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Formation and Evolution of Ideal Interfirm Collaborative Innovation Networks Based on Decision-Making Rules for Partner Selection

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Abstract: On the basis of an external and static perspective on the topological structure of collaborative innovation networks, it is extremely difficult to answer the two most important concerns, namely, which structure is ideal and how to develop it in practice. By contrast, this study transfers to internal and dynamic perspectives, and then proposes that the essence of developing the ideal network lies in choosing the best partners. Therefore, we firstly propose the basic decision-making rules for selecting partners. In order of priority: knowledge distance, knowledge complementarity and barter exchange. Secondly, a model is constructed to describe this process of selecting partners and exchanging knowledge. Thirdly, the simulation results show that a small-world network is ideal in the initial stage of collaborative innovation. However, a random network is ideal in the mature periods. This result shows that the ideal network structure is not fixed, but affected by the life cycle of collaborative innovation alliance. Furthermore, this supports the notion that a small world is spontaneously generated in the real world, and also confirms that the formation of a small-world network will be driven intrinsically by a firm's demand for external knowledge, and not necessarily by the external driving force of social capital. Finally, these findings solve the above two most important questions.

Keywords: collaborative innovation; knowledge sharing; network structure; partner selection; decision-making rules

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1. Introduction

Economic growth and prosperity are closely related to the innovation process, which is driven by participants' capabilities in acquiring, applying, restructuring and generating new knowledge. According to the definition of the Organization for Economic Cooperation and Development, the knowledge economy is "directly based on the production, distribution and consumption of knowledge" [1]. Therefore, as the knowledge economy develops, knowledge is becoming a key resource enabling firms to continuously innovate and improve their position among international and domestic competitors. The significance of knowledge has gradually become more widely recognized and has attracted attention from academia, private-sector corporations and government entities who focus on science and technology development, knowledge production and diffusion [2,3].

It provides a good way for firms to obtain new knowledge due to the continuously expanding scale of the market for technology exchange. As we all know, a single firm will find that it is very difficult to benefit from certain breakthroughs, because they require huge investment and are accompanied by uncertainty of income. Consequently, there is a need to disperse risk for firms. In addition, in the real world, a large number of key technologies are in the hands of a few firms. Therefore, other firms can only gain access through licensing or other contractual arrangements, which inevitably leads to serious technical dependence and potential risks for these firms. As Baum et al. emphasized, the difficulty of acquiring knowledge and competitiveness through market transactions led to the formation of partnerships, but the knowledge gained from partners constitutes shared knowledge [4]. Therefore, firms need to actively engage in bilateral or multilateral cooperation for knowledge exchange and innovation [5]. Collaborative innovation among firms should be promoted as a form of extensive knowledge interaction and diffusion, which is also an effective way for firms to break their own boundaries and gain knowledge throughout the technology space. Obviously, the interfirm collaboration constitutes a specific type of social network for knowledge diffusion, and it plays an important role in effective knowledge sharing among firms. Moreover, it is believed that the collaborative network provides the market with channels and paths for the flowing of information and knowledge. Especially, the network structure is similar to the layout of pipelines. Thus, whether the layout is reasonable is vital for smooth knowledge flow throughout the structure [6–9].

Furthermore, when it comes to many more complex structures of knowledge interaction, knowledge transfer between participants becomes multi-layered. There is no doubt that the structure of a network is likely to influence the knowledge exchange process both at the micro and the system levels [3]. For example, at the micro-level of a firm, Schilling and Phelps have pointed out that the structure of a corporate alliance network affects its knowledge creation potential [10]. In particular, firms embedded in an alliance network with high agglomeration and short paths show greater innovation output than those without the above features. At the macro-level, Fleming et al. reveal the existence of regional small-world structures in patent collaboration networks, but do not provide evidence that small-world networks enhance innovation productivity in geographic regions [11]. All of these indicate that social network is the premise of knowledge exchange, and as systems become more complex, it is necessary to thoroughly analyze and understand the link between the underlying network structure and knowledge formation and diffusion [3,12]. In other words, the question is: what kind of network structure is most conducive to the knowledge sharing among firms, and thereby enhancing the effects of collaborative innovation?

In the existing literature, the issue of what kind of network topology is most conducive to knowledge diffusion and innovation has been controversial. For example, based on the structural embeddedness [13] and social capital [14] perspectives, dense networks are considered to be superior because clustering or agglomeration enables firms with mutual partners to have information sources about mutual trust, capabilities, competitiveness and goals. In addition, two firms can understand each other through a common third party, which is magnifying the reputation effect and effectively curbing opportunistic behavior. However, Burt's theory of structural holes suggests that excessive local agglomeration creates information redundancy, which may cause the sense of perception and acquisition of innovative information to be lost in remote groups. Therefore, sparse networks with structural holes are better [15–17].

Other scholars compare different network topologies to choose the best network structure for knowledge diffusion based on network structure characteristics. Laciana and Rovere argue that regular networks tend to be more conducive to innovation diffusion when physical similarity between nodes is more important [18]. Some scholars believe that compared with regular networks and completely random networks, small-world networks are most beneficial to knowledge diffusion because they have shorter average path lengths and larger aggregation coefficients [19–25]. Morone et al. found that small-world networks perform better than regular networks by analyzing individual learning strategies, network typologies and individual geographic distributions, as well as relative initial knowledge levels. However, they are not as good as random networks [26]. Other scholars have pointed out that the degree distribution in the real world is often heterogeneous and satisfies the power–law distribution, and therefore, the scale-free network provides the optimal knowledge transfer model [27–32].

Accordingly, one question worth exploring would be: what causes the above conflicting research conclusions, and is there a more inclusive result that can bridge these conflicts? On the other hand, the analysis of the advantages and disadvantages of different network structures from the comparison of network structure features is traditionally from the perspective of structure exogeneity. As Morone and Taylor have emphasized, the theoretically optimal randomness p (the values of p determine whether it belongs to a regular network, a small-world network, or a random network) may not be realized in the real world [33]. In other words, in practice, firms cannot build a corresponding network structure based on theoretically optimal results because no matching conditions can be found. This is the second question worth exploring: how to develop the ideal network for knowledge diffusion in practice.

Finally, based on graph theory, we think that the essence of network formation is to develop the relationship among nodes. Therefore, if the firm can select the appropriate partners according to certain rules, a collaborative innovation network can be built in practice. In other words, a firm's establishment of an effective collaborative innovation network structure depends on an accurate choice of partners.

In general, the purpose of this paper is to explore which structure is ideal and how to develop it in practice. The main hypotheses are that dynamic and endogenous of network formation and an effective collaborative innovation network structure depends on accurate choice of partners. The main methods are decision-making rules for partner selection, social network analysis and simulation.

2. Methods and Methodology

The purpose of this study is to find and develop the ideal network structure for knowledge sharing in the interfirm collaborative innovation network. *Thus*, according to the topological structure, we first need to describe different network structures such as regular network, small-world network and random network. For example, we set the number of node n = 20, links of each node m = 4 and randomness p = 0, 0.1 and 1, respectively. The different network structures are characterized as follows in Figure 1. The first is a regular network, the second is a small-world network and the last one is a random network.

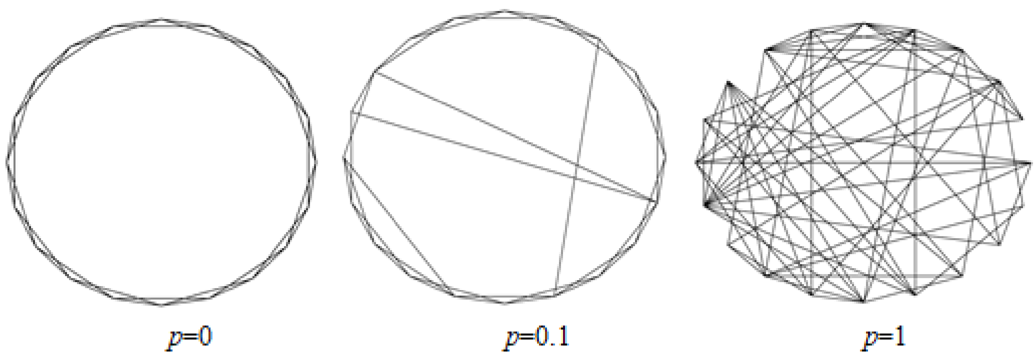


Figure 1. Forming different network structures based on different randomness p.

Secondly, which network structure is the best? In this paper, we evaluate the advantages and disadvantages of the structure by the efficiency of knowledge sharing. Therefore, we need to describe the knowledge stock of each firm. Thirdly, the network is dynamic and its evolution depends on selecting partners. As a result, we need to describe the decision-making rules of selecting partners for each firm. Finally, the purpose of selecting partners is to exchange knowledge between partners. So, we also need to describe the rules and process of knowledge exchange. Overall, the modelling in our study refers to above mentioned four main issues. For ease of writing formulas, we organize and describe the content in a new order as follows.

2.1. Settings of Firms' Knowledge Stocks

In this subsection, our purpose is to measure the knowledge stock of each firm, total knowledge accumulation of the innovation network and the level of knowledge differentiation among firms. First, suppose that the number of participants in an inter-firm collaborative innovation network is n, let it be $N = \{1, 2, \cdots, n\}$. Second, as stated in the introduction, firm innovation requires different kinds of knowledge, so we use a knowledge vector to represent the ownership of knowledge. It is assumed that there are a total of k categories of knowledge in the firm alliance, let it be $K = \{1, 2, \cdots, k\}$. $\kappa_i(t) = \left(\kappa_i^1(t), \kappa_i^2(t), \cdots \kappa_i^r(t), \cdots, \kappa_i^k(t)\right)$ refers to the distribution of knowledge owned by firm i at time t, where $\kappa_i^r(t)$ represents the amount of the r-category knowledge owned by firm i at time t, $r \in K$. The knowledge stock $S_i(t)$ owned by the firm i at time t can be expressed by the norm of $\kappa_i(t)$ as:

$$S_i(t) = \sqrt{\sum_{r=1}^{k} (\kappa_i^r(t))^2} \tag{1}$$

The larger the value of the knowledge stock is, the farther away it is from the knowledge origin (i.e., coordinate origin, $\kappa_i(t) = 0$). Therefore, the greater the amount of knowledge a firm has, the stronger the potential capacity for innovation.

We use the *average knowledge stock* (*AKS*) to measure the total knowledge accumulation of the group. It describes the change in the average length of distance from the knowledge origin in the knowledge space.

$$AKS(t) = \frac{1}{n}\sum_{i=1}^{n} S_i(t) \tag{2}$$

In addition, we use the *average knowledge deviation* (*AKD*) to measure the level of knowledge differentiation among firms within a group. It describes the proximity of firms to each other in the knowledge space. The greater the value is, the higher the degree of knowledge deviation between firms is. The lower the value is, the higher the degree of knowledge overlapping between firms is. In particular, in previous studies, the formulation (3) measures the differences of distance from the knowledge origin for the two firms in the knowledge space. However, in this paper, it measures the differences in distance between any two nodes in the knowledge space. In that case, it can measure not only the interfirm difference in knowledge stock but also the differences in knowledge categories, making the index be a better measure of the convergence or divergence characteristics between firms.

$$\begin{aligned} AKD(t) &= \tfrac{1}{2n(n-1)} \sum_{i=1}^{n} \sum_{j\neq i}^{n} \left\| \kappa_i(t) - \kappa_j(t) \right\| \\ &= \tfrac{1}{2n(n-1)} \sum_{i=1}^{n} \sum_{j\neq i}^{n} \sqrt{\sum_{r=1}^{k} (\kappa_i^r(t) - \kappa_j^r(t))^2} \end{aligned} \tag{3}$$

where $\| \ \|$ represents the norm (Euclidean distance) between vectors.

2.2. Settings of the Rules of Partner Selection

In this subsection, our purpose is to describe the rules to select a probable partner for each firm. As stated in the introduction, an effective collaborative innovation network structure depends on an accurate choice of partners. Baum et al. have pointed out that participation in networks affects a firm's behavior and performance, so it is important to understand how these partners are selected theoretically and practically [4].

2.2.1. Influence of Social Capital on Partner Selection for Collaborative Innovation

Cowan and Jonard emphasized that individuals are heterogeneous [20]. Thus, location, endowment, technology, experience and specific characteristics of a subject's communication objects will affect the optimal choices, behaviors and benefits of some individuals. However, most of the research on strategic alliance focus on the selection of allies based on social capital considerations. In particular, the interpretation of the selection of allies largely comes from the concept of structural embedded exchange proposed by Granovetter [13]. For example, Oxley believes that there may be risks in the exchange relationship between firms due to imperfect information on the capabilities, reliability and motivation of potential partners [34]. Therefore, firms may reduce risk through past ties (i.e., contacts that have occurred) and indirect ties (i.e., third-party ties) [35]. In other words, repetition generates inertia.

According to the explanation of repeated games, the reason why the completeness of information affects the equilibrium result is that the participant is likely to actively establish a good reputation in exchange for long-term benefits if a participant's characteristics are not known to other participants. Alternatively, firms tend to repeat past connections, and this repetitiveness creates trust, enhancing the willingness to form alliances. On the other hand, Burt and Knez have also pointed out that endorsements and referrals from common partners can also reduce uncertainty about the quality and motives of potential partners [36]. In other words, the common connection produces transitivity. For example, if A and B, and B and C are partners, but A and C are not, then the indirect connection through B allows A to obtain more information about C, thereby reducing risk. Further, if C engages in opportunistic behaviors, then this information can be passed to other groups via B. This not only promotes the dissemination of information but also magnifies the effects of reputation and effectively suppresses opportunistic behavior. Obviously, these situations inherently contribute to the formation of inner clustering. In a more closed network structure, successful business leaders are also less willing to cooperate with members outside the network [37]. In general, as put forth by Baum et al. embeddedness allows firms to align more closely and more intensively with a defined set of partners because information value via connection can motivate firms to rebuild relationships with past partners and form a new connection with the partner of a past partner through referrals [4].

This paper proposes that social capital theory (including structural intrinsicality) overemphasizes the role of social relations. As Baum et al. [4] and Cowan & Jonard [38] have pointed out that we do not deny the importance of such relationships or social embeddedness to firms. However, if innovation is an alliance goal and success requires knowledge complementarity, regardless of social capital considerations, knowledge complementarity and the driving force behind it can completely determine the network topology. In other words, the need for knowledge complementarity inherently drives firms to form specific network topology.

2.2.2. Influence of Knowledge Distance on Partner Selection for Collaborative Innovation

Collaborative innovation implicitly involves creating new knowledge by integrating (at least) the knowledge stocks of two firms. As these knowledge stocks can be located in different locations in the knowledge space, the knowledge distance between partners may be an important issue [38]. If the positions of the firms within the knowledge space are too close to each other, then their knowledge stocks overlap too much and there is not much to share; if they are too far apart, it is difficult to understand each other, making sharing and recombining too difficult [4,39,40]. Nooteboom proposed a notion about cognitive distance "*A trade-off needs to be made between cognitive distance, for the sake of novelty, and cognitive proximity, for the sake of efficient absorption. Information is useless if it is not new, but it is also useless if it is so new that it cannot be understood.*" [41]. Thus, there should be an optimal knowledge distance between firms and then the possibility of forming alliances between firms will decrease as these two potential partners move away from this optimal distance [42]. Ahuja and Katila also found a similar inverted U-type relationship between knowledge overlap and innovation performance between two firms [43].

2.2.3. Influence of Knowledge Complementarity on Partner Selection for Collaborative Innovation

Cowan and Jonard pointed out that the discussion on alliances in the existing literature emphasizes that an important reason for firms to form alliances is to find complementary intellectual assets and such arguments have been strongly supported by many cases [38]. The intellectual assets of firms and mutual integration have played an important role in partnership success according knowledge innovation. In other words, they believe that the important role of knowledge complementarity in the selection of allies can explain the formation of a collaborative innovation network structure. Furthermore, Baum et al. believe that collaboration enhances the firm's external innovation activities and outputs [4]. By providing complementary assets and technical knowledge, a firm's need for knowledge and competence stimulates motivation for collaboration. Its knowledge base and competitiveness determine the attractiveness to potential partners, so partnerships are driven by complementarity from a knowledge perspective [4].

2.2.4. The Formulation of the Rules of Partner Selection

Based on the above-mentioned literature, we find that repeated and frequent interactions can increase trust, which will make the two parties lose any reservations about their proprietary knowledge (or opportunistic free-riding behavior). This, in turn, may increase the speed of knowledge transfer and even increase the probability of creating new knowledge.

However, if the partner with less knowledge obtains the required knowledge from frequent interactions in the early stages of the relationship, then he/she may no longer cooperate with the other partner. Instead, the partner will choose to be alone or find new superior parties. On the contrary, in any case, participants in collaborative innovation must consider whether the chosen partners have the knowledge they need and the ability to absorb new knowledge. Therefore, this paper believes that social capital has an important influence on the selection of allies, but it is not fundamental. Knowledge distance is the basis for partner selection. The principle of knowledge complementarity is the basis of the interaction and the internal driving force of the collaborative innovation alliance. The barter exchange is the specific mechanism of knowledge interaction and adding value. Therefore, his paper proposes that knowledge distance is the first principle and knowledge complementarity is the second principle in partner selection. Two firms can only establish contact by satisfying these two principles, in sequence, to lay the foundation for further knowledge interaction.

Therefore, according to the above, this section will use mathematical expressions to interpret the principle of knowledge distance and the principle of knowledge complementarity as shown below. First, for any two firms i and j $(i, j \in N)$ and their knowledge stock are $\kappa_i(t) = \left(\kappa_i^1(t), \kappa_i^2(t), \cdots, \kappa_i^k(t)\right)$ and $\kappa_j(t) = \left(\kappa_j^1(t), \kappa_j^2(t), \cdots, \kappa_j^k(t)\right)$, respectively. Given that each firm is located in the k-dimensional knowledge space, the knowledge distance between firms i and j is the Euclidean distance between two nodes, that is,

$$\delta_{ij}(t) = \sqrt{\sum_{r=1}^{k} \left(\kappa_i^r(t) - \kappa_j^r(t)\right)^2} \tag{4}$$

The minimum and maximum values of the knowledge distance for $\forall\ i,j \in N$ are as follows:

$$\delta_{\min}(t) = \min\{\delta_{ij}(t)\} \tag{5}$$

and

$$\delta_{\max}(t) = \max\{\delta_{ij}(t)\} \tag{6}$$

Therefore, the rule of knowledge distance can be expressed as:

$$\alpha\delta_{\min} \leq \delta_{ij}(t) \leq \beta\delta_{\max} \tag{7}$$

where α, β are control parameters of the upper and lower limits of the knowledge distance, respectively.

Second, if $\exists r_1, r_2 \in K$, and $r_1 \neq r_2$, then there is:

$$\kappa_i^{r_1}(t) > \kappa_j^{r_1}(t) \tag{8}$$

and

$$\kappa_i^{r_2}(t) < \kappa_j^{r_2}(t) \tag{9}$$

Then, it shows that the principle of knowledge complementarity is satisfied between i and j.

2.3. Settings of Knowledge Exchange between Firms

In the subsection, our purpose is to describe the process of knowledge exchange between firms. Cowan and Jonard believe that if a common interest exists, when individuals repeatedly encounter others directly connected to them, there will be transactions between them [20]. In other words, the processes of exchanging different types of knowledge between individuals are regarded as a "barter". From the perspective of economic production and incentives, only through reciprocity can this kind of knowledge exchange be maintained for a long time and promote innovation and sustainable development. Otherwise, gift-style sharing (or free-riding) can only benefit some partners in the short term; it can be a fatal blow to group collaboration and innovation performance in the long term. Therefore, Cowan and Jonard have emphasized that the exchange of knowledge between individuals is not a gift but a barter; they also considered the situation where barter and gift-giving modes could coexist [21]. Based on this, the process of knowledge exchange between the partners of the alliance is firstly seen as a process of exchanging needed goods. The knowledge possessed by the firm is regarded as a k-dimensional vector (k represents the number of knowledge types required in the group), and the component value of the vector is 1 or 0, which means that the knowledge is either possessed or not possessed. Firms can share knowledge through barter or free-gift sharing. However, these two modes of interaction only achieve the exchange of knowledge without adding value to knowledge innovation.

Another hypothesis considers value-added knowledge. The extent of knowledge growth by the recipient is a function of the relative level of knowledge between the recipient and the sender [39]. Therefore, a simple model is a linear function that represents the industrial absorptive capacity [4] or the knowledge absorptive capacity of the firm [19]. In particular, the above growth pattern highlights its equity where both parties in an interaction acquire the same knowledge, while Cowan et al. proposed an unequal interaction mode [39].

Moreover, in value-added knowledge exchange, this paper believes that the simple linear growth relationship is not in line with the law of knowledge innovation. The speed of learning ability is slow initially, and then becomes faster and finally stabilizes with the potential occurrence of many cycles. Considering this, our study replaces the fixed value or the simple knowledge stock ratio with the logistic curve to calculate the absorption capacity coefficient.

Therefore, having satisfied the principles of spatial distance and complementarity (i.e., satisfying Equations (7)–(9)), firms i and j have established a direct relationship (i.e., the edge of the network), at that time the shortest path length between the two firms' networks $d_{ij} = 1$. Therefore, there is a basis and a possibility for interaction between the two firms.

Based on the previous discussion, it is assumed that the knowledge interaction process satisfies:

$$\kappa_i^{r_2}(t+1) = \kappa_i^{r_2}(t) + \lambda_i(t) \cdot \left| \kappa_j^{r_2}(t) - \kappa_i^{r_2}(t) \right| \tag{10}$$

and

$$\kappa_j^{r_1}(t+1) = \kappa_j^{r_1}(t) + \lambda_j(t) \cdot \left| \kappa_i^{r_1}(t) - \kappa_j^{r_1}(t) \right| \tag{11}$$

where $\lambda_i(t), \lambda_j(t)$ represent the knowledge absorptive capability of firms i and j at time t, respectively. $\left|\kappa_j^{r_2}(t) - \kappa_i^{r_2}(t)\right|$ is the absolute value of their potential difference in the r_2 knowledge.

The knowledge absorptive capabilities of firms are obviously closely related to their knowledge stock. In general, the initial absorption capacity of firms is slow. As the knowledge accumulates, the absorption capacity of learning will accelerate. After reaching a certain level, the learning absorption capacity will become saturated. In other words, this process follows the pattern of "slow–fast–slow," which is very similar to the logistic curve. Therefore, a simple logistic function is used to calculate the learning ability coefficient, as shown below:

$$\lambda_i(t) = \frac{1}{1 + e^{-S_i(t)}} \tag{12}$$

2.4. Settings of Network Structure

In this subsection, our purpose is to construct the innovation network and measure its different topological structures. From the perspective of graph theory, each firm is a node and the relationship between the firms forms an edge, which constitutes an undirected graph. We believe that the network structure is endogenous. It changes due to the influence of the selection conditions of the partners. The essence of the process of network structure formation is the selection process of partners. Therefore, we assume that each firm should select its interaction partners according to the partnership selection rules (i.e., satisfies Equations (7)–(9)) to form corresponding edges.

Furthermore, some scholars have pointed out that the partners with the initial complementary knowledge combination tend to become more similar after some time. As they continue to interact and learn from each other and they become unattractive partners gradually [42,44]. This view shows that partnership is not fixed but to evolve continuously throughout the process of collaborative innovation and fits the endogenous view we emphasize. On the other hand, this re-selection may not happen immediately due to the stability of the collaborative relationship. Therefore, in order to bridge the gap between the two, this paper proposes a network structure that is "fixed in the short-term and evolves in the long-term". Specifically, in the beginning, the firms select the corresponding partners according to the rules of partner selection and form the initial network structure. After $T1$ cycles, when the knowledge interaction has finished, the state of knowledge stock of each firm has been changed. According to existing interaction rules, each firm re-selects partners to form a new network structure. This process is repeated until the end of the entire interaction period T.

Finally, the feature index of network structure is used to measure the corresponding topological structure in the change of the firm's collaborative innovation network structure to find the network structure that is most beneficial to knowledge sharing. Previous research has shown that the *average path length* (*APL*) and the *average clustering coefficient* (*ACC*) can be used to measure the structural characteristics of a network [20,45]. The *APL* is a global feature of the graph and simply measures the average distance between nodes, at the same time the *ACC* is a measure of local connectivity and reflects the extent to which an individual neighbors are also neighbors to each other. The equations are as follows:

$$APL(t) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n}\frac{d_{ij}}{n-1} \tag{13}$$

and

$$ACC(t) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j,h\in\Gamma_i}\frac{\varphi_{jh}}{\|\Gamma_i\|(\|\Gamma_i\|-1)/2} \tag{14}$$

where Γ_i represents all neighbors of firm i, that is, $\Gamma_i = \{l | d_{il} = 1, l \in N, l \neq i\}$, $\|\Gamma_i\|$ refers to the number of all neighbors of firm i. If $h \in \Gamma_j$, $\varphi_{jh} = 1$; otherwise, $\varphi_{jh} = 0$.

Furthermore, the *density of global network* (*G-Density*) and *node degree distribution* (*NDS*) are also used to show the dynamics of network evolution as follows:

$$G - Denity = \frac{\sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} d_{ij}}{n(n-1)} \tag{15}$$

and

$$NDS = \sum_{j=1, j\neq i}^{n} d_{ij} \quad i \in N \tag{16}$$

3. Results and Discussions

3.1. Settings of Basic Parameters

The simulation experiment is based on the MATLAB R2017. It is assumed that the scale of the firms participating in collaborative innovation is 500 (i.e., n = 500), and the number of knowledge types is 20 (i.e., k = 20). The heterogeneity of firms suggests that the distribution levels of initial knowledge stock are different. Therefore, the distribution parameter is set as q = 0.25, indicating that 25% of the group firms have higher levels in each type of knowledge, and 75% have lower levels. Specifically, when assigning an initial value to each type of knowledge within each firm, a random number is generated using the random function *Rand*(). If the random number is less than q, we use the uniform distribution function *Unifrnd*() in the interval of [0.8, 1] to generate a knowledge inventory number; if the random number is greater than q, we generate a knowledge inventory number in the interval of [0, 0.8]. The total period of knowledge interaction is represented by T = 100, and the interval period of structural evolution is indicated by $T1$ = 5. α = 2 and β = 0.6 are the control parameters of the upper and lower limits of the knowledge distance, respectively.

This parameter is set as above because we consider the relative readability of graphical results. The simulation is run many times based on different values of parameter. In addition, we will check the robustness of parameters by following Section 3.3, "sensitive analyse", in order to ensuring that the set of parameter is reasonable. Furthermore, each result is presented by isolated simulation runs.

3.2. Simulation and Analysis

3.2.1. Evolution of Knowledge Stock in a Collaborative Innovation Network

In this subsection, there are two purposes. One is to confirm that knowledge exchange would increase the total knowledge stock of firms (i.e., improving the firms' innovation ability) and make the firms converged by analyzing the changes in the total knowledge stock of the collaborative innovation group and the differentiation of the group during the process of knowledge interaction. The other is to provide evidence for the next subsection (see in Section 3.2.2.). The results of the simulation are shown in Figure 2. In the figure, the solid line represents the *AKS*, and the dotted line represents the *AKD*. It can be seen from the figure that the initial growth of the *AKS* curve is very fast and then grows slowly, while, on the contrary, the *AKD* curve drops sharply initially and then slowly decreases.

How can we explain the above findings? First, with the implementation of collaborative innovation between firms, firms exchange and share their respective superior knowledge, but sharing their superior knowledge with others does not reduce their original knowledge stock, so the overall knowledge stock still increases. Moreover, in the initial situation, most of the firm's knowledge stock is pretty low. There are more opportunities for knowledge interaction, so that the knowledge stock can increase rapidly through interaction. However, as the interaction progresses, the increase in the individual knowledge stock leads to a reduction in trading opportunities (see the interaction conditions of Equations (7)–(9)). Therefore, the growth of group knowledge stock gradually slows. Secondly, the increase in the knowledge stock of each firm is not only reflected in the total amount but also each type of knowledge. Therefore, from a knowledge space perspective, firms gradually become closer to each other, which reduce the degree of knowledge deviation between them. This indicates that the group tends to converge. In particular, the fastest growth of group knowledge aligns with the fastest group convergence, which is located on the left side of the dotted line L.

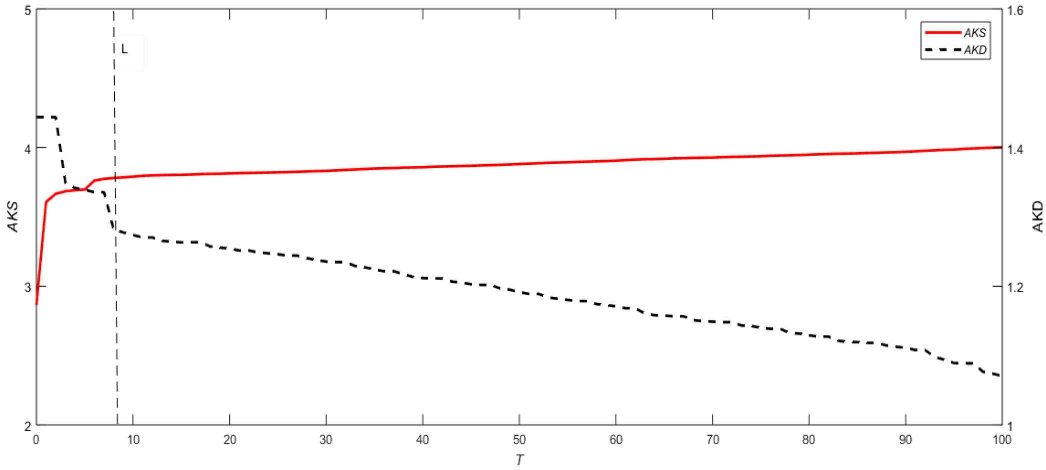


Figure 2. Evolution of *AKS* and *AKD* in a collaborative innovation network.

3.2.2. Evolution of the Knowledge Diffusion Network Structure in Collaborative Innovation Groups

In this subsection, one of our purposes is to find different optimal network structure by analyzing the process of knowledge interaction in collaborative innovation groups and another is to analyze the evolution of the corresponding optimal network structure by measuring the average path length and average clustering coefficient of the collaborative innovation network in order to identify the optimal network topology in reverse, and then promote the efficiency of knowledge transmission and the effectiveness of collaborative innovation. In particular, the density of the global network and node degree distribution are used to show the dynamics of network evolution from other perspectives. The simulation results are shown in Figures 3–5.

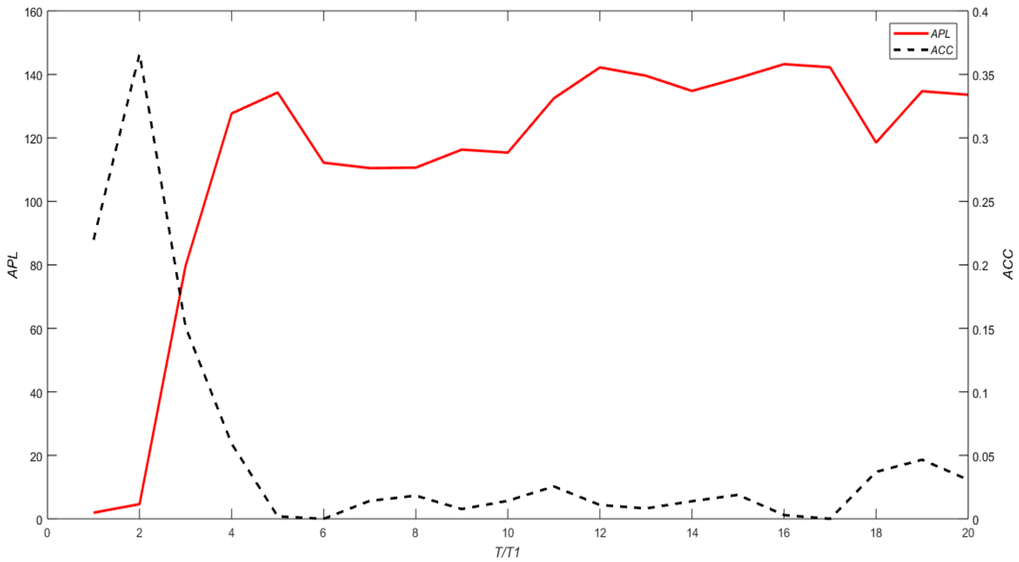


Figure 3. Evolution of *APL* and *ACC* in a collaborative innovation network.

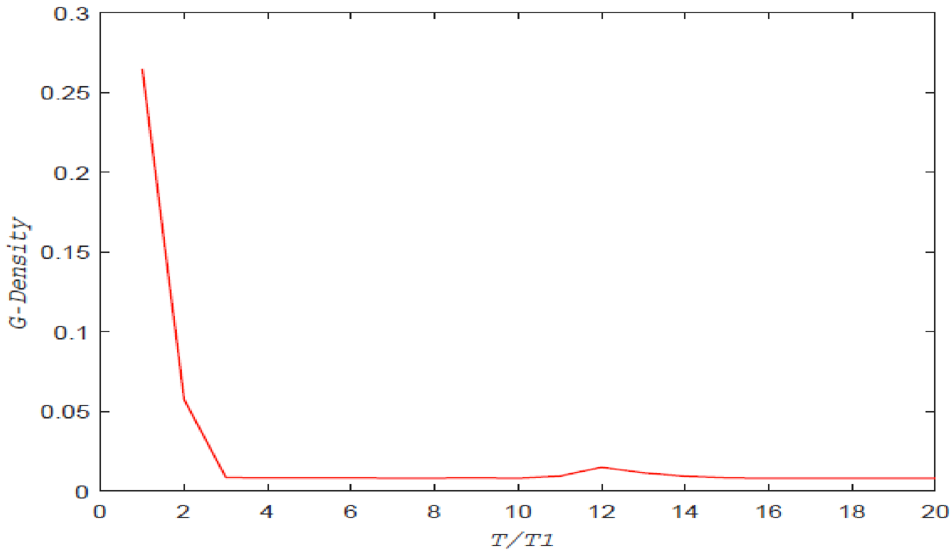


Figure 4. Evolution of global density in a collaborative innovation network.

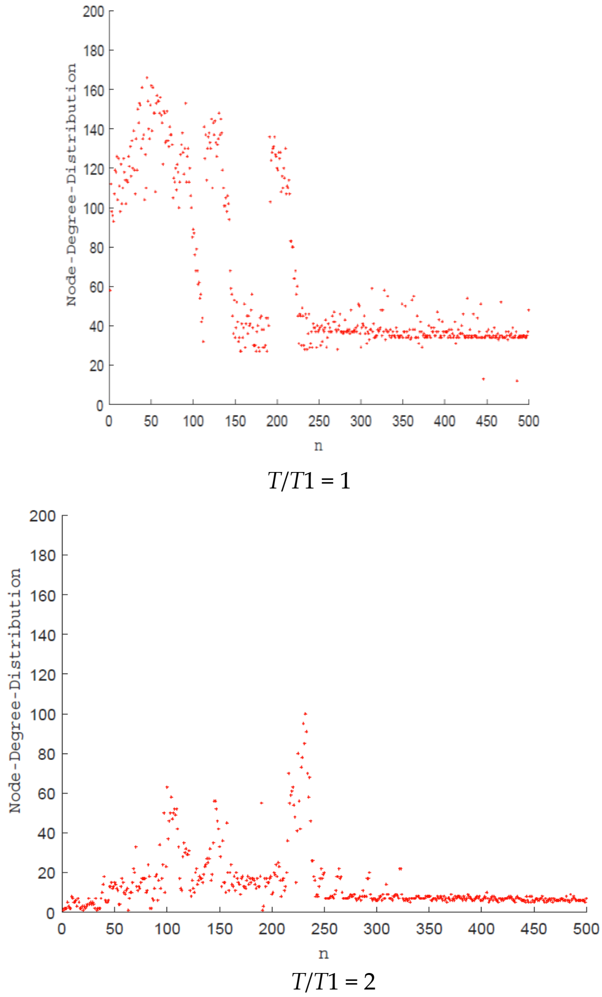
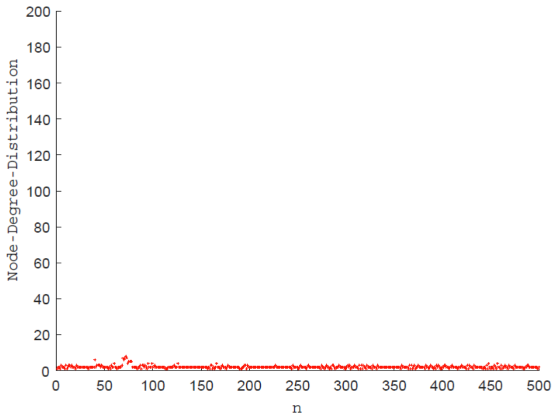
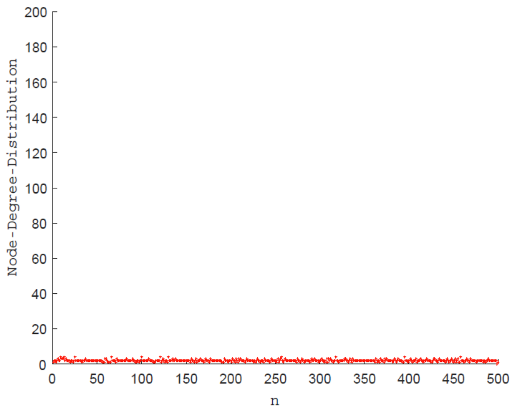


Figure 5. *Cont.*



$T/T1 = 3$



$T/T1 = 20$

Figure 5. Evolution of node degree distribution with time.

In Figure 3, the horizontal axis presents time that the network structure evolves; the solid line refers to the *APL* and the dotted line indicates the *ACC*. In particular, according to graph theory, the maximum value of the shortest path length between any two points is $n-1$. When there is no communication between the two nodes, the shortest path length is infinity. Furthermore, if the group constitutes a connected graph, the largest average path length is $(n-1)/2$. Conversely, if the value of the curve exceeds $(n-1)/2$, it means that some isolated points are formed because these nodes do not satisfy the conditions of partner selection. The *APL* curve in Figure 1 indicates that the collaborative innovation network does not have isolated points.

First, in order to better explaining the results in Figure 3, we look at the description of the relationship between average clustering coefficient, average path length and network topology by Watts and Strogatz [45] and Cowan and Jonard [20], as shown in Figure 6. In Figure 6, the randomness p is used to describe the parameters of the network topology ($0 \leq p \leq 1$). $p = 0$ means a completely regular network; $p = 1$ denotes a complete random network; and $0 < p < 1$ suggests a combined network; when $0.01 < p < 0.1$, it is called a small world. The small-world network is characterized by its small *APL* and large *ACC*. The details are provided by Cowan and Jonard [20].

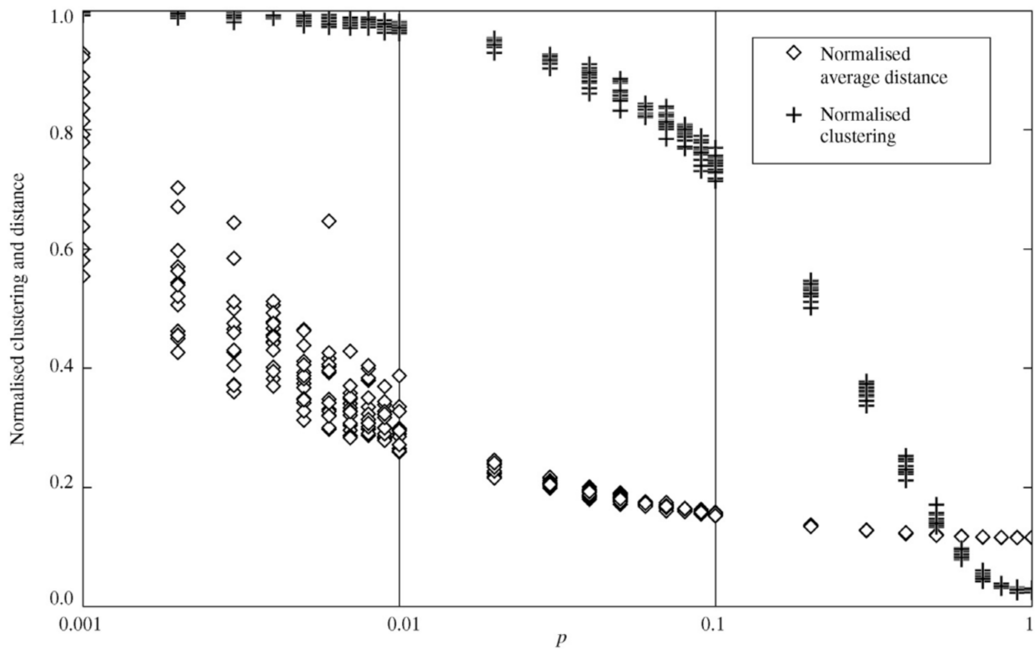


Figure 6. Relationship between average clustering coefficient, average path length and randomness p.

Secondly, as can be seen from Figure 3, in the initial stage of collaborative innovation (i.e., on the left side of $T/T1 = 2$), as firms begin to find suitable alliances for knowledge interaction, they gradually form close small groups as "birds of a feather flock together". Correspondingly, the *APL* increases slowly, and the *ACC* increases rapidly. Therefore, according to the explanation in Figure 2, the randomness changes from large to small, similar to the movement of p from 1 to 0.1 and to 0.01. The *APL* is small and the *ACC* is large when reaching the best matching point near $T/T1 = 2$. In other words, in the initial stage of the alliance for collaborative innovation, the small-world network is the most conducive to collaborative innovation and is the best for the growth of knowledge stock. In particular, this finding is confirmed in Figure 2: the *AKS* just reaches the maximum from $T = 0$ to $T = 10$. In addition, this result further shows that the forming of small-world network structure is driven by the intrinsic demand for knowledge and not the external force of social capital because there are no parameters about social capital in our model. This also supports the findings from Baum et al. [4] and Cowan and Jonard [38].

Thirdly, as the knowledge interaction progresses, the average clustering coefficient in Figure 4 drops sharply and the average path length rises sharply, which seems to be inconsistent with the pattern of changes in the curve variation in Figure 6. This is because the formation mechanism of the network structure in Figure 6 differs from that in this article. This finding implies that the original group has changed the selection conditions of the partners due to the change of the knowledge stock (i.e., the *AKD* is decreasing gradually). Either past partners are no longer to ally with others now or larger groups have become smaller groups (as shown in Figure 7). That is why the *ACC* and the *APL* do not match. Thus, we think that it is similar to the movement of p from 0.1 to 1 as shown in Figure 6. We believe that in the middle and later stages of knowledge interaction, the random network with greater randomness p will become a better choice compared to the small-world network.

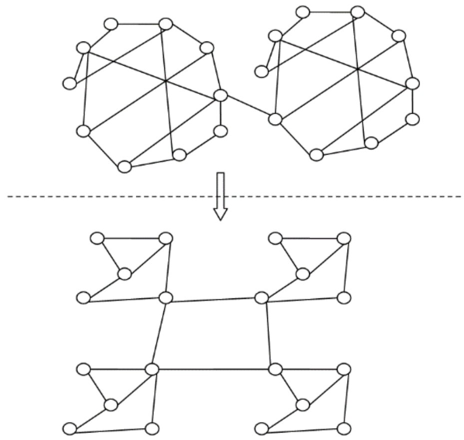


Figure 7. Deviation of the *ACC* and the *APL*.

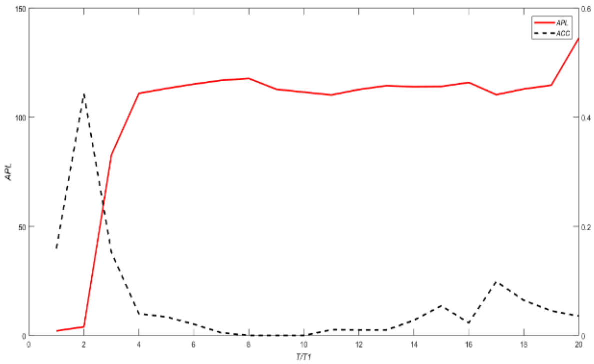
Fourthly, as shown in Figure 4, the curve of *G-Density* is decreasing with the time, and this is consistence with *APL*. Moreover, the scatters of node degree distribution indicate that with the knowledge interaction between nodes, links between nodes are broken because they do not satisfy the rules of partner selection. Thus, dense links located in one node gradually become sparse links. Consequently, the *APL* is gradually increasing. Furthermore, in the following knowledge interaction, the node with local smaller links will select global partners to form new links to access new knowledge. This indicates that the network structure is changing from a small-world network with smaller p to a random network with higher p as shown in Figure 1.

Finally, these results can answer the two key questions presented in the Introduction. On the one hand, we resolve the dispute about which topological network structure is best for collaborative innovation. Briefly, the optimal network structure depends on the life cycle of collaborative innovation alliance rather than a fixed structure. In the early days, the small-world network is optimal, but in the mature period, the random network is optimal. The previous studies reflect a point of view on a static network. On the contrary, we present the viewpoint on a dynamic network.

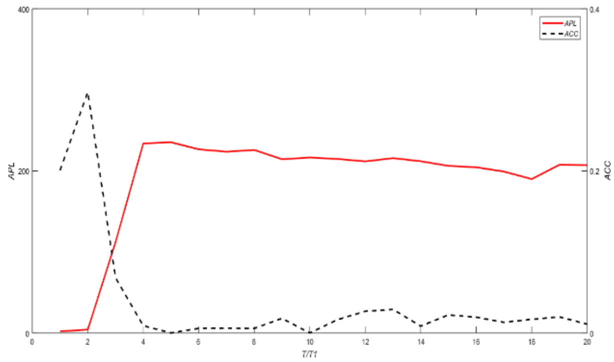
On the other hand, we resolve the problem of how to construct the optimal network in reality. In previous studies, the researchers choose the best topology structure by comparing different network form (i.e., random network, regular network, small-world network and so on), regardless of how they are constructed in reality. Unfortunately, the parameters for forming the optimal topological network are often not implemented in reality. By contrast, in this paper, the collaborative innovation network is constructed firstly, and then its optimality is proved. In short, the forming of a collaborative innovation network is transformed into selecting of partners based on need for knowledge. Furthermore, as shown in our model, we only consider the need for knowledge (including knowledge stock and knowledge distance), and then the social capital and randomness p are not considered. Therefore, the realization of such a network structure is relatively simple in practice.

3.3. Sensitivity Analysis

In the above simulation, the setting of the basic parameters is arbitrary to some extent, so an important question is whether such arbitrariness will distort simulation results or whether the experimental results are robust. Therefore, in this section, we will investigate this issue through the analysis of sensitivity. We have performed sensitivity analyses of the group size n (see Figure 8), the number of knowledge types k (see Figure 9), the initial knowledge richness of the group q (see Figure 10), the structural evolution period $T1$ (see Figure 11), and the knowledge distance control coefficients α, β (see Figure 12). The results are shown in below.

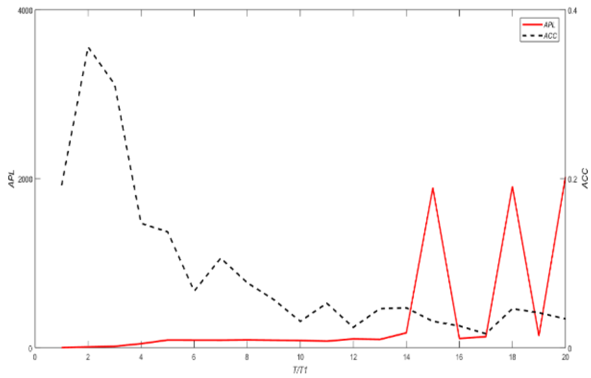


n = 300

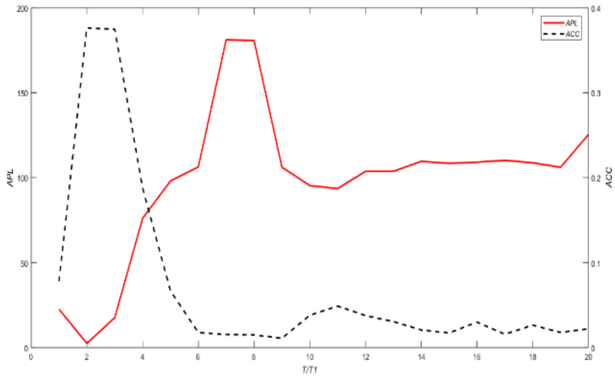


n = 700

Figure 8. Effect of changes in population size *n* on *APL* and *ACC*.

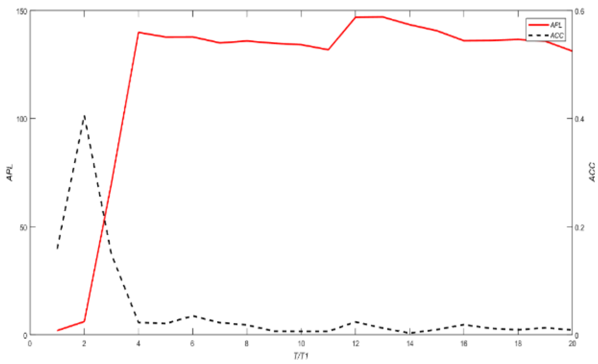


k = 10

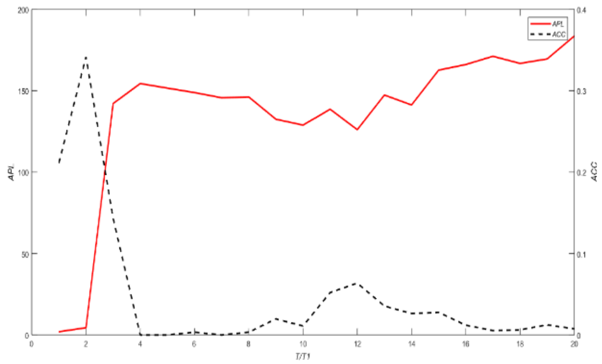


k = 30

Figure 9. Effect of changes in the number of knowledge types *k* on *APL* and *ACC*.

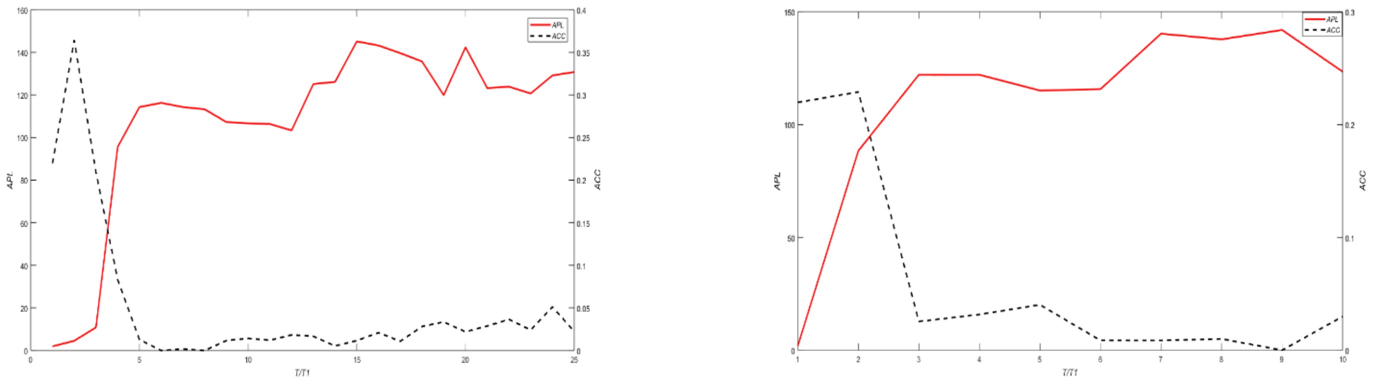


q = 0.15



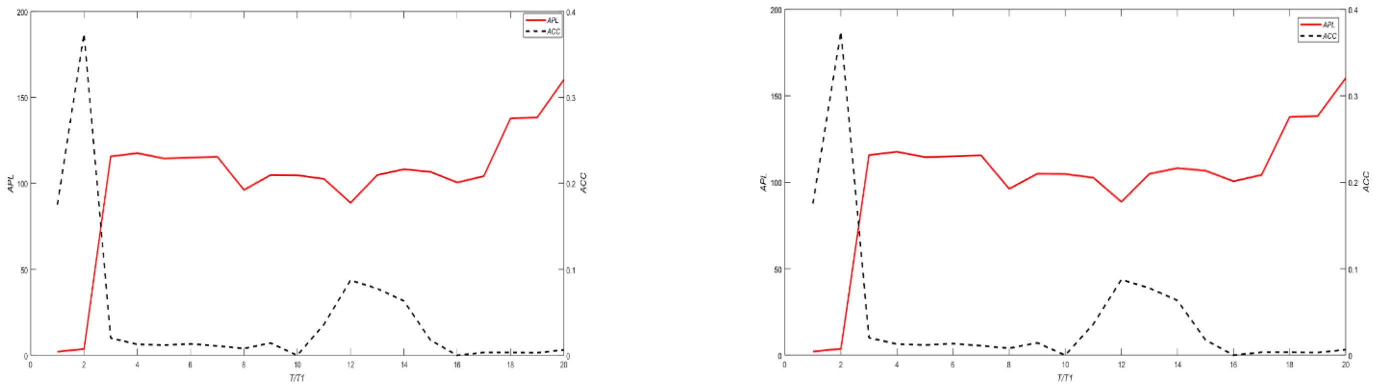
q = 0.65

Figure 10. Effect of changes in group initial knowledge richness *q* on *APL* and *ACC*.



$T1 = 4$ $T1 = 10$

Figure 11. Effect of changes in structural evolution period $T1$ on *APL* and *ACC*.



α=1.5, β=0.8 α=1, β=1

Figure 12. Effect of changes in control coefficients α, β of knowledge distance on *APL* and *ACC*.

Undoubtedly, as shown in Figures 8–12, the parameter changes make the *APL* and *ACC* curves change. However, according to the changes of the curve, there is an initial stage in all figures with a short *APL* and large *ACC*, so small-world networks are more suitable at this time. In later stages, the *APL* is large, and the *ACC* is small, so a sparse network is more suitable.

In addition, it is worth noting that in Figure 9, when the number of knowledge types k = 10, apart from the short *APL* and a large *ACC* in the initial stage, some regions also show a short *APL* and large *ACC*, as can be seen from the curve relationship in Figure 4. The randomness is between 0.1 and 1, indicating that the sparse network at this time is a random network with a large degree of randomness in terms of topology. The reason behind this may be that it is difficult to find the missing knowledge within the small group because of the small number of knowledge types at this time. Therefore, it is necessary to find the heterogeneous knowledge of external groups, and then causing a decrease in internal group contact, prompting more external connections.

In sum, the simulation analysis and experimental results of this paper have a strong level of robustness and the research findings are reliable.

4. Conclusions

4.1. Conclusions

How to build an effective interfirm collaborative innovation network and improve innovation efficiency is a hot topic, which has always been of concern in both theory and practice. One popular view is that the small-world network is considered the ideal because it has a shorter path length and higher agglomeration coefficient. Additionally, some empirical studies have shown that many small-world networks exist in reality. However, as some scholars have highlighted, even if it has been theoretically proven that the small-world network has optimal network characteristics, constructing such a small-world network in practice is still a huge challenge for managers. For example, according to Figure 6, a region with randomness p between 0.01 and 0.1 is called a small world, but how does this randomness correspond to those factors in the real world?

This paper concludes that building a collaborative innovation network attributes to the process of selecting the best partners. More concretely, when constructing an interfirm collaborative innovation network, firms are connected by choosing the most appropriate partners. Furthermore, after every firm has chosen its suitable partners, the corresponding collaborative innovation network is formed. More importantly, since each firm chooses the most suitable partner, the network structure formed at this time is ideal.

In addition, this paper also believes that from a dynamic life cycle perspective, the optimal structure should not be fixed to a certain type but should adapt to the changes with external conditions in the whole evolutionary processes of collaborative innovation networks. The simulation results show that, on the one hand, the small-world network is indeed the ideal in the early stage of network formation. This not only confirms that the small world is spontaneously generated in the real world, but also confirms that the demand for external knowledge will intrinsically drive the formation of a small world network, not necessarily from the external driving force of social capital. On the other hand, when firm collaborative innovation develops to a certain stage, the network will be transformed into a sparse network, compared to the small-world network with high density. Sometimes it may be a random network with higher randomness. This also verifies our inference about the dynamics of network structure.

4.2. Contributions

This paper can answer the two key questions presented in the Introduction. On the one hand, we resolve the dispute about which topological network structure is ideal for collaborative innovation. Briefly, the ideal network structure depends on the life cycle of collaborative innovation alliance rather than a fixed structure. In the early days, the small world network is ideal, but in the mature period, the random network is the ideal. The previous studies reflect a point of view on a static network. On the contrary, we present the viewpoint on a dynamic network.

On the other hand, we resolve the problem of how to construct the ideal network in practice. In previous studies, the researchers choose the best topological structure by comparing different network forms (i.e., random network, regular network and small world network), regardless of how they are constructed in practice. Unfortunately, the parameters for forming the optimal network structure are often not implemented in practice. By contrast, in this paper, the collaborative innovation network is constructed firstly and then its optimality is proved. In short, the forming of an ideal collaborative innovation network is transformed into selecting best partners based on need for knowledge. Furthermore, as shown in our model, we only consider the need for knowledge (including knowledge stock and knowledge distance), and then the social capital and randomness p are not considered. Therefore, the realization of such a network structure is relatively simple in practice.

In detail, this paper also makes several contributions in the following aspects: Firstly, it has proposed a new decision-making rule for selecting partner—that knowledge distance is the basis for partner selection, knowledge complementarity is the basis of the interaction and the internal driving force of the collaborative innovation alliance, barter exchange is the specific mechanism of knowledge interaction and adding value.

Secondly, in our model, we have integrated the knowledge transfer and innovation process and proposed a new model. For example, in past studies, this index measured the differences of distance from the knowledge origin between two firms in the knowledge space. However, in this paper, it measures the differences of the distance between any two nodes in the knowledge space. In that case, it can measure not only the interfirm differences in knowledge stock but also the differences in knowledge categories, making the index a better measure of the convergence or divergence characteristics between firms. Moreover, we propose a new index of absorbing capacity based on Logistic function to make it more practical.

Thirdly, it is based on the endogenous view on the evolution of structure. The partnership (network structure) is not fixed but evolves continuously throughout collaborative innovation between firms. This is consistent with the actual situation. Certainly, this re-selection may not happen immediately due to the stability of the collaborative relationship. Therefore, in order to bridge the contradiction between the two views, this paper proposes a compromise network structure that is "fixed in the short-term and evolves in the long-term". In other words, it has also considered the short-term stability and long-term evolution of the group structure through the parameter setting.

Fourthly, we used a new strategy to find which kind of topological structure is suitable in the stage of alliance development. According to the curve of the network structure index parameters (i.e., *APL* and *ACC*) and performance of knowledge exchange (i.e., *AKS* and *AKD*), the pattern of changes in the network topological structure in the process of knowledge interaction is inversely estimated.

4.3. Managerial Implication

There is a very important application in practice. Especially, the firms should adopt a different strategy to select innovation partners in different development periods. For firms, how to develop an ideal innovation network is very important to improve innovation performance. In essence, it comes down to choosing the best allies. Based on the above analysis, we find that it is much more essential to obtain an external knowledge source rather than social capital. However, the firms will own different knowledge resource in their life cycle. For example, it is more suitable for start-ups to selecting nearer neighbors as their partners. Generally, for start-ups, their knowledge sources are not enough, and they need to obtain sufficient knowledge resource from strong ties with neighbors. They tend to form a dense local network. By contrast, it is more optimal for mature firms to select distant nodes as their partners because the enterprises in mature stage may need more heterogeneous knowledge resources.

4.4. Future Work

This paper has limitations. The process of collaborative innovation between firms is still very complicated. Firms innovate based on not only knowledge interaction but also their knowledge reserves. However, the model in this paper does not consider the value-added of innovation from the firm's knowledge. Therefore, in future work, it will be necessary to further improve this model to make it more realistic.

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