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The Partner Selection Modes for Knowledge-Based Innovation Networks: A Multiagent Simulation

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ABSTRACT With the advent of the knowledge economy, technological innovation has become more and more complex. Firms in innovation system need to cooperate with others to upgrade their knowledge level and market competitiveness. Proper partner selection can increase the efficiency of the entire innovation system. Different partner selection mechanism has a significant impact on the efficiency of knowledge transfer for the enterprises and innovation system. In this study, a multiagent simulation is conducted to explore the effects of four different partner selection modes on knowledge transfer of innovation network: random selection mode, mode of selection based on space, mode of selection based on knowledge capital and mode of selection based on complementary knowledge. The results indicate that: in a period time, (1)the spatial selection mode limits the scope of partner selection and reduces the knowledge transfer path;(2)mode of selection based on the knowledge capital enables the large firms to have more cooperation opportunities;(3)complementary knowledge based selection mode improves the knowledge transfer efficiency of the system.

INDEX TERMS Partner selection, knowledge transfer, innovation network, agent-based simulation.

I. INTRODUCTION

With the arrival of the knowledge economy and the process of global integration, technological innovation has become more and more complicated. A competitive new product often requires the integration of multiple domain knowledge [1], which is more prominent in knowledge-intensive industries such as communications, biology and advanced materials. Knowledge plays a pivotal role in the contemporary market. Due to the uneven distribution of knowledge and the limitations of each enterprise's own resource, it is not enough for enterprises to rely on their own independent R&D and innovation. In order to obtain the required knowledge and share risks for enhancing competitiveness, they also need to seek cooperation from partners across the enterprise boundary. Dynamic cooperation of enterprises with different knowledge spaces has formed the innovation network [2]. The innovation network is a coupled system composed of independent firms and the innovative individuals are connected with each other. At the same time, the enterprise ensures the creation and extraction of network values through coordinated methods such as knowledge mobility and innovation specificity [3].

The connection between innovative individuals is considered to be a specific form of interaction between organizations [4]. Partner selection is a key part of organizing the itinerary, where value creation and ultimate success are shown in choosing the right partner [5], [6]. Inappropriate partner choices may lead to failures in innovation systems [7], or make higher costs and risks [8]. Therefore, in the process of inter-organizational cooperation, the choice of partners is one

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of the critical elements that affect the innovation efficiency of innovation networks [9]. ''Smart'' partner selection is widely recognized as an important factor in the project [9], [10]. Therefore, how to choose partners in the innovation network is a problem that cannot be ignored.

Many scholars have studied the different mechanisms and influencing factors of partner selection in innovation system. Some of them have emphasized the importance of knowledge complementarity to individual cooperation in innovation networks [11]–[13]. Companies that choose to collaborate with their partners with complementary knowledge and resources can make up for their own deficiencies and improve their innovative products and efficiency. In addition, compatibility and complementarity are equally important in business innovation [14]. Some scholars believe that geographic proximity can have an impact on partner selection and knowledge transfer. Due to a large amount of implicit knowledge in the innovation organizations, tacit knowledge is mostly based on face-to-face communication as it is difficult to code and geographical distance can hinder the transmission of tacit knowledge [15]. Some researchers have found that enterprises can obtain more capital by selecting core enterprises with more resources in the network [16], which will result in the scale-free nature of the network. For example, Gay and Dousset [17] found that biotechnology innovation networks are scale-free. Other studies have shown that companies are more inclined to choose companies with a history of cooperation as partners [18], which can reduce the cost of coordinated conversion, but the diversity of corresponding knowledge is insufficient. It can be seen that a large number of researchers have studied the different mechanisms and influencing factors of partner selection, but few have compared the different partner selection mechanisms horizontally. This is the focus of this research.

Based on this, this study will establish an innovative network partner selection model based on knowledge transfer and explore the mechanism of different enterprise partner selection modes in the innovation network and the impact on system knowledge transfer efficiency. It will also reveal the intrinsic motivation of knowledge transfer in innovation networks and give some recommendations. The main contributions of this research include the following: 1. Constructing a multiagent simulation model of partner selection in innovation network from the perspective of knowledge transfer; 2. Comparing the impact of different partner selection modes on the knowledge transfer efficiency of the innovation system.

II. THEORETICAL FRAMEWORK

The core competitiveness of innovation is knowledge. Knowledge is the result of the combination of supply and demand factors and it is spread throughout society. Knowledge generation is interdisciplinary, diverse and socially reflective [19], and knowledge sharing is affected by a variety of factors [20]. In the highly competitive market, the complexity of innovation is further strengthened and cooperation between enterprises is essential. Cooperation in the form of networks becomes normal [21], which promotes knowledge transfer between organizations.

Firms are linked to each other and form the innovation networks. Resources and activities are the necessary components of the network, where the subject refers to the network node and the activity corresponds to the formal and informal relations in the network [22]. Network organization is the basic institutional arrangement for system innovation, which can be regarded as the form of mutual penetration between market and organization. The main linkage mechanism of the innovation network architecture is the innovative cooperation between enterprises [23]. In a specific industry cluster, when the knowledge stock is complex and the professional skills resources are widely dispersed, the learning network will be a place for innovation [24]. The innovation networks consist of nodes and chains which connect nodes. The inherent feature of the network structure is that its composition needs to provide unique services and the components in the network are complementary [25]. Knowledge diffusion between companies has a close relationship with network structure [26]. Therefore, the formation of an innovation network is crucial to the knowledge transfer of the system.

The formation of innovation networks is driven by the different dynamics. The complementarity of knowledge and skills, geographic location, social relations, cooperation history and other factors are the driving factors for both parties to choose partners. These factors affect the whole process of knowledge transfer between the two parties. Knowledge transfer is a dynamic continuous learning process, including the process of knowledge acquisition, communication, application and assimilation [27]. On the one hand, knowledge itself has a certain complexity and ambiguity in the process of transfer [28], so that the transfer of knowledge can't easily occur. On the other hand, the lack of absorptive capacity of the recipient and the relationship between the source and the recipient may also be factors to knowledge transfer [29]. The process of knowledge transfer is directly related to the complexity of knowledge itself, the relationship between enterprises and the ability of communication and learning between the two firms. These factors will also be considered in this study. Therefore, these different partner selection mechanisms will inevitably affect the efficiency of knowledge transfer in the system. How do these different mechanisms affect the efficiency of knowledge transfer in the system? The comparison between different mechanisms is the focus of this study.

The framework of this study is as follows (Figure 1):

Based on the knowledge complexity theory and the knowledge transfer process, this research establishes a framework from the perspective of organizational network cooperation. First, it generates the main body of innovation and knowledge transfer in the system - the enterprise. Considering the complementarity of knowledge and skills, geographic location and skills capabilities, companies choose partners according to different mechanisms and form an innovation network.

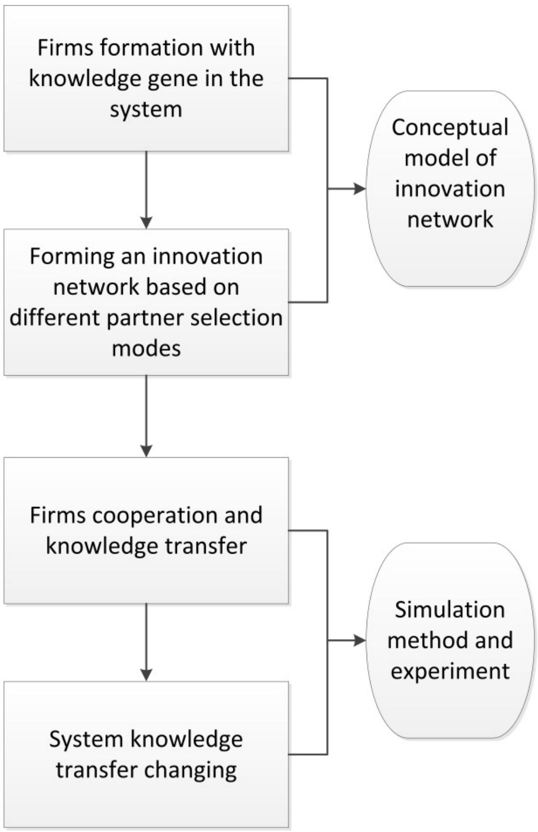

FIGURE 1. Framework of the study.

When an innovative product or project occurs in the market, relevant knowledge can be transferred between enterprises. Different companies not only serve as recipients of knowledge, but also as exporters of knowledge. They can transfer knowledge in the field of knowledge and skills with potential differences between the two sides and learn knowledge from connected companies dynamically. The innovation system is updated constantly and the state of the firm is determined by itself and the companies that work with it. According to different modes, the knowledge transfer efficiency of the same system is compared and the internal mechanism and motivation of different enterprise partner selection are analyzed.

The method used in this study is the agent-based model (ABM). Current methods for researching partner selection issues include: AHP [30], [31] and Game Theory [32], [33]. However, these traditional methods have certain limitations. It is difficult to reveal the micro partner selection mechanism and the dynamics of knowledge transfer between different enterprises. At the same time, it is difficult to compare the different selection mechanisms under the same system horizontally. ABM can link micro-individual interactions with macro-economic phenomena and analyze systems from micro to macro [34]. ABM has been widely used in innovation networks, knowledge transfer and other fields [35]–[37], which can well simulate the interaction between knowledge-based innovation subjects. Therefore, ABM can be well applied to this study.

TABLE 1. Mapping of innovation networks system and model system.

Real innovation networks	Model system
Size of innovation networks	Total number of agents
Innovative individuals	Firm agents(large firms and small firms)
State of individual	State of the agent
Knowledge and technical skills of firms	Knowledge gene of the agents
Partner selection of firms	Partner selection mechanism of agents
Knowledge learning	Interaction of knowledge gene from cooperative agents

III. CONSTRUCTION OF THE MODEL

A. ANALYSIS OF CHARACTERISTICS OF INNOVATION NETWORK AND MODEL SYSTEM

There are two ways for a firm to improve its innovation performance: One is the enterprise's independent innovation, the other is learning from other companies through cooperation. In this study, the innovation network consists of numbers of nodes with different sizes (small firms and large firms). These firms are randomly distributed in different spatial locations with different technical knowledge and the corresponding expertise level. In order to adapt to the fiercely competitive environment, enterprises will adopt different mechanism to select a partner to carry out cooperative R&D. The firms take part of their knowledge and skills for learning and exchange. With the collaboration, the knowledge level of the firms and the entire innovation system will be improved. Table 1 shows the mapping of innovation networks system and model system. The model system simplifies the real innovation system to a certain extent but maps the key elements such as network scale, enterprise scale and enterprise skills, which can reflect the state of the real innovation system.

B. DESIGN OF AGENT

The agent is adaptive and autonomous to simulate the intelligent behavior of individuals and the behavior is defined as Agent = {Sm, Agi}. Sm denotes the internal state of the agent and Agi indicates the interaction with the outside [38]. This study uses NetLogo platform, which was first proposed by Uri Wilensky in 1999 [39]. Compared with other multiagent simulation platforms, it has many strong points such as easy programming language, good user interaction, visualization, etc.

Gilbert *et al.* [35] used a series of triples to represent the type and level of knowledge and skills in the innovation network. This study learns and simplifies their ideas and uses a series of two-tuple $\begin{pmatrix}\text{Capabilities}\\ \text{Expertises}\end{pmatrix}$ (abbreviated as $\begin{pmatrix}\text{C}\\ \text{E}\end{pmatrix}$) to represent the firm's different knowledge skills and expertise level. Each firm contains a knowledge gene which consists of a two-tuple $\begin{pmatrix}\text{C}\\ \text{E}\end{pmatrix}$. C indicates different area of knowledge and is represented by a different

TABLE 2. The parameters of the agent.

Parameters of the agent	Realistic meaning
Capability	Research direction and knowledge skill of the firm
Expertise	The level of knowledge skills
Previous partners	The list of firms which agent has cooperated with
Number of collaboration	Number of cooperation which is corresponding to the previous partners list

integer. E indicates the expertise level of knowledge and skills and is expressed by a certain range of a decimal. Because of more resources, the large firm has more types of skills than the small firm and its length of knowledge gene is longer than that of the small firm. For example, the knowledge gene of a large firm can be expressed as $\left\{\left(\frac{C1}{1.1}\right), \left(\frac{C3}{1.5}\right), \left(\frac{C4}{2.4}\right), \ldots, \left(\frac{C9}{3.6}\right)\left(\frac{C16}{1.8}\right)\right\}$. In order to explore the cooperation rules between firms and their partners, firm agents will record the name of their partners and the number of their previous cooperation. Table 2 shows the parameters setting of the agent in this model.

C. PARTNER SELECTION MODES

The partners refer to organizations that work together on an activity and contact with others. In this study, the partners refer to different firms that are engaged in research and development. In the process of R&D, knowledge transfer and learning are carried out between them. Different firms are connected to each other through cooperation and innovation networks are formed. Firms can select a partner based on the different mechanism. Many studies have shown that geographic proximity, skills capabilities and skill complementarity can affect partner selection of a company [8], [40]–[43]. Based on this, this study constructs four partner selection modes: random selection mode, spatial selection mode, knowledge capital selection mode, and knowledge complementarity selection mode. Random selection mode can be regarded as a benchmark experiment to compare with other modes.

1) RANDOM SELECTION MODE

In random selection mode, firm(i) randomly selects firm(j) as its partner in a small world and it establishes a link between them. They conduct collaborative research and knowledge exchange. Within a step in the simulation, the two firms will cooperate only once. After the firm (i) randomly selects firm (j) as its partner and they establish a connection, firm (j) will exclude firm (i) as its potential partners and choose another agent as partner. This mode does not have any constraints, so that it can be used as a comparative experiment for other modes.

2) MODE BASED ON SPATIAL SELECTION

Space proximity is also a factor for enterprise collaboration. Companies are more likely to conduct face-to-face communication in project collaboration and it can save the cost of cooperation. Some firms prefer to choose an enterprise nearby as partner and it forms many industrial innovation clusters in some areas. In this mode, the firm will take the space into consideration when choosing a partner. Firm(i) selects its partner within a certain area in the small world. Coordinates of firm(i) are (xi, yi) and coordinates of firm(j) are (xj, yj). The distance between two agents is D_{ij}: $Dij = \sqrt[2]{(xi - xj)\,2 + (yi - yj)2}$. Firm(j) can only enter the potential partners list of firm(i) when $0 < D_{ij} < D_0$. D_0 is the critical distance. Firm(i) randomly chooses its partner within the distance D_{ij}.

3) MODE BASED ON KNOWLEDGE CAPITAL SELECTION

Firms prefer to choose enterprises with high levels of knowledge and skills as their partners. On the one side, it can help to improve their own knowledge level so as to adapt to the competition. On the other hand, the strong companies with high-level skills are often with a strong ability to resist risks. In this mode, the firm with more extensive total knowledge stock will have a higher probability to be selected as other firm's partner. The total knowledge stock of a firm can be represented as the sum of all expertise corresponding to the capabilities, $\text{Expertise (i)} = \sum_{k=1}^{l} \text{expertise}_i^k$, l is the length of knowledge gene of the firm(i). Expertise(total) is the total expertise of firms in the system except for firm(i), $\text{Expertise (total)} = \sum \text{Expertise (m)}, m \neq i$. The probability P(ij) for firm(i) to choose firm(j) as partner is:

$$p(ij) = \frac{\text{Expertise(j)}}{\text{Expertise(total)}}$$

4) MODE BASED ON COMPLEMENTARY KNOWLEDGE SELECTION

In high-tech industries, firms prefer to cooperate with the companies which have complementary knowledge to update technological progress. So they can learn from each other in high efficiency. In this mode, if firm(j) wants to be the partner of firm(i), it must meet the requirement that there are at least two same capabilities in both firm(i) and firm(j)'s knowledge gene and they can be complementary. For example:

Knowledge gene of firm(i) is: $\left(\frac{C1}{1.1}\right), \left(\frac{C3}{1.8}\right), \left(\frac{C5}{3.1}\right), \left(\frac{C15}{3.6}\right), \left(\frac{C16}{3.5}\right)$ Knowledge gene of firm(j) is: $\left(\frac{C4}{1.5}\right), \left(\frac{C7}{2.5}\right), \left(\frac{C8}{3.5}\right), \left(\frac{C15}{2.7}\right), \left(\frac{C16}{5.1}\right)$ Firm(i) and firm(j) have the same capabilities: C15,C16. The expertise of C15 in firm(i) is bigger than C15 in firm(j) while C16 in firm(i) is smaller than C16 in firm(j). Thus they can be complementary and firm(j) can be selected as firm(i)'s potential partner. If firm(i) has many potential partners, it will choose one randomly among them.

D. KNOWLEDGE LEARNING AND AGENT UPDATING

1) UPDATE OF KNOWLEDGE GENE

After the firm selects a partner according to one mechanism, the two companies begin to learn from the partner and exchange knowledge. In order to retain their core competitiveness, firms only take part of their knowledge to communicate with partners.

For example, a small firm(firm(i)) chooses a large firm (firm(j)) as the partner in one step. The knowledge gene of firm(i) is: $\left\{\binom{C1}{1.1}, \binom{C2}{1.5}, \binom{C6}{2.4}, \binom{C15}{3.6}, \binom{C16}{1.8}\right\}$. The knowledge gene of firm(j) is: $\left\{\binom{C3}{1.1}, \binom{C4}{1.5}, \binom{C6}{2.4}, \binom{C8}{3.6}, \binom{C9}{1.8}, \binom{C10}{1.8}, \binom{C12}{1.8}, \binom{C13}{1.8}, \binom{C15}{1.7}, \binom{C16}{5.1}\right\}$. Each firm selects 3 capabilities from its knowledge gene for knowledge exchange and interaction.

Interactive capabilities selected from firm(i) are: $\binom{C1}{1.1}$, $\binom{C15}{3.6}$, $\binom{C16}{1.8}$.

Interactive capabilities selected from firm(j) are: $\binom{C4}{1.5}$, $\binom{C15}{1.7}$, $\binom{C16}{5.1}$.

The interactive capabilities of the two firms have two common items: C15, C16. The firm with a lower technical level learns from the firm with a higher technical level and its expertise will have a greater growth. The increment is half the difference between the expertise of two firms. The increment of C16 of firm(i) is 1.7((5.1-1.8)/2=1.65≈1.7). The expertise of C16 of firm(i) becomes 1.8+1.7=3.5 after the interaction. The increment of C15 of firm(j) is 1.0((3.6-1.7)/2=0.95≈1.0). The expertise of C15 of firm(j) becomes 1.7+1=2.7 after the interaction.

Interactive capabilities selected from firm(i) after interaction become: $\binom{C1}{1.1}$, $\binom{C15}{3.6}$, $\binom{C16}{3.5}$

Interactive capabilities selected from firm(j) after interaction become: $\binom{C4}{1.5}$, $\binom{C15}{2.7}$, $\binom{C16}{5.1}$

Because the two firms conduct cooperative innovation in all interactive capabilities in this step, the expertise of each interactive ability also has a small growth with 0.1.

Interactive capabilities selected from firm(i) after interaction become: $\binom{C1}{1.2}$, $\binom{C15}{3.7}$, $\binom{C16}{3.6}$

Interactive capabilities selected from firm(j) after interaction become: $\binom{C4}{1.6}$, $\binom{C15}{2.8}$, $\binom{C16}{5.2}$

The other capabilities of firms which are not selected for interaction stay the same. Finally, the knowledge gene of firm(i) becomes $\left\{\binom{\mathbf{C1}}{\mathbf{1.2}}, \binom{C2}{1.5}, \binom{C6}{2.4}, \binom{\mathbf{C15}}{\mathbf{3.7}}, \binom{\mathbf{C16}}{\mathbf{3.6}}\right\}$ and the knowledge gene of firm(j) becomes: $\left\{\binom{C3}{1.1}, \binom{\mathbf{C4}}{\mathbf{1.6}}, \binom{C6}{2.4}, \binom{C8}{3.6}, \binom{C9}{1.8}, \binom{C10}{1.8}, \binom{C12}{1.8}, \binom{C13}{1.8}, \binom{\mathbf{C15}}{\mathbf{2.8}}, \binom{\mathbf{C16}}{\mathbf{5.2}}\right\}$.

2) UPDATE OF LIST OF PREVIOUS PARTNERS

After the first collaboration between firm(i) and firm(j), it adds one item $\binom{\text{Firm(j)}}{1}$ into the two-tuple $\binom{\text{list} - \text{of} - \text{previous} - \text{partner}}{\text{number} - \text{of} - \text{collaboration}}$ of firm(i) and add one item $\binom{\text{Firm(i)}}{1}$ into the two-tuple $\binom{\text{list}-\text{of}-\text{previous}-\text{partner}}{\text{number}-\text{of}-\text{collaboration}}$ of firm(j). If they have the second collaboration, $\binom{\text{Firm(j)}}{1}$ in $\binom{\text{list} - \text{of} - \text{previous} - \text{partner}}{\text{number} - \text{of} - \text{collaboration}}$ of firm(i) becomes $\binom{\text{Firm(j)}}{2}$ and $\binom{\text{Firm(i)}}{1}$ in $\binom{\text{list}-\text{of}-\text{previous}-\text{partner}}{\text{number}-\text{of}-\text{collaboration}}$ of firm(j) becomes $\binom{\text{Firm(i)}}{2}$. Figure 2 shows the whole operation process of the simulation.

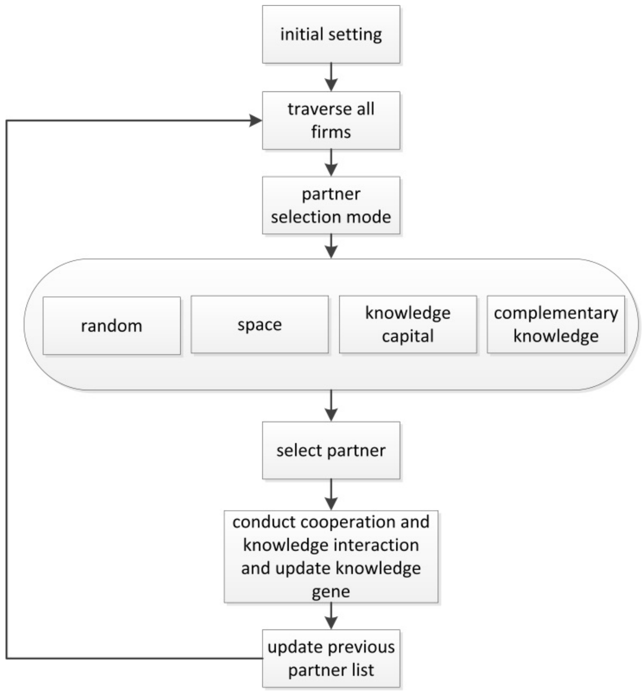

FIGURE 2. Simulation operation process.

E. THE MEASUREMENT OF COOPERATIVE INNOVATION PERFORMANCE

The total amount of increased knowledge in a period of time can reflect the efficiency of knowledge transfer of firms in the innovation network. In this study, it uses the total amount of incremental expertise to represent cooperative innovation performance. The cooperative innovation performance of the system can be expressed as: the sum of all firms' expertise at time t=T minus the sum of all firms' expertise at time t=0.

$$\text{performance}\Delta = \sum_{1}^{i}\sum \text{expertise}_{\text{agent(i)}}(t = T) - \sum_{1}^{i}\sum \text{expertise}_{\text{agent(i)}}(t = 0)$$

IV. RESEARCH METHODOLOGY

A. SIMULATION SYSTEM INTERFACE

The NetLogo simulation platform provides a user-friendly interface. It can easily set different model parameters on the interface. The status of the innovation network can be visualized. The big node represents the large firm and the small node represents the small firm. They are randomly distributed in a [60 ∗ 60] small world. If two firms cooperate, it creates a link between them. The plot "Knowledge increment" shows the increment of knowledge expertise of small firms, large firms and the whole system. The plot "Average partners"

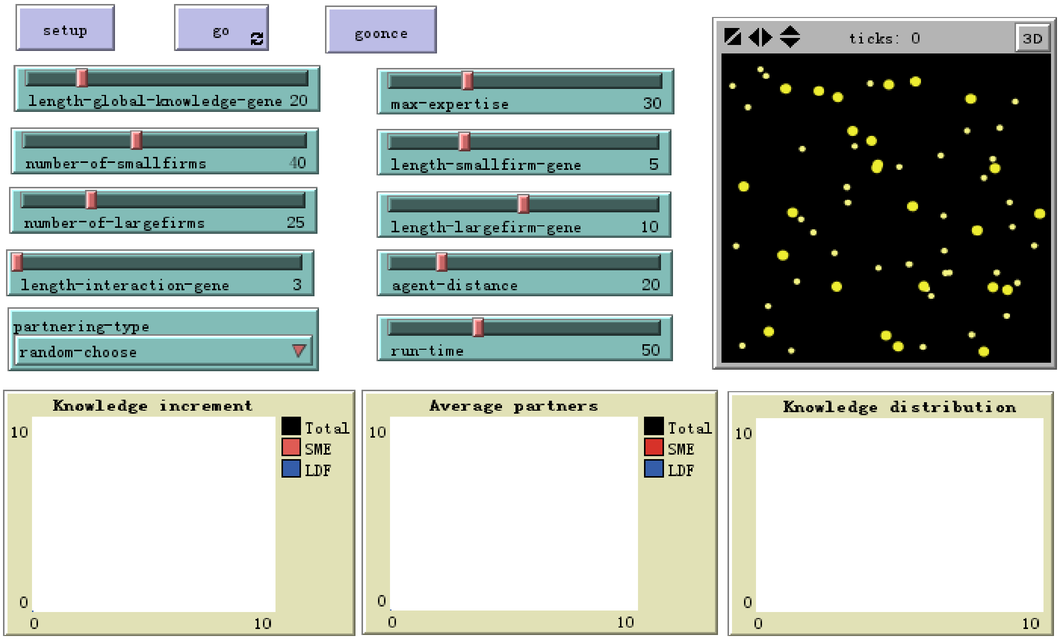

FIGURE 3. System interface.

illustrates the average number of previous partners for small firms, large firms and all the firms. The histogram "Knowledge distribution" shows the distribution of the expertise level for each capability in the system. Figure 3 shows the System Interface.

B. PARAMETERS SETTING

Before the initialization of the system, the simulation parameters must be set, including running steps of the simulation 'run-time, RT', variety of capabilities in the system 'length-global-knowledge-gene, LGKG', initial maximum of each expertise 'max-expertise, ME', number of small firms in the system 'number-of-smallfirms, NS', variety of capabilities of small firm 'length-smallfirm-gene, LSG', number of large firms in the system 'number-of-largefirms, NL', variety of capabilities of large firm 'length-largefirm-gene, LLG', variety of capabilities for interaction when firms conduct cooperation 'length-interaction-gene, LIG', critical distance to select partner for space selection mode 'agent-distance, AD'. Usually in an innovation system, the number of large firms is smaller than that of small firms. Therefore, in the simulation system, 'NL' is set to 25 and 'NS' is set 40. Due to the size and resource advantages of large firms, their knowledge storage types of knowledge are higher than those of small firms, 'LSG' and 'LLG' are set to 5 and 10 respectively. In order to maintain their own advantages, firms will not take all their knowledge to communicate with partners. 'LIG' is set to 3. As the whole system is [60 $*$ 60] small world, 'AD' is set to 20. In the space selection mode, the firm will only choose enterprises within the distance of 20 to cooperate with. Each simulation step represents one cooperation period. After 50 simulation steps, the system will stop. Table 3 shows the basic parameters setting of the simulation experiments.

TABLE 3. Parameters setting.

Parameters	Value
run-time	50
length-global-knowledge-gene	20
max-expertise	30
number-of-smallfirms	40
length-smallfirm-gene	5
number-of-largefirms	25
length-largefirm-gene	10
length-interaction-gene	3
agent-distance	20

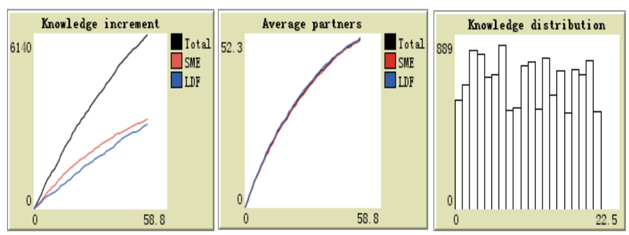

FIGURE 4. Simulation results of random mode.

V. SIMULATION RESULT ANALYSES

A. RANDOM SELECTION MODE

In random mode (Figure 4), after 50 ticks, the increment of the knowledge in the system is 6090.4. Among it, the increment of small firms and that of large firms are 3129.8, 2960.6 respectively. In the system, each firm has 50.8 previous partners on average. The number of small firms' average former partners is 50.5 while that of large firms is 51.3. There is no obvious difference between them. The histogram shows the distribution of 30 capabilities in the whole system.

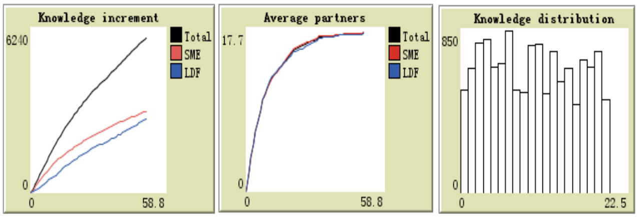

FIGURE 5. **Simulation results of space selection mode.**

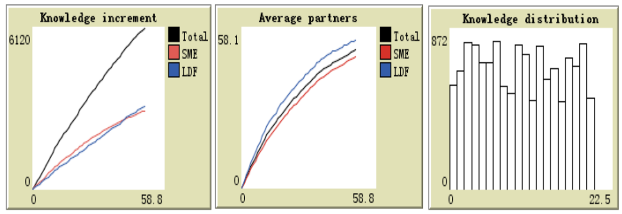

FIGURE 6. **Simulation results of knowledge capital selection mode.**

Capability (7) has the highest level of knowledge which is 839.1, while the lowest level of knowledge is 491.4 which belongs to capability (16). In this mode, there is no limitation for selecting partners and it can be used as the comparative experiment for other modes.

The random selection mode is non-instructive. This mode assumes that companies have no strategy when choosing a partner. There are several reasons for this: First, the level of innovation strategy of the company is limited. The company may not be aware of the important contribution of the partner to its innovation performance and knowledge level. Second, it may be aware that it should choose the right partner. Due to its financial capacity constraints, there is not enough capital to select the right partner. This is a problem that small and micro enterprises are likely to encounter. Third, the external information is asymmetry. Although the company has established relevant partner selection strategies and funds, due to information asymmetry, the company cannot get the knowledge information of other companies in the system. It is also impossible to select suitable partners. The above reasons lead to the blindness of the company when choosing a partner. This mode can be considered as a benchmark comparison experiment that the firm selects a partner without a clear strategy.

B. SPACE SELECTION MODE

In space selection mode (Figure 5), after 50 ticks, the increment of the knowledge in the system is 5833 which is smaller than that in random mode. Among it, the increment of small firms and that of large firms are 3067.8 and 2765.2 respectively. In the system, each firm has 17.1 previous partners on average. The number of average previous partners of small firms and that of large firms are all around 17 which are significantly lower than that of random selection mode. Space constraints greatly reduce the scope for choosing partners and limit the channels of knowledge transfer, which have a negative impact on knowledge transfer of the whole system. There is no obvious difference in knowledge distribution histogram compared with random selection mode.

Some scholars believe that spatial proximity has an impact on inter-organizational cooperation. First, spatial proximity can help both partners save transaction costs. The cooperation between the two parties needs to be carried out through transportation, negotiation, communication, etc. The short distance can substantially save the transportation costs of both parties, which makes many enterprises give priority to geographically adjacent organizations when selecting partners. Second, it helps to transfer tacit knowledge. Nowadays, knowledge is becoming more and more complicated and tacit knowledge in cooperation between enterprises is not easy to spread through documents. Enterprises with geographical proximity can frequently conduct face-to-face communication, thus absorbing the tacit knowledge of both parties. In this study, since the model does not consider transaction costs and the implicit knowledge, the knowledge increment of the overall system are not improved compared to the random selection mode, but has slightly decreased. The reason is that selecting a partner only within a specific restricted area will significantly limit the range of options, thus reducing the diversity of knowledge absorption. With the development of technology, geographical proximity has dramatically reduced its importance in partners selection and it is increasingly popular for technicians and organizations to cooperate across regions [44].

C. KNOWLEDGE CAPITAL SELECTION MODE

In knowledge capital selection mode (Figure 6), after 50 ticks, the increment of the knowledge in the system is 6081.3 which is almost the same as that in random mode. The increment of small firms is 2959.6 which is significantly lower than that in random mode but that of large firms turns out to be opposite with an increase of 3121.7. This is because a large firm with a large amount of knowledge has more cooperation opportunities which can promote knowledge transfer. The number of average previous partners of small firms and that of large firms are 47.5, 53.6 respectively. Large firms have more previous partners. It shows slight changes in knowledge distribution histogram compared with random selection mode.

Under the knowledge capital selection mode, companies in the innovation network tend to seek cooperation with partners who have more resources and knowledge. This will not only enable a firm to benefit from cooperative innovation, but also reduce the risk. It also can expand the relationship network and vision. It can be understood that the enterprises in the system have the willingness of cooperating with the large firms. Under this mode, the innovation networks formed by enterprises have certain scale-free characteristic. That is, large enterprises with large knowledge stock have more partners and develop a certain core network. This will create the Matthew effect that enterprises with large knowledge stock grow faster because they can cooperate with more partners. Companies with less knowledge stock have fewer knowledge increments due to fewer partners. Therefore, the average

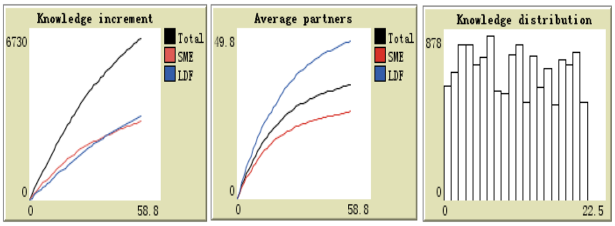

FIGURE 7. Simulation results of complementary knowledge selection mode.

number of partners of large companies in simulation results is higher than that of small businesses. In this mode, although small businesses have the willingness to cooperate with the strong, this cooperation is not necessarily the most efficient. For the overall system, knowledge transfer efficiency of the system is not significantly increased compared to the random mode.

D. KNOWLEDGE COMPLEMENTARY SELECTION MODE

In knowledge complementary mode (Figure 7), after 50 ticks, the knowledge increment of the system grows to 6361.4 which is significantly larger than that in random mode. Compared with random mode, the increment of knowledge in large firms also shows an increase (3282.9) and that of small firms shows a decrease (3078.5). This is because the large firms have more capabilities which can be complementary with other firms. They have more potential partners to collaborate and learn from other firms. Small firms have a limited variety of knowledge, so their choice of partners is limited. Their knowledge proliferates during the initial phase, but as time progresses, the knowledge gap between different firms becomes smaller. In the later stages, although they conduct complementary cooperating, the difference in knowledge that can be obtained is limited. The number of average previous partners of small firms and that of large firms are 25.6, 46.1 respectively. The large firms conduct more cooperative innovation. Compared with random selection mode, the trend of the knowledge distribution histogram shows no significant difference.

Technology is developing rapidly and the complexity of technology is getting higher and higher. Every company must have its own core knowledge and resources. The types and levels of knowledge between different companies are not the same. This difference is one of the critical driving forces for cooperation between the two parties. Under the mechanism of knowledge complementarity, the types of knowledge of both sides must have certain similarities and compatibility. The excessive differentiation of knowledge types will lead to difficulties in communication between the two parties. At the same time, both sides should have a certain knowledge potential difference. There is room for mutual complementarity between both sides, thus achieving a win-win situation in cooperation. It can be seen from the simulation results that the overall knowledge increment of the system is much higher than the other three modes. At the same time, the average number of historical partners of the companies is lower than that of random mode, indicating that the company is more targeted when selecting partners and it can improve the innovation efficiency.

VI. CONCLUSION

In this study, it establishes a multiagent simulation model of knowledge-based partner selection, which compares four different partner selection modes in the same innovation system. The random selection mode is used as a benchmark comparison. Based on the simulation results, it can draw the following conclusions:

Firstly, under certain conditions, the space selection mode limits the efficiency of cooperative R&D between firms to some extent. This is consistent with some current research findings [45], [46]. In the real world, some companies regard geographic distance as one of the important factors for partner selection [47]. They prefer to establish cooperation with geographically adjacent partners. If the cooperation has the character of geographical proximity, communication with partners will be more efficient, which is reflected in the ability to conduct more face-to-face interaction, similar geographic location, similar cultural concept and fewer transportation costs. In this study, the model does not take many factors into account. It is carried out only from the perspective of knowledge learning. However, the fixed-range partner selection mechanism dramatically reduces the possibility of finding a partner who can bring improvement. Therefore, in the space selection mode, the knowledge transfer efficiency of the system is lower than the random selection mode. This conclusion suggests that geographical distance should not be considered as the primary factor when choosing a partner. Especially in the era of rapid technological development nowadays, face-to-face communication has a limited role in promoting cooperation and innovation and the use of high-tech communication can improve the efficiency [48]. Therefore, knowledge-based enterprises should expand their partner selection range through advanced technology, which can accelerate the growth of enterprises.

Secondly, the knowledge capital selection mode is more conducive to the growth of knowledge for large enterprises. From the perspective of enterprise resource capabilities, the technical capabilities and technical level can influence the partner selection [42]. Diestre and Rajagopalan's study has shown that high-tech companies are more inclined to cooperate with companies with high-value creation capabilities [49]. For technology-based companies, the level of knowledge is undoubtedly the most important manifestation of their value capabilities. In the real world, small businesses with weaker capabilities are more willing to cooperate with large enterprises which have more extensive capabilities. From the perspective of knowledge capabilities, cooperation with the strong can help enterprises achieve technological progress faster. From the perspective of network structure, it is reflected that the core enterprises in the industrial cluster are linked with many small enterprises. The whole innovation network has scale-free property which shows that a small number of nodes have a large number of links. However, if firms choose this strategy for a long time, it will form the Matthew effect of the accumulation advantages. That is, large enterprises can acquire more partners because of their own resource advantages and their knowledge grows faster than that of small enterprises. They stabilize their knowledge resource advantages. However, its impact on the innovation efficiency of the entire system deserves further study. In the experimental results of this study, this mode of partner selection does not promote the overall knowledge growth efficiency of the system. Therefore, policy makers of small businesses and innovation systems should avoid this excessive Matthew effect in the innovation system to some extent.

Thirdly, knowledge-complementary cooperation is the optimal cooperation strategy for innovation systems. Many studies have shown that complementarity can significantly promote the efficiency of cooperation [50], [51], which is consistent with the conclusions of this study. In this study, the knowledge growth rate of the system under the knowledge complementarity selection mode is much higher than other several selection modes, which shows that knowledge-competitive cooperation is the optimal cooperation strategy. However, this conclusion is based on a hypothesis of the model: the company knows that the knowledge ability of other firms can complement itself as a partner. But this is not so simple in the real world. Generally, information asymmetry is the biggest obstacle for enterprises to choose partners. Enterprises do not know the variety of capability and the knowledge level of other firms. In order to benefit from cooperation, some enterprises will conceal some of their true information and influence other's decision-making. The situation is not as simple as the simulation model. It takes a lot of time and money to find a potential partner and the real information of its ability. Not every firm will do this. The ideal situation is that a large number of high-efficiency complementary cooperation can be achieved in the real innovation system. It needs a role to eliminate this negative impact of information asymmetry from the macro perspective, such as government, technology intermediaries, etc. Specific measures may include: First, it can establish an open-ended online information platform within the innovation system and collect innovative individual information (qualifications, knowledge capabilities, etc.) so that enterprises can reduce their cost for searching partners with complementary capabilities. Second, it can improve the corresponding laws and regulations. For enterprises that engage in information fraud, they should bear corresponding punishments and be included in the information blacklist to increase the cost of fraud. Through a series of measures to reduce the negative effects of information asymmetry, complementary cooperation can be achieved in the real world. Cooperation between enterprises can be more efficient and the innovation performance of systems can be further optimized.

The main contributions of this paper are reflected in two aspects. First, the study builds a multiagent simulation model of innovation network based on knowledge transfer, which can reveal the relationship between the macro emergence of knowledge growth and the micro interaction mechanism of the organizations. It provides some inspiration for scholars who may go on to investigate partner selection and knowledge transfer. Second, several different partner selection mechanisms of existing research are compared in the same system, which has enlightenment for the decision-making of enterprises and other stakeholders in the innovation system. However, this study still has limitations: First, the choice of a partner is a complex process, including absorptive capacity of firms, cost of cooperation, firm culture and other factors, which the model has not considered. Second, this study only established a mechanistic model that was not validated using real-world cases. Questions like these are sophisticated and need to be solved by further research.

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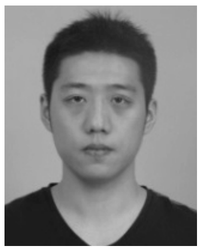

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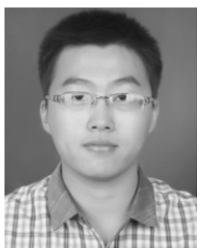

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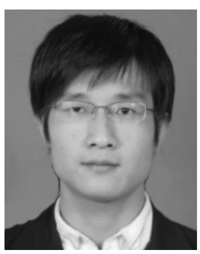

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