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Long Qingqi, Li Shuliang

This is a copy of the author's accepted version of a paper subsequently published in the proceedings of mathematics and computers in sciences and industry (MCSI 2014), 13th-15th September 2014, Varna, Black Sea, Bulgaria, IEEE, 9781479943241.

It is available online at:

https://dx.doi.org/10.1109/MCSI.2014.34

Long, Qingqi and Li, Shuliang (2014), "A multi-agent-based evolution model of innovation networks in dynamic environments". In: Proceedings of 2014 mathematics and computers in sciences and in industry (MCSI 2014), 13th-15th September 2014, Varna, Black Sea, Bulgaria. IEEE-CPS, pp. 27-32. ISBN 978-1-4799-4324-1/14. DOI 10.1109/MCSI.2014.34.

A multi-agent-based evolution model of innovation networks in dynamic environments

Qingqi Long [1], Shuliang Li [2,3]

[1] School of Information, Zhejiang University of Finance & Economics, Hangzhou, Zhejiang, 310018, China
longqingqi1116@163.com

[2] Westminster Business School, University of Westminster, London, NW1 5LS, United Kingdom
lish@westminster.ac.uk

[3] School of Economics & Management, Southwest Jiaotong University, Chengdu, Sichuan, 610031, China

***Abstract*—An innovation network can be considered as a complex adaptive system with evolution affected by dynamic environments. This paper establishes a multi-agent-based evolution model of innovation networks under dynamic settings through computational and logical modeling, and a multi-agent system paradigm. This evolution model is composed of several sub-models of agents' knowledge production by independent innovations in dynamic situations, knowledge learning by cooperative innovations covering agents' heterogeneities, decision-making for innovation selections, and knowledge update considering decay factors. On the basis of above-mentioned sub-models, an evolution rule for multi-agent based innovation network system is given. The proposed evolution model can be utilized to simulate and analyze different scenarios of innovation networks in various dynamic environments and support decision-making for innovation network optimization.**

Keywords- Innovation network; evolution model; multi-agent system; computational and logical modeling; dynamic environment

I. INTRODUCTION

Nowadays firms have paid more and more attention to product or service innovations to meet the customers' demands and gain their sustainable development in the global market. Only innovation can help firms to obtain dominant market positions and keep competitive advantage. With increased globalization, firms are woven into a network for cooperative innovations. This network can be called as an innovation network with contributors and collaborators involved. Firms in the network are heterogeneous and play such different roles as suppliers, technology suppliers, cooperators, service providers, etc. by ways of outsourcing, contract, and even strategic alliance. Thus the traditional in-house innovation has been unable to meet the needs of firms' current and even future development. Firms remain independent innovations and also pursue cooperative innovations. Cooperative innovation has become an inevitable choice for each firm. Firms can access to a variety of resources, including their suppliers, technology suppliers, universities/research centers, cooperators, customers [1] and social media, and can integrate these resources to help innovate for high performance with low costs and risks.

It has increasingly been recognized that firms' individual behaviors and their interactions jointly emerge aggregated innovation phenomena [2]. Network structure, social influence, information and knowledge flows, and dynamic environment were studied in the literature of innovation network research with the most widely used methodology—complex adaptive system theory [12]. The literature mainly focuses on knowledge diffusion [3], innovation network formation [4], relationship between network structure and innovation performance [5], and network evolution [6]. These studies aim to gain an in-depth understanding of the nature of innovation networks for related decision making by exploring the formation mechanisms, structural characteristics, dynamics, performances, and evolutionary laws of innovation networks. In most of these studies, a two-dimensional aperiodic structure called knowledge space [5] is used to describe innovation networks. In this way, an innovation network is transferred into a graph in which the nodes of firms as well as their relationships can be easily modeled according to their knowledge endowments. The research idea is efficient in exploring the general nature of innovation networks, such as their structural dynamics and evolution laws. But it has some deficiencies in handling their complexity.

Obviously, the current studies ignore the effects of dynamic environments on the evolution of innovation networks. A real innovation network cannot be isolated from its environment. The complex adaptive system theory also emphasizes the interactions between individuals and their environments. Actually, dynamic environments directly affect the evolutionary path and scope of innovation networks. Taking dynamic environment into consideration in innovation network evolution research will enable the research conclusions more realistic. In this paper dynamic environments will be considered in the proposed evolution model of innovation networks. Moreover, the current evolution models in literature can be further improved when firms' heterogeneities [7], knowledge production [8], knowledge learning, knowledge decay are considered. In addition, the complexity of innovation networks calls for a more powerful tool, for example multi-agent system. Agent is active, and can make decisions autonomously based on self-perception of its environment and interactions with other agents. Firms have similar characteristics to agents. A multi-agent system composed of multiple agents can be used to model an innovation network. It is a complex systems research methodology, and is powerful in building a link between micro-level agents' behaviors as well as their interactions and macro-level emergence of a multi-agent system, and has incomparable advantages in handling

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complex problems that are difficult to be solved by pure mathematical models. Therefore, in this paper multi-agent system paradigm is applied to build an evolution model of innovation networks.

Taking into account the above issues, this paper inherits the current research and focuses on the theoretical extension research. On the basis of the analysis of real characteristics of innovation networks, this paper abstracts a general conceptual model of innovation networks and builds a multi-agent based innovation network system by specifying its network topology and knowledge space. A multi-agent-based evolution model of innovation networks under dynamic settings is proposed, where three factors of technology supply, cooperation with universities/research centers, and demands from end customers are covered. This evolution model is composed of several sub-models of agents’ knowledge production by independent innovations with dynamic environment, knowledge learning by cooperative innovations considering agents’ heterogeneities, decision-making for innovation selections, and knowledge update considering decay factor. Based on above-mentioned sub-models, an evolution rule for multi-agent based innovation network system is given. The proposed evolution model can be used to simulate and analyze different scenarios of innovation networks with different dynamic environments and support decision-making for innovation network optimization.

II. AN MULTI-AGENT-BASED EVOLUTION MODEL OF INNOVATION NETWORKS

A. *Agent-based innovation network system*

An innovation network can be considered as a complex adaptive system consisting of multiple agents. System boundary separates innovation network and its survival environment. Figure 1 is an agent-based conceptual model of innovation networks. This model is composed of two parts: an innovation network and its environment. Agents in the innovation network can communicate with each other and exchange information and knowledge for cooperative innovations in a direct or indirect way. Agents in the innovation network may act such multiple roles as core firm, supplier, competitor, and customer (not end-customer). In this paper, the agents’ heterogeneities are taken into consideration. The heterogeneities determine agents’ cooperation attitudes to other agents. An innovation network is affected by some factors in its environment. These factors include government policies, culture, region, technology supply, cooperation with universities/research centers, market, and end customers. According to [1], three factors of technology supply, cooperation with universities/research centers, and demands from end customers are included in the follow-up evolution model. The three factors may affect any agents in the innovation network. In this paper, they are treated as external variables to affect agents’ independent innovations.

Following the current literature, graph theory is used to describe the topology of a multi-agent based innovation network system. An innovation network composed of n agents can be abstracted as a graph g [9]. The nodes and their edges in the graph respectively represent agents and agents’ cooperation relationships. Agent set of innovation network is notated as $V=\{1,2,...,n\}, n\geq 3$. The cooperation relationship between agent i and agent j is represented by the edge $ij(ij\in g)$. Due to agents’ mutual willingness for cooperation, the edge ij is undirected. Thus the innovation network g is an undirected graph. In non-empty network, agent i can communicate with agent j through a path $\{ii_1, i_1i_2,..., i_{k-1}i_k, i_k j\}$ which are connected successively by multiple agents $\{i_1, i_2,..., i_k\}$. The number of the edges in the path is called its length. The distance d_{ij}^{g} between agent i and agent j in the network topology is defined as the length of the shortest path. It shows that the indirect communication between agent i and agent j must go through at least the number of $d_{ij}^{g}-1$ agents.

Knowledge is a kind of important resources in the innovation process. The innovation can be treated as the knowledge production process. This paper assumes that agents’ knowledge structure is composed of two knowledge elements x and y. Each agent’s knowledge endowment is determined by the amount of the two elements. Knowledge space ψ is defined as a two-dimensional aperiodic structure $[0,1]*[0,1]$ [5]. The location of agent i in knowledge space is a pair (x_i, y_i), with $0\leq x_i, y_i\leq 1$. All agents are located in knowledge space according to their knowledge endowments. The distance d_{ij}^{ψ} between agent i and agent j in knowledge space is defined as Euclidean distance $d_{ij}^{\psi}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}$. This distance describes the knowledge difference between agent i and agent j.

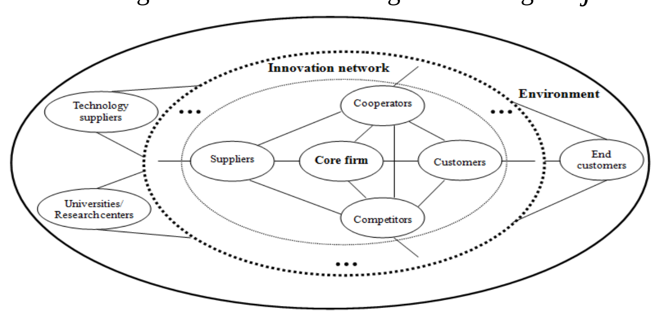

Figure 1. An agent-based conceptual model of innovation networks

According to above-mentioned definition, an innovation network is modeled as a multi-agent system specified by its network topology and knowledge space.

B. *Independent innovation of agents*

Previous research has paid more attention to knowledge learning by cooperative innovations but has ignored knowledge growth mechanisms of individual agents. Except for knowledge learning, agents’ knowledge can grow along with their independent innovations by research and development. Agents’ independent innovations are largely affected by their dynamic environments. Agents can make better decisions for independent innovations after careful analysis of their dynamic environments. Successful independent innovations increase agents’ knowledge endowments. As mentioned in Section A, this paper focuses on agents’ independent innovation activities driven by the demands from end customers under cooperation with technology suppliers and universities/research centers. Following [1], agents’ independent innovation is closely associated with their current knowledge endowments, technology supply, cooperation with universities/research centers, and demands from end-customers/consumers. Referring to the knowledge production function given in [10], this paper defines the growths of knowledge elements x and y of agent i after one time independent innovation activity at the evolution period t as follows:

$$\Delta x_{i,t}^{S} = \delta_i K_{i,t}^{\beta} L_{i,t}^{\lambda} x_{i,t}^{\varphi} \tag{1}$$

$$\Delta y_{i,t}^{S} = \delta_i K_{i,t}^{\beta} L_{i,t}^{\lambda} y_{i,t}^{\varphi} \tag{2}$$

In the formulas, K and L are dynamic variables, respectively representing capital investment and technology/labor inputs for independent innovation. The capital investment is completely determined by the demands from end-customers/consumers. If the demands increase, a firm will increase its capital investment for independent innovation to satisfy more and more customers. More capital is invested, more new knowledge is produced. Technology/labor inputs are totally determined by the amount of technology supply and the degree of cooperation with universities/research centers. The larger amount of technology supply and the higher degree of cooperation with universities/research centers produce more new knowledge. β and λ are respectively the efficiency of capital investment and technology/labor inputs in knowledge production process. φ describes the spillover efficiency of knowledge production based on the knowledge endowment at the previous period. If $\varphi > 0$, it is called positive effect. If $\varphi < 0$, it is called drag effect. δ is a comprehensive factor except for factors of capital, technology, labor, and previous knowledge endowment, which may affect knowledge production.

Agents’ independent innovation is not always successful. In this paper, we assume that the probability of successful independent innovations at each evolution period is P_1. Successful innovations will change agents’ knowledge endowments and agents’ locations in knowledge space.

C. *Knowledge learning between agents*

Except obtaining new knowledge from independent innovations, agents can learn knowledge from their direct and indirect cooperators by cooperative innovations. Extending the knowledge learning function in [9], the knowledge that agent i learns from agent j of its direct or indirect cooperator at the evolution period t is calculated as follows:

$$x_{i\leftarrow j,t}^{L} = \alpha_{ij}\theta^{d_{ij}^{g_t}} \mu^{d_{ij}^{\psi_t}} \max\{0, x_{j,t} - x_{i,t}\} \tag{3}$$

$$y_{i\leftarrow j,t}^{L} = \alpha_{ij}\theta^{d_{ij}^{g_t}} \mu^{d_{ij}^{\psi_t}} \max\{0, y_{j,t} - y_{i,t}\} \tag{4}$$

In the formulas, g_t and ψ_t respectively represent the network topology g and the knowledge space ψ at the evolution period t. $\theta(0 \le \theta \le 1)$ is a decay coefficient of agent’s learning capability related to the distance between two agents in the network topology. The decay coefficient illustrates that agent’s learning efficiency is inversely proportional to the distance between two agents in the network topology. The larger is the distance; the lower is the learning efficiency. In particular, if there does not exist a cooperation relationship between two agents, then $\theta^{d_{ij}^{g_t}} = 0$ because of their distance $d_{ij}^{g_t} = 0$. It means no knowledge learning activity occurs between the two agents. The formulas also show that only when knowledge elements of agent j is higher than that of agent i, can agent i successfully learn part of this knowledge element from agent j and make its knowledge grow. Otherwise, the knowledge that agent i learns from agent j is zero. $\mu(0 \le \mu \le 1)$ is a decay coefficient of agent’s learning capability related to the distance between two agents in the knowledge space. In theory, the larger is the knowledge difference between two agents, the more knowledge one agent can learn from the other. In fact, neither large knowledge difference nor knowledge similarity between agents is beneficial to knowledge learning. Baum et al. [5] elaborated that “if firms’ knowledge and competence are too similar, their knowledge overlaps too much leaving little to learn; if they are too dissimilar, they have difficulty understanding each other, making learning difficult”. Therefore, this paper further improves the formulas given in [9] by introducing a decay coefficient μ to balance agent’s learning performance when considering knowledge difference and similarity. The decay coefficient illustrates that agent’s learning efficiency is inversely proportional to the distance between two agents in the knowledge space. The larger is the distance (or called knowledge difference); the lower is the learning efficiency. Knowledge similarity is beneficial to agent’s knowledge understanding in knowledge learning process and brings a high learning efficiency. $\alpha(0 \le \alpha \le 1)$ is another coefficient of agent’s learning capability related to the type of cooperation relationship between two agents. In reality, the types of cooperation relationships between any two agents are heterogeneous due to agents’ heterogeneities. This paper treats these heterogeneities as different cooperation preferences of agents. Different cooperation relationships lead to different efficiencies of knowledge learning between agents. In general, the relationship between two agents is complex, and

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is neither complete cooperation nor complete competition. Therefore, cooperation and competition coexist between two agents. α can be used to adjust the proportion of cooperation and competition. Especially, if an agent builds a full strategic cooperation relationship with the other agent, it can learn all knowledge from the other one. It means that there is no knowledge confidentiality between them and α can be set as 1. If an agent completely competes against with the other agent, it cannot learn any knowledge from the other one due to knowledge confidentiality. In this situation α can be set as zero.

The final knowledge increment $\Delta x_{i,t}^{L}$ and $\Delta y_{i,t}^{L}$ of agent i after knowledge learning is the maximum amount of knowledge that it learns from the network by cooperative innovations at the evolution period t.

Similar to agents’ independent innovations, cooperative innovations are not always successful. This paper assumes that the probability of successful cooperative innovations at each evolution period is P_2. Knowledge learning activities occur after successful cooperative innovations. Knowledge learning activities will also change agents’ knowledge endowments and agents’ locations in knowledge space.

D. Decision making for cooperative innovation

In the evolution process, agents can make decisions on building new cooperation relationships, keeping the current cooperation relationships, or canceling the current cooperation relationships with any other agents to pursue their maximum utilities. When agents can get greater utilities by building new cooperation relationships or canceling the current cooperation relationships with other agents than that by keeping the current cooperation relationships, they tend to make changes. Knowledge utility is an important criterion for cooperation innovation evaluation. On the basis of [9], this paper also uses Cobb-Douglas utility function to represent the relationship between agents’ knowledge utilities and their knowledge endowments. Assuming that knowledge elements x and y have the same contribution to utility, the knowledge utility $U_i^{g_t}$ of agent i at the evolution period $[t, t+1]$ is calculated as follows [9]:

$$U_i^{g_t} = \sqrt{x_{i,t} y_{i,t}} \tag{5}$$

At the evolution period t, agents need to make decisions for the above-mentioned three kinds of selections according their utilities. If agent i decides to build a new cooperation relationship with agent j, the network graph g_t will be changed as $g_t' = g_t + ij = g_t \cup \{ij\} (ij \notin g_t)$. If agent i decides to cancel the current cooperation relationship with agent j, the network graph g_t will be changed as $g_t'' = g_t - ij = g_t \setminus \{ij\} (ij \in g_t)$. All agents are selfish and pursue the maximum benefits. Therefore, if there does not exist a cooperation relationship between agent i and agent j $(ij \notin g_t)$, the new cooperation relationship will be built when $U_i^{g_t'} \geq U_i^{g_t}$ and $U_j^{g_t'} \geq U_j^{g_t}$ are satisfied, and at same time $U_i^{g_t'} > U_i^{g_t}$ or $U_j^{g_t'} > U_j^{g_t}$ is also satisfied. If there exists a cooperation relationship between agent i and agent j $(ij \in g_t)$, the current cooperation relationship will be canceled when $U_i^{g_t''} > U_i^{g_t}$ or $U_j^{g_t''} > U_j^{g_t}$ is satisfied. Except for these two situations, agents will not make changes in other circumstances.

E. Knowledge update of agents

The above-mentioned analysis shows that agents can adapt to other agents and dynamic environments by independent innovations and knowledge learning activities. Independent innovation and knowledge learning are two forces driving the evolution of innovation networks. Agents’ knowledge endowments also grow with their independent innovation and knowledge learning activities. At same time, agents’ knowledge endowments decay over time. Knowledge decay is common. The more frequent changes of the environment and the deeper innovation process, the more quickly agents’ knowledge decays. On one hand, the more frequent changes of the environment forces agents to gain more knowledge for innovation activities, which means the amount and value of their original knowledge decrease; on the other hand, the deeper innovation process makes the part of their original knowledge no longer satisfy the requirements of future innovation activities. Therefore, after the evolution period t the knowledge endowment of agent i is updated as follows:

$$x_{i,t+1} = x_{i,t} + \Delta x_{i,t}^{S} + \Delta x_{i,t}^{L} - \Delta \varepsilon_{i,t,x} \tag{6}$$

$$y_{i,t+1} = y_{i,t} + \Delta y_{i,t}^{S} + \Delta y_{i,t}^{L} - \Delta \varepsilon_{i,t,y} \tag{7}$$

In the formulas, $\Delta \varepsilon_{i,t,x}$ and $\Delta \varepsilon_{i,t,y}$ are the decay variables of knowledge elements x and y of agent i at the evolution period t.

F. System evolution rule

The topology of multi-agent innovation network system and locations of agents in knowledge space change over time in the evolution process. The innovation network system will become stable after a number of evolution periods. Based on the above-mentioned evolution model, the innovation network system evolves according to the following rule.

Step 1 (Random selection phase) [9]: At the evolution period t, any couple of agent i and agent j is randomly selected. If $(ij \in g_t)$, it is selected according to the probability $2/n(n-1)$. Because the number of all potential cooperation relationships between any two agents in the innovation network is $n(n-1)/2$, the chance of the couple of agent i and agent j being selected is $2/n(n-1)$. If $(ij \notin g_t)$, the probability of the couple of agent i and agent j being selected is determined by their distance in the network topology and their distance in the knowledge space. Therefore, the couple of agent i and agent j is selected according to the probability $\frac{\rho}{d_{ij}^{g_t}} + \frac{\sigma}{d_{ij}^{\psi_t}}$ [11]. ρ and σ are positive, representing the importance of the distance in the network topology and the distance in the knowledge space. The values of ρ and σ need to ensure $\sum_{ij \in g_t} \frac{2}{n(n-1)} + \sum_{ij \notin g_t} (\frac{\rho}{d_{ij}^{g_t}} + \frac{\sigma}{d_{ij}^{\psi_t}}) = 1$.

Step 2 (Decision-making phase): At the evolution period t, according to decision-making model, the selected agents calculate their knowledge utilities and make their decisions about building a new cooperation relationship, keeping the current cooperation relationship, or canceling the current cooperation relationship with the other one.

Step 3 (Innovation phase): This paper assumes that the unit cost of independent innovation is higher than that of cooperative innovation. Agents tend to carry out cooperative innovations with other agents. But once their current cooperative relationships are canceled, in order to meet the demands from end customers and adapt to their dynamic environments, agents will still turn to independent innovation. At the evolution period t, if $(ij \in g_t)$ and the cooperation relationship between agent i and agent j is canceled, agent i and agent j respectively still carry out their independent innovation on the basis of formulas (1) and (2) with success probability of P_1. If $(ij \notin g_t)$ and a new cooperation relationship between agent i and agent j is built, agent i and agent j tend to carry out their cooperative innovation with success probability of P_2 and learn knowledge according to formulas (3) and (4).

Step 4 (Network update phase): Regardless of independent innovations or cooperative innovation, agent i and agent j update their knowledge endowments following formulas (6) and (7) after the innovation activities finishing. At same time, the network topology and locations of agent i and agent j in the knowledge space are updated. If the innovations all failed, both will not be changed.

Step 5 (Cycle phase): Set $t = t + 1$ and go to Step 1 into a next evolution period. When the stable situation of the innovation network system arrives, the evolution if finished.

During the evolution process, the data are collected for simulation analysis to support innovation network optimization.

III. CONCLUSIONS AND FURTHER WORK

Innovation networks are inevitably affected by their dynamic environments. Therefore, dynamic situations need to be considered in the innovation network evolution research. In this paper, a multi-agent-based evolution model of innovation networks under dynamic setting has been established and discussed, with agents' heterogeneities and knowledge decay integrated and modeled. The proposed evolution model can be applied to simulate and analyze various scenarios of innovation networks under different circumstances, and support decision-making for innovation network optimization. The follow-up research will focus on multi-agent innovation network system construction, implementation and evaluation in real-world case studies.

ACKNOWLEDGEMENTS

This work was supported by the Humanities and Social Science Youth Foundation of the Ministry of Education of the Republic of China (No. 14YJC630090), Zhejiang Provincial Natural Science Foundation of China (No. LQ13G010003), Zhejiang Philosophy and Social Science Planning Project of China (No. 13NDJC039YB), Sichuan 100-Talent Scheme (bai ren ji hua) grant, and the University of Westminster staff research allowances.

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