the organization. As we mentioned, we model the informal communication structure of an organization as a complex system where the experts might be located at the rewiring point of a small world network or hubs of a scale-free one. We followed the same experimental setup in Fang et al. [14] and the details are presented in the experimental setup section.

## 3 Model

The situation we want to model is the following scenario: Distribution and transfer of knowledge is an important part in the knowledge management process. Obtained knowledge within the organization should be generalized and be available to the others through social interactions. As the workforces of an organization are capable of obtaining new knowledge according to their own capabilities, joining to a network provides them an additional opportunity of asking for an information exchange with their direct contacts. We model the informal communication structure of an organization as a complex system with a small world and scale-free connectivity pattern among the members, where learning occurs during the interactions of individuals which are located in it. During such interactions knowledge exchange happens and new knowledge would be created by the individuals. An organization's performance is measured as the average performance across all individuals in the organization.

### 3.1 Entities

Similar to March's model in organizational learning [32], our model has three main entities: an *external reality*, individuals, and an organization with small-world and scale-free connectivity structures under study. External reality is the organizational goal which is described with a binary vector having m dimensions, each of which has a value of 1 or −1. Values are randomly assigned with the probability of 0.5 for each value in each dimension. There are n individuals in the organization. Each of them holds m beliefs about the corresponding elements of reality at each time step. Each belief for an individual has a value of 1, 0, or −1. A value of 0 means an individual is not sure of whether 1 or −1 represents the reality. As mentioned earlier, our model is different from March [32] and Fang et al. [14] in that an organization is seen as a complex system wherein individuals through a small-world and scale-free network interact with one another. Therefore, they are able to utilize individual structural importance as a strategic or expert type of knowledge transfer within the network.

### 3.2 Individual structural importance

A key factor determining the dynamics of our model is its topology of interaction patterns between individuals. We performed the experiments on a small-world and scale-free network. What make such complex networks different from other simple networks such as lattices or random networks are non-trivial topological features which do not exist in other networks. For example, in scale-free networks topological features are related to an underlying network structure which is neither purely regular nor purely random. Therefore, such non-trivial topological features allow us to test how individual structural importance can contribute in the learning performance of the organization. Our view here is that it is reasonable that workforces utilize individual structural importance as a strategic or expert type of knowledge transfer within the network. The experts might be located at the rewiring point of a small world network or hubs of a scale-free one. For example, in a network some people have certain roles and might be located in the bridging positions of the network. If worthwhile information resides on the net, these people have better chance of accessing such information. These people have a high betweenness centrality value. Node betweenness centrality counts the number of shortest paths in a network that will pass a node. The betweenness centrality of a node introduced by Freeman [16], is defined as

where $\sigma_{st}$ is the total number of shortest paths between nodes vs and $v_t$ , and $\sigma_{st}$ ($v_i$ ) is the number of shortest paths between nodes $v_s$ and $v_t$ that pass along node $v_i$ .

$$C_B(v_i) = \sum\nolimits_{v_s \neq v_j \neq v_t \in v} \frac{\sigma_{st}(v_i)}{\sigma_{st}} \tag{1}$$

Betweenness centrality is based on shortest paths in a network. Therefore, if the quickest way between any two nodes on a network disproportionately involves certain nodes, then they are considered to be structurally important from that point of view. Consider a network with N nodes and m edges, our computational goal is to find $(N_2)$ shortest paths between all pairs of nodes. We can use Floyd-Warshall algorithm [42] in which computation time grows as $O(N^3)$. We can also use Dijkstra's algorithm or Johnson's algorithm for finding shortest path between two specific nodes. Newman and Brandes [11, 35] also have delivered fast algorithms that compute betweenness centrality and computation times grow as O(mN) for unweighted graphs and $O(mN+N^2 \log N)$ for weighted graphs.

Another group of interesting people might be those who have a large number of trust connections, or those with a high number of degree connections, or even someone who does not have a significant number of degrees, but has connections to most important people. These people have high degree centrality or eigenvector centrality values in the network. Eigenvector centrality is defined as the principal eigenvector of the adjacency matrix defining the network. The defining equation of an eigenvector is given below:

$$C_E(v_i) \propto \sum\nolimits_{v_j \in N_i} A_{ij} C_E(v_j) \tag{2}$$

Let v denote the eigenvector centrality of node from $v_1$ to $v_n$. We can rewrite the above equation in a matrix form: v ∝ Av. Equivalently, we can write $v = 1/\lambda\ Av$, where A is the adjacency matrix of the network, lambda is a constant (the eigenvalue) and v is the eigenvector. It follows that

$$Av = \lambda v$$

Eigenvector centrality is a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes. One of the main practical inconveniences of the eigenvector centrality is that its calculation involves algorithms of high computational complexity. It needs to compute the eigenvectors and eigenvalues of some $n \times n$ matrices. Therefore, the problem of finding low-complexity estimates of the eigenvector-like centralities has been proposed in the literature in order to avoid the main computational limitation of eigenvector centrality measure [8, 9, 28]. Poor man's PageRank algorithm [7] is a variant of the eigenvector centrality measure in which a major iteration has O(n) computational complexity.

Among commonly used centrality measures eigenvector and betweenness centrality measures are used as a strategic or expert type of knowledge transfer within the network. We select a small-world network, which has a small diameter due to the existence of bridging points. The scale-free network is selected based on the idea that distribution of individual eigenvector centrality followed a power function. Therefore, we are able to observe the existence of hubs and lateral connection in scale-free networks and bridging points in small-world networks. We utilize such centrality information for the diffusion of the reality in second part of our experiments where the goal is to check how fast information can propagated from such positions.

## 4 Experimental setup

The experimental settings for our model are as follows: We conduct a multi-agent-based simulation in Netlogo [46] to test our model. One reason for agent-based simulation is that from a computational perspective they help parallel implementations. So we have a separate computational thread for each agent (node) that is responsible for the information exchange. The second reason is that we need a dynamically changing computing environment to model the real scenario. We generate ten suits of experiments (T1, T2….T10) to check the performance of learning organization while individuals exchange the information, and we report the average result over 100 simulations run. There are *n* individuals in each organization (i.e., n = 250). The number of dimensions in the beliefs is set to 100 (i.e., m = 100). Reality is determined by randomly assigning a value of 1 or −1 for each of 100 dimensions, whereas each dimension of an individual's belief set is determined by assigning a value randomly drawn from 1, 0, or −1. Each organization consists of *c* clusters (i.e., c = 1 in this study) of individuals. The organizational communication network is implemented by first connecting each individual to the other individuals in a pattern explained in Fig. 1. The average degree of both networks is set to 4. Similar to Fang et al. [14] model the learning probability is set to 0.3. Simulation's Parameters are shown in Table 1. We adopt generalized learning model of March [32] developed by Fang et al. [14] which is presented below:

$$\phi(x) = s\left(\prod_{j=1}^{s}\delta_j + \prod_{j=s+1}^{2s}\delta_j + \cdots + \prod_{j=m-s+1}^{m}\delta_j\right) \tag{3}$$

Let $x_j$ denote $j_{th}$ element of the bit string x. Then, the linear payoff function can be calculated according to the above formula where $\delta j = 1$ if $x_j$ corresponds with reality on that dimension; $j = 0$ otherwise. As it is discussed in [14], the parameter *s* ($1 \le s \le m$) acts like a tunable parameter and controls the difficulty of the search problems. In fact we have m-bit

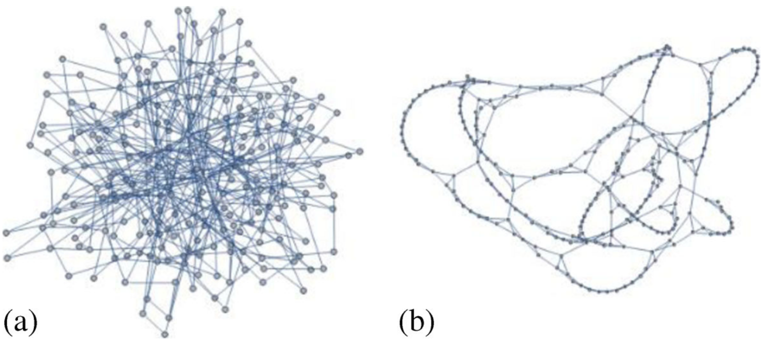



**Fig. 1** Connectivity patterns among group members. **a**) Scale-free network. **b**) Small-world network

**Table 1** Simulation's parameters

| Parameters | Remarks | Range of parameter values |
|---|---|---|
| n | Number of individuals in the organization | 250 |
| m | Dimensions of beliefs | 100 |
| z | Size of a subgroup | 250 |
| T | Simulation running time | 100 |
| c | Number of clusters | 1 |
| s | Degree of complexity | 5 |
| $P_{learning}$ | Probability of individual learning from the majority view | 0.3 |

string which is partitioned into L independent subsets. Within each subset, there are s bits, whose performance is coupled. Larger values for parameter s make the search problem more interdependent and increase the complexity of the problem. As we can see, payoff of each individual is calculated by comparing each bit of his/her belief set with bits of the reality one. Therefore, when s = m, all the bits must be matched with reality bits to produce the payoff which makes the problem too complex to solve in one step. In our formulation we set its value to 5.

Each individual during the interaction with his direct contacts identify those with superior performers than him and consequently make decision to update his belief. The decision to update each of m dimensions of his belief is made with some probability $p_{learning}$ that reflects the ability of individuals to learn from one another. The majority decision rule is based on the idea that belief sets of these higher-performing peers have been closer to the reality. When there is no superior performer, the previous beliefs must be intact. If there are two or more superior performers, a majority belief among them will be determined for each of *m* dimensions in the belief. An organization's performance is measured as the average performance across all individuals in the organization. A perfect numerical calculation of the payoff function is presented in [14]. The graphical user interface (GUI) of our simulation environment is depicted in Fig. 2. The GUI of our simulation consists of a two-dimensional field that contains nodes and their connections.

## 5 Results

As mentioned in the introduction section our goal was to investigate whether a certain complex network topology speed up organizational learning or not. Therefore, we compared the organization learning performance of scale-free and small-world networks over 10 suits of experiments and the average result based upon 100 runs is shown in Fig. 3. For each run of the model, we computed the average payoffs of the population during each period t = 0…….T. Equilibrium occurred when all the individuals has equivalent knowledge levels.

Our first observation in Fig. 3a, b was that the organizational learning performance with small-world connectivity pattern is slower than the scale-free one. Despite the fact that at the end of the simulation the learning curves are very close to each other, the early stage of the simulations is a good indicator of how different network topologies respond to March's payoff function. This clarifies our statement about the fact that in addition to

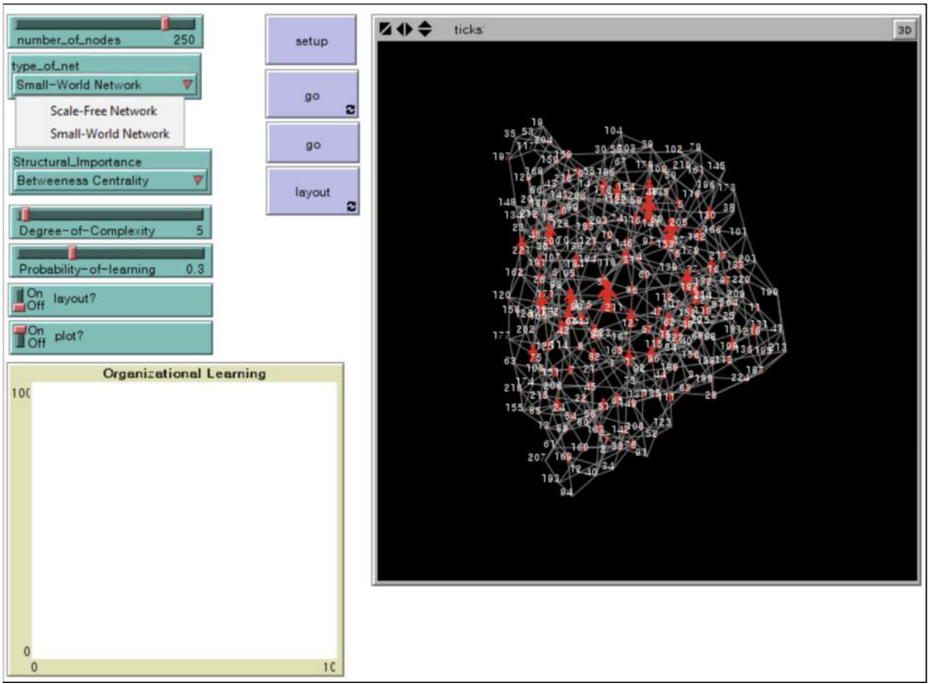
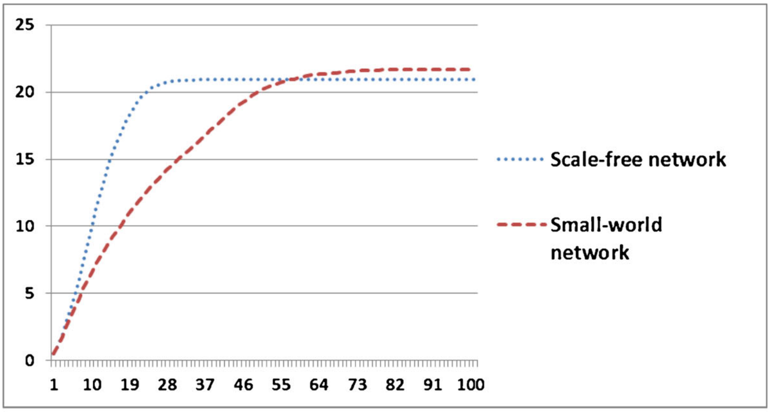



**Fig. 2** GUI of our model developed in NetLogo

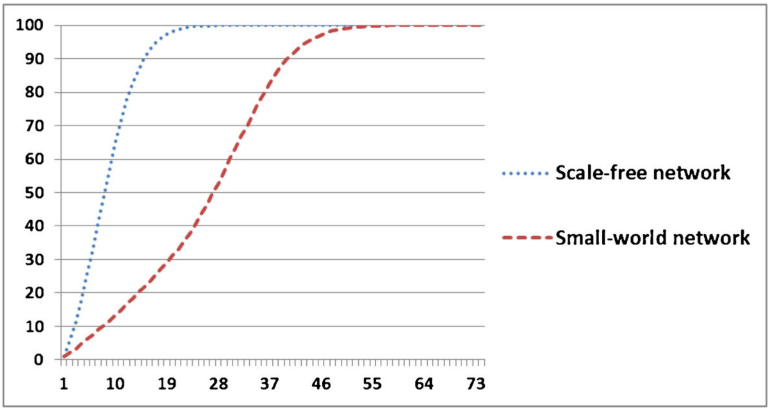
having a realistic model of interactions, with a proper communication network structure organizational learning can be speed up.

We were also interested to check how information diffuses through individual structural importance within a network. The intuition behind selection of such individuals was that from such positions people have better access and control to the ongoing information exchange within a network. We select the individual with high betweenness centrality value in small-world network, because that point acts like a bridging point that shrink the network diameter. We select the individual with high eigenvector centrality value in scale-free network, because that point acts like a central hubs with lateral connection to other nodes with high degree of connections. Therefore, we diffused the reality through individuals with high eigenvector centrality and betweenness centrality values in both networks. The result of our analysis is shown in Fig. 3b. As the result shows, the reality diffuses faster in scale-free network than small-world one. Although at the end of the simulation all the individuals managed to update dimensions of their beliefs, but it seems that in scale-free network the diversity of belief sets is lower in the early stage of the simulation. That means, the organization with a scale-free topology within its communication structure has achieved a high level of eventual knowledge in a shorter time than the one with a small-world topology. Therefore, we can conclude that certain connectivity patterns among the workforces can speedup organizational learning.

Comparing to the obtained result reported by Fang et al., our result in Fig. 3a shows lower average organizational learning performance. Our conjecture is that (1) the author in [14] assumed the full connectivity pattern among the members of the group and (2) there was a huge overlap among the beliefs of network members. Therefore, the complexity of knowledge in our model (a large m) allows lower proportion of correct beliefs. The larger the number of




(a) **Informal Communication Network Structure**: Barabási-Albert Scale-free network and Watts-Strogatz Small-world network, C=1, n=250, $P_{learning} = 0.3$.




(b) **Informal Communication Network Structure**: Barabási-Albert Scale-free network and Watts-Strogatz Small-world network, C=1, n=250, $P_{learning} = 0.3$. Reality is diffused by experts (nodes with high betweenness centrality and high eigenvector centrality in Small-world and Scale-free networks respectively) within the organization.

**Fig. 3** Different communication network structures among individuals and their impact on organizational learning. Organizational learning performance with respect to different network topologies is presented. *X-axis* shows the duration of the simulation while *Y-axis* is set to the organizational learning performance (Average through the population)

elements to learn, the longer the time and correct knowledge required for recombination of beliefs to lead to some level of mastery of a domain.

## 6 Conclusions and discussion

The knowledge itself is not the source of competitive advantage for the organization, rather organizational power lies in its use. The goal of knowledge use is to activate the relevant knowledge in order to create value for the organization, because the organizational knowledge should be embedded and employed in new products, services and processes. Distribution and transfer of knowledge is an important part in the knowledge management process. Obtained knowledge within the organization should be generalized and be available to the others through social interactions.

We argued that the social relationships between individuals in an organization can be utilized to produce positive returns. Therefore, we emphasize the role of individual structural importance within an organizational informal communication structure as a mechanism for knowledge flow and increasing the organizational learning performance. Individual structural importance can be considered as a strategic or expert type of knowledge transfer for communication between the individuals within an organization in the sense that such a configuration by reducing the independence of the individuals and increasing the scale of behavior facilitate and speed up collective learning. The results of our analyses show that organizational learning through an informal communication network of people in the form of scale-free connectivity pattern is faster comparing to the small-world connectivity style. Therefore, a more flexible structure among the individuals within an organization allows the existence of hubs and lateral connections and consequently organizational learning performance can be increased.

In this study we depicted the social interactions of the individuals within an organization with two network topologies, namely small-world and scale-free one. Therefore, regardless of the hierarchical structure of the organization we assumed that their social interactions would produce social networks with mentioned topologies. However, as an extension to the current research we are interested to investigate how March's Payoff function may respond to a traditional hierarchical structure or hybrid structures. We are also interested to test how changes in the dimensionality of the belief set can improve the results. We plan to test the model for organizations with different sizes in which multiple team knowledge modules exist.

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