**Ph.D. Dissertation in Engineering**

# Analyzing Socio-Economic Complex Adaptive Networks: A Hybrid Approach

사회경제적 복잡계 네트워크에 대한
하이브리드 방식의 분석

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**Graduate School of Seoul National University**

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**Technology Management, Economics and Policy Program**

**Somayeh Koohborfardhaghighi**

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**Professor Jörn Altmann**

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**Confirming the doctoral thesis written by**

**Somayeh Koohborfardhaghighi**

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**Chair_____**

**Vice Chair_____**

**Examiner_____**

**Examiner_____**

**Examiner_____**

# Abstract

# Analyzing Socio-Economic Complex Adaptive Networks: A Hybrid Approach

Somayeh Koohborfardhaghighi
Technology Management, Economics, and Policy program
College of Engineering
Seoul National University

In this thesis, we aim to explain the structural changes within socio-economic complex adaptive networks with respect to social characteristics of individuals. Actors of socio-economic complex adaptive networks are social units that undergo various strategic processes to achieve their goals. So there is a need to study such networks systematically with respect to their actors and their strategic interactions as it evolves over time. Variety of stochastic and strategic network formation models has been introduced in the literature to explain the emergence of certain network's characteristics. However, each of those techniques has their own limitations. While both stochastic and strategic network formation models are able to tell us what the interesting characteristics of the network are, the extent to which those characteristics affect the outcome of individuals and the whole society is still unclear and has received little attention in the literature.

Our focus is on human-to-human communication environments, where the process of link establishment among network members is not random and the process of a

network growth requires a proper economic inventive modeling among its members. We aim to show that a proper incentive modeling is needed for the process of link establishment within socio-economic complex adaptive networks and its effects will be reflected on the emerging network characteristics as well as the networking outcome (i.e., learning outcome or utility gain at the individual level). Networking outcome can be considered as whatever an individual gains out of his or her connectivity within a network (i.e., learning outcome or utility gain at the individual level). That is to say, individual actions determine the network structure and similarly structure also influences individual actions and thinking. They constrain and enable actions. Therefore, there is a feedback loop between individual actions and network structure. We argue in this thesis that, a hybrid approach based on complex adaptive system theory is needed for studying socio-economic complex adaptive networks. Consequently, we can justify why the underlying network structure is constantly changing and as the result a certain type of network with specific characteristics emerges. The structural changes (emerging network characteristics) are the changes in the clustering coefficient value and the average shortest-path length. For capturing, comparing, and explaining the structural changes and outcome of individuals within socio-economic complex adaptive networks, we developed a multi-agent based model. With the help of agent-based modeling, we are able to test and evaluate this approach.

**Somayeh Koohborfardhaghighi**
**Student ID: 2012-31308**

# Abbreviations

| Abbreviation | Meaning |
|---|---|
| **CC** | Clustering Coefficient |
| **AVL** | Average Path length |
| **CAS** | Complex adaptive system |
| **$S_{PN}$** | Size of Personal Network |
| **$P_{RAN}$** | Probability of having links of Random type |
| **$P_{FOAF}$** | Probability of having links of friend-of-a-friend type |
| **$P_{GN}$** | Probability of the network growth |

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# Chapter 1. Introduction to Socio-Economic Complex Adaptive Networks

## 1.1. Introduction

Networks of opportunity seeking actors within socio-economic complex adaptive systems are more than a simple collection of nodes and the links among them. Each individual's behavior and group dynamics among the population make the network setting more dynamic and complicated. Actors of socio-economic complex adaptive systems are consciously social units that undergo various strategic processes to achieve their goals. So there is a need to study a socio-economic complex adaptive system systematically with respect to its actors, the social system which indicates the arrangement of social interactions of its actors and their strategic interactions as it evolves over time.

Socio-economic complex adaptive networks inherit several common features of general complex adaptive systems (Holland 2006) such as

- Hierarchical Structure: Many different elements interacting on many different scales, it means there is hierarchy within the system.
- Connectivity: Connections between elements of system. Interactions of elements of the socio-economic complex adaptive systems through their connectivity at different levels insure the emergence of new systemic social qualities within such systems. Therefore, we can imagine that a higher level of connectivity shows a better flow of information within the system.
- Autonomy: There is no top-down centralized mechanism for coordinating the whole system and there is a great deal of autonomy for the elements of

complex systems (Paiva and Braga 2008). They are heterogeneous with high levels of diversity. The greater the autonomy and capacity of adaptation (Kauffman 1989), the more complexity will be observed in the system.

- Adaptation: Adaptation can be defined as the capacity for a system to change its state in response to some changes in its environment. Therefore an adaptive system is a system that can change given some external perturbation in order to optimize or maintain its condition within an environment (Nicolis and Prigogine 1977, Smit and Wandel 2006).
- Feedback Loops: Due to local interactions among the elements of the system, some phenomena cascade through the population and system's actors (agents) synchronize and update their states rapidly.
- Nonlinearity: Input and output of the system are not proportional to each other. Non linearity is an indicator of deep interdependent nature among the elements of the system. Systems often become chaotic when there is feedback present (Devaney, Siegel et al. 1993).
- Simple Rules: In complex adaptive systems usually simple rules govern the interactions among the elements of the system. In the context of socio-economic complex adaptive systems decision rules incorporate the key aspects of their decision making (Beresford and Sloper 2008, Farmer, Gallegati et al. 2012). New systematic social qualities are coming out from the dynamic interplay between the structure and the function (economic decision making process) of the underlying pattern of connections. Modeling the dynamics of interactions within socio-economic complex systems requires identification of agent's strategies (e.g., costly sophisticated

strategies and simple rules of thumb) with respect to different contexts. This involves designing techniques and models within which the agents are equipped with reasoning capabilities that leads to economic decision makings.

Socio-economic complex adaptive networks have several interesting features that distinguish them from general classes of complex adaptive systems (CAS).

- An economic model exist that involves diverse economic agents (individuals), objects, and institutions (firms, regulatory agencies, etc.) (Jackson and Wolinsky 1996).
- Study of network dynamics among agents requires the addition of a whole new set of parameters to our network growth models.
- Basic psychological biases cause major deviations from rational behavior (Zeigler-Hill, Welling et al. 2015). We should mention that the concept of equilibrium has dominated economics. This is the rationality of economists. However, considering variety of strategic behavior of heterogeneous agents, non-equilibrium phenomena and bounded rationality are also from other source of challenges for modeling socio-economic complex adaptive systems.
- We are able to observe inflexibility and mal adaptiveness in the structure of the social system (Foster 2005). As structural development proceeds, the socio-economic complex adaptive systems exhibit some degree of structural irreversibility due to the inherent hierarchical and 'bonding' nature of the connections between components that are formed. For example within big enterprises, in order to have a long run competitive advantage, senior managers need to investigate new opportunities through both exploration of new assets and exploitation of existing assets to overcome path dependencies.

- The evolutionary process that such a system experiences can only be understood in an explicit historical time dimension (Foster 2005).

In this thesis we argue that understanding, designing, and managing socio-economic complex adaptive systems require an in-depth understanding of

(1) Economic behaviors of their agents as well as

(2) The social system, which indicates the arrangement of social interactions of their agents.

We point to the necessity of capturing the economic incentives among components of the socio-economic complex adaptive system as well as the importance of social system there which depicts the connectivity pattern among the components.

In the following section, we will see that capturing the economic incentive for the process of link establishment among the network members falls into the individualism approach and the study of the social system falls into the structuralism approach (Mayhew 1980, Mayhew 1981).

Structuralism approach characterizes networked structures in terms of nodes (individual actors, people, or things within the network) and the ties or edges (relationships or interactions) that connect them (Deleuze 1953, Sturrock 1979). This approach is sometimes referred to as "structural analysis" because of focusing on the way that individuals are interconnected in a system.

On the other hand, researchers in individualism approach assume that entities are rational and that opportunity seeking actors and establish links with other actors if they find the process of link establishment beneficial. Such scholars believe that an individual's outcome out of a network is assumed to be derived from embeddedness in systems of relations (Wood 1972, Jackson and Wolinsky 1996, Jackson 2008, Hayek and Caldwell

2014). Two examples are the symmetric connection model (with positive externalities) and the co-author model (with negative externalities) (Jackson and Wolinsky 1996). We elaborate on the differences between the two approaches in the following.

As it is shown in Figure 1.1 (A), structuralists may examine relations between different forms of organization at the same or different points in time. Many researchers follow the structuralists approach specially those who take snapshots of networks and compare their topologies. Similarly as it is shown in Figure 1.1 (B), individualists examine relations between one individual action and another at the same or different points in time.

To mention a concrete case on structuralism approach, we can consider Bureaucratic vs. Flat organizational structures. Bureaucratic organizations are centralized structures while flat organizations are decentralized structures. As it is shown in Figure 1.2 [1]big enterprises in the market may follow different organizational structures. Amazon's organizational structure, for example, is effective in supporting international growth but has limited flexibility and responsiveness. This is due to the dominance of the global function-based groups and global hierarchy characteristics of Amazon enterprise. It is

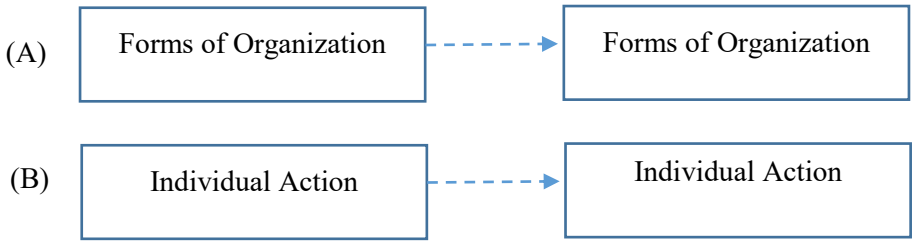



Figure. 1.1. Different views on Network Analysis. (A) Structuralism approach. (B) Individualism approach.

also so difficult to climb Amazon's corporate ladder. Microsoft organizational structure is poorly connected and less cohesive. Microsoft's divisional structure sometimes

[1] http://www.bonkersworld.net/organizational-charts/

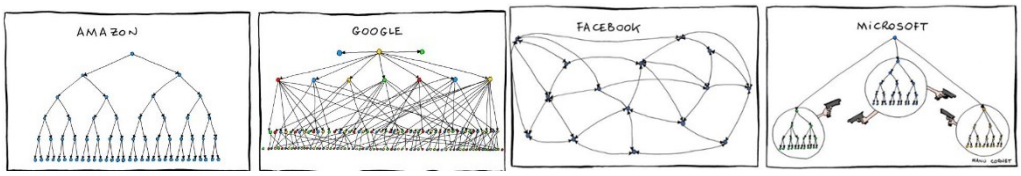


Figure. 1.2. Organizational structures of big enterprises.

contributes to a situation where its own products were incompatible across internal business units.

Organizational structures defines how the organization operates. This includes the arrangements of the lines of authority, power distance within the organization, how responsibilities are distributed and how information flows.

Structuralists are interested to analyze purely structural properties of the organizational structures of big enterprises. They believe that such organizational structures are derived from the organization of the network itself, not from the characteristics of individuals occupying various positions in them. Structuralists might be interested to capture how does changes in the organizational structure of a big enterprise (Within a time interval) help the enterprise to earn more profits. Structuralists might be also interested to calculate a priori likelihood that an organizational structure of a big enterprise will be disrupted by a break in communication. In such a case, they introduce measures that point to the magnitude of an organizational structure's disruption potential. Such measures are purely based on structural properties of networks and according to structuralists have nothing to do with the characteristics of individuals or elements occupying those positions in the network.

To mention a concrete case on individualism approach, we can consider dynamics of network formation through co-author model or symmetric connection model.

Consider a network of 4 individuals in the configuration of 2 dyads such as the one showed in Figure 1.3.


Figure. 1.3. An example of the individualism approach. Individual A and Individual B perform their strategic behavior to establish a link together.

From the individualists' point of view each individual within such a configuration gains some amount of benefit and bears some costs during the process of link establishment. Therefore, if both individuals A and B perceive the net utility beneficial for themselves then they interrupt the network structure and establish a link among themselves. That is how the network structure changes over time. As we can see, individualists speak of certain social, economic, or psychological characteristics of individuals to explain the emergence of certain structures.

## 1.2. Problem Description

Both structuralism and individualism approaches have their own limitations. For example, structuralists neglect the fact that individual level variables can determine the structure. That is to say, individuals have the power to apply some changes to the structure of the network. Similarly, individualists need to consider that interconnectedness within a system can be forced by the system. That means sometimes individuals encounter lack of flexibility for themselves to change the structure. Individualists should pay attention that in addition to individual factors, there are also other factors that affect how people behave in certain ways. For example, there is another level that has to do with the influence on

human behavior that comes from institutions. These are rules and regulations within any organizations which impact employees' behavior so it can be influence by environment within which they work. Since both structuralism and individualism approaches target and have the potential to explain different aspects of the process of link establishment, they can complement each other. But we need a hybrid approach to model direct and indirect communications processes that occur among people, to model their beliefs and learning process that occurs among them, to point to their heterogeneity, lack of flexibility and mal adaptiveness, to models feedbacks in interactions, and finally to capture the evolution of the network. In the following we will see how complex adaptive approach can help us to address such issues. Complex adaptive systems approach points to several common features of complex adaptive systems such as their hierarchical structure, connectivity between elements of the system, autonomy feature for its elements, capacity of adaptation for system's elements, feedback loops in interactions and simples rules governing the dynamic and evolution of such systems. Figure 1.4 (A)[2] shows the general complex adaptive systems approach in which connectivity and interactions among the elements of the system leads to the emergence of system behavior. Although complex adaptive system approach would seem to be a promising approach to the study of socio-economic complex adaptive systems, we should mention that socio-economic complex adaptive systems have several interesting features that distinguish them from general classes of complex adaptive systems. First of all, in comparison to complex adaptive systems in the field of natural science and physics, actors of socio-economic complex adaptive systems are social units that undergo various behavior to achieve their goals.

[2] https://commons.wikimedia.org/wiki/File:Complex_adaptive_system.svg

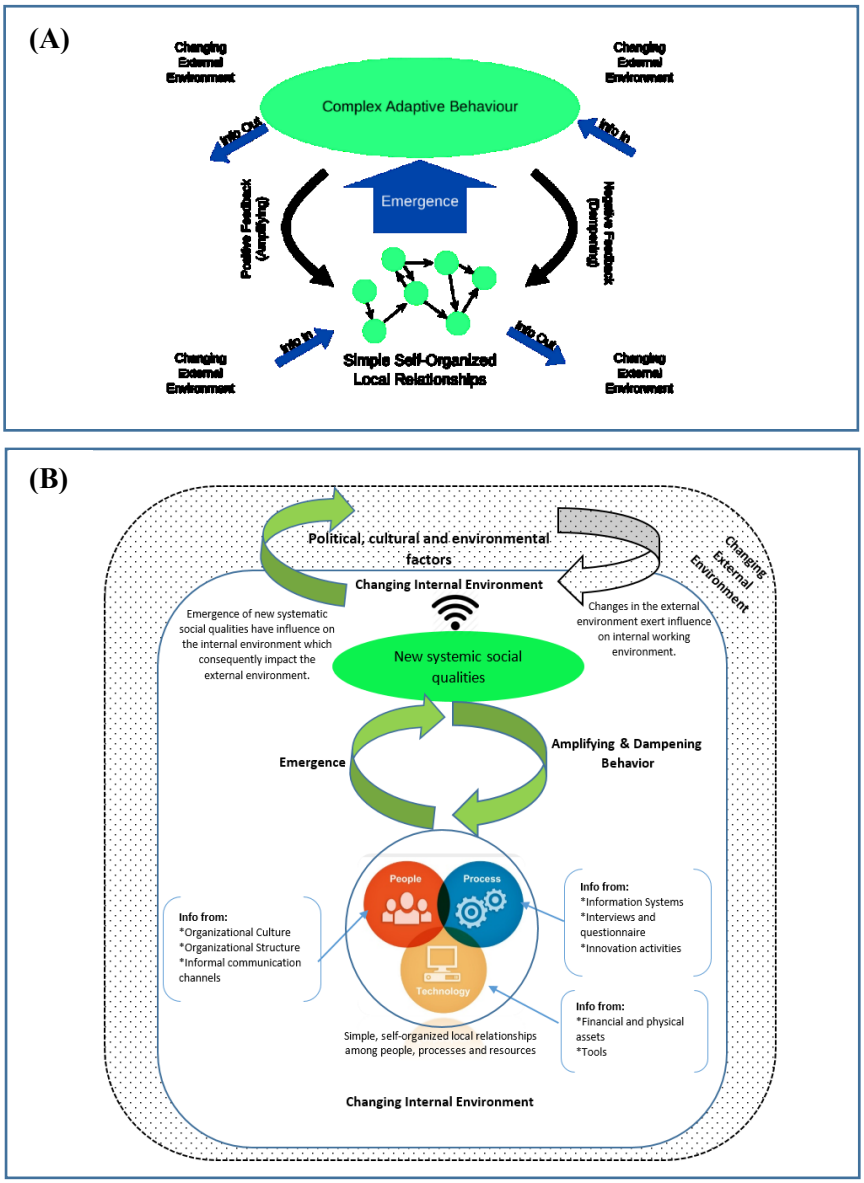



Figure. 1.4. (A) A general complex adaptive system approach for natural and biological complex systems. (B) A complex adaptive system approach for socio-economic complex adaptive systems.

Therefore, considering variety of individual behavior and their economic incentives are at the heart of socio-economic complex adaptive systems. As it is shown in Figure 1.4. (B), while studying socio-economic complex adaptive systems, we are dealing with diverse economic agents (individuals), objects (processes and resources), and institutions (e.g., firms, regulatory agencies) (Jackson and Wolinsky 1996) that interact

with each other through variety of economic models. Since we are dealing with human beings and their interactions (i.e., human-human, human-process, human-resources) within such system, we should also consider that basic psychological biases which cause major deviations in such agents to act according to their rational behavior (Zeigler-Hill, Welling et al. 2015). That is to say, the human decision making is affected by systematic cognitive biases, habits, and social norms. Therefore, we need more insights from behavioral sciences to determine factors which influence and shape human behavior within socio-economic complex adaptive systems. In addition to mentioned individual level attributes, other factors may also influence people's behavior within any socio-economic complex adaptive systems. Such factors can be originated from different sources such as organizational structure and organizational culture. Overall, identification of influencing factors which shape and explain human behavior within a socio-economic complex adaptive system can help us to encourage further changes within the system (i.e., to encourage a higher degree of collaboration or to motivate knowledge sharing behavior among employees).

Another noticeable difference between a general complex adaptive system and a socio-economic complex adaptive system is that as structural development proceeds within a socio-economic complex adaptive system, such a system exhibits some degree of structural irreversibility due to the inherent hierarchical and 'bonding' nature of the connections between components that are formed (Foster 2005). For example within big enterprises, in order to have a long run competitive advantage, senior managers need to investigate new opportunities through both exploration of new assets and exploitation of existing assets to overcome path dependencies among them. Lack of a vision for explorations within big enterprises makes them vulnerable to technological and market

changes. Managers and organizations need to learn new strategies, try new approaches, and evaluate rigorously failed policies which offer the strongest potential for constructive changes.

The interaction among elements of the socio-economic complex adaptive system is not only limited to human actors, the interaction can also be among processes inside the system.

Based on the information presented so far, it can be stated that the biggest limitation of structuralism approach for the study of socio-economic complex adaptive systems is the lack of proper incentive modeling for the process of link establishment at the micro level. Although the structuralism approach has the potential to tell us what the interesting features of networks are from both theoretical and practical perspectives, the extent, to which such varieties of structural properties affect the outcome of individuals (i.e., learning outcome or utility gain at the individual level), has received little attention. Therefore, in this thesis, we argue that a hybrid approach (based on CAS theory) is needed to study a socio-economic complex adaptive network and to model the interactions among its components. In this thesis we aim to deliver an interaction model to explain and compare the emerging characteristics of the social system within socio-economic complex adaptive networks. This interaction model shows how the combination of a utility scheme, underlying network structures, strategic interaction of the individuals, their heterogeneity in behavior and finally their bounded rationality can result into the changes in emerging characteristics of the social system as well as the outcome of individuals and the whole system. This interaction model is presented in Figure 5.1.

## 1.3. Thesis Objectives and Questions

Our first objective (w.r.t 1st RQ) is to categorize different types of interactions that may lead to the formation and changes of a social system (network) among the members of a socio-economic complex adaptive system. Therefore, we formulate our first research question as:

1. What types of interactions may contribute to the formation of a social system and lead to further changes in its baseline properties?

Our second objective (w.r.t 2nd RQ) is to capture how structural properties of a social system affect the outcome of individuals and the whole system (i.e., learning outcome or utility gain at the individual level). Therefore, we formulate our second research question as:

2. What would be the benefits of having a social system with certain network characteristics?

Our third objective (w.r.t 3rd RQ) is to provide an interaction model for capturing the changes in the utility of individuals within the social system with respect to underlying network structure, different method of network growth, network visibility and strategic responses of individuals within the social system. Our research questions with respect to this objective are presented below.

3. If individuals are entitled to respond to strategies of others within the social system, what can be the effect of having such behaviors on the
    a. Emerging network characteristics?
    b. Outcome of the individuals and the whole system?

## 1.4. Methodology and Contribution

The overall objective of this thesis is to provide an interaction model to capture the change in the structural properties of a social system and the outcome of individuals and the whole society within a socio-economic complex adaptive network. Therefore, we divided this overall objectives in to three sub objectives to address the points we made in the section 1.3. First, by categorizing dynamic processes within a social system and later with the help of stochastic modeling we model the evolution of a social system. We consider the clustering coefficient and average shortest path length of the social system as the emerging characteristics of a socio-economic complex adaptive network. Second, we simulate the collective learning of individuals within the social system to highlight the importance of having social systems with specific structural properties. Third, we add several features such as economic incentive, bounded rationality and heterogeneity in agent's behavior to make our interaction model more in line with the characteristics of socio-economic complex adaptive networks.

To achieve our first objective, in chapter 3 of this thesis, we model the evolution of a social system and measure the clustering coefficient and the average shortest-path length of it. The clustering coefficient is a fundamental measure in social network analysis, assessing the degree, to which nodes tend to cluster together, while the average shortest-path length provides a measure of how close the individuals within the network are. Consequently, we propose the following features that a network growth model should incorporate:

(1) Variability of individuals' behavior patterns (Koohborfardhaghighi and Altmann 2014). The establishment of links of different types needs to be considered due to the differences of behaviors of people in social environments.

(2) Different rate of variability in individuals' behavior patterns (Koohborfardhaghighi and Altmann 2014).

(3) Limitations on the size of personal networks (Koohborfardhaghighi and Altmann 2014).

To achieve our second objective, in chapter 4 of this thesis, we develop an agent-based model to simulate the collective learning of individuals within the social system (Koohborfardhaghighi and Altmann 2014). With this model, the organizational learning performance under different structural properties (i.e., the clustering coefficient and the average shortest path length) of the social system is captured and compared with one another.

The necessity of applying a hybrid approach for the study of socio-economic complex adaptive networks has been the motivation for delivering an interaction model in chapter 5 of this thesis to explain and compare the emerging characteristics of the social system. This interaction model shows how the combination of a utility scheme, underlying network structures, strategic interaction of the individuals and network visibility can result into the changes in emerging characteristics of the social system as well as the outcome of individuals (i.e., learning outcome or utility gain at the individual level) and the whole system. That is to say, by applying a hybrid approach we can make predictions on the benefits of the integration of economic behavior of their agents and their social interactions that result in the emergence of new systemic social qualities. Consequently we can develop mechanisms and techniques that can guide and regulate the evolution of

such systems. To achieve our third objective, in chapter 5 of this thesis, we design an interaction model to show that changes in the utility gain of individuals in a network are consequences of four factors impacting their interactions (Koohborfardhaghighi and Altmann 2016a, Koohborfardhaghighi and Altmann 2016b):

(1) Underlying network structure.

(2) Different strategies of network growths.

(3) Adoption of strategic responses of the network actors towards what others do within the network.

(4) Network visibility, with the idea that higher or lower visibility towards global topology of the network leads to emergence of certain network characteristics.

Key features of our proposed interaction model with respect to this hybrid approach are (Koohborfardhaghighi and Altmann 2016a, Koohborfardhaghighi and Altmann 2016b):

- Heterogeneity of agents
- Working with adaptation (Synchronization and Self-Organization)
- Connectivity
- Bounded rationality of actors
- Feedback loops

That is to say, what actually results in the emergence of new systemic social qualities within socio-economic complex adaptive systems are the integration of economic behavior of their agents as well as the social system within which they interact with each other. Individual actions determine the network structure and similarly structure also influence individual actions and thinking. They constrain and enable actions. Therefore,

there is a feedback loop between individual actions and the network structure. With the help of an agent based modeling approach, we test our interaction model and capture the dynamics among the individuals within a network.

## 1.5. Significance of the Studies

Our simulation results (w.r.t 1st RQ) provide an explanation for the different values of interconnectivity that empirical studies of the famous small world theory have found. Existing research on "small world" theory focused only on calculating the average shortest path length of networks that utilize all the existing connections among people (Ugander, Karrer et al. 2011, Backstrom, Boldi et al. 2012). Therefore, placing limitations on the size of personal networks distinguishes our analysis of the network's average path length from previous analyses in literature. Our hypothesis in this research contributes and plays a major role to the existing research in the sense that we stress the fact that in addition to variability in individual patterns of behavior (having heterogeneity in the population), having limitation on size of personal network leads to changes in the structural properties of a complex network.

Our simulation results (w.r.t 2nd RQ) show that despite the creation of new knowledge and the process of learning at an individual level, organizational structure affects the nature of human interactions and information flow. We show that the social relationships between individuals in an organization can be utilized to produce positive returns. We also show that structural changes within a network of people in an organization affect organizational learning. Therefore, the role of such structural changes within an organizational structure can be considered as a mechanism for increasing the knowledge flow and organizational learning.

Our simulation results (w.r.t 3rd RQ) show that strategic interaction of individuals with an economic motif can affect the utility of the individuals and the whole system as well as further changes in the structural properties of the social system. Therefore, contrary to existing works that demonstrate how simple utility functions produce different network structures from scratch (e.g., from isolated nodes, dyads, or star) (Jackson and Wolinsky 1996, Jackson 2008), or that utilized centrality measures to depict the strength of an agent's position in a network of relationships (Buechel 2008, Bei, Chen et al. 2009, Buechel 2009, Gallo 2012), we focused on the process of network growth and strategic responses of existing network members towards it and we quantify their effects.

## 1.6. Thesis Outline

The following thesis outline provides an explanation of the material contained in this thesis, and of the flow of the thesis, and presents an overview of the contents of this work.

Chapter 2. The mentioned principles and theoretical background on the theory of network formations, organizational learning and complex adaptive systems are discussed in this chapter.

Chapter 3. In this chapter, we deliver a network formation model to address our first research question. With the focus on human to human interactions within our society, we explain the structural changes within a growing social system with respect to social characteristics of individuals (e.g., expanding the social relations beyond an individual's social circles).

Chapter 4. This chapter addresses our second research question. We model a learning organization, in which learning occurs during the interactions of individuals.

With the help of the proposed network formation model in chapter 3, we explain what characteristics of the networks positively or negatively affect the organizational learning performance.

Chapter 5. This chapter addresses our third research question. We deliver an interaction model for human to human communication environments, where the process of network growth triggers a strategic response among existing network members and consequently its effect will be reflected both on the network characteristics and utility gain of the individuals.

Chapter 6. We conclude our thesis with a summary in this chapter. Discussion and limitations of the studies are also presented.

# Chapter 2. Theoretical Background on Network Formation Models

This thesis provides a three-step literature review to present the related works on the dynamic models of network formation.

First part of the literature review in this section covers research papers on stochastic network formation models and the second part focuses on strategic network formation models. In the third part of the literature review we discuss how a complex adaptive system approach would seem to be a promising approach to the study of socio-economic complex adaptive systems comparing to stochastic and strategic network formation models.

Before going into the details of each of mention approaches, let us see first of all what a dynamic model is.

**Dynamic model:** A dynamic model is a mathematical model or a set of rules describing the time dependence of a point's position in space (either physical space or a more abstract idea of space). The network of interactions within a dynamic model is compounded by stochasticity (probabilistically determined variation).

## 2.1. Stochastic Network Formation Models

A Stochastic network formation model follows a stochastic modeling approach which its definition is presented in the following.

**Definition of Stochastic Modeling:** Stochastic modeling concerns the use of probability to model real-world situations in which uncertainty is present (Bartholomew

1967). The network of interactions in stochastic modeling is compounded by stochasticity (probabilistically determined variation).

From the viewpoint of researchers that follow stochastic network formation models, it would be very interesting to propose a stochastic model to produce predetermined structural properties of a network. Therefore, they basically follow the structuralism approach and investigate major topologies of a network and their characteristics.

The essential steps in building stochastic models are: (1) Identifying the sample space; (2) Assigning probabilities to the elements of the sample space; (3) Identifying the events of interest.

The use of a stochastic model does not imply that the modeler fundamentally believes that the system under consideration behaves "randomly". Use of a stochastic model reflects only the best currently available description of the phenomenon under consideration, given the data that is available and the universe of models known to the modeler.

For example, the behavior of an individual in the formation of a certain network topology may appear to be "random", however, by observing the individual behavior we may reveal a set of preferences under which that person's behavior can be explained. In chapter of this thesis, for example, we considered three types of dynamic processes for the formation of online social networks. For this purpose, three parameters (i.e., $P_{GM}$, $P_{FOAF}$ and $P_{RAN}$) are used, which represent the rate of a network growth, the rate of establishing potential links of FOAF-type, and the rate of establishing potential links of random type, respectively.

In this category of literature review, we find mainly different network formation models which are able to produce networks with specific network topologies. Examples include random, regular, preferential attachment, and small-world network formation models.

There are different networks in real world, such as biological networks, social networks, and technological networks. Regardless of the way of representing the relationships among their constituents, a network property (e.g., degree distribution) describes an entire network. According to this property, networks can be classified into being similar or different to each other. Network formation mechanism based on degree distributions can be attributed to different stochastic network growth models. As an example, empirical data on web and social networks show power law degree distributions. The preferential attachment growth model introduced by Barabási and Albert (Barabási, Albert et al. 1999, Albert and Barabási 2002) is capable of generating such power law degree distributions. In that model, new nodes are more willing to link to high degree nodes during the growth of a network. The high degree nodes can be imagined to be nodes with better social skills than the other nodes (Ishida, Toriumi et al. 2008). For example, individuals having more activities in a network would be even more likely to establish relationships with other people with similar social character or social position. However, in some other types of the network the attachment point for the new nodes can be chosen randomly with the same probability of attachment for all nodes (Erdős and Rényi 1959, Erdős and Rényi 1960, Erdős and Rényi 1961). Although a random network formation model is not suitable for all kinds of emerging networks in different scenarios, but there are situations where new kinds of social media platforms give its actors same chance or probability of link establishments to others (e.g., Shake feature in Tango application).

When we look at the topological formulation of different network models presented in the literature, such as Erdős-Renyi Random graph model, Watts-Strogatz Small-World model or Barabási–Albert Scale-Free model, it seems there is no line of communication between the topology of a network itself and the principles underlying strategic choices of the players that are locating in it. Currently those topologies are only explainable by the type of behavior actors of a network generate which are mainly random and preferential attachment. There have been considerable amounts of social network research with the focus on capturing the characteristics of certain networks. Although such researches have the potential to tell us what the interesting features of networks are from both theoretical and practical perspectives, the extent to which such varieties of structural properties affect the outcome of individuals (i.e., learning outcome or utility gain at the individual level), has received little attention in the literature. Having said, such analysis are done independent of capturing the causes of the observed features. Those issues will be addressed in chapter 3, 4 and 5 respectively.

### 2.1.1. Limitation on the Size of Personal Network

The emerging network of people in the society, which is a product of their interactions, can be seen as a map that connects each of us with other people. Since 1991, it has been an important issue to find out to what extent people are connected. Stanley Milgram, in his famous experiments (Milgram 1967, Travers and Milgram 1969), was interested in computing the distance distribution of the acquaintance graph. The main conclusions outlined in Milgram's paper were that, depending on the sample of people chosen, the average path length of individuals within the network is smaller than expected. Despite the existence of some empirical studies on the small world theory, the results

obtained in various empirical environments are not consistent with the magic number six. A summary of the reported values on average path length of the networks which were under study is presented in Table 2.1.

Dodds et al. performed a global social search experiment to replicate small-world hypothesis and showed that social searches could reach their targets in a median of five to seven steps. They classified different types of relationships and observed their frequencies and strength. The result of their analysis showed that senders preferred to take advantage of friendship rather than family or business ties. It also indicated the fact that the origin of relationships mainly appears to be family, work, or school affiliations. Furthermore, strengths of the relationships were fairly close. Therefore, we can say that the most useful category of social ties were medium-strength friendships that originated in social environments (Dodds, Muhamad et al. 2003). Backstrom et al. repeated Milgram's experiment by using the entire Facebook network and reported the observed average distance of 4.74, corresponding to 3.74 intermediaries or "degree of separation" (Backstrom, Boldi et al. 2012). The study indicates the fact that various externalities such as geography have the potential to change the degree of locality among the individuals and, finally, increase or decrease the average path length. Ugander et al. studied the anatomy of the social graph of Facebook and computed several features of that (Ugander, Karrer et al. 2011). Their main observations showed that the degrees of separation between any two Facebook users are smaller than the commonly cited six degrees, and, even more, it has been shrinking over time. They also found that the graph neighborhood of users has a dense structure. Furthermore, they found that there is a modular community structure driven by nationality.

The result reported by Backstrom et al. can be considered as admissible evidence that technology can shrink the world (Backstrom, Boldi et al. 2012). However, we argue that just because the network among people becomes denser than before, it does not mean that there is an increase in the trust between the individuals within the network. People still have to manage their connections. It requires spending time and effort to maintain them. Another issue, which should be considered, is that, if we do not have many people that we can really trust among our existing connections, we are not able to send critical information since utilization of all the existing connections would be costly, therefore, we need to spend our time and effort productively. Actually that is a point where Kleinfeld argues that the low success rate in Milgram experiments is disappointing (Kleinfeld 2002). Some experiments revealed a low rate of chain completion and majority of chains died before reaching the target point. He considered the possibility that people could have gotten connected but they just did not bother to forward the information to other intermediaries. Therefore, in the chapter 3 of this thesis, we build our own hypothesis based on the discussion so far. We test the hypothesis that putting limitation on the size of personal networks (having few trusted friends) lead to an increase or decrease in the structural properties of a complex network.

| **Study** | **Reported Average Path Length** |
|---|---|
| (Milgram 1967, Travers and Milgram 1969) | 5 |
| (Dodds, Muhamad et al. 2003) | 5~7 |
| (Backstrom, Boldi et al. 2012) | 4.74 |
| (Ugander, Karrer et al. 2011) | 4.7 |

Table 2.1: Empirical studies on the small world theory.

Among the literature reviews related to the size of personal network, we can point to the work performed by Aristotle, who noted that warm friendship is only possible with a few people (Rackham 1996). Therefore, “The number of one's close friends must be limited”. Several studies pointed to the fact that the maintenance of social networks is not costless and, depending on the type of the network being modeled, it results in cut-offs in real networks (Watts and Strogatz 1998, Amaral, Scala et al. 2000, Barthélemy 2003, Gilbert 2006).

### 2.1.2. Exploration & Exploitation within a Social Structure

As the resulting social network of individuals within an organization is a product of its constituents’ interactions, the structural analysis of such a network is possible. It is an indicator of various roles, the hierarchy of these roles, and the distribution of power and authority within an organization. Therefore, during the structural analysis, we encounter the network structure and the location of people within it. Based on this, we observe collective learning, which can be internal as well as external to an organization.

With the development of science and technology, the business environment has become a challenging and competitive one. In such an environment, it is natural to see changes in the context of competition. The greatest competitive advantage in this new business environment is learning. Hence, the only way for an organization to overcome the uncertainty, complexity, and dynamics in the business environment is to have a competent and efficient workforce. The workforce is considered to be an important asset of an organization and the foundation of wealth. Thus, organizations are more successful, if they learn faster than their competitors. That is why more and more organizations

employ learning as a competitive advantage. The learning is a combination of exploration and exploitation of knowledge.

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 organization decision making(March 1989, March 1994). Similar to recent researches in this area(Lewin, Long et al. 1999, Fleming 2001, Crossan and Berdrow 2003, Siggelkow and Rivkin 2005, Gupta, Smith et al. 2006, Jansen, Van Den Bosch et al. 2006, Miller, Zhao et al. 2006, Argote and Greve 2007, Kane and Alavi 2007), Fang et al. point to the problem of trade-off between exploration and exploitation in organizational learning (Fang, Lee et al. 2010). According to their model, individuals have the choice either to explore the environment by themselves for achieving the organizational goal or to take part in social activities (which can be regarded as exploitation). The detailed research question, which they investigated in their model, is: "Does a semi-isolated subgroup structure improve the balance of exploration and exploitation, leading to superior long-term learning performance outcomes?" Their research results showed that a modest amount of cross-group linking is associated with a high performance level in learning.

According to organizational learning theory, an organization is considered to be an adaptive system, which is able to sense changes from the environment and evolve to produce the desired outcome. Therefore, a learning organization actively creates, stores, transfers, and uses 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" (Senge 2006), which describes his vision of systems thinking and learning organizations. In the literature, we can find various proposals for models that

facilitate organizational learning (Argyris and Schön 1978, March 1991, Kofman and Senge 1993, Bontis, Crossan et al. 2002, Nonaka 2008). One of those models is the one of March (March 1991). March's model, which we follow in this study, captures the development and diffusion of organizational knowledge as a consequence of individuals' socialization.

Successful implementation of knowledge management requires a flexible structure, which facilitates and speed up collective learning. Having a flexible social structure is an important element in the organizational structure in the sense that it provides team members with a chance for knowledge exchange with other team members who have the same interest or similar knowledge. Moreover, it can be considered as a strategy for improving organizational learning performance. A lot of research has been done to determine critical success factors of knowledge management implementations. However, we contend that these critical success factors do not pay sufficient attention to the social networks of people. There is a meaningful social network, through which people communicate with one another. Through this interpersonal learning in an organization, knowledge exploitation mainly happens. In order to understand how such networks affect organizational learning, we need to clarify first of how such networks are formed and what characteristics of the networks affect positively or negatively affect organizational learning. This issue will be covered in chapter 3 and 4 of this thesis.

## 2.2. Strategic Network Formation Models

In the context of strategic network formation models, researchers try to identify the effects of individuals' strategic interactions on the upcoming network structures. Three major categories of topics in this area are network games (Galeotti, Goyal et al. 2010),

public good provision (Rittenberg 2009), and bargaining and power in networks (Jackson 2008). Each of these topics can be represented with different theoretical models.

Game theoretic models have been proposed to analyze the strategic interactions of individuals in a network. From this point of view, each individual in a system obtains a utility due to its interaction with others in the network. The utility is defined through a utility function (utility function) and it describes the level of an individual's utility from interactions with others. For example, the utility function might consider the number of connections or the distance between the source and the destination. The utility can also be used to measure the social welfare (i.e., a society's collective utility), which represents a level of well-being of an entire society.

A comprehensive introduction to social and economic networks has been offered by Jackson (Jackson 2008). He presented different strategic link establishment models, in which choices of individuals have an impact on the topological features of the network (Jackson and Wolinsky 1996). Two examples are the symmetric connection model and the co-author model [8].

Symmetric connection model is a model, in which individuals directly communicate with their direct contacts and the obtained utility of an individual through interactions with others are proportional to his or her distance to the target players. As this distance increases, the obtained utility decreases. The symmetric connection model always produces positive externality for the individuals within the network. Variations of symmetric connection models are also presented in the literature. They are degree-distance-based versions or have negative externalities (Morrill 2011, Möhlmeier, Rusinowska et al. 2013).

Co-author model focuses on the collaboration among the individuals. All the obtained utilities for the individuals in the co-author model are due to the collaboration with direct contacts, and there is no utility for communicating with indirect contacts. In the co-author model (Jackson and Wolinsky 1996), the utility function is defined in a way to encourage the cooperation between two individuals. That means, two isolated individuals do not receive any utility in case of no cooperation but, as soon as they establish a link with each other, the co-author utility function assigns a positive utility to both parties. However, the co-author model negatively changes the pay-off of other indirect neighboring individuals within the network. For example, if a new individual joins the network and establishes a link with an existing node, the receivers of the link gain a credit, while the neighbors of the existing node face a lower utility due to the negative externality caused by the co-author utility function. Therefore, contrary to the symmetric connection model, individuals do not receive positive externality from establishment of the indirect links in the network.

Strategic complements and strategic substitutes are also two specific classes of network games, in which every player wishes to adjust her action in response to the activity of other players (Galeotti, Goyal et al. 2010). The decisions of two or more players are called strategic complements, if they mutually reinforce one another, and they are called strategic substitutes, if they mutually offset one another.

A strategic complement model shows the tendency of the network participants to follow actions or beliefs of others. It is based on the idea that a given player's relative utility of taking an action increases in the context of neighbors who took actions. In fact, the decision of some people in a network can have a positive effect on the choices of other members of the network.

Under a strategic substitute model, network participants tend to take the opposite choices of others. They do not adopt their decisions. Lamberson presented a model of friendship-based games played on a social network (Lamberson 2011). It allows games of strategic complements and strategic substitutes. Finally, a comprehensive tutorial on strategic substitute models has been introduced by Michael et al. (Michael and Battiston 2009).

In addition to these game theoretic models, some studies linked individuals' incentives for establishing links with the target node's structural importance. Therefore, in such cases, the utility function depends on the centrality measure. Konig et al. (König, Tessone et al. 2009) presented a link establishment model, in which links are formed on the basis of agents' centrality. Other studies investigated centrality measures even further (Freeman 1978, Borgatti 2005, Borgatti and Everett 2006, Buechel 2008, Newman 2008, Bei, Chen et al. 2009, Gallo 2012), showing some instability of the network structure. Buechel (Buechel 2009) proposed a model, in which individuals strive for two types of benefits measured by closeness and betweenness centrality.

Compared to these studies, our proposed interaction model in chapter 5 is based on complex adaptive system theory and aims to captures the changes in the utility gain of individuals in an evolving network. Changes in the network structure (network evolution) in our interaction model are consequences of four important factors: which are mainly: (1) initial underlying network structures; (2) process of network growth; (3) adoption of strategic interactions of individuals; and (4) network visibility. Furthermore, strategic interactions of the individuals are modeled as a utility maximization behavior in response to what others have performed within the network.

## 2.3. Complex Adaptive System Approach

In its most simple form, complex adaptive system approach is a way of analyzing the functionality of systems by recognizing complexity, patterns and interrelationships among the component of the system. The study of complex phenomena is applied to economics (Gintis 2006), psychology (MacLennan 2007), biology (Weisbuch 2006), and natural sciences and over the past decade, the concepts have started to be used more extensively in healthcare (Rouse 2008, McDaniel, Driebe et al. 2013), education (Smith and Palmberg 2009), organization and social science (Eidelson 1997, Schneider and Somers 2006).

The most common definition of a complex adaptive system, based on the work of John Holland, is a dynamic network of agents acting in parallel, constantly reacting to what the other agents are doing, which in turn influences behavior and the network as a whole (Holland 1975, Holland 2006). Control tends to be dispersed and decentralized and the overall behavior of the system is the result of many decisions made constantly by individual agents(Waldrop 1993).

Complex adaptive systems thinking suggests that the agents in any system are all the components of that system and interact and connect with each other in unpredictable and unplanned ways.

The characteristics of complex adaptive systems include:

- a large number of elements which interact dynamically
- any element in the system is affected by and affects several other systems
- nonlinear interactions, so small changes can have large effects

- openness, so it may be difficult to define system boundaries
- a history whereby the past helps to shape present behavior
- elements in the system are not aware of the behavior of the system as a whole and respond only to what is available or known locally.

In comparison to stochastic modeling and strategic network formation models, the Complex Adaptive Systems approach characterizes the following concepts: (1) System (2) Adaptivity and (3) Complexity. A System is a representation of individual entities interacting with each other. An entity in a system is characterized by its state, its transition rules, its behavior and finally a context within which the entity is presented. A system evolves in time due to the local state transition (local state changes) of its individual entities. Adaptivity implies that the system is both flexible and robust and it shows the capability of a system or its entities to perform tuning behavior in contingent situations. Such systems are open and situated, which are important driving force for complexity. As we can see, the Complex Adaptive Systems approach helps the system modeler in investigating both the characteristics of individual entities at the micro level and their interacting forces at the meso and macro levels. In addition to that it considers the feedbacks in interactions during the system analysis. That is why it can be considered as a hybrid approach.

Examples of complex adaptive systems may include the healthcare organizations(Rouse 2008, McDaniel, Driebe et al. 2013), communities, political parties, the brain (Morowitz and Singer 1995), the immune system (Ahmed and Hashish 2006), the stock market (Mauboussin 2002), the ecosystem (Levin 1998, Levin, Xepapadeas et al. 2013), and any human social group endeavor (Eidelson 1997). However, some might argue that not all of these things share every characteristic of complex adaptive systems.

Out of the empirical studies investigated within the scan, few of the systems neatly or unquestioningly corresponded to all of the properties of complex adaptive systems.

Despite mentioned characteristics of complex adaptive systems above, socio-economic complex adaptive networks have several interesting features that distinguish them from general classes of complex adaptive systems (CAS). Therefore, study of network dynamics among agents requires the additional of a whole new sets of parameters to our network growth models. For example, an economic model exists within the diverse economic elements of socio-economic complex adaptive networks and basic psychological biases also cause major deviations from rational behavior. Therefore, it is not a safe to assume that agents follow the same pattern of behaviors. In such networks due to the path dependency among the elements of the system, we are able to observe inflexibility and mal adaptiveness in the structure. Finally, the evolutionary process that such a system experiences can only be understood in an explicit historical time dimension. Therefore, in this thesis we argue that understanding, designing, and managing socio-economic complex adaptive networks require an in-depth understanding of the economic behaviors of their agents as well as the social system, within which the arrangement of social interactions of their agents are identified.

Table 2.2 summarizes different views on the network formation models (stochastic vs strategic network formation models), and it compares them with respect to main characteristics of the proposed approach for studying socio-economic complex adaptive networks. As we can see, lack of having a proper economic incentive modeling is obvious within stochastic network formation models. We assume that Scale-free model (Barabási, Albert et al. 1999, Albert and Barabási 2002) is the only stochastic network formation model in the literature that slightly point to this economic incentive modeling

feature, it is not mentioned explicitly in the literature though. Our assumption is based on the specific network growth model of a Scale-free network. It consider the probability of link establishment to be related to cumulative degree distribution of the nodes within the network. Therefore, we think having such a preference for connecting to high degree nodes (actor's centrality) can be a sort of economic incentive modeling. Time has a certain role in the evolution of such networks and as time goes by network evolution impacts individuals' future choices. Having said that is it difficult to make such an assumption for other network models in this category (i.e., small-world or random network). Strategic network formation models do not have such limitations, they are perfectly designed to target an economic feature among network actors. Utility maximization for example, can be considered as a sort of an economic incentive for the process of link establishment. What is missing in strategic network formation in fact is the lowest flexibility in modeling heterogeneity. Usually such models assume that all the individuals follow the same behavior or the same economic model as others. Following our line of arguments, we believe that a complex adaptive system approach would tackle limitations of both stochastic and strategic network formation models.

In this thesis, we consider the clustering coefficient and average path length as the emerging characteristics of a socio-economic complex adaptive network. We aim to capture and explain the changes in those emerging characteristics as the agents in the system interact in not apparently random ways but with a proper incentive modeling. Out of all those interactions final network characteristics emerge which ultimately determine the outcome of the individuals as well as the whole system. Consequently, change in the behavior of the agents happen and will be feedback to the system itself.

In the following chapters we first highlight the importance and necessity of capturing the economic incentives among component of the socio-economic complex adaptive system, as well as the importance of connectivity pattern among the elements of such system. Our focus is on human-to-human communication environments, where the process of network growth requires an economic inventive and the process of link establishment among network members are not random. We consider them strategic responses towards what others are doing within the network. We also discuss the applicability and necessity of applying a hybrid approach in the theory of network formations. Finally, we show how the emergence of certain network characteristic affect the outcome of the individuals (i.e., learning outcome or utility gain at the individual level) within socio-economic complex adaptive networks .

| Approach | Category | Model | Incentive Modeling | Preference | Heterogeneity | Nonlinear Interactions | Feedback Loops | Presence of a History | Imperfect Knowledge (Bounded Rationality) | Strategic Responses of Actors |
|---|---|---|---|---|---|---|---|---|---|---|
| **Structuralism Approach** | Stochastic Network Formation Model | Erdős-Renyi 1959 Random graph model | × | Random | √ | × | × | × | × | × |
| | | Watts-Strogatz 1998 Small-World model | × | Actor's Centrality | √ | × | × | × | × | × |
| | | Barabási–Albert 1999 Scale-Free model | Node Structural Importance | Actor's Centrality | √ | √ | √ | √ | × | × |
| **Individualism Approach** | Strategic Network Formation Model | Jackson 1996, Symmetric connection model & Co-author model | Economic Incentive Modeling | Utility Maximization | × | × | √ | √ | × | × |
| | | Konig et al 2009 | Economic Incentive Modeling | Actor's Centrality | × | × | √ | √ | × | √ |
| | | Buechel 2009 | Node Structural Importance | Actor's Centrality | √ | × | √ | √ | × | × |
| | | Strategic complement & Strategic substitute | Threshold based | complementing or substituting others | × | √ | √ | √ | × | √ |
| **Combination of Structuralism & Individualism Approach** | Complex Adaptive System approach | Proposed Interaction Model in chapter 5 (Koohborfardhaghighi and Altmann 2016a) | Economic Incentive Modeling | Utility Maximization | √ | √ | √ | √ | √ | √ |

Table 2.2: Different views on the network formation models and their comparisons.

# Chapter 3. Identification of Features that a Network Growth Model Incorporates

Assuming a complex network is a product of its constituents' interactions, the first question that comes to mind is what kinds of interactions take place within it and how these interactions can be categorized. This is a motivating for generating our first research questions in this thesis that is:

What types of interactions may contribute to the formation of the social system (network of connectivity) within humans and lead to further changes in its baseline properties?

As we know, a social network visualizes social activities of users. In such networks, the nodes and links respectively represent the users and the relations among individuals. Accordingly, the social distance between any source individual and destination individual within the network can be utilized for categorization of their relations. This means that different degrees of friendship relations can be observed in the social circle belonging to each person. For instance, only intimate or degree-1 persons who have either familial bonds or share identical or similar social character and personality with the respective person are observed in the social distance equal to 1. These relationships might be established in the living, working, and almost everywhere. On the other hand, in larger social distances such as Friend of a Friend (FOAF), the persons become more socially distant but it is not necessarily concluded that individuals with similar characteristics cannot be found. The user is merely unaware of their presence. It is interesting to note that the social networking platforms including Facebook attempt to reduce these social distances as daily extension of social activities takes place. Once any

user specifies its social circle after registering in the respective websites, the feature "Recommendation of a Friend of a Friend" enables the users to develop their social circles, and for example, to change their social distance from 2 to 1. This is by itself very desirable but it shall not be neglected that providing positive feedback towards such processes certainly leaves significant impacts on the properties of a network. According to the above discussions we present our hypothesis as follow:

*"The interactions among constituents of a network can be regarded as dynamic processes which lead to changes in its baseline properties".*

There are different networks in the real world, such as biological networks, social networks, and technological networks. Regardless of a network's ability to represent the relationships among their various constituents, a network global property such as degree distribution can be the factor that makes them similar to each other or differentiates them from one another through the analysis. Formation mechanism of these degree distributions can be attributed to their different growth models. As an example, web and social networks have power-law degree distributions. The preferential attachment growth model (GPA), introduced by Barabási–Albert (Barabási and Albert 1999, Barabási, Albert et al. 1999) is capable of generating such power law degree distributions. In this model, new nodes are more willing to link to high-degree nodes during the growth of a network. The high-degree nodes can be imagined as nodes with better social skills compared to others (Ishida, Toriumi et al. 2008). The individuals having more activities in a social networking platform would find more friends or are even more likely to establish relationships with other persons with regard to social character or social position, whereas a huge number of users lack such capabilities. However, in some other types of the network the attachment point for the new nodes can be chosen randomly with the same

probability of attachment for all nodes. Having said that, the process of a network growth does not only depend on the method of new node's entrance but also on the establishment of new links between existing individuals within the network. Definitely, these interactions could also play a substantial role in the formation of networks. Based on the former discussions, our hypothesis can be a little extended as:

*"Dynamic processes in turn can be categorized in two groups (1) the process which occurs during growth of a network and represents the tendency of new users to establish links to other members upon entry into a network; (2) The process which occur among the users of a network in order to establish potential links".*

It must be noted that a few models have been offered in literature since mid-19th century based on random linking (Erdős and Rényi 1959, Erdős and Rényi 1960, Erdős and Rényi 1961). The respective models are able to create networks with bell shape or Poisson degree distribution. Although these networks are characterized by their own unique properties, the connections among constituting users in social networks can be hardly referred to as "random". Undoubtedly, adoption of a random network formation model for a growing social network is not an appropriate practice. But, paying attention to the issue more closely, the significance of such random patterns is obviously perceived. As users of a social network, we might attempt to establish relationships with individuals of social distance 1 or 2, but we sometimes realize that our social circle can be easily expanded through getting familiar with strangers in the society as well. For example, an academic professional might meet a broad range of new users with whom s/he share similar characteristics while travelling from a country to another with the purpose of a research work, paper presentation, career mission, and so forth, providing the context for random links. If it is agreed here upon the existence of such random patterns, the question

is posed about the rate or level of influence of the respective processes on the baseline properties of a network. Based on the summary of arguments in this part, our hypothesis can be extended and completed as such:

*"The process which occur among the users of a network in order to establish potential links are also divided into two categories; (a) the first category includes establishment of potential links of FOAF type with social distance equal to 1 and (b) the second category includes establishment of random potential links with other users, who are present in a network".*

Having said that, a personal network in the real world comes with the cost of maintaining the relationships. Therefore, the question rises what could be a genuine size of a personal network? Is it the so-called Dunbar number (i.e., the rule of 150 connections) (Dunbar 1992)? If we think about the size of personal networks, we can agree on that the sizes are different among people. The agreement for variation is based on the fact that individuals have various abilities to make friendship connections. Furthermore, we naturally let go of old ones, which no longer work, at different rates. Therefore, the fraction of the friends that we contact regularly and the fraction of the friends that we find sufficiently attractive for long-term relationships are different across people. We can say that our close friends are people that have a mutual attraction with us. No matter what kinds of attractions causes a true relationship, as it may vary from person to person, the most important fact is that (1) it could be explored and developed over time and that (2) the attractiveness threshold is different from person to person. The attraction concept gives people a chance of link establishments. For example, if we want to have a great deal of control over the ones who truly matter, we need to serve a purpose to them. Otherwise, they will terminate the relationship. In this regard, the maintenance of our personal

network is not costless. It requires spending time and effort to maintain such a relationship. This way, we gradually figure out who our real and close friends are. Consequently, there is a limit on how many close friends one can have. Besides, social interactions among people form social networks of friends. In the real world, our first-degree connections are the people that we personally know and our second-degree connections are friends of our friends (FOAF).

In the real world, it is unrealistic to assume that we know the third-degree connections (i.e., the friends of our FOAF). Social networking platforms such as Facebook, however, provide us with the opportunity of navigating larger chains of connections. If we consider our trusted contacts only, the can reach less people only due to their low number. In this context, the small world theory has been criticized. One of the most popular criticisms is related to the type of the item that was sent to the target people during Milgram's experiments (Milgram 1967, Travers and Milgram 1969). In fact, Kleinfeld argues that what the type of item (e.g., passport or letter) could make a significant difference in whether and how it reaches their targets (Kleinfeld 2002). Although the focus of Kleinfeld's discussion is on the incentive to forward the item, we think that, depending on the type of the item, it can even be propagated through different kinds of people. For example, with respect to a regular letter, the letter could be transferred through people we know, but, with respect to a passport, the passport would be transferred through trusted contacts only. As we discussed, the number of trusted people is a relatively small number and, therefore, requires more steps.

Taking each of the discussed key elements into account, we propose the following features that a network growth model should incorporate:

1. Variability in individual patterns of behavior: The establishment of links of different types needs to be considered due to the difference of behavior of people in social environments.

2. Different rate of variability of new node entrance and link establishments: The rate, at which people join a network, is different than the rate of link creation among existing ones.

3. Limitations on the size of personal networks: The number of trusted contacts is smaller than the number of known contacts. With this, we follow the idea that human behavior is the key to formulate a realistic network growth model. To test these realistic network growth models and to measure the structural property (i.e., the average path length) of the network as a function of time, we developed a simulation environment.

Our major research question at the beginning of this chapter leads us to further sub research questions like: How the rate of influence of these dynamic processes (proposed features) impacts the baseline properties of a network. With respect to our contribution, a generative model is proposed for analyzing the influence rate of a network's growth model, the establishment of FOAF, Random type potential links and Limitations of the size of personal network on the baseline properties of a network. Based on our simulation analysis, these three parameters play a definite role in the formation of final properties of a complex network.

## 3.1. Model

The proposed model is a generative model based on the ideas that individual pattern of behavior in social environment is the key. This model can generate a network, in which the members follow the classical preferential attachment (i.e., attractiveness of

each individuals is modeled by preferential attachment rule (Barabási and Albert 1999, Albert and Barabási 2002)) for connecting to other users. Furthermore, the users in this model have the ability to create potential links. Preferential attachment rule is used to model a situation, where some people have more attractions compared to others. A preferential attachment rule says that a new vertex is linked with already existing ones with probabilities proportional to their degrees. For this purpose, three parameters (i.e., $P_{GM}$, $P_{FOAF}$ and $P_{RAN}$) are used, which represent the rate of a network growth, the rate of establishing potential links of FOAF-type, and the rate of establishing potential links of random type, respectively. This process is shown in the following diagram.

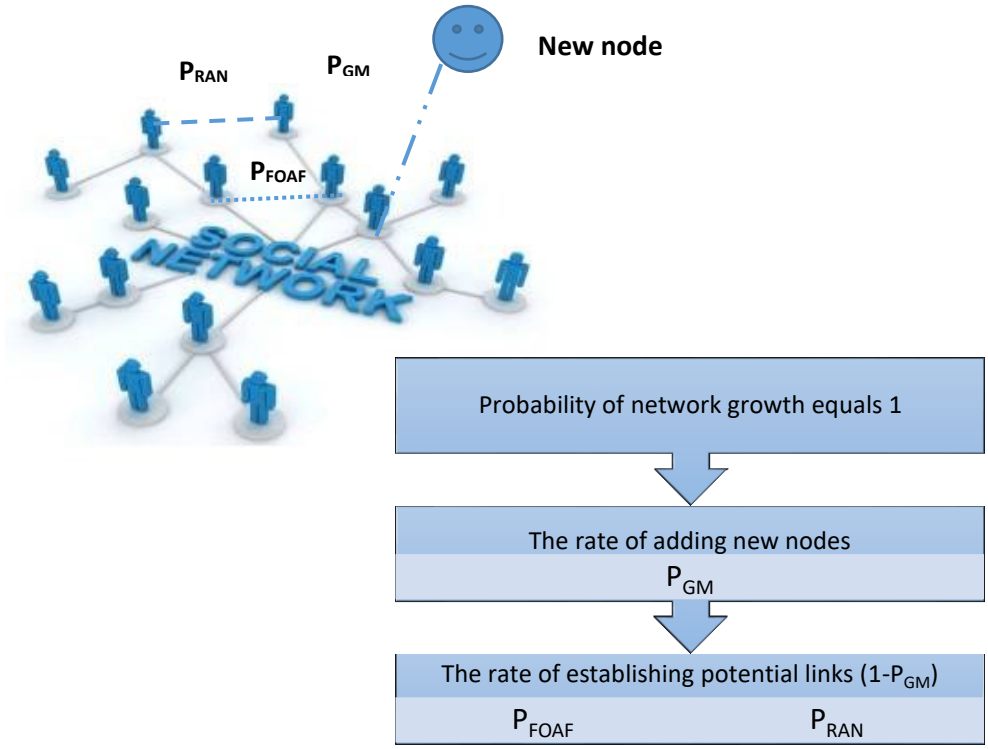



Diagram. 3. 1. A generative model is proposed for analyzing the influence rate of a network's growth model, the establishment of FOAF, Random type potential links.

The value of $P_{GM}$ determines the rate of a network growth. For example, if $P_{GM}$ = 0.25, it signifies that the rate of newly entered individuals is 25% and for 75% individuals have the chance of creating links among themselves.

The value of $P_{RAN}$ is assumed to be equal to 1 - $P_{FOAF}$. Thus, if the value of the $P_{FOAF}$ parameter equals 1, no random link formation process exists in the generative model. These parameters have values in the range [0, 1] and represent the rate of establishing potential links of random and FOAF-type. For example, if $P_{FOAF}$ = 0.5, it signifies that the probability of random link formation or conversion of a link with social distance of 2 to a link with social distance of 1 is 50%. The size of the personal network ($S_{PN}$) is set to 5, 10, 15, and 20, respectively. Such a network modeling approach enables us to simulate and profoundly comprehend the dynamic transformations of a network and its effects on the network's structural properties. The pseudo-code of our stochastic network formation mode is given in Algorithm 1.

| **Algorithm 1: Generating a network with the proposed model** |
|---|
| **Input:**<br>**Initialize N, $S_{PN}$, $M_{NG}$, $P_{GM}$, $P_{FOAF}$, $P_{RAN}$** //N is set to 2 and is the number of nodes at the initial stage of network growth. We set a dyad with 2 initial nodes and then we let it grows. $S_{PN}$ is the size of personal network and its value is selected from the range [5, 10, 15, 20], $M_{NG}$ is the method of network growth and it has two values, "Preferential" and "Uniform". $P_{GM}$, $P_{FOAF}$ and $P_{RAN}$) are used, which represent the rate of a network growth, the rate of establishing potential links of FOAF-type, and the rate of establishing potential links of random type, respectively. |
| **Output:** Clustering coefficient and average path lengths of the network |
| **At each iteration:** |
| a) **CREATE-NEW-NODE** *m* **WITH** probability $P_{GM}$<br>**IF** $M_{NG}$ = "Preferential"<br>**[**<br>**SET** node *i* **ONE-OF NODES WITH** probability $\boldsymbol{p_i} = \frac{\boldsymbol{k_i}}{\sum_j \boldsymbol{k_j}}$<br>**IF COUNT LINK-NEIGHBORS OF** node *i* <= $S_{PN}$<br>**[ASK** node *m* **CREATE-LINK-WITH** node *i***]**<br>**]** |

| | |
|---|---|
| | **ELSE** // *if* $M_{NG}$ = *"Uniform"*<br>**[**<br>**SET** node *i* **ONE-OF NODES**<br>**IF COUNT LINK-NEIGHBORS OF** node *i* <= $S_{PN}$<br>**[ASK** node *m* **CREATE-LINK-WITH** node *i***]**<br>**]**<br>**ENDIF** |
| b) | **IF** $P_{FOAF}$ > $P_{RAN}$ //with probability $P_{FOAF}$ create a potential link of FOAF type<br>**[**<br>**SET** node *s* **ONE-OF NODES WITH [COUNT LINK-NEIGHBORS]** <= $S_{PN}$<br>**SET** node *t* **ONE-OF LINK-NEIGHBORS OF LINK-NEIGHBORS OF** node *s* **WITH** (*s*!= *t* )<br>**AND** (**COUNT LINK-NEIGHBORS OF** node *t* <= $S_{PN}$ )<br>**ASK** node *s* **CREATE-LINK-WITH** node *t*<br>**]**<br>**ELSE** //with probability $P_{RAN}$ = 1- ($P_{FOAF}$) create a potential link of Random type<br>**[**<br>**SET** node *s* **ONE-OF NODES WITH [COUNT LINK-NEIGHBORS]** <= $S_{PN}$<br>**SET** node *t* **ONE-OF NODES WITH ([COUNT LINK-NEIGHBORS]** <= $S_{PN}$ ) **AND** (*s*!= *t* )<br>**ASK** node *s* **CREATE-LINK-WITH** node *t*<br>**]**<br>**ENDIF** |
| c) | **REPORT** Network_Average _Path _Length<br>**REPORT** Network_Clustering_Coefficient |

## 3.2. Network Measures

In this study, the emerging network characteristics are the clustering coefficient (CC) and average shortest-path length (AVL).

Shortest-path length is defined as the shortest distance between node pairs in a network (Albert and Barabási 2002). Therefore, average shortest-path length, AVL, is defined as the following equation:

$$AVL = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} l_{ij}$$

where N is the number of nodes, and $l_{ij}$ is the shortest-path length between node i and j.

The clustering coefficient of a node i, $C_i$, is given by the ratio of existing links between its neighbors to the possible number of such connections (Albert and Barabási 2002). Thus, the clustering coefficient, $C_i$, is defined as the following equation:

$$C_i = \frac{2E_i}{k_i(k_i - 1)}$$

where $E_i$ is the number of links between node i's neighbors, and $k_i$ is the degree of node i, meaning the number of links connected to node i. Averaging $C_i$ over all nodes of a network yields the clustering coefficient of the network (CC). It provides a measure of how well the neighbors of a node are locally interconnected.

## 3.3. Experimental Setup

Three parameters (i.e., $P_{GM}$, $P_{FOAF}$ and $P_{RAN}$) are used, which represent the rate of a network growth, the rate of establishing potential links of FOAF-type, and the rate of establishing potential links of random type, respectively. This process is shown in the following diagram.

The value of $P_{GM}$ determines the rate of a network growth. For example, if $P_{GM} = 0.25$, it signifies that the rate of newly entered individuals is 25% and for 75% individuals have the chance of creating links among themselves.

The value of $P_{RAN}$ is assumed to be equal to 1 - $P_{FOAF}$. Thus, if the value of the $P_{FOAF}$ parameter equals 1, no random link formation process exists in the generative model. These parameters have values in the range [0, 1] and represent the rate of establishing potential links of random and FOAF-type. For example, if $P_{FOAF} = 0.5$, it signifies that the probability of random link formation or conversion of a link with social distance of 2 to a link with social distance of 1 is 50%. The size of the personal network ($S_{PN}$) is set to 5, 10,

15, and 20, respectively. We conduct a multi-agent-based simulation in Netlogo (Wilensky and Evanston 1999), in order to test our model and answer our research question.

## 3.4. Experimental Results

### 3.4.1. Different Rates of Variability in Individual Patterns of Behavior

The properties of the networks derived from the generative model are computed over 10 suits of experiments and the average results are plotted on the diagrams. The model was tested with thirty configurations, which were compared with one another. The Figure 3.1(A-F) belongs to preferential attachment growth style ($P_{GM}$ = preferential attachment strategy) and Figure 3.2(A-F) corresponds to random growth ($P_{GM}$ = uniform attachment strategy). The x-axis shows the simulation period while the y-axis represents the CC value and the AVL value, respectively.

As seen in the successive series of the results in Figure 3.1(A-F), generally CC value decreases and AVL value increases with increase in $P_{GM}$ value (rate of a network growth with preferential attachment style). In the early stage of the simulation, network's clustering coefficient and average path length have a significantly greater variability in their values and as times goes by, the rise and fall of the curves are much steadier.

The Figure 3.2(A-F) demonstrates an analogous trend but it is noteworthy that the results for CC and AVL values are different from the one in Figure 3.1. Discrepancy in the results reflects the influence of different network growth models on its network properties.

As it can clearly be observed, the networks derived from preferential attachment growth model always have smaller AVL and larger CC values compared to the random

one, which in turn indicates influence of growth model parameter on the network properties. The ranges of CC and AVL values of the preferential growth model are [0.03-0.58] and [2.8-6], respectively. The ranges derived from the random growth model are [0.01-0.52] and [3.1-7.9], respectively.

Furthermore, as our objective is also to investigate the influence of the social circle through the establishment of potential links of FOAF and random types in addition to network growth models, we also assign the values [0.25, 0.5, 0.75 and 1] to parameters $P_{FOAF}$ and $P_{RAN}$ embodied in the model. As mentioned earlier, the $P_{RAN}$ value is always assumed as complement of $P_{FOAF}$.

Considering Figure 3.1(A-C) and Figure 3.2(A-C), it is clear that the CC values consistently decline with decrease in value of FOAF-type links and involvement of random links regardless of the $P_{GM}$ value. Nevertheless, if it is intended to analyze the simultaneous impact of the growth model and the previous process, these Figures suggest that the CC value reaches its minimum with an increase in influence of growth model and reduction in influence of FOAF-type links and also with an increase in influence of random links (Figure 3.1(C) and Figure 3.2(C)).

Additionally, the CC value increases with the reduction in the influence of the growth model (Figure 3.2(A-B) and Figure 3.1(A-B)). It must be also noted that CC value reaches its maximum in early simulation stages due to a small population size, and afterwards, oscillation is observed in CC value.

Although the trend of the influence of the growth model and other parameters on AVL value can be similarly explained, it seems that the influence is more intricate than the case for CC. Nonetheless, the AVL value decreases as a result of fixing influence rate

of growth model and reducing the influence of FOAF-type links (Figure 3.1(F) and Figure 3.2(F)).

Summary of the obtained results of Figure 3.1 and Figure 3.2 is presented in Table 3.1. As we can see from the data, the uniform node attachment strategy has the potential to create networks with higher average path length. On the other hand, the level of clustering coefficient is slightly higher in networks which are generated by preferential attachment strategy. Furthermore, by comparison of the results showed in Table 2.1 and Table 3.1 one can easily see that our model provides more insight into the emerging properties of the network and it can explain by which parameter configurations we can expect such properties to emerge. For example, with the following configuration we can expect the network average path length to be a high or low value.

| **Uniform Node Attachment Strategy (AVL)** | **$P_{FOAF} = 1$** |
|---|---|
| **$P_{GM} = 0.75$** | **7.9** |

| **Preferential Node Attachment Strategy (AVL)** | **$P_{FOAF} = 0$** |
|---|---|
| **$P_{GM} = 0.25$** | **2.8** |

The emergence of certain network characteristics is an important issue, especially from the view point of obtaining an improved performance out of the connectivity of individuals within a network. For example, there have been a few studies in literature, which showed how small-world properties within a network can boost performance of a system (Uzzi and Spiro 2005, Smith 2006, Uzzi, Amaral et al. 2007).

A noteworthy aspect of our study is that it examines certain network characteristics from the view point of actors' behavior within the network. That is to say,

if individuals within the network follow certain behavior, we can expect the emergence of networks, which do not follow small-world properties. As an implication of our research, we highlight the fact that network organizers can support network formations that are beneficial to the entire society by considering the connectivity of individuals for the network growth method.

In the next chapter of this thesis we will show that, despite the creation of new knowledge and the process of learning at an individual level, organizational structure affects the nature of human interactions and the information flow. Therefore, we believe that top managers and leaders could apply proper structural changes within the network of employees within the organization, in order to achieve a better organizational learning outcome and a better mechanism for increasing the knowledge flow. Managers within companies with a proper incentive mechanism are able to provide motivations for employees to be more open towards collaboration with others. Those incentive mechanisms will be discussed in conclusion section of this chapter.

Related to these results, it should also be mentioned that the impact of these network properties on the outcome is another interesting aspect to be investigated. We will discuss this issue in chapter 5 of this thesis.

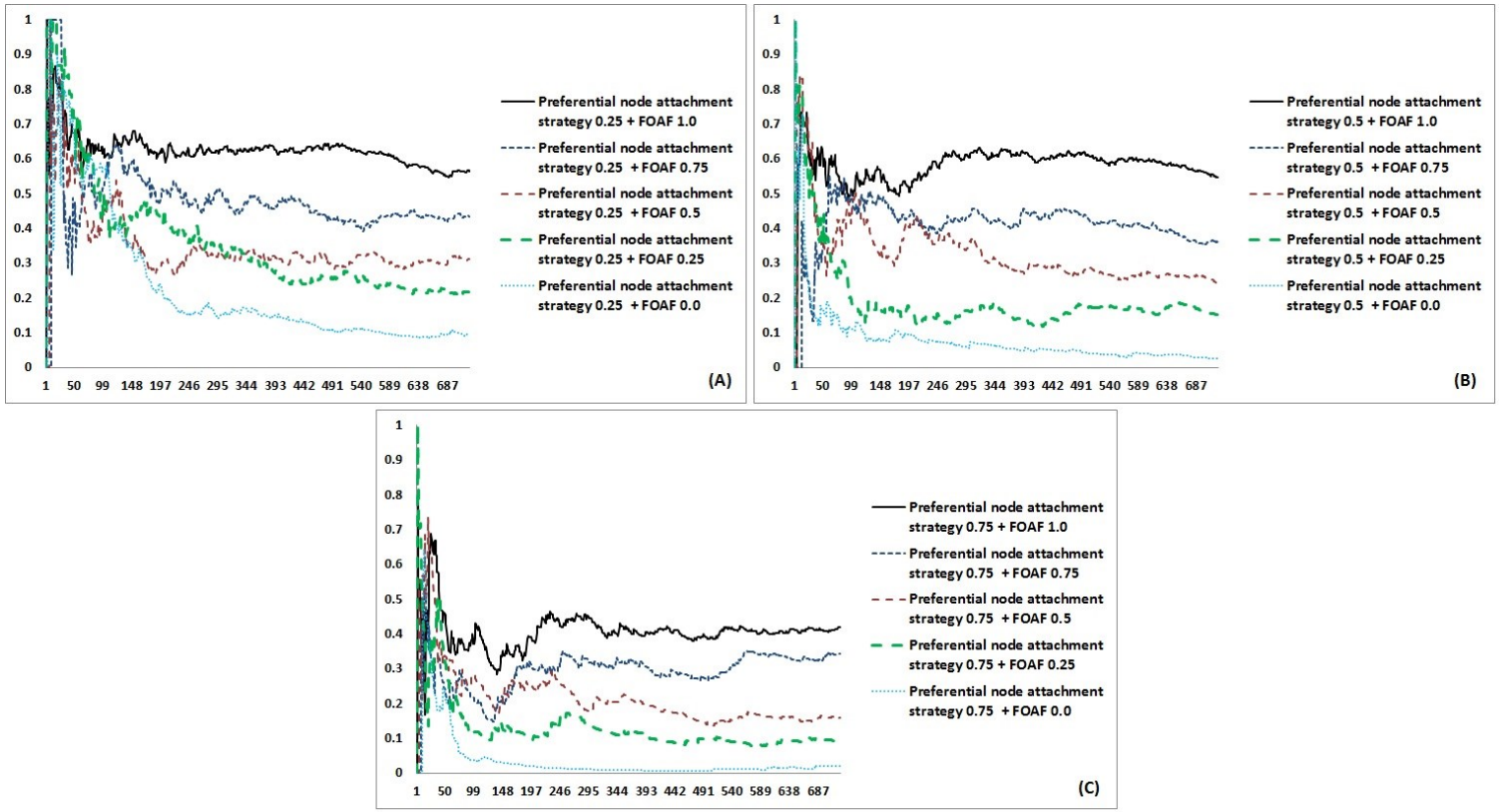



Figure 3.1, A-C. Changes in the clustering coefficient, CC, with respect to the preferential attachment growth model are shown in (A), (B), and (C).

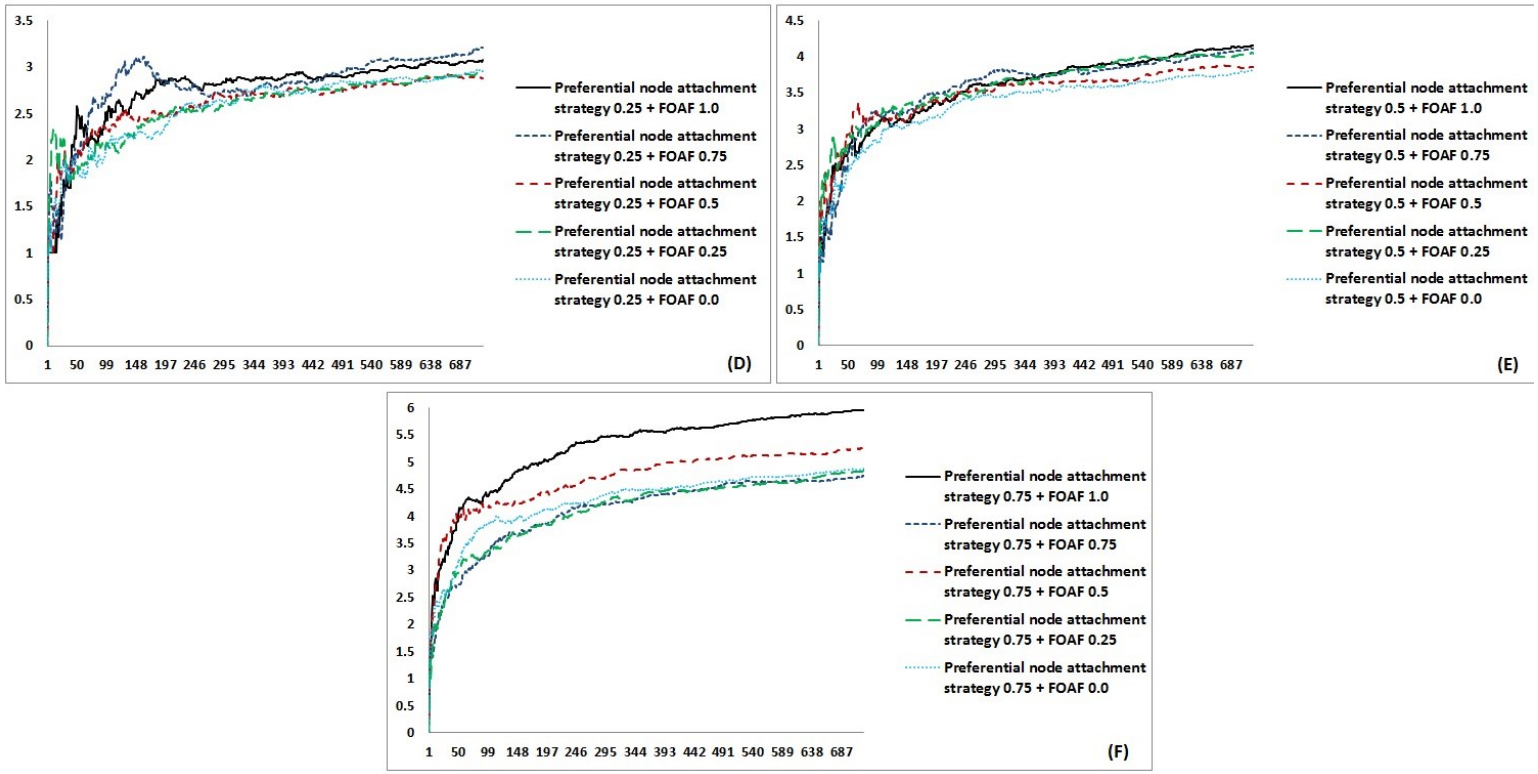



Figure 3.1, D-F. Changes in the average shortest path length, AVL, with respect to the preferential attachment growth model are shown in (D), (E), and (F).

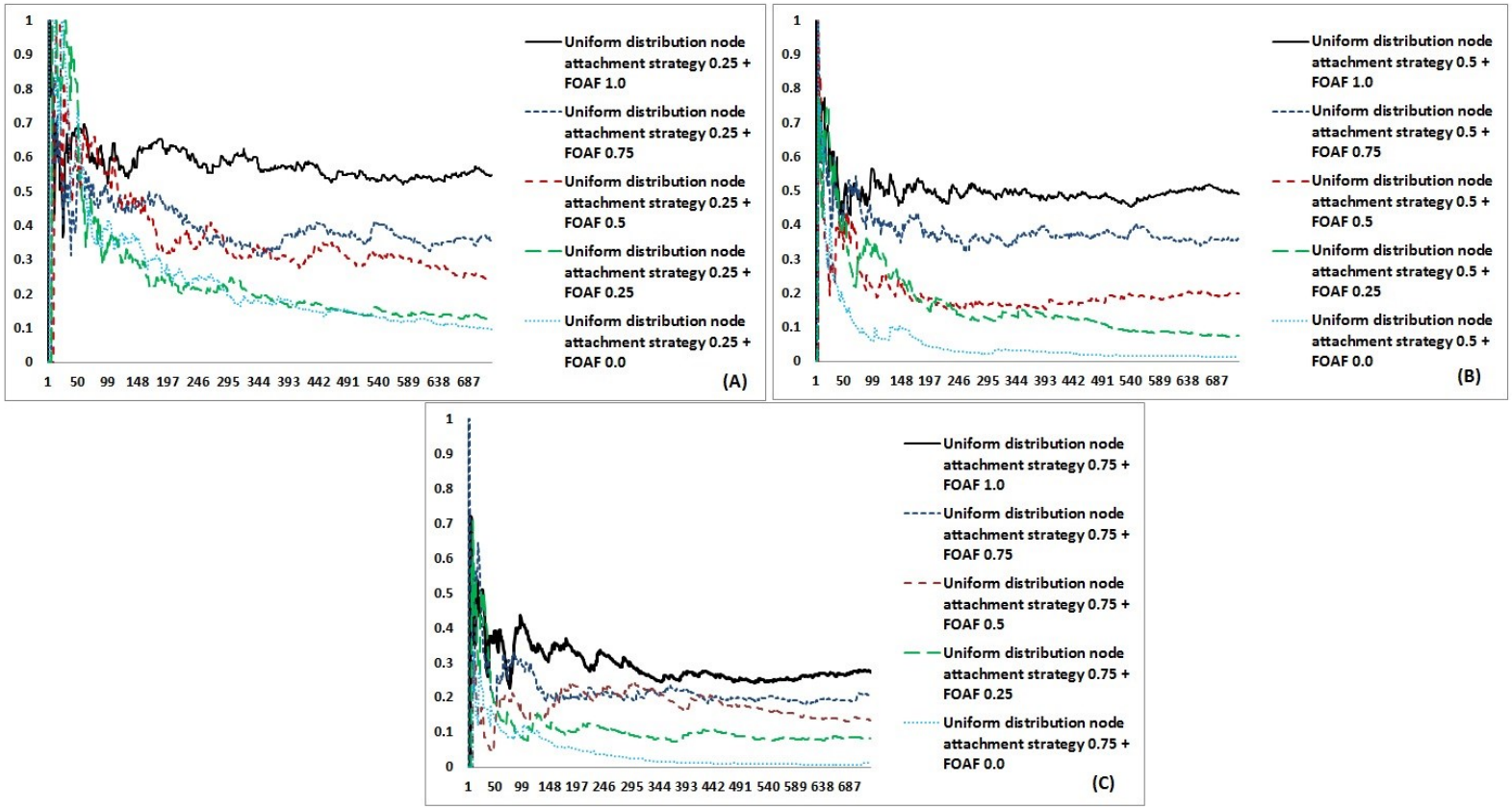



Figure 3.2, A-C.Changes in the clustering coefficient, CC, with respect to the uniform distribution growth model are shown in (A), (B), and (C).

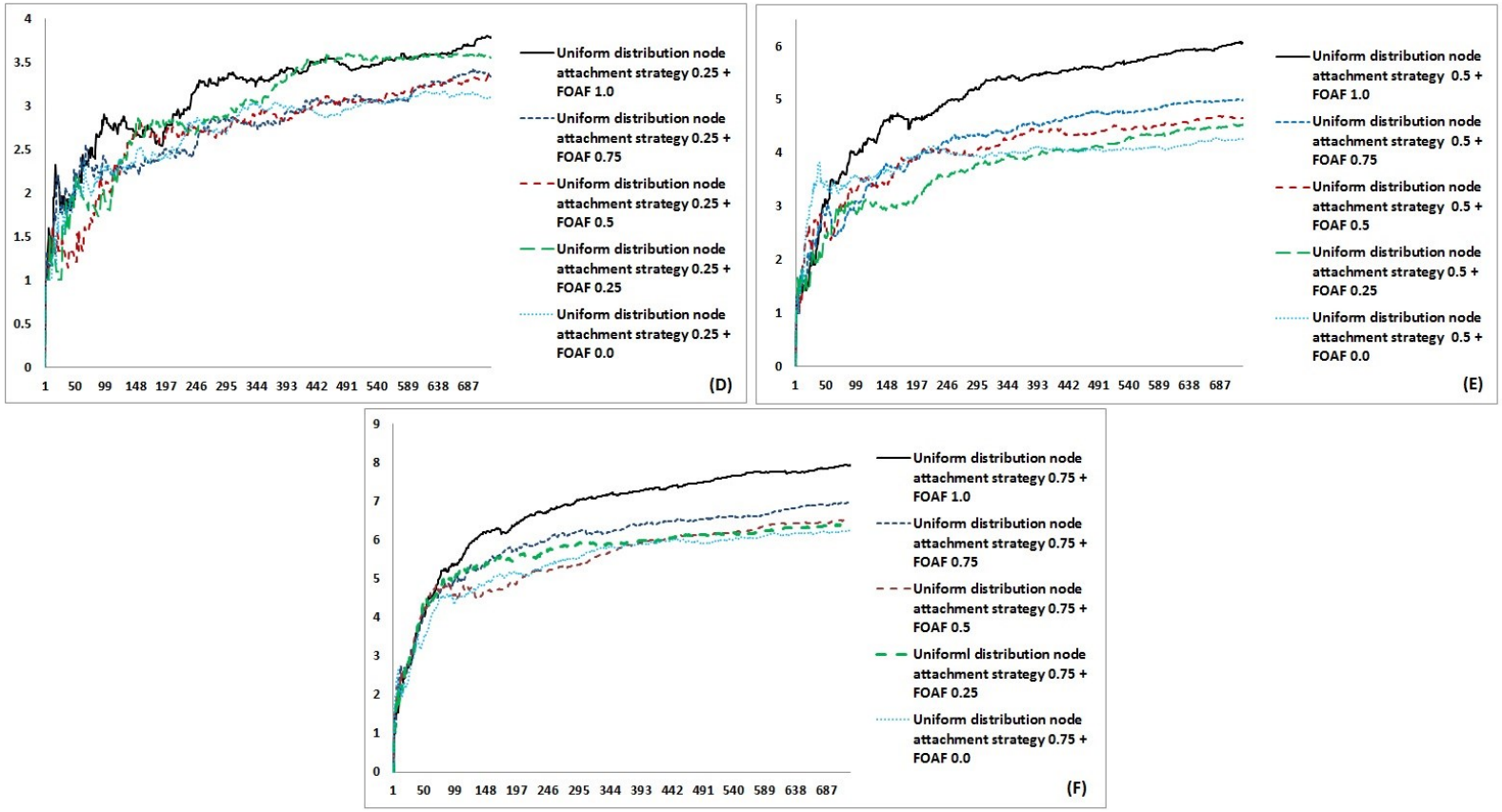



Figure 3.2, D-F. Changes in the average shortest path length, AVL, with respect to the uniform distribution growth model are shown in (D), (E), and (F).

Table 3.1: Comparison of clustering coefficient and average path length of the networks generated by preferential attachment and uniform attachment strategies and in the absence of having limitation on node degree.

| | | | | **Baseline Properties of Networks** **Clustering Coefficient (CC), Average Path Length (AVL)** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Approach** | **Limitation on Node Degree** | **Category of Link Establishment** | | **FOAF link establishment ($P_{FOAF}$)** | | | | | | | | | |
| | | | | **$P_{FOAF}$ = 1** | | **$P_{FOAF}$ = 0.75** | | **$P_{FOAF}$ = 0.5** | | **$P_{FOAF}$ = 0.25** | | **$P_{FOAF}$ = 0** | |
| | | | | **CC** | **AVL** | **CC** | **AVL** | **CC** | **AVL** | **CC** | **AVL** | **CC** | **AVL** |
| **Preferential Node Attachment Strategy** | **NO** | New link establishment ($P_{GM}$) | **$P_{GM}$ = 0.25** | **0.58** | 3.1 | 0.48 | 3.2 | 0.35 | 2.74 | 0.24 | 2.8 | 0.13 | 2.8 |
| | | | **$P_{GM}$ = 0.5** | 0.55 | 4.4 | 0.39 | 4.38 | 0.28 | 3.8 | 0.18 | 4.2 | 0.04 | 3.75 |
| | | | **$P_{GM}$ = 0.75** | 0.42 | **6** | 0.35 | 4.5 | 0.19 | 5.2 | 0.11 | 4.6 | **0.03** | 4.6 |
| **Uniform Node Attachment Strategy** | **NO** | New link establishment ($P_{GM}$) | **$P_{GM}$ = 0.25** | **0.52** | 3.8 | 0.42 | 3.4 | 0.27 | 3.4 | 0.18 | 3.55 | 0.15 | 3.1 |
| | | | **$P_{GM}$ = 0.5** | 0.5 | 6 | 0.38 | 4.9 | 0.22 | 4.5 | 0.1 | 4.3 | 0.01 | 4 |
| | | | **$P_{GM}$ = 0.75** | 0.31 | **7.9** | 0.24 | 7 | 0.15 | 6.4 | 0.1 | 6.3 | **0.01** | 6.1 |

### 3.4.2. Limitations on the Size of Personal Network

In this part of our experiments we focus on the third feature that a network formation model should incorporate, that is the size of personal network.

The properties of the networks derived from our network growth model are computed over 10 suits of experiments and the average results are plotted in the diagrams shown.

Since, in real scenarios, the rate at which people join a network is much shorter than the rate of link creation among the existing ones, it is safe to assume that most of the existing dynamic processes within a social network are related to the establishment of potential links of FOAF or random type. It means that the rate of newly entered individuals is much lower than the rate of creation of links among the existing individuals. Therefore, we consider the value of $P_{GM}$ to be lower than $P_{FOAF}$ variable. The value of $P_{GM}$ is set to 0.25, while the value of $P_{FOAF}$ is selected from the range [0.25, 0.75].

In order to see the effect of limitations on the size of personal network, we set the $S_{PN}$ value to 5, 10, 15, and 20, respectively, and repeated the experiments. As mentioned earlier, the $P_{RAN}$ value is always assumed to be the complement of $P_{FOAF}$. The model was tested with forty configurations for each $P_{FOAF}$ value, which were compared with one another. The result is presented in Figure 3.3(A-C). The x-axis shows the simulation period, while the y-axis represents the AVL value.

In the early stage of the simulation, the network's average path length has a significantly greater variability in its value than later. As time goes by, the fluctuations of the curves are little. Considering Figure 3.3(A-C), it is clear that the AVL values consistently decline with increase in value of $S_{PN}$. It means that the size of personal networks must be large enough, in order to have smaller AVL value among the population.

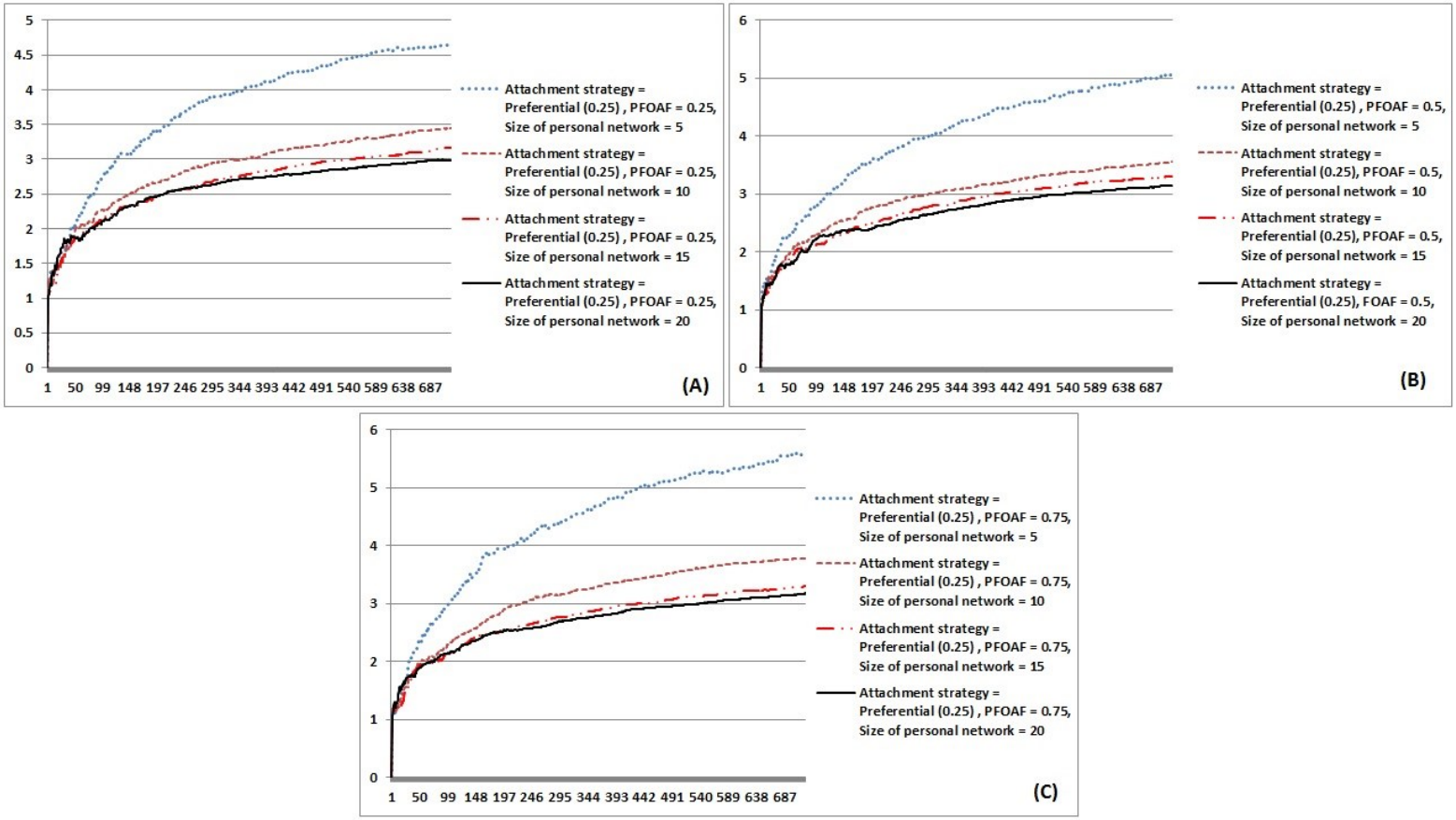



Figure 3.3 (A-C). Changes in AVL with respect to the preferential attachment growth model for different sizes of the personal networks. The x-axis shows the simulation period, while the y-axis represents the AVL value

Therefore, applying more limitation on the size of personal networks leads to an increase in AVL value. The obtained results indicate the fact that, if the size of personal networks are relatively small ($S_{PN}$=5), the AVL value among the population tends to be large. It also shows that network's average path length has a significantly smaller variability in its value, if the size of personal networks is set to larger values ($S_{PN}$=10, 15, 20). Therefore, as the series of figures show, in addition to a different rate of variability of link establishments, a limitation on the size of personal networks also leads to changes in the structural properties of networks (i.e., the average shortest-path length).

The simultaneous impact of the rate of variability in potential link establishments ($P_{FOAF}$) and the limitation on the size of personal networks ($S_{PN}$) suggests that the AVL value reaches its minimum with an increase in $S_{PN}$ and decrease in $P_{FOAF}$. Such a result in its own turn is evidence for the importance of potential links of random type for the formation of a network with smaller average path lengths value. The ranges of AVL values of Figure 3.1(D) are between 2.74 and 3.2. The ranges of values of Figure 3.3(A-C) are in the range [3, 4.6], [3.16, 5.1], and [3.1, 5.5], respectively. The discrepancy in the results reflects the influence of size of personal networks on the whole network's structural properties. The summary of obtained results of Figure 3.3 is presented in Table 3.2.

In this part of our experimental results we actually extended our network formation model with the help of the size of personal networks (i.e., parameter $S_{PN}$). That is to say, we applied some restrictions on the capacity of link establishment in individuals due to lack of time and resources restrict opportunities for ongoing relationship-building. As the results show applying a limitation on the size of personal networks leads to the emergence of networks with higher average shortest-path lengths.

By comparison of the results showed in Table 2.1 and Table 3.2 one can easily see that our model provides more insight into the emerging properties of the network and it can explain by which parameter configurations we can expect such properties to emerge. For example, with the following configuration we can expect the network average path length to be a high or low value.

| | |
|---|---|
| **Preferential Node Attachment Strategy (AVL)** | **$P_{FOAF}$ = 0.25** |
| | **$S_{PN}$=20** |
| **$P_{GM}$ = 0.25** | **3** |

| | |
|---|---|
| **Preferential Node Attachment Strategy (AVL)** | **$P_{FOAF}$ = 0.75** |
| | **$S_{PN}$=5** |
| **$P_{GM}$ = 0.25** | **5.5** |

Table 3.2: Comparison of the average path length of the networks generated by preferential node attachment strategy and in the presence of having limitation on node degree.

| | | | | **Baseline Properties of Networks: Average Path Length (AVL)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Approach** | **Limitation on Node Degree** | **Category of Link Establishment** | | Probability of FOAF link establishment | | | | | | | | | | | |
| | | | | **$P_{FOAF}$ = 0.75** | | | | **$P_{FOAF}$ = 0.5** | | | | **$P_{FOAF}$ = 0.25** | | | |
| | | | | **$S_{PN}$=5** | **$S_{PN}$=10** | **$S_{PN}$=15** | **$S_{PN}$=20** | **$S_{PN}$=5** | **$S_{PN}$=10** | **$S_{PN}$=15** | **$S_{PN}$=20** | **$S_{PN}$=5** | **$S_{PN}$=10** | **$S_{PN}$=15** | **$S_{PN}$=20** |
| **Preferential Node Attachment Strategy** | **YES** | New link establishment ($P_{GM}$) | **0.25** | **5.5** | 3.8 | 3.2 | 3.1 | 5.1 | 3.5 | 3.2 | 3.16 | 4.6 | 3.47 | 3.2 | **3** |

## 3.5. Conclusion

This chapter presents a stochastic network formation model, based on the idea that human behavior is the key to formulate a network growth model. Since social phenomena are complex, we followed an agent-based modeling approach to depict a complex structure emerging from the interaction of many simple parts over time. Our model is able to capture, compare, and explain the structural changes within a growing social network with respect to certain social characteristics of individuals.

We conducted numerical simulations to calculate and compare the clustering coefficient and the average shortest-path length of different networks, in order to capture the impact of different social relationships between people. From the simulation results, it can be observed that different rates of variability in individual's patterns of behavior in social environments lead to a change in the properties of a network. In detail, the results shown in Figure 3.1(A-F) and Figure 3.2(A-F) indicate that the clustering coefficient values decrease and the average shortage path length values increase with an increase in the rate of network growth ($P_{GM}$ value). This result is even true for different network growth models, although the results shown in Figure 3.1(A-F) and Figure 3.2(A-F) also indicate that the networks derived from a preferential attachment based growth model always have smaller average shortest path lengths and larger clustering coefficient values compared to the random attachment based growth model.

The simulation results with respect to the limitation of the size of the personal network show that the limitations on the size of personal networks, in addition to the rate of variability in an individual's pattern of behavior, significantly changes the average shortest path lengths among individuals. As clearly observed from Figure 3.3(A-C) and Figure 3.1(D), the network's average shortest path length had a significantly smaller value,

if the size of the personal network has been set to a large value. Therefore, we can state that a limitation on the size of the personal networks lead to an increase in AVL value.

## 3.6. Discussion & Implication

The main essential implication of our research results is that we can explain the differences in the average shortest path length measured in empirical studies and existing network growth models (which did not consider the size of the personal network before). Our network growth model is able to explain in more detail the structural changes within a growing social network with respect to the social characteristics of individuals. These networks will be different in different social interaction contexts. Examples of such social networks include social network of people within virtual environments or the network of employees within an organization.

It is interesting to note that the social networking platforms including Facebook attempt to reduce these social distances as daily extension of social activities takes place. Once any user specifies its social circle after registering in the respective websites, the feature "Recommendation of a Friend of a Friend" enables the users to develop their social circles, and for example, to change their social distance from 2 to 1. This is by itself very desirable but it shall not be neglected that providing positive feedback towards such processes certainly leaves significant impacts on the properties of the Facebook network. According to our obtained result if the amount of responses towards FOAF style of link establishment increases we can expect further shrink in the average path length of the Facebook network. Having said that, we think that future strategies and algorithms for link predictions are needed to increase the percentage of links of Random type within Facebook platform. Currently, services such as "Recommendation of a Friend of a Friend"

is a static service and it triggers automatically in the Facebook system. However, with the help of new link prediction algorithms, variety of dynamic processes can be triggered within the Facebook that benefit people by bringing them closer together. In this case we are dealing with the emergence of adaptive services within Facebook ecosystem by which personalized services will be offered to its users. In addition to that such new services have this ability to adapt to changes within the Facebook platform (i.e., with respect to individual level or environmental factors).

Compared to the friendship networks in virtual world, what brings employees together and forms the network among them within an organization is actually the organizational goal. As an employee's attitude towards reaching the organizational goal must be in line with the employee's own success within the organization, the employee's perception of being in contact with other employees can be assumed to be different with respect to known employees or trusted employees.

One question that may be raised in the readers' mind is that how can we motivate employees towards knowledge sharing behavior and improve organizational learning performance?

Engaging and empowering employees have the potential to encourage and to reach high levels of information exchange within organizations. By empowering employees, leaders exchange the power, control and supervisions that they have over employees (Chan, Taylor et al. 2008). Empowerment can lead to a positive outcome at both individual and organizational level.

Empowerment has been defined in verity of ways by different scholars. However, scholars mainly look at it from structural and psychological perspectives. Structural empowerment has received much more attention comparing to the

psychological view. According to structural empowerment managers enhance the right to use information and access the resources to the employees at the lower level of the organizations.

The psychological view on the empowerment explains that empowerment is a state of mind and is a result of position, policies and practices. In such a scenario, it is important that managers increase the feeling of self-efficacy and self confidence among organizational members (Conger and Kanungo 1988, Thomas and Velthouse 1990). Psychological empowerment emerges where there is the capacity of competence building, clarity in roles and responsibilities and authority to select and retain work behaviors.

The following factors are essential for empowering the employees within any organization.

1. **Foster Open Communication**

Since so many companies are built on top-down communication from management, employees have no direct channel and don't feel they will have an impact. Therefore, managers need to foster open communication channels within which employees are given structured ways to make their thoughts, feelings and observations. They need to make sure that they acknowledge their employees for sharing their valuable input that helps the company.

2. **Reward Self-Improvement**

Usually management has the idea that monetary incentives are sufficient to get people to advance. However, it is easy to see that people don't have the resources or knowledge of what to do. That is why, managers need to encourage the employees to set a plan for their growth and reward them as they advance. Later employees can apply their newly-learned skills as they step up to leadership opportunities.

3. **Encourage Safe Failure**

Managers need to set up laboratory environments where employees can test new ideas and learn from the failures as well as the successes. Then employees will gain understanding and feel comfortable innovating.

4. **Provide Plenty of Context**

Managers need to impart their vision to their employees. Since managers are dealing with variety of valuable information in different context, it may seem to be confusing from employees' point of view. Therefore, managers need to share all those information in a structured and consistent manner. An employee who clearly understands the core values, purpose and direction of the company can easily make consistent decisions and take appropriate actions.

5. **Support Their Independence**

Managers need to give the employees reasons and opportunity to be independent and even lead others.

6. **Appreciate Their Efforts**

Employees need to feel that managers appreciates their contribution and value their participation in knowledge sharing behavior. Therefore, managers needs to appreciate their employees for sharing their valuable input that helps the company to achieve its objectives.

# Chapter 4. Networking Outcome under the Shade of Emerging Network's Characteristics

In a learning organization, the person-to-person interactions between individuals form a social network of people. It can be understood as an environment, in which learning occurs during the interactions of individuals. Through this meaningful social network, people communicate with one another and knowledge exploitation mainly happens.

Assuming that the resulting social network is a product of its people's interactions, the first question that comes to mind is what characteristics of the networks positively or negatively affect organizational learning performance? This is actually the $2_{nd}$ research question of this thesis which will be addressed in this chapter.

In the previous chapter, we answered the first raised question. We proposed a model of network growth, in which the structure of social networks can be inferred by the variability in individual patterns of behavior. We categorized the dynamic processes involved in the evolution of a complex network into two groups: (1) The process, which occurs during the growth of a network with respect to nodes, represents the tendency of new users to establish links to other members upon entry into the network; (2) The process, which occurs among existing users of a network, in order to establish links between them. We also showed that the process, which occurs among existing users of a network when establishing links, is further divided into two categories: (a) The first category includes the establishment of links of a Friend-Of-A-Friend type (FOAF type) with a social distance equal to 1; (b) The second category includes the establishment of random links with other users, who are present in the network. We showed that variability in individual

patterns of behavior in social environments lead to a change in the structural properties of the network (Koohborfardhaghighi and Altmann 2014).

In order to answer how different networks' characteristics affect organizational learning, we need to focus especially on the structural properties of complex networks and the obtained utility of individuals. Therefore, we develop an agent-based model to simulate the collective learning of workforces within an organization. With this model, the organizational learning performance under different structural properties (i.e., the clustering coefficient and the average shortest path length) of social networks is captured and compared with one another. The clustering coefficient and the average shortest path length are measured as a function of time. We also use our model for creating a network that realistically reflects the social interaction among the work-force of an organization.

## 4.1. Model

The situation that we want to model is described with the following scenario: Distribution and transfer of knowledge is an important part in the knowledge management process. Obtained knowledge within the organization should be available to others through social interactions. As the workforce of an organization is capable of obtaining new knowledge according to their own capabilities, joining a network provides them with an additional opportunity for an information exchange with their direct contacts. During such interactions, knowledge exchange happens and new knowledge is created by the individuals. We model an organization as a complex system with different rates of variability in individual patterns of behavior, where learning occurs during the interactions of individuals that are located in it. An organization's learning performance is measured as the average performance across all individuals in the organization.

### 4.1.1. Entities

Similar to March's model in organizational learning (March 1991, Fang, Lee et al. 2010), our model has three main entities: an external reality, individuals, and an organization. The external reality is the organizational goal, which is described with a binary vector having m dimensions. The binary vector has values of 1 or −1. Values are randomly assigned with the probability of 0.5. Furthermore, 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 Fang et al. in that an organization is seen as a complex system, wherein individuals interact with each other according to different network structures. In Fang et al. (Fang, Lee et al. 2010), a fully connected network structure is considered.

### 4.1.2. Social Network Creation Model

Similar to what we performed in the previous chapter, we generated a network that shows the connectivity pattern among the individuals within an organization. The generation of the network is based on three parameters: $P_{GM}$, $P_{FOAF}$, and $P_{RAN}$. They represent the rate of adding new nodes with one new link, the rate of establishing links of FOAF type, and the rate of establishing links of random type, respectively. The value of $P_{GM}$ determines the rate of network growth. For example, if $P_{GM} = 0.25$, it indicates that 25% of the network growth comes from a new link connecting a newly entered individual to the network. 75% of the network growth comes from individuals creating links among themselves.

The value of $P_{RAN}$ is the complement to $P_{FOAF}$ ($P_{RAN} = 1 - P_{FOAF}$). Thus, if the value of the $P_{FOAF}$ parameter equals 1, no random link formation exists in the model. These parameters have values in the range [0, 1]. They represent the fraction of establishing links of random type or links of FOAF type. For example, if $P_{FOAF} = 0.5$, it signifies that the probability of converting a link with social distance of 2 to a link with social distance of 1 is 50%. The remaining 50% probability is used for link creation of ransom type. This network formation approach enables us to simulate and profoundly comprehend the dynamic transformations of a network and its effects on the structural properties of the network.

### 4.1.3. Utility Function

Our learning model is adopted from the generalized learning model of March (March 1991). The utility function is presented in equation 3:

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

where $x_j$ denotes j-th element of the bit string x. If $\delta_j = 1$, $x_j$ corresponds with reality on that dimension; Otherwise, it does not. The parameter s, which is $1 \leq s \leq m$, serves as a tunable parameter that can control the difficulty of the search problems. In fact, we have a m-bit string, which is partitioned into L independent subsets. Within each subset, there are s bits that are coupled. Larger values for parameter s make the search problem more interdependent and increase the complexity of the problem.

For instance, suppose reality is represented by a string of 1111111111, and we set our parameter s to 5. The utility to one individual, A, whose beliefs are 11100 11111 is 5× 1×1×1×0×0+5×1×1×1×1×1=5. The utility to another individual, B, whose beliefs are 11111 11111 is 5×1×1×1×1×1+5×1×1×1×1×1=10. If we set our parameter s to 10,

A's utility will be 0, whereas B's will remain at 10. Thus, the higher the s parameter, the more complex is the problem. As we can see, the utility of each individual is calculated by comparing each bit of his/her belief set with bits of the reality set. Therefore, if s = m, all bits must be matched with the reality bits to produce a utility, receiving a utility difficult. In our formulation, we set its value to 5. The main benefit of this characterization of the m/s utility function is that we can control the difficulty of a search problem with only a single parameter s.

During the interaction with his direct contacts, each individual identifies those with superior performance than him and, subsequently, makes decisions on updating his belief. The decision to update each of the m dimensions of his belief is made with some probability, $P_{learning}$, reflecting the ability of individuals to learn from one another. The decision rule is based on the idea that the belief sets of the high-performing peers have been closer to reality. When there is no superior performer, the previous beliefs must be intact. If there are two or more superior performers, the new belief will be determined for each of the m dimensions based on the majority of beliefs of the high-performers (i.e., if the majority of high-performers state that the value of a bit is 1 (or -1) then we change our own bit to 1 (or -1), otherwise the bit is set to 0). When there are ties (i.e., the number of superior performers who believe in −1 is equal to that of those who believe in 1), the focal individual keeps her existing belief. All the individuals learn simultaneously from one another based on beliefs at the beginning of the period. An organization's performance is measured as the average performance across all individuals in the organization.

### 4.1.4. Algorithm

Let us assume s=2, in such a case the utilities of agents with respect to the Reality vector are as follow:

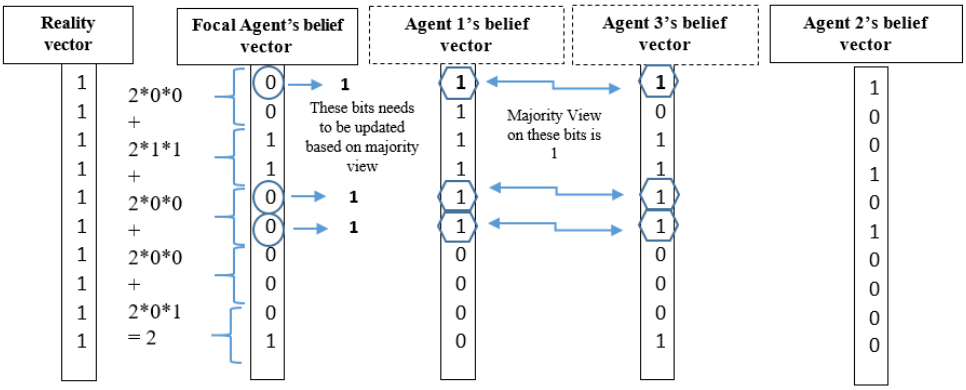
Agent 1: 2*1*1+2*1*1+2*1*1+2*0*0+2*0*0=6

Agent 2: 2*1*0+2*0*1+2*0*1+2*0*0+2*0*0=0

Agent 3: 2*1*0+2*1*1+2*1*1+2*0*0+2*0*1=4

Focal Agent: 2*0*0+2*1*1+2*0*0+2*0*0+2*0*1= 2

Focal Agent decides to learn from agent1 and agent3 because their performance is higher than its own performance. As it is sown below, the focal agent checks the majority view on each of its own bits and updates its belief vector.




The pseudo-code of calculating organizational learning performance is given in Algorithm 1.

| **Algorithm 1: Calculating organizational learning performance.** |
| --- |
| **Input:**<br>**Initialize N, m, s, $P_{learning}$** // N is the number of agents, parameter m is the dimensionality of reality and belief sets, Parameter s serves as a tunable parameter that can control the difficulty of the search problems. $Pl_{earning}$ is the probability of individuals learning from the majority view. Please check the table 4.1 for the initial values. |

**External_Reality_Vector: R =[$r_1$, $r_2$,……, $r_m$]** // Generate the global solution which is a binary vector. We describe reality as having m dimensions, each of which has a value of 1 or −1. The probability that any one dimension will have a value of 1 (or −1) is 0.5; values are randomly assigned.
Belief_Vector: x=[$x_1$, $x_2$,……, $x_m$] // Generate a local solution for each agent. Each belief for an agent has a value of 1, 0, or −1. A value of 0 means that an individual is not sure of whether 1 or −1 represents reality.

**Output:** Organizational learning performance

**REPEAT** ***// at each iteration:***
**ASK AGENTS**
**[**
**Calculate $\phi$(x) OF LINK-NEIGHBORS** // *Each agent calculates $\phi(x)$ of its direct neighbors. $\phi(x)$ is a function that calculates the utility of each agent based on its belief_vector. The formula for its calculation is shown in equation 3.*
**SET best_set LINK-NEIGHBORS WITH MAX[$\phi$(x)]** // *best_set is the list of outperforming neighbors of each agent.*
**IF Not EMPTY best_set [** *// If we find some neighboring agents with better performance*
**FOREACH $x_i$ IN x** *// Checking the belief set bits with respective bits of reality*
**[**
**SET threshold_learning RANDOM-FLOAT 1**
**SET $mv_i$ Get_majority_view_on ($x_i$)**
**IFELSE $x_i$ != $mv_i$** *// If this bit of belief set does not match the majority view on the bit*
**[**
**IFELSE threshold_learning >= $P_{learning}$ [set $x_i$ = $mv_i$ ][ set $x_i$ = $x_i$]** *// The focal individual adapts to each majority belief with probability $p_{learning}$. If agents don't reach the required threshold they do not learn from the majority view.*
**]**
**[ set $x_i$ = $x_i$]** *// If this bit of belief set match the majority view on the bit we don't change this bit*
**]**
**]**
**]**
**ASK AGENTS update [X]** *// Agents update their belief vectors with respect to the unknown bits of their belief vectors*
**REPORT AVG [ $\phi$(x) ] OF AGENTS** *// An organization's performance is measured as the average performance across all individuals in the organization.*
**UNTIL Equilibrium** // *The learning process is repeated until no further change in any individual's beliefs occurs (i.e., when equilibrium is obtained).*

## 4.2. Experimental Setup

To investigate how structural changes within the topology of a complex network affect organizational learning, we simulate the organization learning performance of our generated networks and average the results based upon 10 simulation runs. For this, we compute the average utilities of the population for each time period $t = 0, \ldots, 100$ (Figure 4.1(C)). An equilibrium occurs when all individuals have received a similar knowledge level (i.e., utility). Since the rate, at which people join a network in reality, is much lower than the rate of link creation among existing people, it is safe to assume that most of the existing processes within a social network are related to the establishment of links of FOAF type or random type. It means that the rate of newly entered individuals is much lower than the rate of creation of links among existing individuals. Therefore, we consider the value of $P_{GM}$ to be 0.25, while the value of $P_{FOAF}$ is selected from 0.25, 0.50, and 0.75. Simulation parameters related to collective learning of workforces within an organization is shown in Table 4.1.

N is the number of agents, parameter m is the dimensionality of reality and belief sets, Parameter s serves as a tunable parameter that can control the difficulty of the search problems. $P_{learning}$ is the probability of individuals learning from the majority view. Each of n individuals 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. Similar to the Fang et al. model (Fang, Lee et al. 2010), the learning probability of individuals in our model is set to 0.3 (Table 4.1). We compute the average utilities of the population for each time period $t = 0, \ldots, 100$.

| Table 4.1. Simulation parameters related to collective learning of workforces within an organization | | | |
|---|---|---|---|
| **Simulation Parameters** | **Remarks** | **Parameter Values** | **Source of Parameters** |
| N | Number of individuals in the organization | 250 | Midsize enterprise |
| M | Dimensions of beliefs | 100 | (Fang, Lee et al. 2010) |
| Z | Size of a subgroup | 250 | Midsize enterprise |
| T | Simulation runtime | 100 | Until Equilibrium |
| C | Number of clusters | 1 | We have only one social network |
| S | Degree of complexity | 5 | (Fang, Lee et al. 2010) |
| $P_{learning}$ | Probability of individual learning from the majority view | 0.3 | (Fang, Lee et al. 2010) |

## 4.3. Experimental Results

To investigate how structural changes within the topology of a complex network affect organizational learning, we simulate the organization learning performance of our generated networks and average the results based upon 10 simulation runs. For this, we compute the average utilities of the population for each time period t = 0, …, 100 (Figure 1(C)). An equilibrium occurs when all individuals have received a similar knowledge level (i.e., utility). Since the rate, at which people join a net-work in reality, is much lower than the rate of link creation among existing people, it is safe to assume that most of the existing processes within a social network are related to the establishment of links of FOAF type or random type. It means that the rate of newly entered individuals is much lower than the rate of creation of links among existing individuals. Therefore, we consider the value of $P_{GM}$ to be 0.25, while the value of $P_{FOAF}$ is selected from 0.25, 0.50, and 0.75.

Figure 4.1(A) and Figure 4.1(B) show the measured CC and AVL of the networks derived from our network formation model. Considering Figure 4.1(A), it can

be seen that the CC values constantly decline over time with a decrease in the value of FOAF type links and an increase of random type links. Figure 4.1(B) suggests that the AVL values increase consistently over time with a reduction in influence of FOAF-type links and an increase in influence of random links. It must also be noted that the CC values reach their maximum in the early simulation stages due to a small population size, and afterwards, shows oscillation. With respect to the AVL values, the minimums are in the early simulation stages.

Based on the results shown in Figure 4.1(A) and Figure 4.1(B), we can check which structural changes within a network can be translated into a positive learning outcome. For measuring the learning performance of the n individuals within our generated networks, we assume that the individuals have the same reality and individual belief sets. Hence, the only thing that differs for them is the network structure. The result of our simulation is shown in Figure 4.1(C).

Our first observation is that the organizational learning performance is different with respect to different connectivity patterns of individuals. Second, as the simulation results show, the information exchange within a network having small amount of FOAF type and large amount of random type links provides to the whole population a better learning performance. This shows that, in such a network, the diversity of belief sets is low. Third, the organization has achieved a high level of correct knowledge about reality

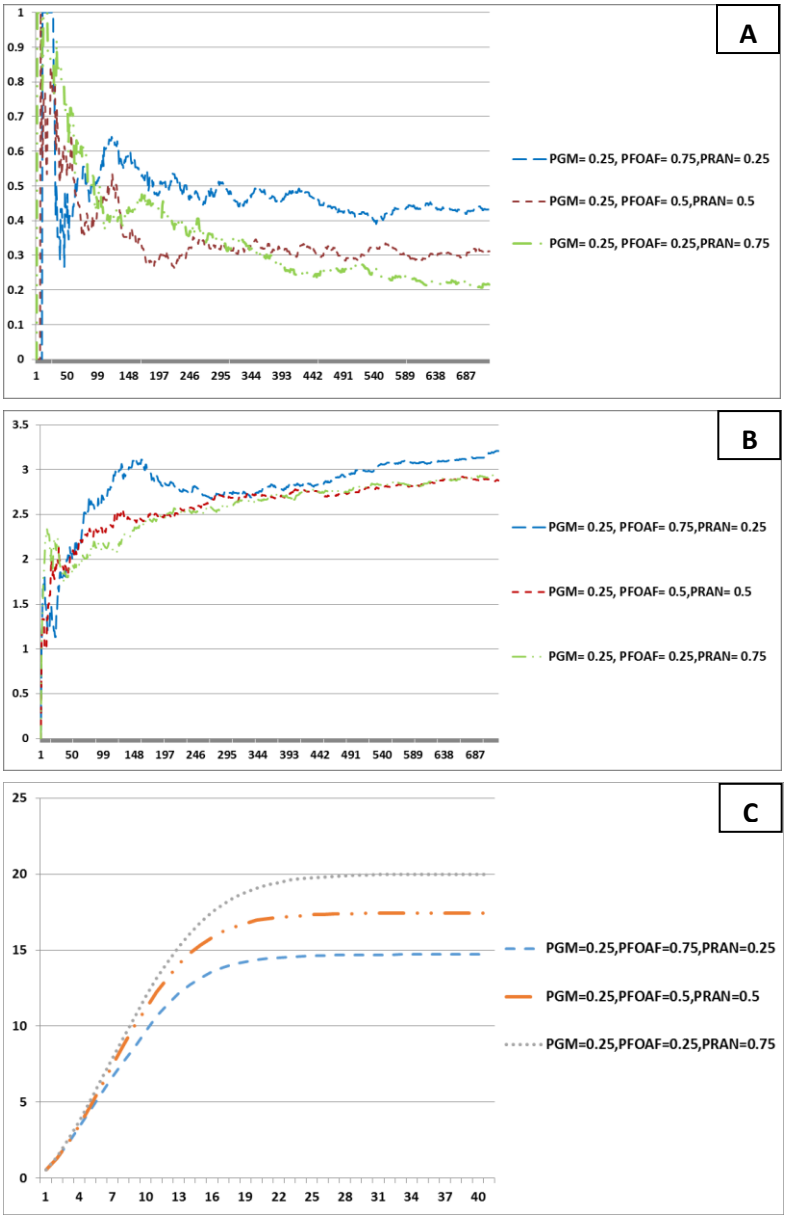



Figure. 4.1. (A) Changes in CC with respect to variability in individual patterns of behavior are shown. The x-axis depicts the simulation period, while the y-axis represents the CC value. (B) Changes in AVL with respect to variability in individual patterns of behavior are shown. The x-axis depicts the simulation period, while the y-axis represents the AVL value. (C) Changes in organizational learning performance with respect to variability in individual patterns of behavior are shown. The x-axis shows the duration of the simulation, while y-axis is set to the organizational learning performance (utility as shown in equation 3).

compared to other network configurations. Therefore, we can conclude that connectivity patterns among the workforce affect organizational learning.

Comparing Figure 4.1(B) and Figure 4.1(C), we can conclude that a network structure with shorter average shortest path lengths can provide a high learning performance for its members. Another conclusion is that a high clustering coefficient within a network does not necessarily produce the highest learning outcome (Figure 4.1(A) and Figure 4.1(C)). This is quite interesting because it indicates that an increase in the number of FOAF type links stops the innovation in learning. Therefore, with a high number of random type links, the diversity of belief sets becomes small and, as a result, the learning outcome increases. This supports our statement that, in addition to having a realistic model of interactions, a proper network structure is needed to capture organizational learning performance.

Contrary to the result reported by Fang et al. (Fang, Lee et al. 2010), our results (Figure 4.1(C)) indicate a low organizational learning performance. Although an explanation could be related to the fact that we model the organization as a single cluster, we conjecture that: (1) Fang et al. assumed a fully connected network among the members of the clusters; (2) There is an overlap among the beliefs of each group, which has not been discussed in (Fang, Lee et al. 2010). Therefore, the high complexity of knowledge in our model (i.e., a large value of m) causes a low proportion of correct beliefs. Consequently, we conclude that the larger the amount of information is, the longer it takes to learn correct knowledge.

## 4.4. Discussion

### 4.4.1. Effects of Environmental Change and Turnover

In our simulation we imposed the assumptions of no environmental turbulence or personnel turnover. If personnel turnover and environmental turbulence happen to take

place, we need to introduce two modifications to our model, while keeping the other parameters the same as before.

For the probability of personal turnover, each individual has the option to leave the organization at each time period with probability $p_{turnover}$. When an individual leaves, his or her position is filled by a new member who starts with randomly assigned beliefs (a value for each of m beliefs is drawn randomly from 1, 0, or −1).

For the probability of environmental turbulence, we let the environment change periodically. In particular, we perturb each of m dimensions of reality (from 1 to −1, or from −1 to 1) with probability $p_{envir}$ at every T period. For example, similar to (Fang, Lee et al. 2010) we set T =200 and $p_{envir}$ =0.1. That is, in every 200 period, about 10% of m elements in reality change their values. The value of T is tuned to allow sufficient time for the organizations to learn and adapt to new environment.

Consistent with what have been shown by (March 1991, Fang, Lee et al. 2010), we estimate that after an environmental shift, the organization suffers an immediate drop in performance. However, with personnel turnover, the organization is able to recover from the environmental shift and improve its performance. Without turnover feature, over

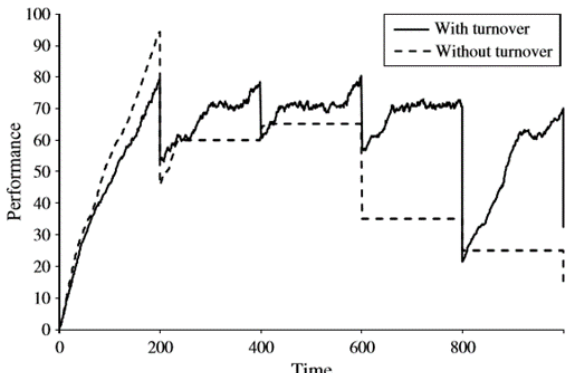



Figure. 4.2. Effects of Turnover on organizational learning performance (Fang, Lee et al. 2010).

time the organization loses its ability to adapt to environmental shifts. Therefore, considering personal turnover preserves diversity in the organization.

### 4.4.2. Considering Law of Diminishing Returns during the Process of Network Growth

It would be also interesting to consider laws of diminishing returns for the

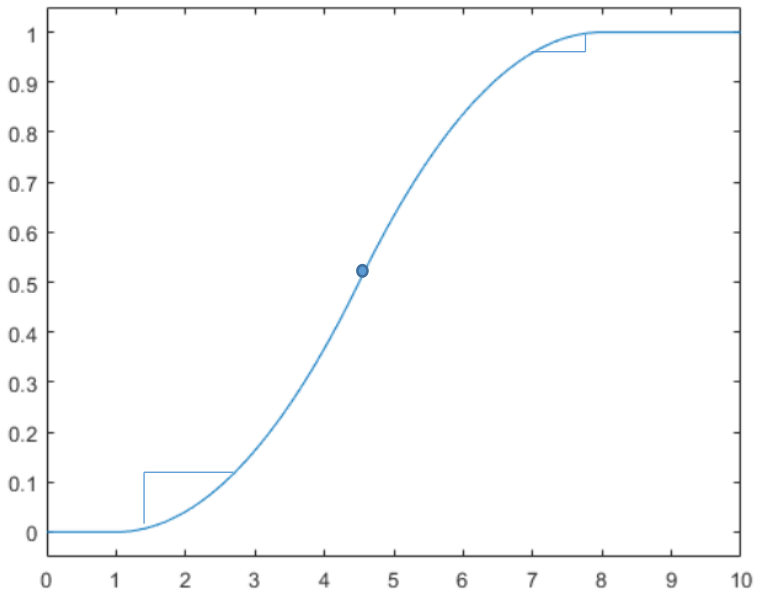



Figure. 4.3. Considering law of diminishing returns during the process of network growth.

process of network growth. For this purpose, we need to think of three phases of the network growth.

In phase 1, the interest for joining the network is slow. In phase 2, the network is expanding, and finally in phase 3, the interest for joining the network reaches its maximum peak. Same thing would happen for the process of potential link establishment. Therefore, we can expect the extended version of our model to produce increase in return to scale (IRTS), constant return to scale (CRTS) and decrease in return to scale (DRTS). This process is shown in Figure 4.3.

In this regard, we plan to combine our three parameters, namely $P_{GM}$, $P_{FOAF}$, and $P_{RAN}$, with the following approach.

$$\exp\left(\sum_{x\epsilon\ (P_{GM}, P_{FOAF}, \text{and } P_{RAN})} \beta x + \lambda t\right) * \exp\left(\sum \lambda t\right) \tag{4}$$

Parameter x points to the known parameters in our network formation model such as $P_{GM}$, $P_{FOAF}$, and $P_{RAN}$ while parameter λ points to the unknown parameters within our model. This can be considered as part of our agenda for future research.

### 4.4.3. Measuring Social Capital

As the result of new researches show (Cutter and Emrich 2006, Cutter and Finch 2008), vulnerable populations are not solely characterized by terms of age and income but also in terms of their lack of connections and embeddedness in social networks.

Social capital is generated at the individual (micro) level and at the collective (macro) level. The social circles of employees within any enterprise enable identifying well connected and embedded individuals. It also enables to identify individuals, who have access to some valuable resources. One question that may be raised in the readers' mind here is that how can we measure social capital with respect to the resources which are available to them. Flap in (Flap 2002) provides a measure for capturing social capital, in which social capital is constituted by the network members, their resources, and the availability of these resources. This is expressed in Equation 5:

$$SC = \sum_i \sum_j r_{ij} p_{ij} \tag{5}$$

where SC is the quantification of an individual's social capital (at micro level), i refers to the direct contacts of the source individual and j represents the resource item that are available through each direct contact. The amount of such a resource is shown as $r_{ij}$. The

probability $p_{ij}$ represents the willingness to let the focal individual to have access to the resource $r_{ij}$ of type j.

Identification of formal connections among employees is not very difficult (based on organizational structure). However, we argue that actual patterns of communication among the employees within an organization do not solely follow their positions within the organizational structure. The complex pattern of communication in an organization is the product of many layers of context and relevance, which act on different scales and lead to the development of organizational social capital (at macro level). We believe that the lack of such information is obvious within organizations and not appealing. We consider such informal connections as additive values that are missing during the measurement of organizational social capital. The latent nature of such information makes them unclassified information within big enterprises' knowledge-based systems. As we mention in the introduction part of this paper, it is also necessary to find out which factors can encourage cooperation over competition to increase the knowledge flow within the organization. It is necessary to identify environmental factors, which have impact on the cooperative and competitive nature of employees' interactions during the life cycle of organizations.

This issue is very important with respect to organizational social capital. With the help of extra information related to the organizational social capital, organizations can create stronger bonds between their employees. As an employee's lack of connections and embeddedness within the organizational social capital, the organization cannot respond to contingencies within the organization, becoming vulnerable.

Identification of hidden patterns of communication within organizational social capital and investigation of those highly successful clusters have the potential to tell us

why certain groups or divisions are more successful compared to others. It may shed light on unexpected events where several experts work on a new task (a project) and the result of their cooperation is not what the company expect to be. This approach has the potential to tell us what the negative social interactions within organizational social capital are and why further changes in the communication structure of employees are needed.

### 4.4.4. Considering Cost of Interactions

We should mention that Equation 3 does not consider the cost of interactions during the process of exploration and exploitation. That is to say while individuals exchange information with each other, this may impose some cost upon them. On the other hand the process of knowledge discovery by themselves can also be costly. In such situations we need to consider two different cost terms in our model. Readers should keep in mind that whenever we point to the utility of individuals, we actually consider it to be the net-utility, because we did not have such cost terms in our model.

## 4.5. Conclusion

We argued in this chapter that structural changes within a network of people in an organization affect organizational learning. Therefore, we investigate the role of such structural changes within an organizational structure as a mechanism for increasing the knowledge flow and organizational learning.

The results of our analysis indicate the fact that structural changes within the topology of the network affect organizational learning. The learning performance consistently increases with a decrease in the rate of FOAF type links and an increase of random type links among the population. Therefore, we concluded that higher clustering

coefficient within a network does not necessarily produce the highest learning outcome and even stops innovation in learning. Instead, shorter average shortest path lengths within a network of individuals positively affect organizational learning. Our experimental results also show that the existence of links of random type within a network facilitate and increase learning among the population. Consequently, we can state that certain topological features of a network can help network members to get better access to information exchange processes within an organization.

## 4.6. Implication

We believe that the social relationships between individuals in an organization can be utilized to produce positive returns. Despite the creation of new knowledge and the process of learning at an individual level, organizational structure affects the nature of human interactions and information flow.

The results of our analysis suggests that managers are able to use organization structure as a tool for improving the balance between exploration and exploitation and helping the organization explore a diverse solution space, and subsequently achieving better long term learning performance outcomes (March 2005, Gupta, Smith et al. 2006).

With respect to improving the balance between exploration and exploitation, we should mention that in socio-economic complex adaptive systems such as organizations, immediate returns from exploitation cause the system to exhibit a myopic bias. Employees within organizations tend to pursue solutions similar to already-known solutions because they do not have access to all possible domains of knowledge. This will push them towards their own prior experiences and utilization of existing routines. Consequently, it decreases the likelihood that new solutions will be found. Therefore, we can argue that adaptive

processes which are only based on exploitations can become self-destructive in the sense that they mislead the organization to become trapped in a suboptimal equilibrium. In the literature this is known as success trap.

This argument is articulated by many researchers (Bower and Christensen 1996, Lenox 2002, Nickerson and Zenger 2002, Benner and Tushman 2003, Siggelkow and Levinthal 2003, O Reilly and Tushman 2004, Argote and Greve 2007, Jacobides 2007). However, further research is needed to understand how organizations can avoid to be stuck in such self-destructive processes. Since this seems to be more a managerial issue, we need to investigate the role of managers in helping organizations to better maintain the balance between exploration and exploitation instead of overemphasizing the already-known solutions.

Finally, while new knowledge is developed by individuals and institutional networks of people, organizations play the key role in the management and flow of such new information. Every organization has a hierarchical structure that defines how the organization operates. This includes the arrangements of the lines of authority, power distance within the organization, how responsibilities are distributed and how information flows. Although analyzing the organizational structure leads to having a better understanding of how organizational communication channels among employees are formed, we cannot restrict patterns of employees' social interactions to only those of work relationships. Employees have their own networks of heterogeneous connections which provide access to information and opportunities (resources) that might not be available within a business setting (e.g. In addition to work with team members employees can perform knowledge exchange with someone in another department or division).

By looking at the organizational structure within big enterprises such as Google one can see that Google's open communication program delivers substantial managerial features. The "70-20-10 rule" in Google for example, gives employees the freedom to spend 70 percent of their time on current assignments, 20 percent on related projects of their choosing, and 10 percent on new projects in any area they desire. The "70-20-10 rule" within this enterprise represents a managerial guideline, but it also authorizes the employees to take risks to explore a diverse solution space and achieve more innovation. Having said that, we need to consider some other cases such as Samsung within which organizational culture exerts dramatic influence on the organizational structure. That is to say due to the culture the level of decentralization is lower and groups are more isolated from each other. This lower level of decentralizing may impact the learning process within subunits of the organization and providing barriers to the rapid diffusion of ideas across those subunits. In this case such organizations needs proper incentive management to motivate managers and employees to be able to adopt to more exploration strategies and to conquer more diverse range of solutions. This can be considered as part of our agenda for future research.

# Chapter 5. Identification of Factors Impacting Individuals' Interactions

Today, complex networks are everywhere and changes of the structural properties in them are caused through a variety of dynamic processes among the constituents of such networks (Gilbert and Hamill 2009, Koohborfardhaghighi and Altmann 2014). The focus of the previous studies so far have been on capturing the main features of the real world networks. In other words, what has been very interesting for most of the researchers is to demonstrate that a certain type of network follows a special network characteristics. However, such analysis independent of capturing the causes of the observed features, try to map them with basic topological formulation models and their inherent characteristics (e.g., random network formation model with its short average path length but low clustering coefficient, small-world network formation model with its short average path length but high clustering coefficient, and scale-free network formation model with the presence of hubs and emergence of power-law degree distribution (Erdős and Rényi 1959, Watts and Strogatz 1998, Barabási and Albert 1999)). Each of these network formation models with their own particular formulation mechanisms has been proposed to produce a desired network structure (Newman, Barabasi et al. 2006). If any network follows their characteristics we can say that, independent of the causes and conditions that exist for the structural changes, the final emerging network structure has such and such specific properties. That actually has been our motivation during writing previous chapters of this thesis.

In this chapter, however, we argue that the direction of current research must change from "what type of network properties emerges…" to "why such network

properties emerges…". We are interested to develop a case as an incentive modeling example and check how it effect the emerging characteristics of the network and utility gain of the population.

We believe that by looking further and deeper into changes in the structural properties of a network, we can also relate its structural properties and changes to the strategic interactions of individuals that are located in it (Jackson and Wolinsky 1996).

In the world of networked individuals, usually the main focus of the focal individual is on his or her own utility. Therefore, it is logically acceptable to consider humans as opportunity seeking actors who act strategically, in order to maximize utilities from their connectivity patterns in the network (Jackson and Wolinsky 1996). And consequently, we can justify why the underlying network structure is constantly changing and as the result a certain type of network with specific characteristics emerges.

Therefore, in this chapter, we design an interaction model in which, while networking, the utility gain of an individual is the main determinant of why a link should be stablished. Through such an interaction model we aim to explain the emerging structural changes among networked individuals and its effect on their utility gains. Comparing to chapter 4, networking outcome in this chapter is the social welfare which is the summation of the utility of all the individuals within the network.

According to our interaction model, we show that changes in the baseline properties of a network are consequences of four factors impacting individual interactions:

(1) Initial underlying network structures,

(2) Process of network growth, with the idea that the process of network growth among people is inevitable,

(3) Adoption of strategic responses, with the idea that individuals act strategically in response to what other individuals do in the network, and

(4) Network visibility, with the idea that higher or lower visibility towards global topology of the network leads to emergence of certain network characteristics.

The main idea and supporting details for proposed interaction model are that people agree to communicate with others and establish links among themselves, knowing that their time is limited, but feeling that the link establishments are beneficial for them. Therefore, the first and second factors are necessary for generating the network. On the other hand, any method network growth will trigger strategic responses among existing network members. Individuals are able to observe the process of network growth and will compete with each other to maximize their own utilities. Consequently, the third factor also play an important role in the formation of final network characteristics. Visibility of the nodes towards the global topology of the network will provide network members a better chance to select the best candidates from all position of the network in the utility maximization process. Therefore, the evolution of the network in our model is the result of four underlying processes, initial underlying network structure, method of network growth, strategic interactions between individuals when they observe how new members enter the network and create links with existing ones and having limitation in having a perfect visibility towards the global topology of the network.

Contrary to existing works that demonstrate how simple utility functions produce different network structures from scratch (e.g., from isolated nodes to dyads and stars) (Jackson and Wolinsky 1996, Jackson 2008), or other research works that explain specific characteristics of networks with their generative mechanism (Erdős and Rényi 1959, Albert and Barabási 2002, Gilbert and Hamill 2009, Koohborfardhaghighi and

Altmann 2014, Koohborfardhaghighi and Altmann 2014), we show that the process of network growth in its own turn is a strategic choice for the new members joining the network. In addition to that, such a strategic growth trigger a strategic response(s) among the existing network members which its consequences will be reflected in network structure and its emerging properties. Performing such strategic link establishments at both levels (i.e., at both growth level and among existing individuals) are due to individuals' interests for their own utility maximization.

Based on our above mentioned arguments, we formulated the third research question of our thesis.

If individuals are entitled to respond to strategies of others within the network (due to competition), what can be the effect of having such behaviors on the

a. Emerging network characteristics?
b. Outcome of the individuals and the whole system?

To answer these research questions we create a generative network formation model based on our proposed interaction model. We consider an initial underlying network structure at startup to depict a population of individuals. Network growth part of our interaction model captures the fact that new individuals are ready to enter the network and consequently the network size increases. At some point when the size of a network becomes bigger and bigger, individuals within a network undergo strategic behaviors to maximize their utilities.

To quantify the effect, we use an agent-based modeling approach. With the help of agent-based modeling, we can test our interaction model and capture the dynamics among the individuals within networks. We utilized the co-author utility function (Jackson

and Wolinsky 1996) that captures the utility of individuals in terms of their connectivity patterns with others.

## 5.1. Model

According to our interaction model, which is depicted in Figure 5.1, changes in the utility gain of individuals and in the emerging network characteristics are consequences of four factors impacting interactions:

(1) Initial underlying network structures,

(2) Process of network growth, with the idea that the process of network growth among people is inevitable,

(3) Adoption of strategic responses, with the idea that individuals act strategically in response to what other individuals do in the network, and

(4) Network visibility, with the idea that higher or lower visibility towards global topology of the network leads to emergence of certain network characteristics.

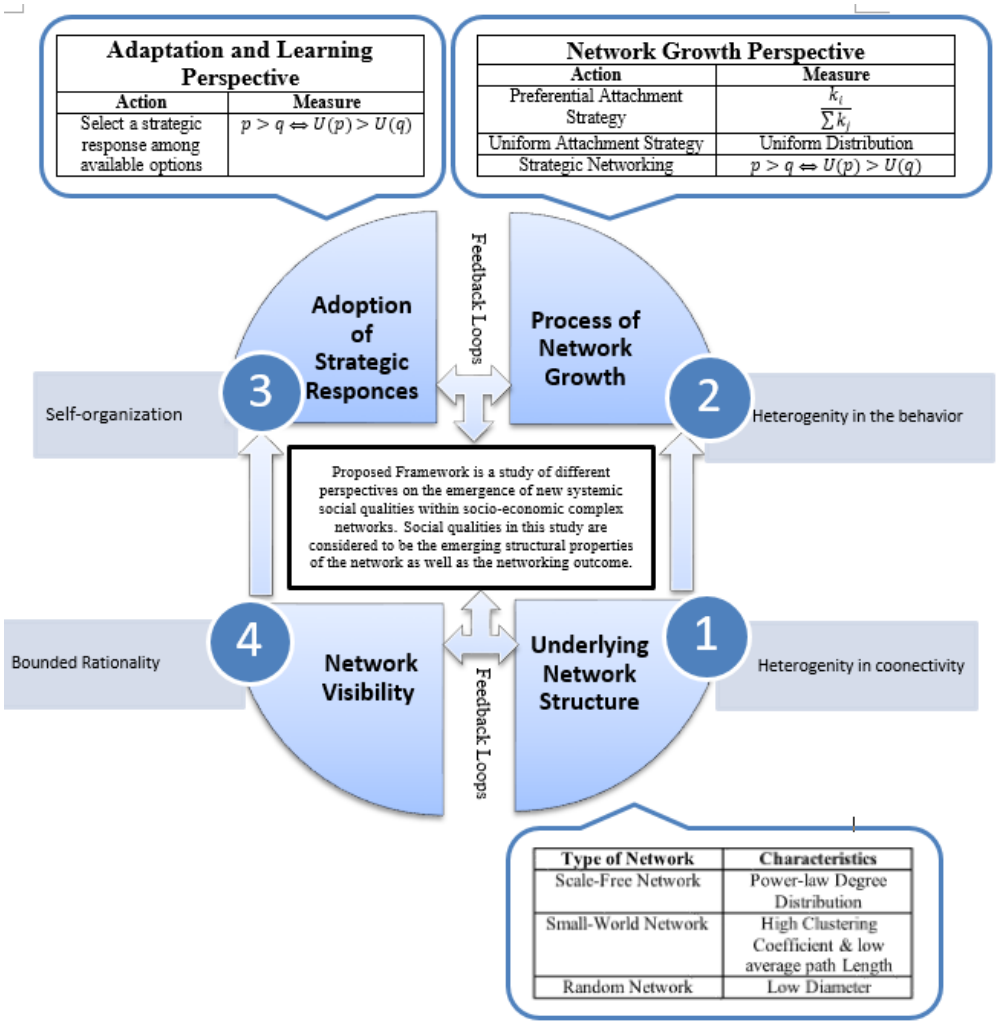



Figure. 5.1: Our proposed interaction model based on complex adaptive system approach.

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```
Get-Graph G(N, E)  // N is the initial set of agents (nodes) in the network G with a size of |N|=p_start and E is the edge set (see example in Figure 5.6)
ASK AGENTS [Update-Utility]  // Update the utility attribute of all agents before the network among them grows. An agent's utility function is defined as U(n, G): N x 𝔾 → ℝ (see Section 5.1.1).
FOR counter = 1 TO P DO  // P is the number of new agents to be created.
    CREATE-AGENT n_new  // A new agent (node) n_new is created.
    IF network_growth = "Random" THEN [  // network_growth is a variable, which controls the method of network growth.
        ASK n_new [CREATE-LINK-WITH n_j]  // New agent n_new establishes link with another agent n_j with an uniform probability.
    ]
    IF network_growth = "Preferential" THEN [
        ASK n_new [CREATE-LINK-WITH n_j]  // New agent n_new establishes link with another agent n_j with a probability that is equal to k_j/Σk_i where k_j is degree of agent n_j.
    ]
    IF network_growth = " Strategic Growth" THEN [
        ASK n_new [CREATE-LINK-WITH nj]  // New agent n_new establishes link with another agent n_j with whom its utility is maximized comparing to other alternatives.
    ]
    ASK AGENTS [Update-Utility]
    IF strategic_response="One" THEN [  // The process of network growth triggers only a strategic response of one direct neighbor.
        ASK ONE-OF LINK-NEIGHBORS OF n_j [CREATE-LINK-WITH n_q]  // The agent, which is one of the neighbors of agent n_j, is known as n_i, agent n_q belongs to the distance-k ball (B^k[n_i]) of agent n_i, q≠ i, link iq∉L(n_i), and U(n_i, G+iq) is larger than U(n_i, G). U(n_i, G) is the utility of agent n_i in graph G. L(n_i) is the set of direct links of agent n_i.
    ]
    IF strategic_response="All" THEN [  // The process of network growth triggers strategic responses of all direct neighbors.
        ASK LINK-NEIGHBORS OF n_j [CREATE-LINK-WITH n_q] //All direct neighbors act in the same way as described in strategic_response="One".
    ]
    ASK AGENTS [Update-Utility]  // Update the utility of all agents based on recent changes.
END FOR
PRINT MIN [Utility] of AGENTS
PRINT MAX [Utility] of AGENTS
PRINT SUM [Utility] of AGENTS
PRINT Network_Clustering_Coefficient
PRINT Network_Average _Path _Length
```

Algorithm 1: Pseudo-code of the interaction model. This algorithm indicates the process of network growth and the strategic responses of agents upon it.

To detail our interaction model, we consider a set of agents N of size |N| and a set of potential candidate agents $B^k(n)$, with which an agent n with n∈N can increase its utility

through interconnection. A utility maximization process can be considered as an agent's strategic response (e.g., a new link establishment) to a link establishment of other network members. Among the potential candidate agents $B^k(n)$, agent n prefers the one that maximizes its utility. The pseudo-code of our interaction model is given in Algorithm 1. In this pseudo-code, agents are representative of nodes within the network (called AGENTS throughout the pseudo-code) and each of them has an attribute called Utility.

At line 1, with procedure Get-Graph, an initial network with $N=p_{start}$ agents is setup. In section 5.2.1 $p_{start} = 25$ while in section 5.2.2 $p_{start}$ has been set to 10. Each agent in this graph can be indexed as $n_j$.

NetLogo (Wilensky and Evanston 1999), the agent-based modeling simulator that is used, uses the ASK command to give commands to the agents. Therefore, as can be seen at line 2, we ask the agents to update their utilities before the network grows. The agent's utility function is defined in Section 3.C. Update-Utility is a procedure that calculates the utility of the agents. At line 3, we start a loop, in which the process of network growth starts and a new agent (a new node) $n_m$ enters the network. This loop (with a variable called counter) repeats P times ($p_{end}$ - $p_{start}$) until the total number of agents reaches 200. CREATE-AGENT is a built-in command in NetLogo for the creation of an agent. Depending on the method of network growth, which is specified with the variable network_growth, agent $n_m$ establishes a link with one of the existing agents $n_j$ (line 5 to line 10). The selection of agent $n_j$ depends on the method of network growth. If it is set to *Random*, then agent $n_j$ will be selected uniformly from the population (line 5 to line 7). If it is set to *Preferential*, then agent $n_j$ will be selected with a probability proportional to its degree and the sum of the degrees of all agents within the population (line 8 to line 10). This way, high-degree agents have a higher chance of link establishment with the new

agent $n_m$ than low-degree agents. If the method of network growth is set to *Strategic Growth,* then node $n_j$ will be selected if $U_m (G + {}_{jm}) > U_m (G)$ (line 11 to 13). This condition guarantees that the process of link establishment with node $n_j$ maximize the utility of $n_m$. CREATE-LINK-WITH is a command in NetLogo for the creation of a link between the source and the target agent. Since existing neighbors of the agent $n_j$ perceive a reduction in their utilities through the new link of agent $n_j$ (line 14), they decide to perform the utility maximization process. The utility maximization process triggers strategic responses among existing neighbors of agent $n_j$ (line 15 to 20). The variable strategic_response controls the number of direct neighbors that perform strategic responses. If the process triggers only one strategic response (strategic_response = "One"), then only one of the direct neighbors of agent $n_j$ responses strategically to maximize its utility (line 15 to line 17). This neighboring agent $n_i$ looks for a potential candidate $n_q$, through which it can maximize its utility. Agent $n_q$ can be any agent belonging to the *distance-k ball* of agent $n_i$, denoted by $B^k[n_i]$, where $q \neq i$, $iq \notin L(n_i)$ and $L(n_i)$ is the set of direct links in the neighborhood of agent $n_i$. The distance-k ball of agent $n_i$ covers all neighboring agents of $n_i$ at distance k, with which an agent $n_i$ can increase its utility (i.e., $U(n_i, G+iq)$ is larger than $U(n_i, G)$). For example, if k=d and d being the diameter of the network, then agent $n_i$ could potentially select any agent of the network with $q \neq i$ and $iq \notin L(n_i)$. When k = 2 individuals are only able to search for the possible candidates (that link establishment with them provide them the highest utilities) only two hops away from themselves. In our experiments, we select the value of k from [2 - 10]. Strategic responses are done with the motivation that the creation of such links leads to a better utility for actor i and at the same time is considered as a penalty for actor j's action. This process can also be considered another constituent of an individual's cognition which leads to a topological change of the

network structure. Hence, link *iq* is a new link for agent $n_i$. The new link between $n_q$ and $n_i$ is the result of the strategic response to the network growth. If the utility maximization process triggers strategic responses of all direct neighbors of $n_j$ (strategic_response = "All"), all of the direct neighbors of agent $n_j$ act strategically to maximize their utilities. For this, each of the agents performs the same steps (line 18 to line 20) as the steps described for a single agent (line 15 to line 17). In detail, LINK-NEIGHBORS is a built-in command in NetLogo, which reports all neighbors found at the other end of undirected links connected to the focal agent (Line 19). If it is used with the term ONE-OF, it reports only one of the neighbors (Line 16). Since changes in the connectivity patterns of the agents have happened, before starting the next loop's iteration, the utilities of the agents are updated (line 21). After the loop ends, we print the minimum, the maximum, and the sum of the utilities (i.e., social welfare) of the whole population (line 23 to 25). Clustering coefficient and average path length of the networks as emerging network characteristics are also reported (line 26 to 27). PRINT, MIN, MAX, SUM are built-in functions of NetLogo.

### 5.1.1. Utility Function

The utility function used in our model is the co-author utility function (Jackson and Wolinsky 1996), which captures the utility of agents in terms of their connectivity patterns with others. We selected the co-author utility function, because the utility of each agent is a function of its own connectivity degree and its neighbors' connectivity degrees. Each agent takes action to increase its utility based on the cognition of the population accessible and the knowledge obtained through the interaction with others. The original utility function of the co-author model is presented in Equation 1. $U(n_i, G)$ is the utility

of agent $n_i$ in graph G. Agent $n_j$ is the neighbor of agent $n_i$. $D(n_i)$ consists of all agents $n_j$, who are direct neighbors of agent $n_i$. Therefore, the term $\left(\frac{1}{l_i(G)} + \frac{1}{l_j(G)} + \frac{1}{l_i(G)l_j(G)}\right)$ in Equation 1 is repeated for all neighboring agents $n_j \in D(i)$. Equation 2 shows just a different representation of the utility function, in which the common terms are factored out:

$$U(n_i, G) = \sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_i}(G)} + \frac{1}{l_{n_j}(G)} + \frac{1}{l_{n_i}(G)l_{n_j}(G)}\right) \quad (1)$$

$$U(n_i, G) = 1 + \left(1 + \frac{1}{l_{n_i}(G)}\right) \sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_j}(G)}\right) \quad (2)$$

The degree of agent $n_i$ is defined as $l_{n_i}(G) = |D(n_i)|$. The more direct neighbors of agent $n_i$ are involved in collaborations with other network members, the lower the obtained utility of agent $n_i$ from their own collaborations is. The term $\frac{1}{l_{n_i}(G)}$ captures the connectivity degree of agent $n_i$, while the term $\sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_j}(G)}\right)$ captures the sum of connectivity degree of all its direct neighbors. In this way, the utility of agent $n_i$ is proportional to the connectivity degree of its own and its direct neighbors. Since the term $\frac{1}{l_{n_i}(G)}$ in Equation 1 is repeated $D(n_i)$ times, their summations equals one, and it creates the first term of Equation 2. Factoring the common term $\sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_j}(G)}\right)$ from Equation 1 produces the second term of Equation 2.

### 5.1.2. Social Welfare

The social welfare in our model is based on the utilitarian measure of a society's welfare (Bentham 1907). The social welfare W is the sum of all utilities of the agents within the network and is defined as:

$$W = \sum_{i=1}^{|N|} U(n_i, G) \tag{3}$$

where $U(n_i, G)$ is the utility of agent $n_i$ that is part of the network. The variable |N| denotes the total number of agents in the network G.

### 5.1.3. Strategic Response of an Individual

Network growth impacts the individuals within the network. Any changes in the structure of the network can be considered the constituents of an agent's cognition. By defining the strategic response of an agent in response to what another agent in the network has done, the changes in the network G can be specified.

The utility function $U(n, G)$, which is needed to evaluate the changes in the network, assigns a value to each agent n, depending on the network structure. The utility changes, if a new link has been established. For example, if agent $n_j$ decides to establish a link with a new agent and a neighboring agent $n_i$ perceives that as a reduction in its utility, the agent $n_i$ may also establish a link with an agent in another part of the network to recover the loss imposed by agent $n_j$. This strategic response of agent $n_i$ is defined as the establishment of a link *iq* as the best response to agent $n_j$'s strategy with two conditions:

**Condition 1:** Agent $n_q$ belongs to the distance-k ball of agent $n_i$, denoted by $B^k[n_i]$, where $q \neq i$ and the link *iq* does not belong to the previous set of links in the neighborhood, which is denoted by $L(n_i)$ of agent $n_i$ in G

**Condition 2:** $U(n_i, G+iq) > U(n_i, G)$

Condition $q \neq i$ insures that agent $n_i$ cannot create a link to itself, so agent $n_i$ and agent $n_q$ are two different agents within the network. The second condition $iq \notin L(n_i)$ also ensures that the link iq is a new link for agent i and does not belong to the previous set of links in its neighborhood. The utility of all agents are generated with the same utility function $U(n_i, G)$.

Based on the utility function of the co-author model, we argue that the creation of a link with an agent at the distance-k ball of agent $n_i$, which has the lowest number of connections gives the highest utility to agent $n_i$ and can be considered as user $n_i$'s rational behavior to maximize its utility. Distance-k ball of agent $n_i$ covers all neighboring agents of $n_i$ at distance k. Therefore, agent $n_i$ can select any of those possible candidates $n_q \in B^k[n_i]$, with whom its link establishment maximizes its utility.

To illustrate the workings of strategic responses with the co-author utility function, the following example gives an insight on how utilities of the agents can be calculated in our interaction model. Consider the graph G depicted in Figure 5.2.

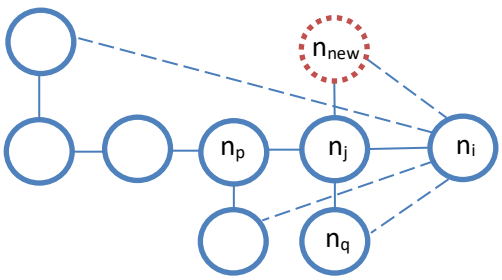



Figure 5.2: Link establishment of agent $n_j$ with newly entered agent $n_{new}$ and the potential strategic response of agent $n_j$'s direct neighbor ni upon it, considering only agents that maximize its utility.

Suppose agent $n_j$ decides to establish a connection with a newly entered agent $n_{new}$ during the network growth. This action imposes a decrease in the utility of agent $n_i$ from $\frac{5}{3}$ to $\frac{3}{2}$ (calculated based on Equation 2). According to the definition of strategic responses, a rational choice of agent $n_i$ is to establish a link to an agent with the lowest degree (depicted with dashed links) as a best response to *j*'s action. This action increases the utility of agent $n_i$ from $\frac{3}{2}$ to $\frac{17}{8}$. It should be noted that agent $n_i$ cannot establish a link *ip*, as it would not maximize its utility (condition 2 of the definition).

## 5.2. Experimental Results

As we discussed our interaction model aims to capture the changes in the social welfare and the baseline properties of the generated network. Therefore, the experimental result section of this chapter contains two parts. In the first part of this section we report the impact of the proposed interaction model on the baseline properties of generated networks and in the second part we deliver its effect on the social welfare and utility distribution of the individuals within the network.

### 5.2.1. How Network Visibility and Strategic Networking Leads to the Emergence of Certain Network Characteristics

#### 5.2.1.1. Experimental Setup

We conducted an agent-based simulation in Netlogo (Wilensky and Evanston 1999), and we performed the experiments on synthetic data sets. An advantage of agent-based simulation is that, from a computational perspective, it allows parallel execution by having a separate computational thread for each agent (node) that is responsible for the information exchange. Another advantage is that it allows dynamically changing the

computing environment to model the real scenario. Simulation parameters and their descriptions are presented in Table 5.1. Three different Initial underlying network structures among individuals are depicted in Figure 5.3.

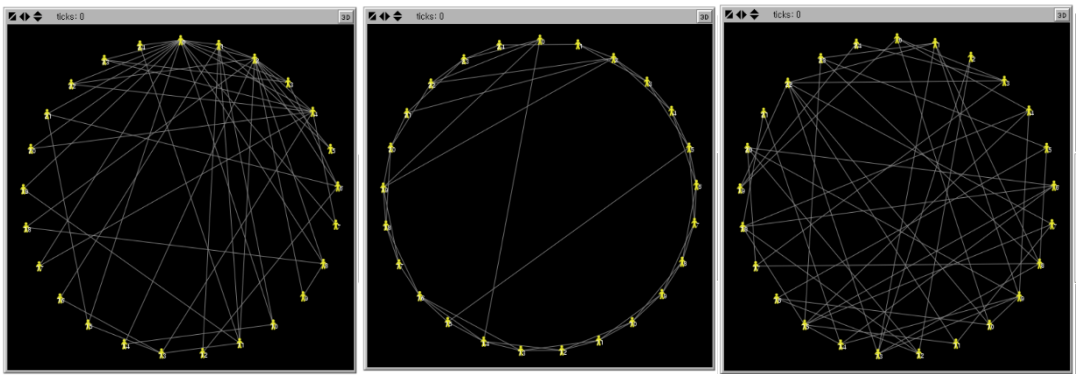


Figure 5.3 : Three different Initial underlying network structures among individuals. From the left to right scale-free network, small-world network with rewiring probability equals 0.1 and finally a random network. We have 25 nodes with 50 links at startup.

Table 5.1. Simulation parameters related to strategic networking and emergence of certain network characteristics.

| Parameter Name | Description | Values | Source of values |
|---|---|---|---|
| network_growth | Methods of network growth.<br>(1) Preferential attachment strategy.<br>(2) Random growth strategy.<br>(3) Strategic Networking | • Preferential<br>• Random<br>• Strategic Growth √ | sensitivity analysis is done over this parameter |
| strategic_response | Number of direct neighbors, who perform strategic responses. | • One<br>• All | sensitivity analysis is done over this parameter |
| d | Diameter of the network. | d is dynamic and grows over time | Dynamic |

| | | | |
|---|---|---|---|
| k | Distance from agent $n_i$ to any other agent $n_j$ in the graph G. | K ∈ [2-10] √ | Sensitivity analysis is done over this parameter |
| $B^k[n_i]$ | Set of potential candidate agents at distance k, with which an agent $n_i$ can increase its utility. | Subset of agents | Dynamic |
| $D(n_i)$ | Set of direct neighbors of agent $n_i$. | Subset of agents | Dynamic |
| $L(n_i)$ | Set of direct links in the neighborhood of agent $n_i$. | Subset of edges | Dynamic |
| $l_{n_i}(G)$ | Connectivity degree of agent $n_i$ in graph G. | Degree of agent $n_i$ | Dynamic |
| $p_{start}$ | Network size at start up. | 25 | Medium-sized enterprises before growth |
| $p_{end}$ | Total size of the network. | 200 | Medium-sized enterprises after growth |
| W | Social welfare | $W = \sum_{i=1}^{\lvert N \rvert} U(n_i, G)$ | (Bentham 1907) |
| $U(n_i, G)$ | Utility of agent $n_i$ in graph G. | $U(n_i, G) = 1 + \left(1 + \frac{1}{l_{n_i}(G)}\right) \sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_j}(G)}\right)$ | (Jackson and Wolinsky 1996) |

### 5.2.1.2. Experimental Results

In this part of our experiments we have two sets of experiments (i.e., Figure 5.4 and Figure 5.5) each of which contains three different configurations (with respect to different underlying network structures and methods and strategic responses towards the process of network growth with different network visibility). In particular, these figures

show how changes in the main characteristics of the network occur with respect to different parameter configurations. The process of network growth continued until the size of the network reached 200 (N = 200). The x-axis shows the simulation periods while the y-axis shows network characteristics (i.e., Clustering coefficient and Average path length). Plot legends show the variability in parameter K. In Figure 5.4, we plotted average path length (AVL) of the networked individuals with respect to different underlying network structures and in the presence of one strategic response upon the process of network growth. The x-axis shows the simulation periods while the y-axis shows Average path length of the network. As we can see regardless of underlying network structure, when the network visibility is set to a small number (i.e., k =2) the average path length of the network appears with bigger values. The maximum values of AVL in figure 5.4(A), 5.4(B) and 5.4(C) range from 9 to 13. When k = 2 individuals are only able to search for the possible candidates (that link establishment with them provide them the highest utilities) only two hops away from themselves. And it reduces the chance of meeting other possible candidates from other parts of the network. Another observation from these series of pictures is that when the visibility of the individuals is set to higher values (i.e., k =10) we are able to observe a huge shrink in the network average path length. The minimum values of AVL in figure 5.4(A), 5.4(B) and 5.4(C) range from 3 to 5. This shows that visibility of the nodes towards the global topology of the network will provide them a better chance to select the best candidates from all position of the network in the utility maximization process. Having said that the smallest AVL belongs to the network which its underlying network structure has been set to Random Network. The resulting network with the AVL of three is generated when K= 10.

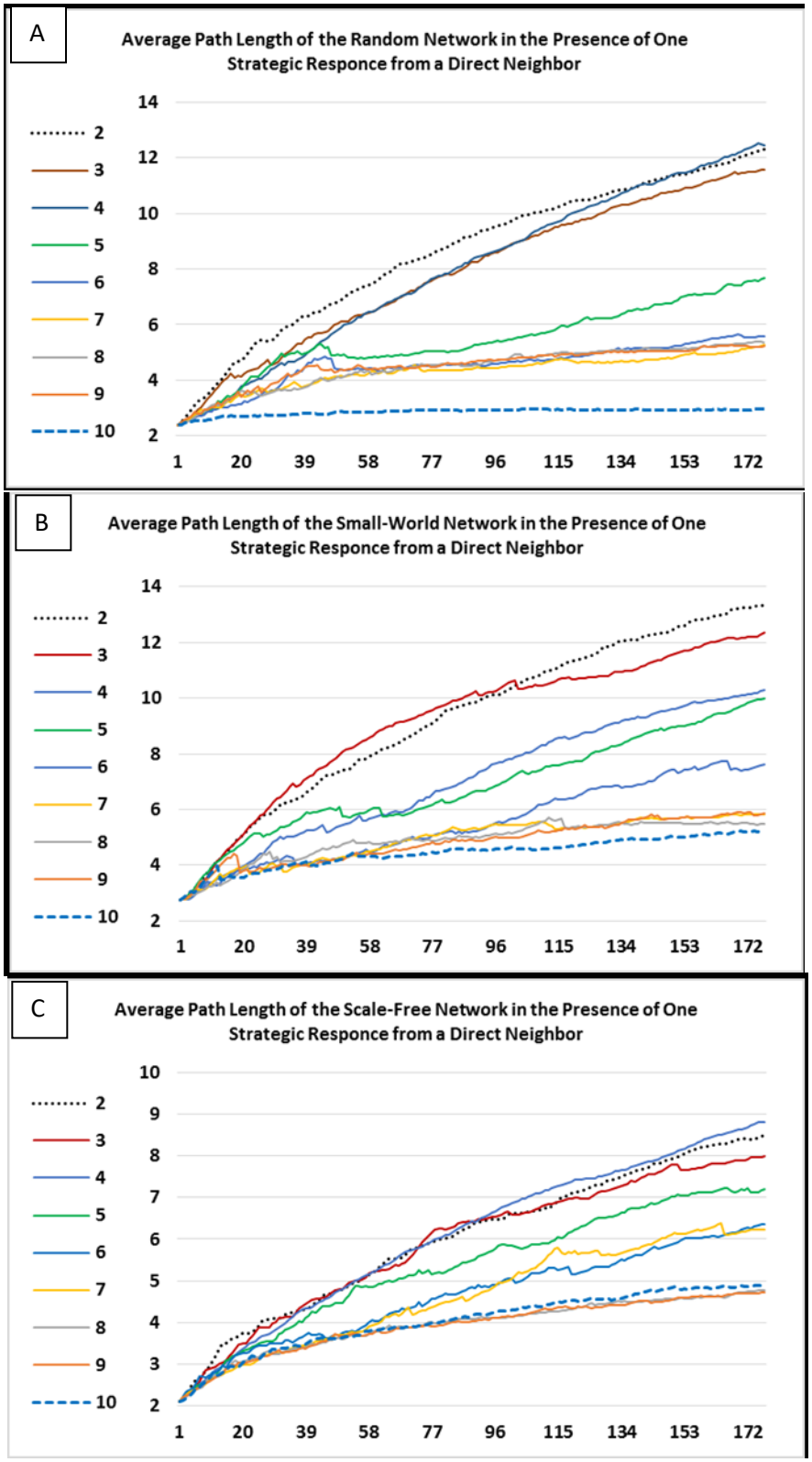



Figure 5.4 : Average path length of the networked individuals with respect to different underlying network structures and in the presence of one strategic response upon the process of network growth. The x-axis shows the simulation periods while the y-axis shows networks' Average path lengths). Plot legends show the variability in the visibility parameter K.

We also tested a new scenario in which the method of network growth triggers strategic responses for all direct neighbors. An interesting observation is that there is no large gap among the AVL values with respect to visibility parameter k in this case. Although still when the visibility is set to higher values the AVL values are smaller but the differences are not really significant. This shows that strategic responses of all direct neighbors help the whole population to reach each other in shorter steps and consequently it reduces the impact of visibility parameter K.

In detail, one can see that average path length of the network is the highest when the method of network growth is set to Strategic Growth. That is to say, new individuals enter the networks in a way to maximize their utilities so they search for the best candidate among the existing network members to provide them the highest utility (based on the co-author formulation the one who has the lowest degree of connectivity). As we observed calculated AVL values in figure 5.4 were quite large. This indicate the fact that utility maximization process of the individuals lead to a network with higher average path length which consequently make the individuals to be far from each other. It can easily be observed that, as long as a large population of individuals adopt such strategic responses, we can expect decrease in the network average path length.

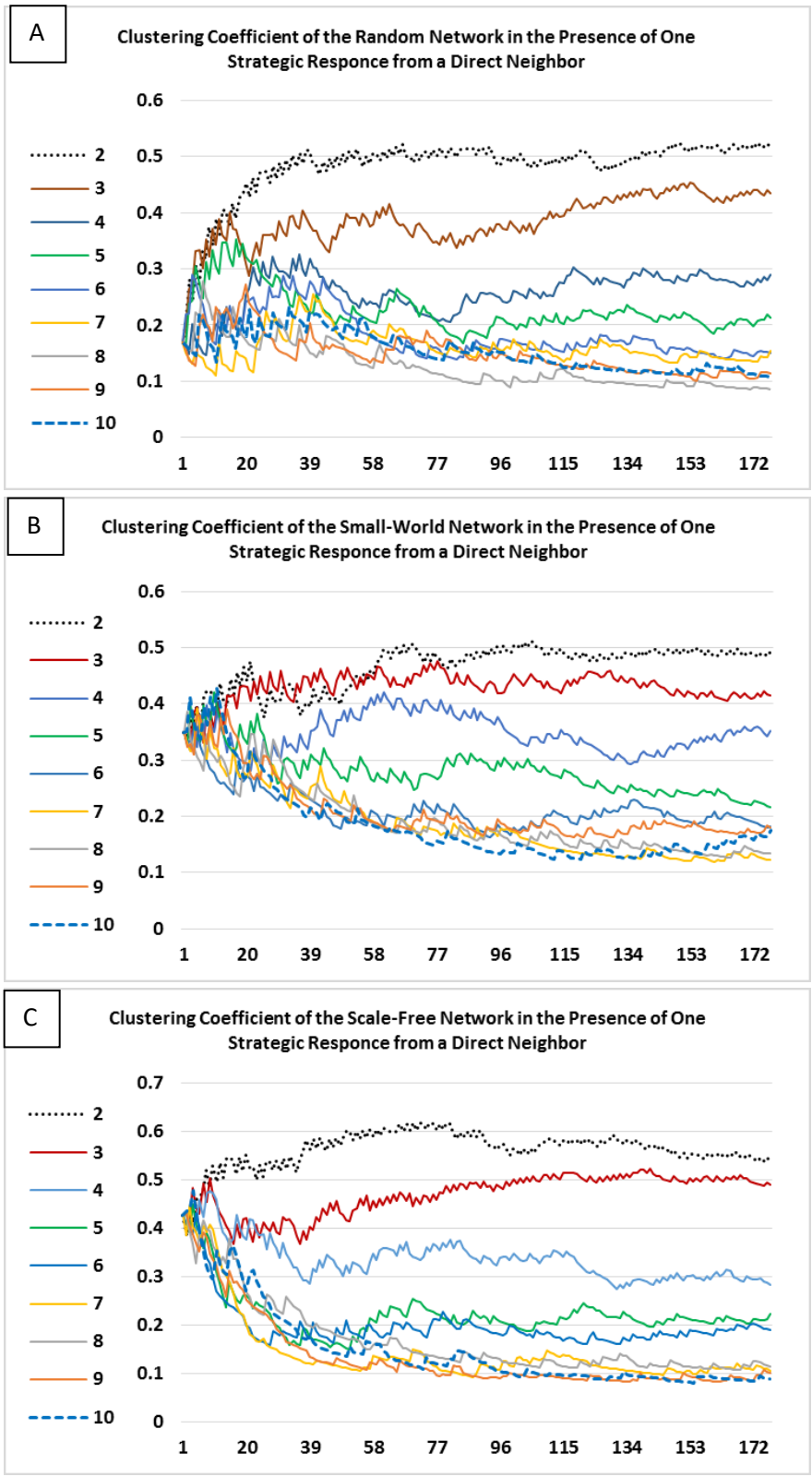



Figure 5.5: Clustering Coefficient of the networked individuals with respect to different underlying network structure and in the presence of one strategic response upon the process of network growth. The x-axis shows the simulation periods while the y-axis shows networks' Clustering coefficients. Plot legends show the variability in visibility parameter K.

We repeat the same set of experiments, however this time we calculated the emerging Clustering Coefficient (CC) of the networks. The result of our experiments are depicted in Figure 5.5. In particular, these figures show how changes in the clustering coefficient of the network occur with respect to different parameter configurations. The x-axis shows the simulation periods while the y-axis shows clustering coefficient of the network. As we can see regardless of underlying network structure, when the network visibility is set to a small number (i.e., k =2) CC values appear to be larger. However, when the visibility of the individuals is set to higher values (i.e., k =10) it leads to a huge change in the Network's clustering coefficient. This shows that better visibility of the nodes towards the global topology of the network does not lead to a network with higher clustering coefficient among its members. This indicates the fact that lower visibility towards global topology of the network leads to emergence of having network structures with higher clustering coefficient among its members.

### 5.2.2. How Strategic Networking Impacts the Networking Outcome

#### 5.2.2.1. Experimental Setup

In this part of the experimental setup, we aim to explain how the utility of networked individuals affected by underlying network structure, different methods of network growth and strategic responses of individuals towards it. We show that changes in the utility gain of individuals in a network are consequences of two factors impacting their interactions: (1) Different strategies of network growths, which allow new individuals to enter a network. (2) Adoption of strategic responses.

We performed sensitivity analysis with respect to four different initial underlying network structure among individuals (A Scale-Free Graph, A Bernoulli

Random Graph, A Regular Graph and A Small-World Graph). Those initial underlying graphs are depicted in Figure 5.6. The difference in the summation of the utilities of the individuals were not significant. For this reason we picked the graph with Scale-free topology as the initial underlying network structure and we performed our experiments. So basically it does not matter what the initial underlying network structure among the individual is, when everybody respond to what others are doing the final social welfare is almost the same. The result of our sensitivity analysis is reposted in Appendix 1.

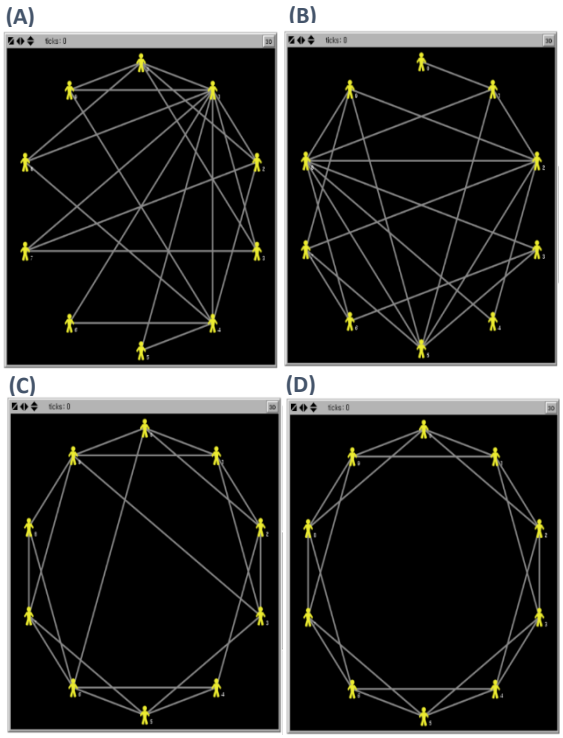



Figure 5.6: Four different initial underlying network structure among individuals.
(A) Scale-Free Graph, (B) Bernoulli Random Graph, (C) Small-World Graph with rewiring probability 0.1 and (D) Regular Graph. We have 10 nodes with 20 links at start up. We basically control the underlying network structure with respect to its size, the only thing that varies now is the underlying topology of the network.

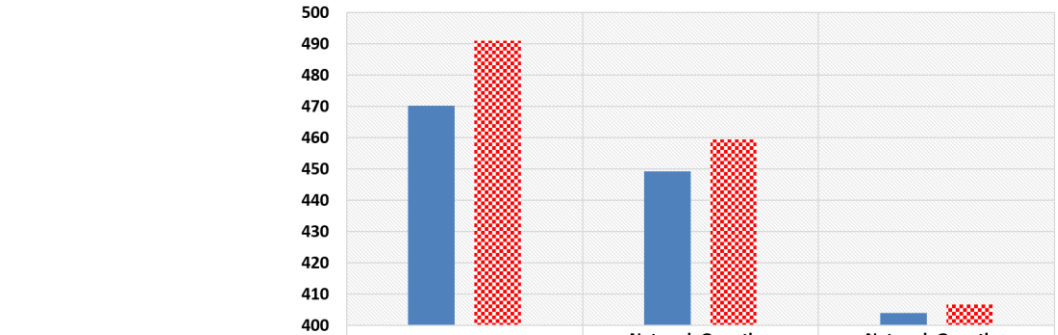
In this part of our experiments, we also select the value of k = d, where d is the diameter of the network and it means access to the entire agent set of the network, in the hope that the creation of such a link leads to a better utility for agent $n_i$. Simulation parameters and their descriptions are presented in Table 5.2.

Table 5.2. Simulation parameters related to strategic networking and networking outcome.

| Parameter Name | Description | Values | Source of values |
|---|---|---|---|
| network_growth | Methods of network growth.<br>(1) Preferential attachment strategy.<br>(2) Random growth strategy.<br>(3) Strategic Networking | • Preferential √<br>• Random √<br>• Strategic Growth √ | sensitivity analysis is done over this parameter |
| strategic_response | Number of direct neighbors, who perform strategic responses. | • One √<br>• All √ | sensitivity analysis is done over this parameter |
| d | Diameter of the network. | d is dynamic and grows over time | Dynamic |
| k | Distance from agent $n_i$ to any other agent $n_j$ in the graph G. | $K \in d$ | Dynamic |
| $B^k[n_i]$ | Set of potential candidate agents at distance k, with which an agent $n_i$ can increase its utility. | Subset of agents | Dynamic |
| $D(n_i)$ | Set of direct neighbors of agent $n_i$. | Subset of agents | Dynamic |
| $L(n_i)$ | Set of direct links in the neighborhood of agent $n_i$. | Subset of edges | Dynamic |
| $l_{n_i}(G)$ | Connectivity degree of agent $n_i$ in graph G. | Degree of agent $n_i$ | Dynamic |
| $p_{start}$ | Network size at start up. | 10 | Medium-sized enterprises before growth |
| $p_{end}$ | Total size of the network. | 200 | Medium-sized enterprises after growth |
| W | Social welfare | $W = \sum_{i=1}^{\lvert N \rvert} U(n_i, G)$ | (Bentham 2007) |
| $U(n_i, G)$ | Utility of agent $n_i$ in graph G. | $U(n_i, G) = 1 + \left(1 + \frac{1}{l_{n_i}(G)}\right) \sum_{n_j \in D(n_i)} \left(\frac{1}{l_{n_j}(G)}\right)$ | (Jackson and Wolinsky 1996) |

#### 5.2.2.2. Experimental Results

The simulation results of social welfare for different network growth models in the presence of or in the absence of strategic responses of individuals towards different network growth strategies is depicted in Figure 5.7. The x-axis shows the type of network growth model while the y-axis shows the social welfare. Each simulation has been repeated 100 times.




| | Simple network Growth without any Strategic Response | Network Growth + Performing one Strategic Response by a direct neighbor | Network Growth + Performing Strategic Response by all direct neighbors |
|---|---|---|---|
| Preferential Attachment Growth Strategy | 470 | 449 | 404 |
| Random Growth Strategy | 491 | 460 | 407 |

Figure 5.7: Total utility of the whole society (social welfare) with respect to two network growth strategies (preferential attachment growth strategy and random growth strategy) and in the absence of or in the presence of strategic responses by none, one, or all direct neighbors.

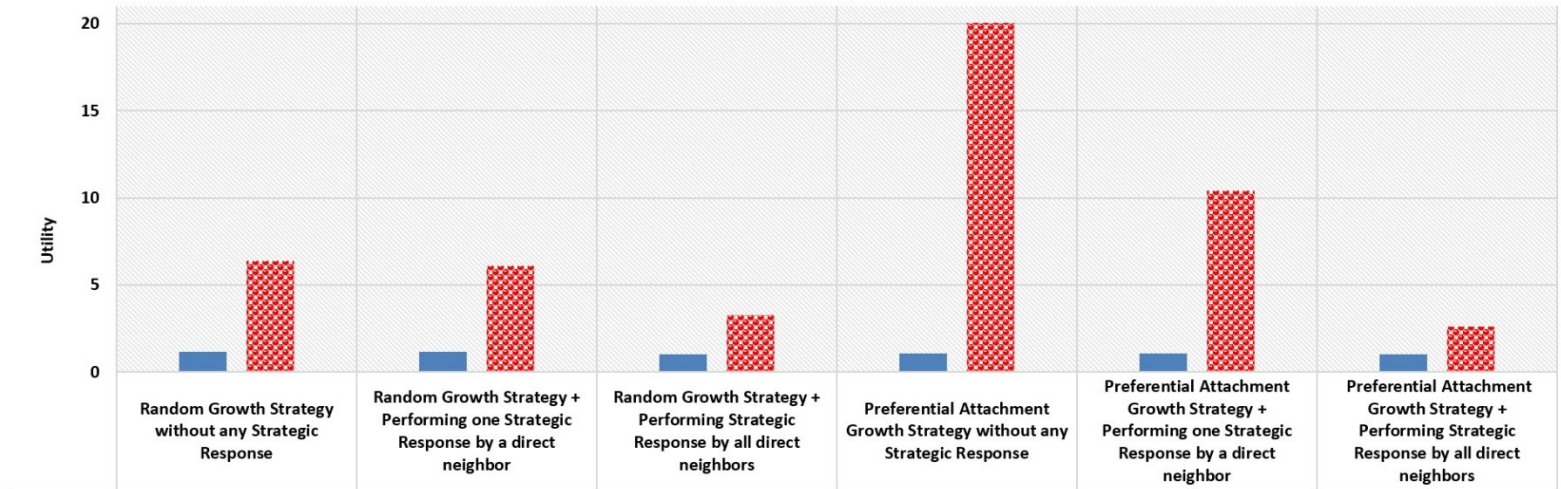
Figure 5.7 shows that different models of network growth lead to different social welfare results. In detail, the computed social welfare is the highest, if new agents enter the network with the random attachment strategy (i.e., the social welfare is 407, 460, and 491). That means the entrance of new agents with preferential attachment strategy negatively affects social welfare due to the fact that these agents attach themselves to agents with high degree of connectivity with a high likelihood. Another observation from this figure is that, in the presence of strategic responses of agents, social welfare decreases independent of the growth strategy chosen. That is to say, utility maximization behaviors

of agents in networks, which have been generated in response to different growth models, reduce the social welfare of the whole society. This is due to the fact that the strategic responses add new links to the networks, making these networks substantially different to networks formed without strategic responses with respect to the number of links in the networks.

In order to understand the characteristics of the networks in more detail, the minimum utility and the maximum utility for the whole society for each network growth method is compared. Figure 5,8 shows the simulation results with respect to the two network growth strategies and in the presence of and the absence of strategic responses of agents. The x-axis shows the six networks while the y-axis shows the utility. For the simulation, we used the same parameter settings as in the previous simulation.

Figure 5.8 shows that the maximum utility is achieved in the presence of preferential attachment strategy (in the absence of strategic responses of individuals). However, we observe a large gap between the minimum utility and the maximum utility in the network. The minimum utility calculated is 1.06 and the maximum utility is 20.06. Figure 5.8 also shows that the gap between the minimum utility and maximum utility gets smaller for networks that are formed through strategic responses. For example, the minimum utility is 1.02 and the maximum utility is 2.6, if all direct neighbors perform a strategic response. We relate this observation to having added a large amount of links by direct neighbors of highly connected agents (hubs). Since high-degree agents have a very high probability of being selected during the network growth, a large portion of direct neighbors select and perform their strategic responses.

Our simulation results in Figure 5.8 showed that the preferential attachment strategy favors agents, who have a high degree of connectivity to other agents. Therefore,




| | Random Growth Strategy without any Strategic Response | Random Growth Strategy + Performing one Strategic Response by a direct neighbor | Random Growth Strategy + Performing Strategic Response by all direct neighbors | Preferential Attachment Growth Strategy without any Strategic Response | Preferential Attachment Growth Strategy + Performing one Strategic Response by a direct neighbor | Preferential Attachment Growth Strategy + Performing Strategic Response by all direct neighbors |
|---|---|---|---|---|---|---|
| Min Utility | 1.18 | 1.15 | 1.04 | 1.06 | 1.06 | 1.02 |
| Max Utility | 6.4 | 6.1 | 3.3 | 20.06 | 10.4 | 2.6 |

Figure 5.8: Minimum utility and maximum utility of the whole society with respect to different network growth strategies and in the presence of and in the absence of strategic responses of agents.

it is of interest to understand the utility distribution for the whole society. The intention behind this new set of experiments is to identify a network with a homogeneous distribution of utilities. In this network, agents would be happier, as they do not observe a huge difference between their own utilities and those of others. The utility distributions of the whole society with respect to different network growth strategies are presented in Figure 5.9 and Figure 5.10. The x-axis shows the utility values while the y-axis shows the number of agents.

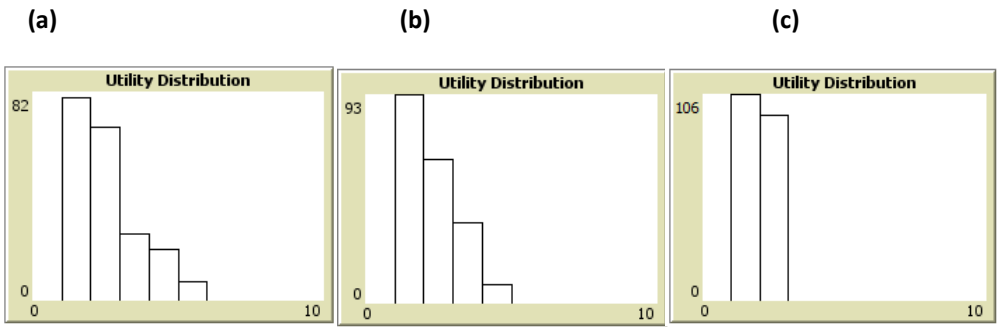



Figure 5.9: Utility distributions of the whole society with respect to the random growth strategy and (a) in the absence of strategic responses of agents; (b) in the presence of one strategic response of a direct neighbor; and (c) in the presence of strategic responses of all direct neighbors. The x-axis shows the utility values, while the y-axis shows the number of agents.

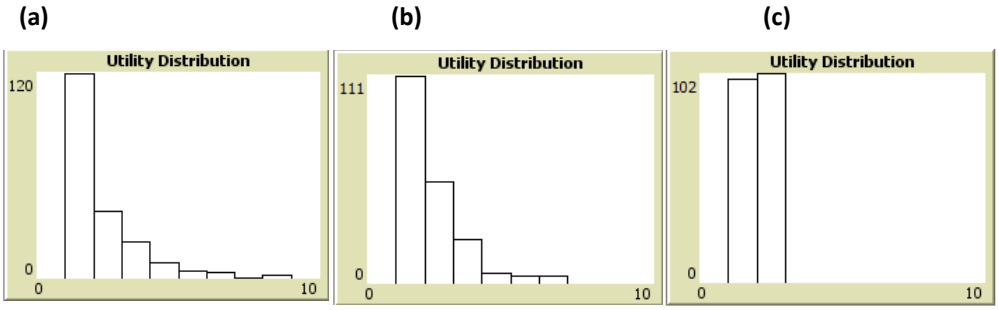



Figure 5.10: Utility distribution of the whole society with respect to preferential attachment growth strategy and (a) in the absence of strategic responses of agents; (b) in the presence of one strategic response of a direct neighbor; and (c) in the presence of strategic responses of all direct neighbors. The x-axis shows the utility values, while the y-axis shows the number of agents.

The results of both figures show that, regardless of the method of network growth, in the presence of strategic responses of all direct neighbors, utilities of the whole population are evenly distributed (Figure 5.9(c) and Figure 5.10(c). It can also be observed that, as long as a small population of agents performs their strategic responses, the variability in the utilities of the whole population is more visible (Figure 5.9(b) and Figure 5.10(b)). Compared to the linear utility distribution of networks formed through the random growth strategy, the utility distribution of network formed through the preferential attachment growth strategy follows a power law pattern (Figure 5.9(a) and Figure 5.10(a)).

We repeat our experiments one more time to observe how strategic growth model impact social welfare and the utility distribution of the whole population. New findings in this section will help us to compare the obtained results of previous experiments (i.e., Preferential and Random network growth models). The results of our analysis presented below.

Social welfare of the whole network is depicted in Figure 5.11 with respect to different network growth models and to the presence and absence of strategic responses of individuals towards different network growth strategies. In this part of our experiments we have three sets of experiments with three different configurations (with respect to different methods of the network growth and strategic responses to it). In particular, this figure shows how social welfare changes occur with respect to different parameter configurations. The process of network growth continued until the size of the network reached 200 ($n_{end}$ = 200). The x-axis shows the type of network growth model while the y-axis shows social welfare.

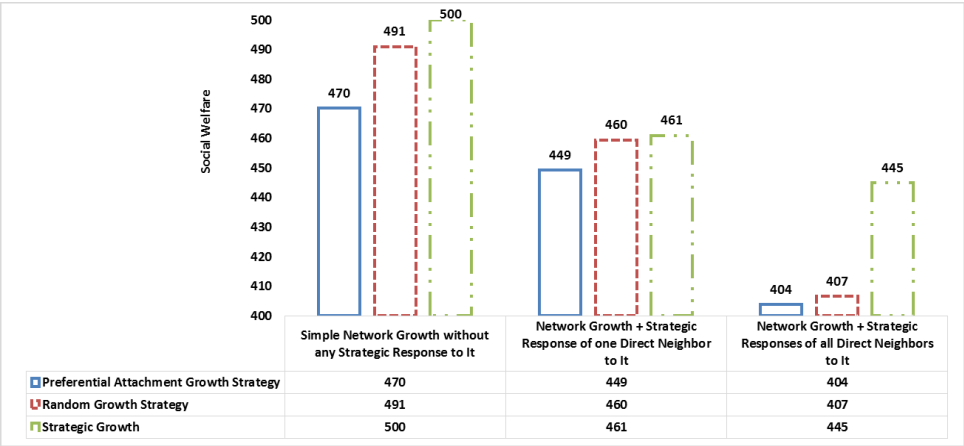
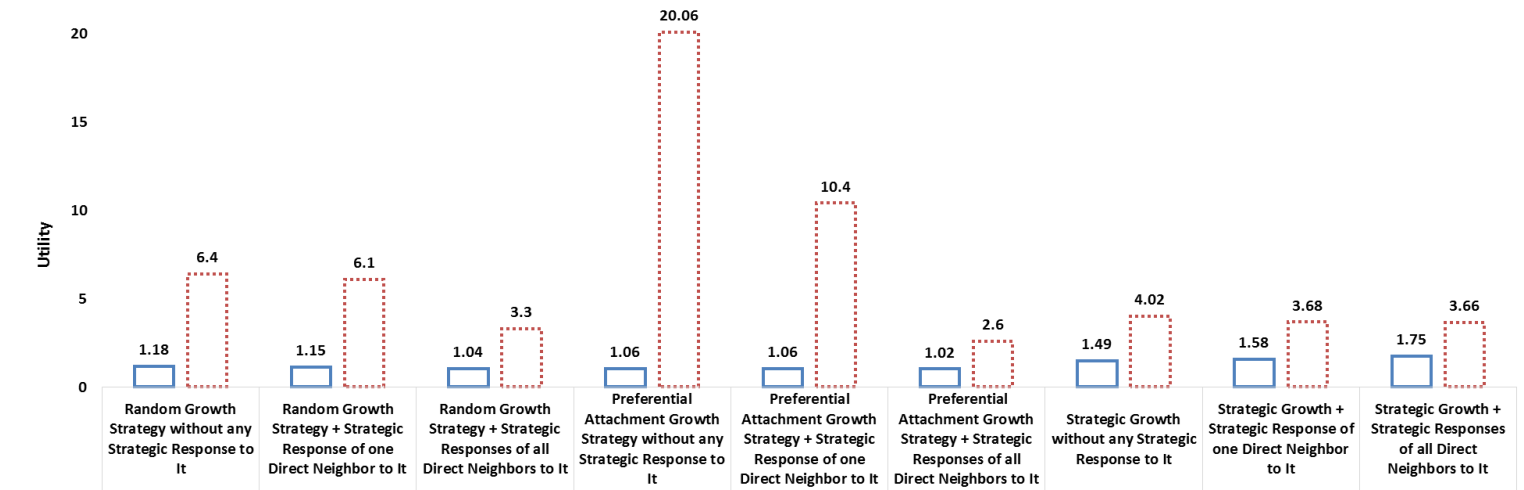



Figure 5.11: Total utility of the whole society with respect to different network growth strategies and in the presence of strategic responses of individuals. Strategic growth produces the highest social welfare. Adoption of strategic responses by all direct neighbors leads to lowest social welfare.

As we can see in Figure 5.11, different models of network growth lead to different results in the social welfare. In detail, the computed social welfare is the highest when the method of network growth is set to Strategic Growth. That is to say, new individuals enter the networks in a way to maximize their utilities so they search for the best candidate among the existing network members to provide them the highest utility (based on the co-author formulation the one who has the lowest degree of connectivity). As you can see our observations for social welfare in this method range from a score of 445 to 500. The second rank goes to Random node attachment strategy in which new individuals select their partners randomly (i.e., the observations range from a score of 407 to 491). That means the entrance of new individuals with preferential attachment strategy negatively affects social welfare. Another observation from this figure is that in the presence of strategic responses of the individuals, social welfare decreases. That is to say, utility maximizing behaviors of existing individuals in networks, which have been generated in response to different growth models, reduce the social welfare of the whole society. It can easily be observed that, as long as a small population of individuals adopt

such strategic responses, we can expect increase in the social welfare. Although this has been recognized as a general trend, the result of our third sets of experiment shows an interesting phenomena. When the method of network growth is set to Strategic Growth and all direct neighbors act strategically upon it the difference between calculated social welfare is the highest (i.e., the observations range from a score of 445 for strategic growth to 407 for random growth and 404 for preferential growth). This gives us the idea that strategic growth of a network triggers less number of strategic responses and it reduces the negative impact of it. That is to say, based on the co-author utility function connectivity to low degree nodes not just provides the focal individual the highest utility but also provoke fewer number of strategic responses. This in in its own turn positively impact the overall social welfare comparing to random and preferential node attachment strategies. The negative impact of sudden strategic responses of all direct neighbors of hubs (high degree nodes) in preferential attachment, for example, reduces the social welfare from 449 to 404.

Minimum and maximum utility of the whole society with respect to different network growth strategies and in the presence of strategic responses of the individuals are depicted in Figure 5.12. In particular, this figure shows which methods of network growth is able to produce highest and lowest utilities. The process of network growth continued until the size of the network reached 200 (N = 200). The x-axis shows the type of network growth model (different combinations) while the y-axis shows utility values.




| | Random Growth Strategy without any Strategic Response to It | Random Growth Strategy + Strategic Response of one Direct Neighbor to It | Random Growth Strategy + Strategic Responses of all Direct Neighbors to It | Preferential Attachment Growth Strategy without any Strategic Response to It | Preferential Attachment Growth Strategy + Strategic Response of one Direct Neighbor to It | Preferential Attachment Growth Strategy + Strategic Responses of all Direct Neighbors to It | Strategic Growth without any Strategic Response to It | Strategic Growth + Strategic Response of one Direct Neighbor to It | Strategic Growth + Strategic Responses of all Direct Neighbors to It |
|---|---|---|---|---|---|---|---|---|---|
| Min Utility | 1.18 | 1.15 | 1.04 | 1.06 | 1.06 | 1.02 | 1.49 | 1.58 | 1.75 |
| Max Utility | 6.4 | 6.1 | 3.3 | 20.06 | 10.4 | 2.6 | 4.02 | 3.68 | 3.66 |

Figure 5.12 : Min and max utility of the whole society with respect to different network growth strategies and in the presence of strategic responses of the individuals. Preferential attachment growth strategy produces the highest gap between minimum and maximum of social welfare.

Figure 5.12 shows that the highest utility (observations which range from a score of 2.6 to 20.06) can only be achieved in the presence of preferential node attachment strategy (In the absence of strategic responses of individuals). However, we observe a large gap between the minimum utility and the maximum utility of an individual in the network. The minimum utility calculated based on co-author formulation is 1.06 and the maximum utility is 20.06. An interesting observation from Figure 5.11 was related to a case when all direct neighbors decide to undergo their strategic responses. Social welfare heavily dropped in such a scenario, indicating that the strategic behavior of individuals as a response to what others were doing in a network in general were not beneficial to the whole society. However, Figure 5.12 shows that another consequence of such behavior is that the gap between the minimum utility and maximum utility gets smaller. The minimum utility is 1.02 and the maximum utility is 2.6. We relate this observation to having a denser population as a consequence of link formation between them. In case of preferential attachment growth higher density can be seen as the result of collusive behavior of direct neighbors in utility maximization process. Since high degree nodes have higher probability of being selected during the networks' growth, a larger proportion of direct neighbors select their strategic behaviors. Another interesting observation here is that the minimum utility has bigger value when the method of network growth is set to Strategic Growth (i.e., the observations range from a score of 1.49, 1.58 and 1.75).

Utility distribution of the whole society with respect to different network growth strategies are presented in Figure 5.13, Figure 5.14 and Figure 5.15. The x-axis shows the utility values while the y-axis shows the number of individuals with respect to a certain utility value.

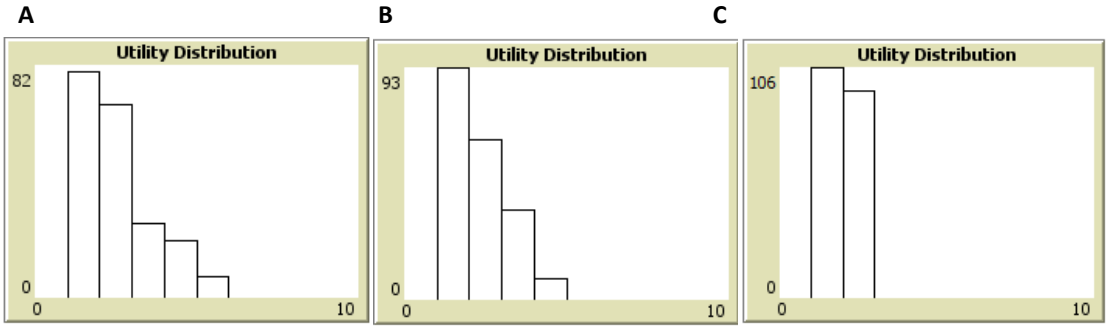



Figure 5.13 : Utility distribution of the whole society with respect to random growth strategy. The x-axis shows the utility values while the y-axis shows the number of individuals with respect to a certain utility value.
A) in the absence of strategic responses of the individuals.
B) in the presence of one strategic response of a direct neighbor.
C) in the presence of strategic responses of all direct neighbors.

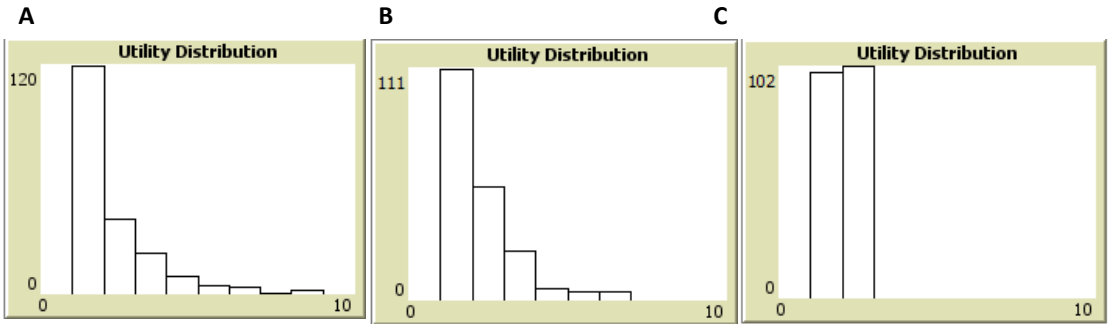



Figure 5.14 : Utility distribution of the whole society with respect to preferential attachment growth strategy. The x-axis shows the utility values while the y-axis shows the number of individuals with respect to a certain utility value.
A) in the absence of strategic responses of the individuals. .
B) in the presence of one strategic response of a direct neighbor.
C) in the presence of strategic responses of all direct neighbors

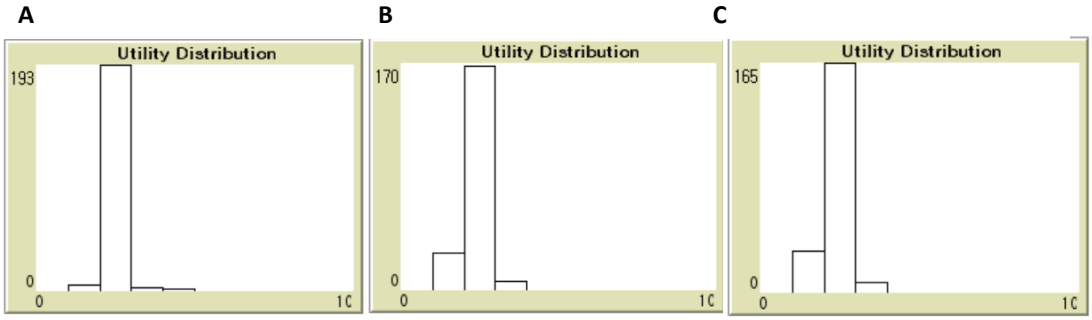



Figure 5.15 : Utility distribution of the whole society with respect to strategic network growth strategy. The x-axis shows the utility values while the y-axis shows the number of individuals with respect to a certain utility value.
A) in the absence of strategic responses of the individuals. .
B) in the presence of one strategic response of a direct neighbor.
C) in the presence of strategic responses of all direct neighbors

The results of both figures show that regardless of the method of network growth, in the presence of strategic responses of all direct neighbors, utilities of the whole population is evenly distributed (Figure 5.13(c), 5.14(c) and 5.15(c)). It can easily be observed that as long as a small population of individuals undergo their strategic responses variability in the utilities of the whole population becomes more visible (Figure 5.13(b) and 5.14(b)). Comparing to random growth strategy, utility distribution of the whole society with respect to preferential attachment growth strategy follows a power law pattern (Figure 5.13(a) and 5.14(a)). And finally utility distribution of the whole society with respect to the strategic growth does not change a lot in the presence of strategic responses (Figure 5.15(b) and 5.15(c)). We relate this observation to provoking fewer number of strategic responses.

## 5.3. Conclusion

What we can conclude from the obtained results is that all introduced factors in our interaction model, namely, methods of network growth and strategic responses towards them, have impact on the utility gain of the individuals, social welfare and emerging characteristics of the networks.

Regarding the emerging network characteristics, our experimental results show that all three factors have direct influence on the final network characteristics. When the process of network growth triggers strategic responses of all direct neighbors, we observe a heavy drop in average path length among the networked individuals. In such a scenario regardless of having a perfect visibility towards global topology of the networks (i.e., when visibility is set to two) the value of average path length shrinks to three. Fluctuations in the calculated network clustering coefficients are not really significant when network

visibility for the individuals is set to a value higher than 2. However, In the presence of only small fraction of strategic responses when network visibility is set to a higher value we are able to observe shorter average path lengths and higher clustering coefficients.

The result of introduced factors in our interaction model on the social welfare also were noticeable. For a utility function like co-author model in which the utility of an individual is a function of its own and its direct neighbors connectivity degrees, strategic growth always produces higher social welfare comparing to random and preferential connectivity style. Random growth model provides the whole population a uniform probability of link establishment to other new members joining the network and in comparison to preferential node attachment strategy produces higher social welfare. The preferential attachment strategy favors some specific individuals obtaining a high utility, but collusive behavior of direct neighbors in utility maximization process cause a huge drop in social welfare. It leads to the lowest social welfare, the lowest minimum utility, and lowest maximum utility among the whole population. Our observations also show that variability in the utility distribution is more visible in preferential attachment growth strategy comparing to a random and strategic growth. However, utility distribution of the whole society with respect to the strategic growth does not change a lot in the presence of strategic responses which is due to provoking fewer number of strategic responses within the network.

## 5.4. Discussion & Implication

One question that may be raised in the readers' mind is that what will happen if we relax the assumptions that of the designed interaction model in this chapter. One possibility could be to use other utility functions in the proposed interaction model which

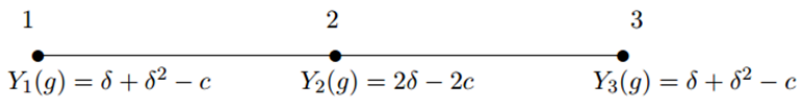
provide positive externality to the whole population. Symmetric connection model can be considered as an alternative, for example (Jackson and Wolinsky 1996).

Formally, we can express the utility player *i* receives from network g within symmetric connection model as:

$$Y_i(g) = \sum_{j \neq i} \delta_{ij}^{d(i,j)} - \sum_{j:ij \in g} c_{ij},$$

Through this model, in addition to direct links, individuals also benefit from indirect communication from those to whom their adjacent nodes are linked, and so on. According to symmetric connection model, the obtained benefit has a direct relationship with the distance between source and destination players in a network. Cost is a linear cost which depends to the cardinality or the degree of the nodes.

Consider a network of 3 individuals in the configuration of a line topology. As it is shown below, individual 1 in addition to receiving a benefit from link establishment with individual 2 (it is shown with benefit term $\delta$) receives another indirect benefit from link establishment of individual 2 and individual 3 (it is shown with benefit term $\delta^2$). The cost term (it is shown with benefit term $c$) only occurs for direct links, so individual 1 does not need to be worry about maintenance cost of link establishment between individual 2 and individual 3. The interesting part of the formulation model is that, although the amount of indirect benefit is a small value but still can be considered as an additive value to the gained net utility of all the individuals within the network.




If that happens in our interaction model, the process of link establishment increases the net utility of all the individuals within the network. In such a case there is no

need to model strategic interactions of the individuals, because actually everybody will benefit from existence of more links within the network. However, in the context of socio-economic complex adaptive networks, lack of time and resources restrict opportunities for ongoing relationship-building. These limiting conditions are created and shaped by environmental factors, revealing that actors' attitudes, capabilities, and behaviors are not completely self-directed.

Another question that may be raised in the readers' mind is related to the way co-author utility function models direct and spillover benefits out of collaboration with others. Direct benefits are those explicit benefits which we transfer to each other during the process of link establishment. On the other hand, spillover benefits are those which we send out to and receive indirectly from other contacts in the network. In the literature the spillover benefit is known as collective/network or common utility. The spillover part of the overall benefit is like an accumulative stock and if it does not grow it does not attract utility at the individual level.

The original utility function of the co-author model sees the utility of agent $n_i$ in graph $G$ as:

$$U(n_i, G) = \sum_{n_j \in D(n_i)} \left( \frac{1}{l_{n_i}(G)} + \frac{1}{l_{n_j}(G)} + \frac{1}{l_{n_i}(G) l_{n_j}(G)} \right)$$

$D(n_i)$ consists of all agents $n_j$, who are direct neighbors of agent $n_i$. Therefore, the term $\left( \frac{1}{l_i(G)} + \frac{1}{l_j(G)} + \frac{1}{l_i(G) l_j(G)} \right)$ in Equation 1 is repeated for all neighboring agents $n_j \in D(i)$. All the three term $\frac{1}{l_{n_i}(G)}$, $\frac{1}{l_{n_j}(G)}$ and $\frac{1}{l_{n_i}(G) l_{n_j}(G)}$ in the above formula capture the direct benefits out of link establishment with the other partner. However, the

this process of link establishment sends out the following negative externalities which results in decrease in the utility of the direct neighbors of agent $n_i$.

$$\sum_{n_j \in (D(n_i)-1)} \left( \left( \frac{1}{l_{n_j}(G)+1} - \frac{1}{l_{n_j}(G)} \right) + \left( \frac{1}{l_{n_i}(G) * (l_{n_j}(G)+1)} - \frac{1}{l_{n_i}(G) l_{n_j}(G)} \right) \right)$$

Therefore, it is easy to see that the co-author utility function produces negative spillover effect.

And finally, since in this chapter we used co-author utility function we did not need to consider individual level variables and variety of subgroups within the network. However, we should mention that socio-economic complex adaptive networks consists of verity of subgroups and individual level variables. Therefore, we may have different observations with respect to distributional changes in social welfare amongst subgroups. In such cases we can utilize nonparametric tests which enable us to assess such relations to a degree of statistical certainty. Stochastic dominance (Hadar and Russell 1969, Bawa 1975) is one of those approaches which unlike average outcome from complete order ranking, identify dominance relations. Stochastic dominance provides us with an incomplete ordering of distribution (i.e., First-order, Second-order, Third-order, Higher-order stochastic dominance), as soon as we know the parameters of two distributions of the same type (i.e., Mean and Standard Deviation). If dominance relations are inferred, one can distinguish the better off group from its counterparts and therefore have a clear vision of the future policies, strategies and programs for helping the targeted groups (Maasoumi, Su et al. 2013). In the mathematical theory of probability, stochastic dominance is a form of stochastic ordering and is utilized in analysis of income inequality and well-being within or between different regions (Maasoumi and Heshmati 2000, Maasoumi and Heshmati 2005).

# Chapter 6. Conclusion & Discussion

## 6.1. Summary

Both structuralism and individualism approaches for network analysis have their own limitations when it comes to study socio-economic complex adaptive networks. Structuralists neglect the fact that individual level variables can determine the structure and individualists need to consider that interconnectedness within a system can be forced by the system (lack of flexibility for individuals to change the structure). Therefore, in this thesis we argued that a hybrid approach (based on CAS theory) is needed to study the social system within socio-economic complex adaptive networks and its networking outcome. Key features to this new hybrid approach for us are: (1) Heterogeneity of agents, (2) Working with adaptation, (3) Connectivity, (4) Bounded rationality of actors and (5) Feedback loops. That is to say, what actually results in the emergence of new systemic social qualities within socio-economic complex adaptive systems are the integration of the economic behavior of their actors as well as the social system within which they interact with each other Individual actions determine the network structure and similarly structure also influence individual actions and thinking. They constrain and enable actions. Therefore, there is a feedback loop between individual actions and the network structure.

In chapter 3 we argued that a more realistic approach for the study of socio-economic complex adaptive networks would be to categorize dynamic processes within them. After a perfect categorization, stochastic style of link establishment in each category is applicable. Stochastic style of link establishment is considered to be the structuralism approach. However, categorization of those dynamic processes within socio-economic

complex adaptive networks makes it more meaningful because this way we can identify what types of interactions may contribute to the formation of the social system (network of connectivity). We followed an agent-based modeling approach to depict a complex structure emerging from the interaction of simple rules over time. Our model is able to capture, compare, and explain the structural changes within a growing social system. The simulation results showed that in addition to the rate of variability in an individual's pattern of behavior, the limitations on the size of personal networks significantly changes the average shortest path lengths among individuals within a socio-economic complex adaptive network. The importance of this issue will be more understood and highlighted in situations when further changes within the baseline characteristics of the network are needed to produce a better networking outcome. We covered this issue in chapter 4 of this thesis.

In chapter 4 we argued that although structuralism approach has the potential to tell us what the interesting characteristics of a social system are, the extent to which such varieties of structural characteristics affect the outcome of individuals has received little attention. We considered the organizational learning to be an example of networking outcome in this chapter. In order to answer how different networks' characteristics affect organizational learning, we needed to focus especially on the structural properties of the social system and the obtained utility of individuals there. Therefore, we developed an agent-based model to simulate the collective learning of workforces within an organization. With this model, the organizational learning performance under different structural properties (i.e., the clustering coefficient and the average shortest path length) of social networks was captured and compared with one another. The clustering coefficient and the average shortest path length were measured as a function of time. We

also used our proposed model presented in chapter 3 for creating the social system that realistically reflects the social interaction among the work-force of an organization. The results of our analysis indicated the fact that structural changes within the topology of the social system affect organizational learning performance. The learning performance consistently increased with a decrease in the rate of FOAF type links and an increase of random type links among the population. Therefore, we concluded that higher clustering coefficient within a network does not necessarily produce the highest learning outcome and even stops innovation in learning. Instead, shorter average shortest path lengths within a network of individuals positively affected organizational learning. Our experimental results also showed that the existence of links of random type within a network facilitate and increase learning among the population. Consequently, we can state that certain topological features of a social system can help its members to get better access to information exchange processes within an organization and it impacts their learning outcome.

In chapter 5 of this thesis, we argued that by looking further and deeper into changes in the structural properties of a social system within socio-economic complex adaptive systems, we can also relate them to the strategic interactions of individuals that are located in it. In the world of networked individuals, usually the main focus of the focal individual is on his or her own utility. Therefore, it is logically acceptable to consider humans as opportunity seeking actors who act strategically, in order to maximize utilities from their connectivity patterns in the network. And consequently, we can justify why the underlying network structure of a social system is constantly changing and as the result a certain type of network with specific characteristics emerges. This is actually the gap that we had observed in traditional strategic network formation models. In order to fill this gap,

we provided an interaction model to show that the changes of the structural properties of a social system are caused through a variety of dynamic processes such as underlying network structure, different methods of network growth, strategic responses of the individuals and network visibility. Consequently, we made a connection between the social welfare and emerging network characteristics. Our experimental results showed, almost all introduced factors in our interaction model, namely, methods of network growth, strategic responses towards them and network visibility, have impact on the utility gain of the individuals and emerging characteristics of the networks.

Regarding the emerging network characteristics, our experimental results showed that when the process of network growth triggers strategic responses of all direct neighbors, we observed a heavy drop in average path length among the networked individuals. In such a scenario regardless of having a perfect visibility towards global topology of the networks (i.e., when visibility is set to two) the value of average path length turned to be a small value (shrinks to three). However, in the presence of only small fraction of strategic responses when network visibility was set to a higher value we were able to observe shorter average path lengths and higher clustering coefficients.

Regarding the networking outcome, our experimental results showed that different models of network growth lead to different results in the social welfare. In detail, the computed social welfare is the highest when the method of network growth is set to Strategic Growth. That is to say, new individuals enter the network in a way to maximize their utilities so they search for the best candidate among the existing network members to provide them the highest utility. The second rank goes to Random node attachment strategy in which new individuals select their partners randomly. That means the entrance of new individuals with preferential attachment strategy negatively affects social welfare.

Another observation is that in the presence of strategic responses of the individuals, social welfare decreases. That is to say, utility maximizing behaviors of existing individuals in networks, which have been generated in response to different growth models, reduce the social welfare of the whole society. It can easily be observed that, as long as a small population of individuals adopts such strategic responses, we can expect an increase in the social welfare. In the presence of strategic behaviors (i.e., network members compete to maximize their own utilities), we can expect a low social welfare but an even distribution of utility of each member of the system. Another interesting observation is that when everybody respond to what others are doing (i.e., when all neighbors of a node strategically respond to the process of network growth) the social welfare value is almost the same. Therefore, in the presence of a large fraction of strategic responses within the social system the social welfare is almost the same. So basically it does not matter what the initial underlying network structure among the individual is, when everybody respond to what others are doing the final social welfare is almost the same.

## 6.2. Discussion & Implication

When we look at the topological formulation of different network models presented in the literature, such as Erdos-Renyi Random graph model, Watts-Strogatz Small-World model or Barabási–Albert Scale-Free model, it seems there is no line of communication between the topology of a network itself and the principles underlying strategic choices of the players that are locating in it. Currently, those topologies are only explainable by the type of behavior actors of a network generate, which are mainly random and preferential attachment. There have been considerable amounts of social network research with the focus on capturing the characteristics of certain networks. That is

actually a trend of network analysis which is emphasized by structuralism approach. Structuralists are more interested in the pattern of connectivity among the components of the system. Although structuralism approach has the potential to tell us what the interesting features of networks are from both theoretical and practical perspectives, the extent to which such varieties of structural properties affect the utility gain of individuals has received little attention in the literature.

Furthermore, existing works in the area of strategic network formation models suffer from other issues. They only explain how different network structures emerge from scratch (e.g., from isolated nodes to dyads, stars) with respect to specific utility functions. They also assume the rationality of network players while playing a certain strategy. This assumption helps researchers in this area to simplify the research question and discuss about observing an equilibrium within the system. Consequently with those approaches, we are not able to consider heterogeneity in the behavior of the network members. We observed those gaps for stochastics network formation models and for strategic network formation models.

The necessity of applying a hybrid approach for the study of socio-economic complex adaptive networks gave us the motivation to deliver an interaction model to explain and compare how the combination of a utility scheme, underlying network structures, network visibility, different methods of network growth and strategic interaction of the individuals within a network can determine the networking outcome of socio-economic complex adaptive networks. That is to say, by applying a hybrid approach we can make predictions on the benefits of the integration of economic behavior of their agents and their social interactions that result in the emergence of new systemic social

qualities. Consequently, we can develop mechanisms and techniques that can guide and regulate the evolution of such systems.

For example, if we are going to model the evolution of innovative cooperation within a socio-economic complex adaptive network, we should consider this socio-economic complex adaptive network following a hierarchical structure. That is why we are dealing with variety of interrelated networks which appear within different social interaction contexts. Consequently, the underlying processes which determine the evolution of innovative cooperation are different within different contexts. Hence, in situations where we are dealing with empirical data, the following steps will help us to have a better modeling techniques and realistic view of real world scenarios.

1. We need to identify the determinants of cooperative behavior
2. We need to estimate the effect of the determinants identified at previous step
3. We generate future policy implications

This approach requires econometric approaches for identifying the factors that lead to cooperative behavior in order to achieve innovation. The determining factors must be defined according to empirical findings from the real world. We also need to define simulation algorithms and parameters based on the determinants of actors' likelihood to participate in cooperation with other network members. The calibration process needs to be conducted to the point where artificially generated scenarios becomes equivalent to the one observed in the real world. Calibration is the process by which the system modeler establishes input parameter values in order to reflect the local conditions being modelled. Refinements and modifications must be made to the model parameter values, if the established criteria for the evaluation of the calibration process are not met. This approach

will subsidize further research by applying agent based modelling to simulate innovation networks in different industry sectors. An example of this approach is conducted by (Lenz-Cesar and Heshmati 2009, Heshmati and Lenz-Cesar 2013, Heshmati and Lenz-Cesar 2015) .

The main essential implication of our research in chapter 3 is that we can explain the differences in the average shortest path length measured in empirical studies and existing network growth models (which did not consider the size of the personal networks before). Our network growth model is able to explain in more detail the structural changes within a growing social network with respect to the social characteristics of individuals. Examples of such social networks include social network of people within virtual environments or the network of employees within an organization.

For example, a social networking platform such as Facebook attempts to reduce social distances among people through daily social activities. Once a user specifies its social circle after registering at the Facebook website, the feature "Recommendation of a Friend of a Friend" enables the users to develop their social circles, and for example, to change their social distance from 2 to 1. This is by itself very desirable but it shall not be neglected that providing positive feedback towards such processes certainly leaves significant impacts on the properties of the Facebook social network. According to our obtained result if the amount of responses towards FOAF style of link establishment increases, we can expect further shrink in the average path length of the Facebook network. Having said that, we think that future strategies and algorithms for link predictions are needed to increase the percentage of links of random type within Facebook platform. Currently, services such as "Recommendation of a Friend of a Friend" is a static service and it triggers automatically in the Facebook system. However, with the help of new link

prediction algorithms, we can expect to have an increase in the percentage of links of random type within the Facebook that benefit people by bringing them closer together. We can imagine a scenario where people in Facebook are introduced to each other (randomly selected members) based on similarity of their profiles or based on a neat mechanism to consider their friendship selection criteria. In this case we are dealing with the emergence of adaptive services within Facebook ecosystem by which personalized services will be offered to its users. In addition to that such new services have this ability to adapt to changes within the Facebook platform (i.e., with respect to individual level or environmental factors).

The obtained results of chapter 4 have managerial implications. Our experimental results showed that social relationships between individuals in an organization can be utilized to produce positive returns. Despite the creation of new knowledge and the process of learning at an individual level, organizational structure affects the nature of human interactions and information flow. Therefore, we believe that top managers and leaders by applying proper structural changes within the network of employees within the organization can achieve a better organizational learning outcome. This can be considered as a mechanism for increasing the knowledge flow and improving organizational learning performance. The results of our analysis suggests that managers are able to use organization structure as a tool for improving the balance between exploration and exploitation and helping the organization explore a diverse solution space, and subsequently achieving better long-term learning performance outcomes (March 2005, Gupta, Smith et al. 2006).

With respect to improving the balance between exploration and exploitation, we should mention that in socio-economic complex adaptive systems such as organizations,

immediate returns from exploitation cause the system to exhibit a myopic bias. Employees within organizations tend to pursue solutions similar to already-known solutions because they do not have access to all possible domains of knowledge. This will push them towards their own prior experiences and utilization of existing routines. Consequently, it decreases the likelihood that new solutions will be found. Therefore, we can argue that adaptive processes which are only based on exploitations can become self-destructive in the sense that they mislead the organization to become trapped in a suboptimal equilibrium. In the literature this is known as success trap. This argument is articulated by many researchers (Bower and Christensen 1996, Lenox 2002, Nickerson and Zenger 2002, Benner and Tushman 2003, Siggelkow and Levinthal 2003, O Reilly and Tushman 2004, Argote and Greve 2007, Jacobides 2007). However, further research is needed to understand how organizations can avoid to be stuck in such self-destructive processes. Since this seems to be more a managerial issue, we need to investigate the role of managers in helping organizations to better maintain the balance between exploration and exploitation instead of overemphasizing the already-known solutions.

The obtained results out of the proposed interaction model in chapter 5 showed that, in the absence of strategic responses of individuals, the preferential attachment strategy favors some specific individuals to get a high utility. In the presence of strategic behaviors (i.e., network members compete to maximize their own utilities), the results showed that the consequence of such interactions is a low social welfare but an even distribution of utility of each member of the society. Our observations gave us the idea that, if competition among individuals in a society exists, we can avoid certain network members to gain high utility compared to others as well as avoid network structures, in which utilities of the network members are widely dispersed. In such a setting, individuals

experience no discrimination in utility against other people in their communities. Therefore, the strategic responses of individuals create a society with increased happiness.

As an implication of our research in chapter 5, we highlight the fact that network organizers by considering the connectivity of individuals for the network growth method, can support network formations that are beneficial (i.e., finding a trade-off between high social welfare and a homogenous utility distribution) to the entire society.

Finally, we observed how a complex adaptive systems approach helps the system modeler in investigating both the characteristics of individual entities at the micro level and their interacting forces at the macro level. In addition to that, it considers the feedbacks in interactions during the system analysis. This is an important issue with respect to socio-economic complex adaptive systems such as our educational systems, political systems and health care systems which are all components of our world. They are around interactions among people, processes and resources of their own types. In order to understand each of those societal constructs, we need to have knowledge about their actors, as well as the relationships and interactions between them. This way we can understand the whole system and explain its functionality and emerging global patterns within them.

## 6.3. Limitations

The proposed interaction model in this thesis is suitable for human-to-human communication environments, where the process of network growth triggers a strategic response among the existing network members. It is built on the assumption that a utility maximization process can be considered as a form of incentive for link establishment among network members. However, socio-economic complex adaptive networks are

everywhere. These complex networks will appear within different social interaction contexts and for sure the underlying processes which determine the emerging characteristics of the social system are different.

Organizational social capital (network of employees) within an organization can be considered as a concrete example of socio-economic complex adaptive networks. Compared to friendship networks in real world, what brings employees together and forms the network among them is actually the organizational goal. An employee's attitude towards reaching the organizational goal must be in line with the employee's own perception of success within the organization. There are a lot of factors that may impact the level of cooperation and competition within an organization. Extended studies of social capital within an organization could provide more detailed insight. For more insight, we also plan to apply our interaction model to other contexts and domains.

Two issues that may arise in chapter 4 and 5 are around the way that we related those network characteristics to the outcome of individuals within the network (i.e., the learning outcome or the utility gain) and second the possibility of imposing such structural changes within the social system. Regarding the first issue, we need to think about a performance measure, which depends on the type of the socio-economic complex adaptive network. Therefore, it would be interesting to test other performance measures in our future studies. Regarding the second issue, we can argue that managers within companies with a proper incentive mechanism are able to provide motivations for other employees to be more open towards collaboration with others. Since, in this thesis, our main goal had been to make a connection between emerging network characteristics and a performance measure, we did not consider the effect of incentives and other factors (e.g., organizational culture), which might influence the level of collaboration between individuals within the

network. Considering quality of the relationships and the limitation which might be imposed from the organizational hierarchy to the employees are also from interesting points for our future studies.

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# Appendix 1

In section 5.2.2.1 of this thesis, we performed sensitivity analysis with respect to four different initial underlying network structure among individuals (A Scale-Free Graph, A Bernoulli Random Graph, A Regular Graph and A Small-World Graph). Those initial underlying graphs were depicted in Figure 5.6. As we can see in the series of pictures here (Figure 5.16, Figure 5.17, Figure 5.18), the difference in the summation of the utilities of the individuals were not significant. Figure 5.18 is the summary of data observed in Figure 5.16 and Figure 5.17 which is grouped based on each network topology. As Figure 5.18 shows it does not matter what the initial underlying network structure among the individual is, when everybody respond to what others are doing (i.e., where X axis is "All") the final social welfare is almost the same. For this reason we picked the graph with Scale-free topology as the initial underlying network structure and we performed our experiments.

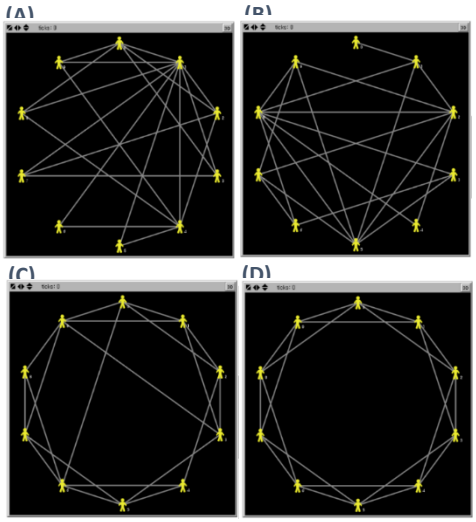
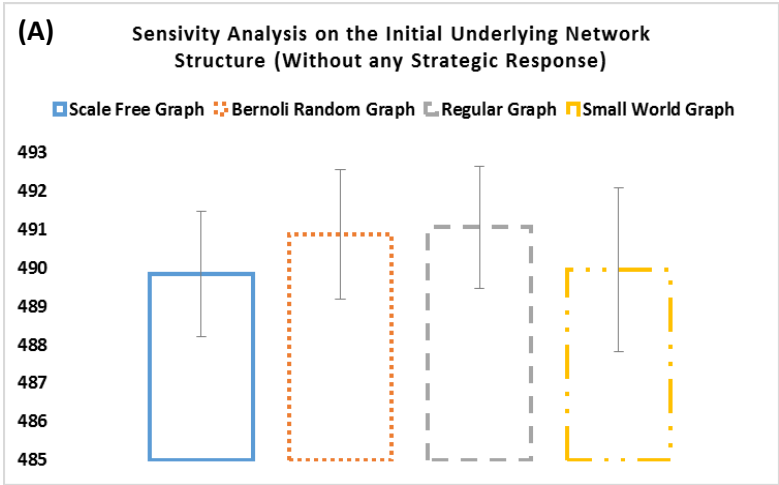
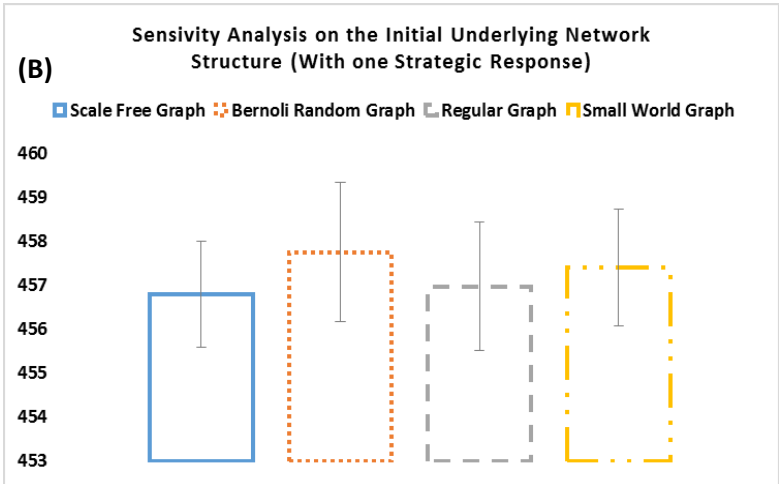



Figure 5.6: Four different initial underlying network structure among individuals. (A) Scale-Free Graph, (B) Bernoulli Random Graph, (C) Small-World Graph with rewiring probability 0.1 and (D) Regular Graph. We have 10 nodes with 20 links at start up. We basically control the underlying network structure with respect to its size, the only thing that varies now is the underlying topology of the network.



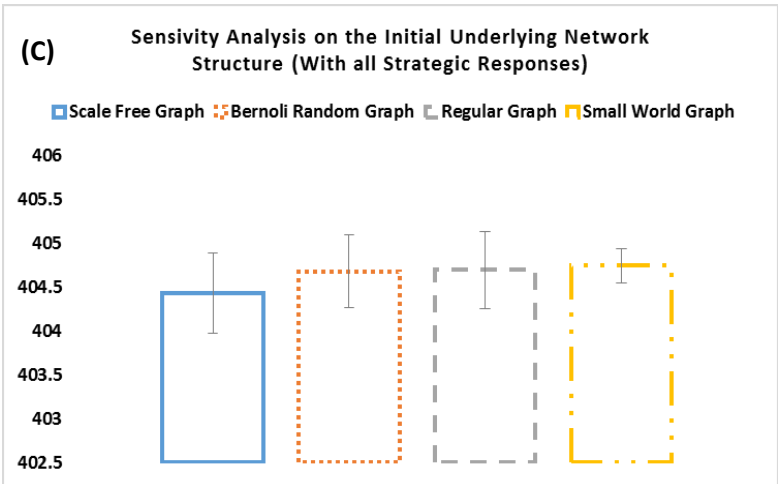
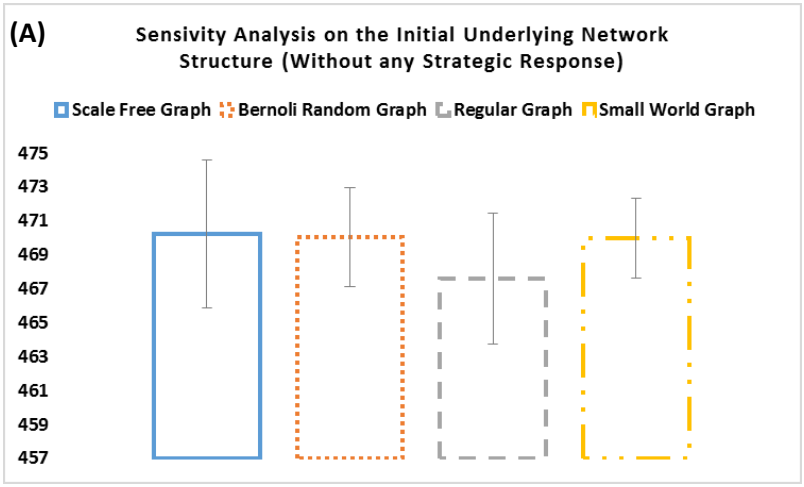
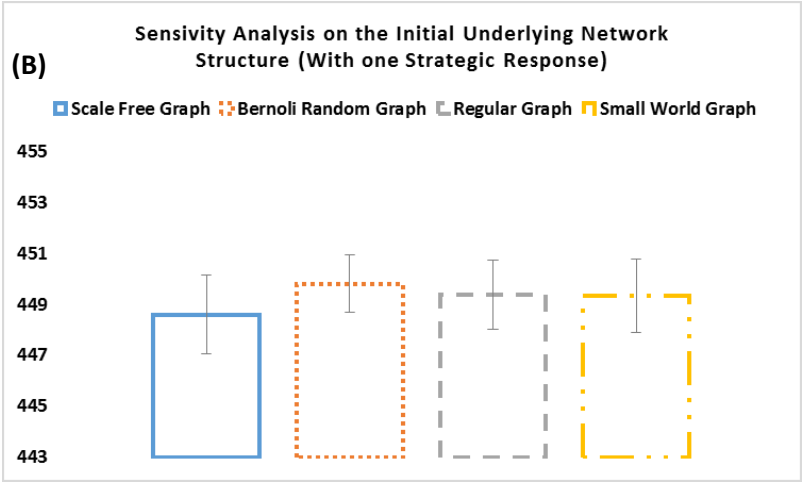




Figure 5.16 : Sensitivity analysis with respect to different initial underlying network structure among individuals and in the presence of Random Growth Model. Y Axis shows the total utility of the network or social welfare.



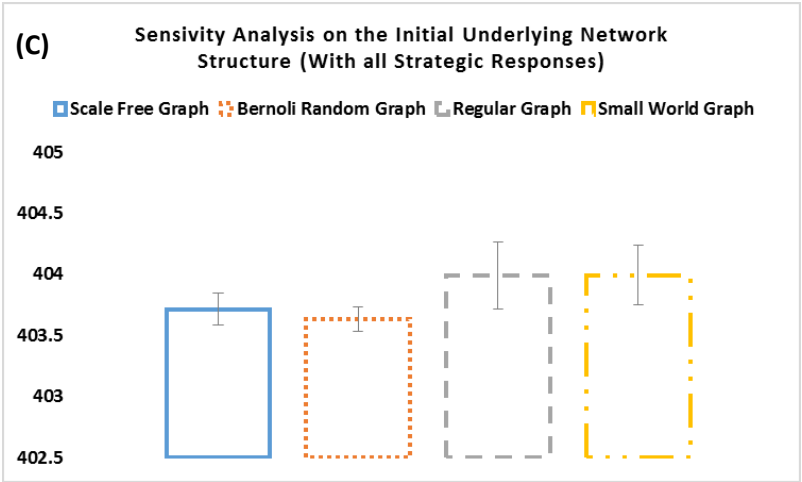




Figure 5.17 : Sensitivity analysis with respect to different initial underlying network structure among individuals and in the presence of Preferential Growth Model. Y Axis shows the total utility of the network or social welfare.

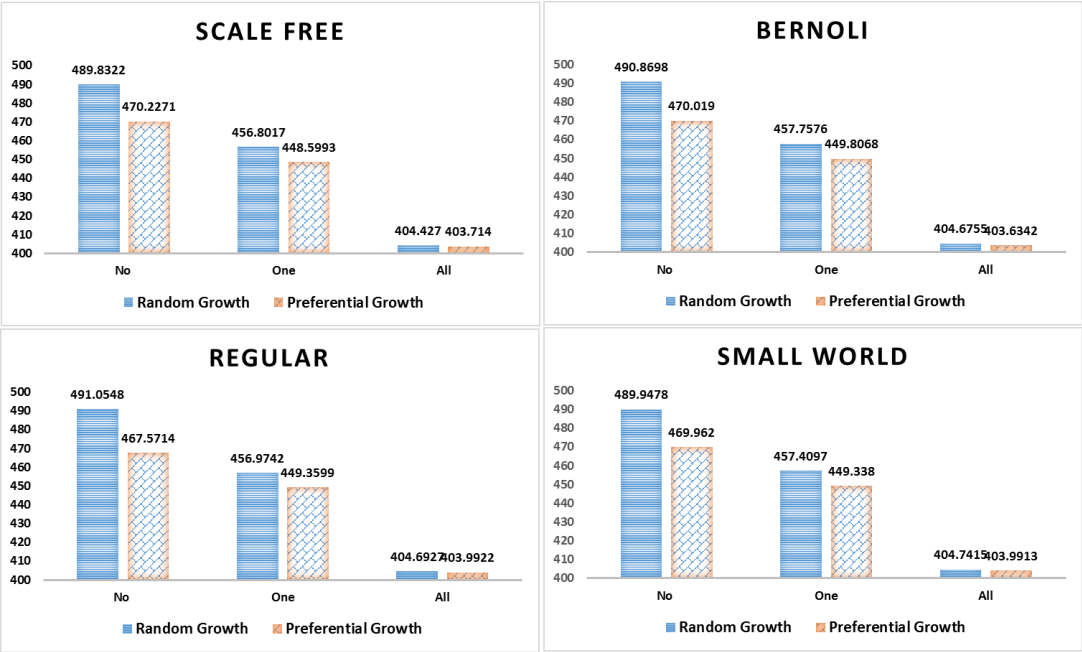



Figure 5.18 : Sensitivity analysis on the total utility of the whole society with respect to different initial underlying network structure among individuals. Y Axis shows the total utility of the network or social welfare. X axis shows the absence or presence of strategic responses of the individuals towards the method of network growth.

# Abstract in Korean ( 국문 초록 )

## 사회경제적 복잡계 네트워크에 대한 하이브리드 방식의 분석

**Somayeh Koohborfardhaghighi**

기술 경영, 경제, 및 정책 프로그램

공과 대학

서울 대학교

본 논문의 목적은 사회경제적 복잡계 네트워크에서 개인의 사회적 속성 관점에서의 구조적 변화를 설명하는 것이다. 사회경제적 네트워크의 참여자들은 자각을 가진 사회적 단위로서, 그들의 목적을 이루기 위해 다양한 전략적 과정을 거치게 된다. 그리하여 이러한 네트워크를 참여자들 및 시간에 따라 변화하는 그들의 상호작용의 관점에서 체계적으로 분석할 필요가 있다. 특정 네트워크의 발생을 설명하기 위해 기존 문헌은 확률적 네트워크와 전략적 네트워크 형성 모델을 소개하였다. 그러나, 이러한 기법들은 그 자체로 한계를 지닌다. 확률적 네트워크와 전략적 네트워크 모두 네트워크의 흥미로운 특징들이 무엇인지 설명해 줄 수 있는 반면, 이들이 개인간 상호작용에 어느 정도의 영향을 미치는지는 불분명하며 기존 문헌에서도 충분히 다루지 못했다.

본 논문에서 우리의 초점은 인간과 인간 사이의 소통 환경에 맞추어져 있다. 인간과 인간 사이의 소통 환경에서 네트워크의 성장은 경제적 인센티브에 기반하여 네트워크 멤버간의 링크 형성 과정은 랜덤하지 않다. 우리는 적절한 인센티브 모델링이 사회경제적 복잡계 네트워크에서 링크 형성에 필요하다는 것을 보이고자 한다. 다른 말로 하면, 개인의 행동이 네트워크 구조를 결정하고, 마찬가지로 구조 역시 개인의 행동과 사고에 영향을 미친다. 구조는 행동을

제약하는 동시에 가능케 한다. 그리하여 개인의 행동과 네트워크 구조 사이에 피드백 고리가 존재한다. 우리는 본 논문에서 복잡적응계 이론에 기반한 하이브리드 방식이 사회경제적 복잡계 네트워크를 연구하는데 필요하다고 주장한다. 결과적으로, 우리는 왜 네트워크의 구조가 지속적으로 변화하는지와 구체적 특징을 지닌 특정 네트워크가 왜 발생하는지를 정당화 할 수 있다. 구조적인 변화란 클러스터링 계수의 변화와 평균 최단 거리의 변화를 의미한다. 구조적인 변화와 사회경제적 복잡계 네트워크 내의 개인의 결과를 확보, 비교, 설명하기 위해, 우리는 다중 에이전트 기반의 모델을 개발하였다. 에이전트 기반의 모델링을 이용해, 우리는 우리의 방식과 상호작용 모델을 본 논문의 여러 장에 걸쳐테스트하고 평가할 수 있었다.

주요어: 네트워크 형성 모델, 전략적 링크 형성, 효용, 사회적 후생, 클러스터 계수, 평균 최단 거리, 인센티브 모델링

**Somayeh Koohborfardhaghighi**

**학번:2012-31308**