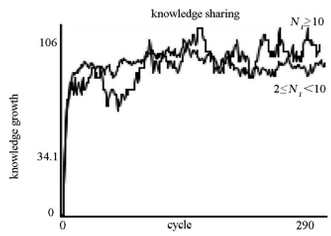
Modeling and simulation of the knowledge growth process among new energy technology firms in the distributed innovation network



Modelización y simulación del proceso de crecimiento del conocimiento en las empresas de nuevas tecnologías energéticas en la red de innovación distribuida

Guoxin Liu[1], Jun Ye[1*] and Christophe Argyres[2]

[1] School of Management, Wuhan University of Technology, Luoshi Road, 122#, Wuhan, Hubei, 435000, P.R, China. Email: ddong11221@sina.com
[2] School of Business Rauma, Satakunta University of Applied Technology, Satakunta, Finland

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RESUMEN

- En el contexto de la red de innovación distribuida, la innovación colaborativa entre las nuevas empresas de tecnología energética es el eslabón más importante de la red. El proceso de colaboración en I+D implica un importante intercambio de datos y gestión del conocimiento a través de las barreras de las empresas. El contexto (estratégico, cultural, institucional y el de la red) de las nuevas empresas de tecnología energética en la red y la I+D entre estas empresas tiene un impacto masivo en la generación global de conocimientos. Con el fin de explorar el proceso óptimo de crecimiento del conocimiento entre las nuevas empresas de tecnologías energéticas en la red distribuida, se analiza la influencia del contexto colaborativo y el comportamiento colaborativo frente al crecimiento del conocimiento, basado en las características de la tecnología multiagente desde la perspectiva de la I+D colaborativa entre las empresas. A partir de una deducción teórica y una prueba empírica, se construye el modelo de interacción conductual entre múltiples agentes y se aplica la simulación al modelo a través de la plataforma Netlogo. Los resultados muestran que, en un solo ciclo, el contexto de colaboración ejerce un impacto positivo en el crecimiento del conocimiento entre las nuevas empresas de tecnología energética. Sin embargo, existen ciertas diferencias, como el hecho de que el efecto multiplicador del intercambio de conocimientos sobre el crecimiento de este disminuye a medida que disminuye la diferencia de potencial de conocimiento entre las empresas de la red, hasta que desaparece. Además, cuando las nuevas empresas de tecnología energética con un alto potencial de conocimiento dejan de difundirlo, el crecimiento del conocimiento en toda la red se estanca. Si no hay intercambio de información entre las nuevas empresas de tecnología energética de la red, entonces la colaboración entre ellas puede colapsar. La inversión en activos específicos desempeña un papel positivo en la promoción de la difusión de conocimientos entre las empresas, al tiempo que facilita el crecimiento de los conocimientos entre las nuevas empresas de tecnología energética y mejora la eficiencia de la colaboración.
- **Palabras clave:** empresa de nuevas tecnologías energéticas, contexto colaborativo, comportamiento cooperativo, multiagente, crecimiento del conocimiento.

ABSTRACT

Against the background of the distributed innovation network, collaborative innovation among new energy technology firms is the most crucial network link. The process of collaborative R&D involves significant data exchange and knowledge management across firm boundaries. Moreover, the context(refers to the strategic context,the cultural context, the institutional context and the network context) of new energy technology firms in the network and the R&D among these firms massively impact overall knowledge emergence in the network. In order to explore the optimal knowledge growth process among new energy technology firms in the distributed network, the influence of collaborative context and collaborative behavior vis-à-vis knowledge growth was discussed in this study based on the features of multi-agent technology from the perspective of collaborative R&D among the firms. On the basis of a theoretical deduction and empirical test, the model of behavioral interaction among multiple agents was built and the simulation applied to the model via the Netlogo platform. The results show that, in a single cycle, the collaborative context exerts a positive impact on knowledge growth among new energy technology firms. However, certain differences exist. Such as the fact that the promotional effect of knowledge sharing vis-à-vis collaborative behavior on knowledge growth decreases as the difference in knowledge potential among firms in the network decreases,until it disappears. Moreover, when the new energy technology firms with a high knowledge potential cease diffusing knowledge, knowledge growth in the whole network stagnates. If there is no information sharing among new energy technology firms in the network, then the collaboration between them may collapse. Specific asset investment plays a positive role in the promotion of knowledge spillover and knowledge diffusion among the firms, while also facilitating knowledge growth among new energy technology firms and improving collaborative efficiency.

Keywords: new energy technology firm, collaborative context, cooperative behavior, multi-agent, knowledge growth.

1. INTRODUCTION

At the United Nations Conference on New and Renewable Sources of Energy in 1981, the idea of developing and exploiting traditional renewable energy in a modern manner using new technologies and new materials was put forward. Thus, the development and exploitation of new energy technology featured in China's national energy strategy.With the emergence of different organizational forms, like strategic alliances, enterprise clusters and virtual firms, alongside the development of information and network technologies, the traditional enterprise management model shifted from focusing on internal innovation in indi-

vidual firms to the construction of an external R&D network for the purpose of realizing collaborative resource innovation, which has since become a crucial method for quickly acquiring separate knowledge among technology R&D firms.

Knowledge growth among new energy technology firms in the distributed innovation network comes from knowledge innovation, knowledge diffusion [1] and the recombination of information and experience among such firms. The new energy technology firms cannot completely control and monopolize the majority of information and knowledge during the innovation process due to their own knowledge boundaries and bounded rationality. Hence, new energy technology firms must cross fields and disciplines in their search for heterogeneous technology firms with excellent knowledge and technological resources for cooperation.

Considering that it is hard to control the effects of a change in network size and other factors on knowledge growth in the distributed innovation network, as well as the fact that the measurement models and other empirical research approaches which require large sample data collection are not sufficiently accurate, multi-agent modeling is employed in this study in order to build a multi-agent interaction model for knowledge growth in the distributed innovation network. Hence, this paper seeks to uncover the relationship between the collaborative context, collaborative behavior and knowledge growth from a theoretical perspective, while simultaneously providing practical guidance for technological innovation and collaborative knowledge among new energy technology firms.

2. STATE-OF-THE-ART

2.1. THE DISTRIBUTED INNOVATION NETWORK

The term distributed innovation network was initially defined by Freeman [2], who stated that a series of institutional arrangements for systematic innovation are composed of nodes and links. Karlgaard [3] indicated that the development of the Internet and communication technologies allowed for real-time communication and the sharing of substantial information and knowledge among innovation partners across regions in the distributed innovation networks of multinational corporations (Fig.1(supplementary material)).

Distributed innovation refers not only to the behavior of individual participating firms within the innovation network, but also the structure of the organization and application processes of knowledge. In the distributed innovation network, the path dependence of knowledge evolution, the diversification of knowledge sources, the speed of knowledge evolution and the misappropriation of knowledge profits are essential attributes in the network environment. Moreover, the interactive influence of the network environment intensifies these features and further impacts the technological innovation process in the network [4].

2.2. THE EVOLUTION RULES OF KNOWLEDGE GROWTH

The purpose of organizational learning is to realize the growth of organizational knowledge as reflected in the growth in the quantity and quality of knowledge, which are broadly categorized as horizontal expansion (i.e. the increase in the quantity of knowledge) and vertical development (i.e. the increase in the quality of knowledge)[5].

Studies on the evolution rules of knowledge growth mainly rely on knowledge innovation and diffusion as they focus on research that examines the influence of knowledge diffusion [6, 7-8] and knowledge spillover [9-10] on knowledge growth. The majority of these studies utilize simulation analysis vis-à-vis knowledge growth models based on complex network research. However, due to the dynamic process model and its complexity, these studies adopt an overtly simple approach to the processes of knowledge innovation and knowledge diffusion, while the knowledge diffusion functions set by evolution models are mostly linear and exponential growth functions [11-12].

2.3. THE MECHANISM OF KNOWLEDGE GROWTH

Knowledge potential theory [13-14] explores the mechanism for and factors that influence knowledge growth from the perspectives of static and dynamic knowledge accumulation and knowledge integration. Accordingly, as a result of differences in knowledge potential between various knowledge agents, knowledge flows from high-potential agents to low-potential agents. In R&D activities among firms, low-potential knowledge agents continuously increase their knowledge stock by learning from their high-potential counterparts. Firms with varying knowledge potentials learn from each other, so as to increase the knowledge stock among those in the R&D alliance. The idea that knowledge stock influences knowledge growth [15] can be described as $K=K_0 + (KL^+-KL^-)$ where K_0 refers to the original knowledge stock; KL^+ to an increases in the flow of knowledge and KL^- to a decrease in the flow of knowledge. Despite an increasing number of studies examining the mechanism of knowledge stock growth, few research perspectives and methods are adopted. While most scholars have examined the influencing factors and growth methods from a qualitative perspective, very few have quantitatively analyzed knowledge stock growth using economic growth models[6, 12-13]

2.4. THE FACTORS THAT INFLUENCE KNOWLEDGE GROWTH

Driven by knowledge potential, the principal factors that influence knowledge growth are the ability of knowledge agents to find knowledge, their motivation to acquire knowledge, their learning and integration abilities, the level of knowledge potential and the atmosphere for eliminating differences in knowledge potential [13,16-17]. (Fig.2(supplementary material)).

In fact, collaborative R&D among new energy technology firms is itself a context. Hence, this study holds that context, which covers various external forces, is an uncontrollable and dynamic factor, which facilitates not only knowledge R&D, the flow and transfer of information and knowledge growth, but also the full exploitation of economies of scale for the purposes of optimizing resource allocation, enhancing R&D performance and realizing the goal of cooperation and development.

3. METHODOLOGY

A MAS (Multi-Agent System) is composed of multiple agents with different goals who exhibit different behavior. The overall goal of the system can be achieved through collaboration. In the process of collaborative innovation, each new energy technology firm in a different context is a physical entity, which can impact itself and the environment in addition to being able to communicate with other new energy technology firms. Hence, this study chose the simulation tool Netlogo (http://ccl.northwestern.edu/netlogo/). Based on the Logo language, Netlogo can control multiple agents in the modeling process and simulate the development and evolution of various complex agents in different contexts for the purpose of understanding behavioral rules. The agents in the

model were categorized as turtles, patches and observers. Patches are static agents who divide the virtual space into networks. Turtles are dynamic agents who can either move randomly on patches, interact with themselves or interact with patches. Observers are the issuers and coordinators of major commands as well as the observers of operating status, who are responsible for controlling the environment after setting agent-agent and agent-environment behavioral rules. Hence, the behavior of microscopic individuals in different contexts can be better simulated.

3.1 MODELING

Collaborative behavior among new energy technology firms involves substantial data exchange between these firms and process management across firm boundaries. The collaborative effect reflects the level of knowledge growth. Against the distributed background, however, knowledge is not isolated but is instead inserted into a certain context. This study predominantly considers the strategic context, the cultural context, the institutional context and the network context. Among them, the strategic context and the cultural context are the objective situational factors at the organizational level; the institutional context and the network context are objective situational factors beyond the organizational level.The dynamism reflected in the collaborative context interferes with collaborative management and control among new energy technology firms. Hence, process management and specialized process management tools are required so that targeted management can be carried out. Hence, in the distributed innovation network, given the decentralized distribution of new energy technology firms, the collaborative R&D activity process among firms involves seeking optimal solutions in the whole distributed network.

Drawing from the knowledge growth model of the agent-based technology innovation network designed by Yu [1] the MAS in this study makes each new energy technology enterprise in the distributed innovation network an agent. After determining the properties, behavior and interaction rules for agents, the workflow model for multi-agent collaboration in the collaborative context is built as shown in Fig. 3.

3.2 MODEL HYPOTHESES

In the distributed innovation network, each agent represents a node and has certain knowledge endowments. In view of knowledge type differences, as well as the knowledge structure and degree of specialization for each agent, every node should input systematic knowledge stock, while knowledge potential difference should be reduced through synergy. Watts [18] pointed out that network density d represents the size of the knowledge stock in the network. Moreover, Watts noted that, when there are more node links in a fixed-size network, network density is higher, which facilitates knowledge interaction and innovation. The expression for network density when there is multi-agent collaboration is as follows:

$$d = \frac{l}{N(N-1)/2} \tag{1}$$

In the above expression, l is the number of actual link edges for each node in the network, while N denotes the scale of the node in the network. d is actual connections divided by the pontential connections.

Vectors are used to represent agents' R&D knowledge and consist of m dimensions. Each dimension represents a category of knowledge, the value of which denotes the size of the knowledge stock. Then, the knowledge stock of the i th new energy technology firm is:

$$ks_i(t) = (ks_i^1(t), ks_i^2(t), \ldots, ks_i^m(t)) \tag{2}$$

where $ks_i^1(t), ks_i^2(t), \ldots, ks_i^m(t)$ are mutually independent and follow a random distribution in (0,1). In this case, each new energy technology firm that participates in collaboration may be an expert in one field, but unskilled in others.

In order to simplify the model and enhance simulation success, this study has the following hypotheses:

H1: The members in a network are fixed;

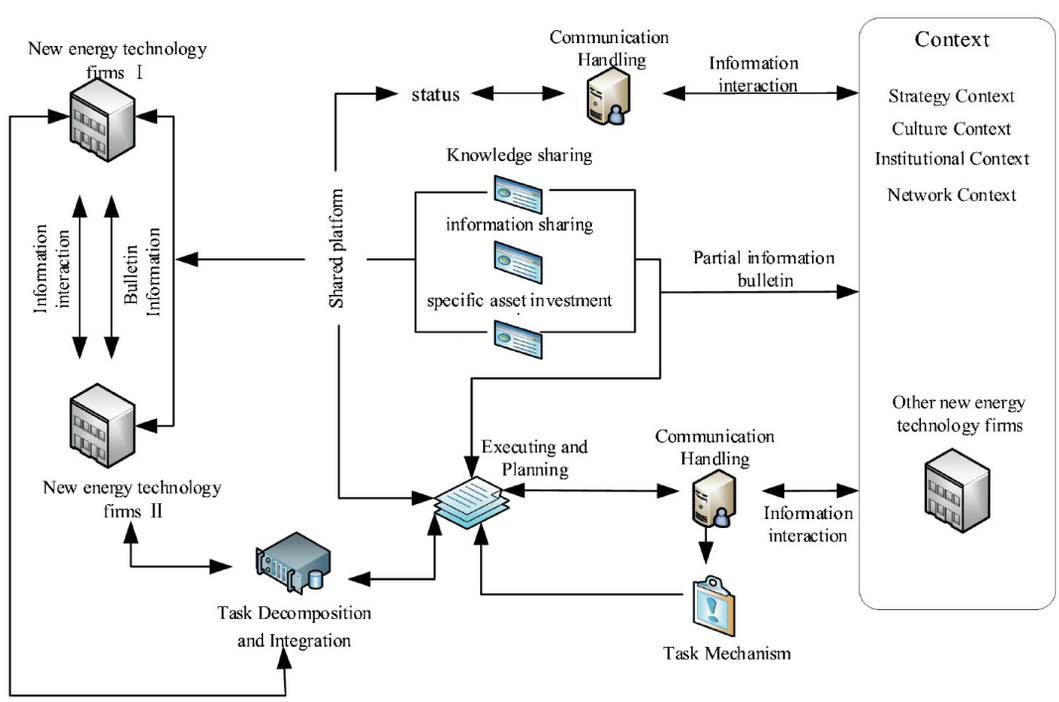


Fig. 3: The workflow for multi-agent collaboration in the collaborative context

H2: The direct link among new energy technology firms is set as $Link_1$; the link among new energy technology firms that can be realized through 1 existing energy technology firm is set as $Link_2$; and the link among new energy technology firms that can be realized through 2 or more existing energy technology firms is set as $Link_3$ ($Link_1 > Link_2 > Link_3$);

H3: New energy technology firms have relatively transparent knowledge stocks in different knowledge fields and firms typically seek to cooperate with those firms that possess complementary knowledge;

H4: Each new energy technology firm can only carry out one knowledge transfer activity per cycle (i.e. from the end of the t th cycle to the end of the $t+1$ th cycle). In other words, each firm can only acquire knowledge in a certain field from another new energy technology firm.

3.2.1. Seeking Knowledge Sources

New energy technology firms first determine the fields in which they possess relatively little knowledge, then seek appropriate sources of knowledge as per their own needs before increasing their knowledge stock through collaborative R&D. As a variable that grows with practice, knowledge stock determines the model of knowledge interaction among new energy technology firms as well as the state of the next cycle. Assuming that there are two new energy technology firms A_1 and A_2 that possess knowledge in the same field, then A_1 has knowledge equal to $ks(t)^1_1$, and A_2 has knowledge equal to $ks(t)^1_2$, $ks(t)^1_2$. When $ks(t)^1_1 \leq ks(t)^1_2$, A_1 acquires knowledge in the field through knowledge collaboration with A_2. Hence:

$$\frac{\partial ks(t+1)^1_1}{\partial(t+1)} = b \quad (b \text{ is knowledge transfer efficiency; } t \text{ is the length of time}) \tag{3}$$

If knowledge transfer occurs in period $t+1$, then $ks(t+1)^1_1 = ks(t)^1_1 + bt$, $ks(t+1)^1_1$ denotes the knowledge stock possessed by firm A_1 in the given field following the knowledge transfer.

In addition, knowledge sources should meet the following requirements:

The new energy firms should be willing to collaborate in technological R&D and offer complementary knowledge, the difference in knowledge potential among new energy firms participating in collaborative R&D should not be excessively large, else the relevant knowledge absorption could be affected.

H5: When the knowledge ratio of two new energy technology firms in a given technology field exceeds 0.85, knowledge diffusion should be stopped for several reasons, including protecting core competitiveness;

H6: When the difference in knowledge potential between new energy technology firms in a certain field is below k_{min}, the knowledge receiver meets the knowledge absorption conditions.

3.2.2. Knowledge Diffusion

According to the model by Cowan [19], if α_{ij} means that knowledge transferor i is willing to diffuse knowledge to knowledge receiver j and β_{ij} means that the knowledge receiver j can assimilate the knowledge diffused by the knowledge transferor i, then the knowledge ratio of the knowledge transferor i to the knowledge receiver j after diffusion should be:

$$\begin{cases} kd_i^s(t) = kd_i^s(t-1) \\ kd_j^s(t) = kd_j^s(t-1) + \alpha_{ij}\beta_{ji}\left[kd_i^s(t-1) - kd_j^s(t-1)\right] \end{cases} \tag{4}$$

Where s denotes the s th field of knowledge for the new energy technology firm, while α_{ij} and β_{ij} are both proportional to the link between the knowledge transferor i and the knowledge receiver j, which displays generality. Assuming $\alpha_{ij}\beta_{ij} = k_0 Link_{ij}$ (k_0 is a constant greater than zero), Hence:

$$\begin{cases} kd_i^s(t) = kd_i^s(t-1) \\ kd_j^s(t) = kd_j^s(t-1) + k_0 Link_{ij}\left[kd_i^s(t-1) - kd_j^s(t-1)\right] \end{cases} \tag{5}$$

3.2.3. Knowledge Spillover

In the process of collaborative R&D, new energy technology firms may show knowledge spillover through formal and informal communication. Knowledge spillover is both unconscious and involuntary. Assuming that the s th knowledge field of the new energy technology firm i is higher than the s th knowledge field of the new energy technology firm j, then the knowledge spillover between the two is given by:

$$\begin{cases} k^s_{j,spillover}(t) = \lambda_1 \times \left[ks_i^s(t) - ks_j^s(t)\right] \\ k^s_{j,spillover}(t) = 0 \end{cases} \tag{6}$$

Where λ_1 is the spillover coefficient and $\lambda_1 < \alpha\beta$ denotes the fact that the knowledge increment generated by knowledge spillover is far less than that generated by knowledge diffusion.

3.2.4. Knowledge Growth

H7: When the knowledge stock of a new energy technology firm exceeds ks_{min} and knowledge diffusion reaches kd_{min}, knowledge growth takes place. Assuming that knowledge stock in the m th field for the new energy technology firm i is equal to ks_i^m, then after knowledge diffusion occurs with the m th knowledge field for the new energy technology firm j, then the stock of knowledge in the m-th field for firm i should equal:

$$ks_i^m(t) = \lambda_2 \times kd_i^m(t) \times e^{\left[kd_j^m(t) - kd_i^m(t)\right]} \tag{7}$$

Where λ_2 is the collaboration coefficient and e is a constant.

It can be seen that knowledge spillover and knowledge diffusion not only facilitate knowledge growth among collaborative new energy technology firms in the distributed innovation network, but also promote the growth of overall knowledge in the network.

3.3 PARAMETER-SETTING IN THE MODEL

For the purpose of smooth simulation, relevant model parameters are set as shown in Table1. N_1=2, 3, 5,10, 15, 20, 25, 30, d=0.01, 0.04, 0.07, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.6, 0.7, 0.9 are applied for the collaboration among the selected new energy technology firms with 10 simulation tests carried out for collaboration in different circumstances. Hence, a total of 150 simulation tests are completed. At the same time, in order to simplify the model and enhance simulation success, a distributed innovation network with 80 firms is used as an example (the initial number of new energy technology firms in the network was similar to that of existing energy technology firms and the initial

default value was 80 after adding the two numbers). Every firm has five distinct fields of knowledge and the maximum number of times knowledge diffusion can occur for each firm in the whole network is 5 (N_{time}=5).

Parameter Name	Symbol	Set Value and Description
The number of cooperative new energy technology firms in the distributed network	N_1	$2 \leq N_1 < 30$
The number of existing energy technology firms in the distributed innovation network	N_{time}	$N_2 = 80 - N_1$
The number of knowledge fields for new energy technology firms	m	5
The maximum number of times that knowledge diffusion can take place among new energy technology firms in the whole network	N_{time}	5
Knowledge spillover coefficient	λ_1	0.01
The direct link among new energy technology firms	$Link_1$	0.7
The link among new energy technology firms that is realized through 1 existing energy technology firm	$Link_2$	0.5
The link among new energy technology firms that is realized through 2 or more existing energy technology firms	$Link_3$	0.2
The maximum difference in knowledge potential that satisfies the absorption conditions	K_{min}	1
The minimum knowledge stock for R&D collaboration among new energy technology firms	Ks_{min}	0.7
The minimum knowledge diffusion for R&D collaboration among new energy technology firms	Kd_{min}	0.2
Collaboration coefficient	λ_2	1

Table 1: Parameter-Setting in the Model

4. RESULTS ANALYSIS AND DISCUSSION

4.1 THE INFLUENCE OF THE COLLABORATIVE CONTEXT ON KNOWLEDGE GROWTH IN NEW ENERGY TECHNOLOGY FIRMS

Fig.4a to Fig.4d display the results of the analysis of the simulation results concerning the influence of the collaborative context on knowledge growth among new energy technology firms:

It can be seen from Fig.4a that, for a single cycle, when $2 \leq N_1 < 10$, the promotional effect of the strategic context on knowledge growth fluctuates in the range [0.05, 0.1]. Moreover, when $N_1 \geq 10$, the strategic context affects knowledge growth in such a manner that the promotional effect fluctuates in the range [0.1, 0.118]. It can be seen that, as the number of collaborative new energy technology firms increases, the complementary resource coupling among new energy technology firms intensifies; thus contributing to knowledge creation and innovation, while also increasing the rate of knowledge growth.

According to Fig. 4b It can be seen that new energy technology firms in the distributed innovation network have different advantages in terms of geography and core technology fields. Moreover, these new energy technology firms possess multi-synthetic cultures. Cultural differences can produce cultural synergies, which only promote knowledge growth, but also facilitate the realization of organizational goals.

Fig. 4c (supplementary material) shows that the institutional and technological innovation are engaged in an interactive dynamic evolution process, institutional context defines the scope of activities, norms, rules and cognition for the collaboration among new energy technology firms.

According to Fig.4d (supplementary material), in a single cycle, when $2 \leq N_1 < 10$, the promotional effect of the network context on knowledge growth does not vary to a great extent. Hence, knowledge growth is relatively stable. Meanwhile, when $N_1 \geq 10$, the promotional effect of the network context on knowledge growth is much higher. One possible explanation for this difference is that, as the number of new energy technology firms engaged in collaborative R&D increases, so too does the number of fields involved. Moreover, because different firms possess distinct knowledge reserves, knowledge structures and knowledge types, the content of knowledge flowing in the network is richer and the degree of knowledge isomerization is improved, which makes up for the knowledge defects of individual new energy technology firms and facilitates the promotion of creation of knowledge value.

Therefore, in a single cycle, the collaborative context has a positive impact on knowledge growth among new energy technology firms, although a degree of difference persists. One possible explanation for this is that, in the distributed innovation network, when firm boundaries are minimized, new energy technology firms that possess specific strengths also have irreplaceable expertise, which not only facilitates their own knowledge growth, but also plays a positive role in knowledge growth in the entire network through mutual support in the collaborative context. When the number of new energy technology firms engaged in collaboration is small, few sharing points exist and knowledge growth in individual new energy technology firms is significant. Meanwhile, when several new energy technology firms engage in collaboration, there are more sharing points, which facilitates learning from others and knowledge growth.

4.2 THE RELATIONSHIP BETWEEN KNOWLEDGE SHARING AND KNOWLEDGE GROWTH IN NEW ENERGY TECHNOLOGY FIRMS

The results shown in Fig. 5a. suggest that knowledge stocks differ in terms of knowledge types and scopes (including the degree of specialization and professional fields) among new energy technology firms, which creates potential difference in knowledge structures. Thus, several new energy technology firms in the network must input systematic knowledge stock, reduce the difference in knowledge potential through the collaborative effect and establish a modular knowledge sharing interface, so as to increase knowledge stock.

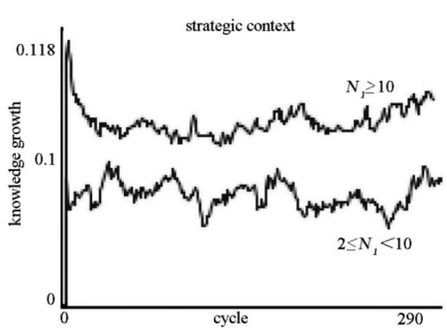


Fig. 4a: Knowledge growth in the strategic context

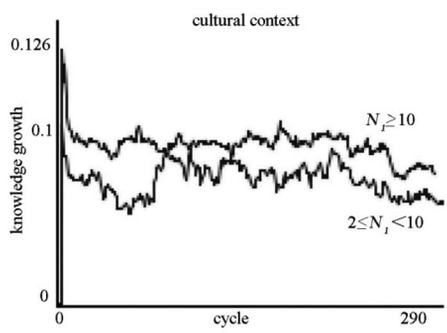


Fig. 4b: Knowledge growth in the cultural context

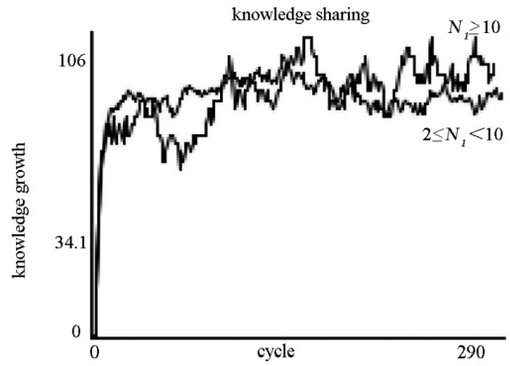


Fig. 5a: The impact of knowledge sharing on knowledge increment

In this study, it is found that, through the simulation and selection of varying differences in knowledge potential, when the difference in knowledge potential between new energy technology firms in the network is minimized, the promotional effect of knowledge sharing on knowledge growth typically disappears. Thus, energy technology firms that possess sufficiently high knowledge potential may cease diffusing knowledge and the growth in knowledge stock in the whole network may stagnate. The results of the simulation tests also show that, once any differences in knowledge potential among new energy technology firms disappear, knowledge sharing activities also stop. It can be seen that the difference in knowledge potential among new energy technology firms should not be allowed to grow indefinitely.

4.3 THE RELATIONSHIP BETWEEN INFORMATION SHARING AND KNOWLEDGE GROWTH IN NEW ENERGY TECHNOLOGY FIRMS

The simulation results are shown in Fig.5b. When $2 \leq N_1 < 10$ or $N_1 \geq 10$, as information sharing increases, so too does the collaborative efficiency between firms and the significance of the level of knowledge growth. R&D collaboration among new energy technology firms is a kind of information-based cooperation between firms, where information refers to not only information flow, but also the link presented by the data in the context, and the organized, structured, and generalized data. It can be seen that frequent and deep interactions among new energy technology firms accelerate the flow of information and enhance information transmission capabilities, which exerts a positive impact on knowledge growth in new energy technology firms and in the network as a whole. The simulation results show that, when no information sharing, knowledge diffusion or knowledge spillover occurs between new energy technology firms in the network, then collaboration among firms in the entire network tends to collapse.

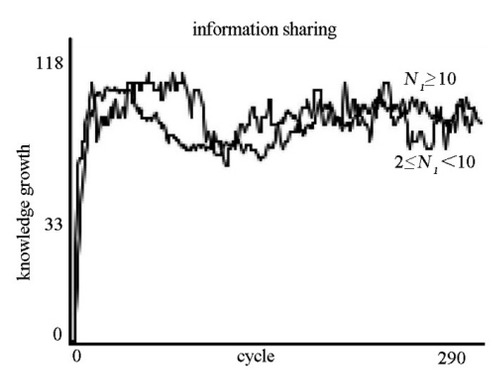


Fig. 5b: The impact of information sharing on knowledge increment

4.4 THE RELATIONSHIP BETWEEN SPECIFIC ASSET INVESTMENT AND KNOWLEDGE GROWTH IN NEW ENERGY TECHNOLOGY FIRMS

The simulation results are shown in Fig.5c. According to the results for multiple simulation tests, when $2 \leq N_1 < 10$ or $N_1 \geq 10$, specific asset investment is conducive to the establishment of interdependent relationships; the transference and acquisition of information via mutual learning; and the effective integration of resources. Since there is a close symbiotic relationship among such firms on the basis of specific asset investment, those engaged in specific asset investment can obtain advanced or core technology from cooperative firms; thereby assisting those firms that participate in collaborative R&D to achieve significant knowledge growth.

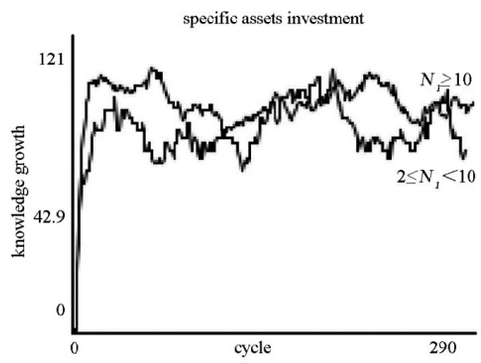


Fig. 5c. The impact of specific asset investment on knowledge increment

4.5 THE RELATIONSHIP BETWEEN COLLABORATIVE BEHAVIOR AND OVERALL COLLABORATION IN THE DISTRIBUTED INNOVATION NETWORK

As shown in Fig.6a. when $2 \leq N_1 < 10$, the effect of specific asset investment on knowledge growth is significant. Moreover, the sharing of knowledge and information in the early/middle stage of knowledge and information interaction is typically stable. Furthermore, the effect of information sharing in the later period tends to increase. On the whole, collaborative behavior makes a smaller contribution to knowledge growth. As shown in Fig.6b (supplementary material) when $N_1 \geq 10$, the effect of collaborative behavior on knowledge and information interactions, in addition to specific asset investment development, is very stable, which can quickly promote knowledge increment growth in the entire network.

Nonetheless, there are certain differences in knowledge potential among new energy technology firms in the distributed innovation network. Moreover, because growth in the knowledge stock is slow, any differences in knowledge potential cannot close

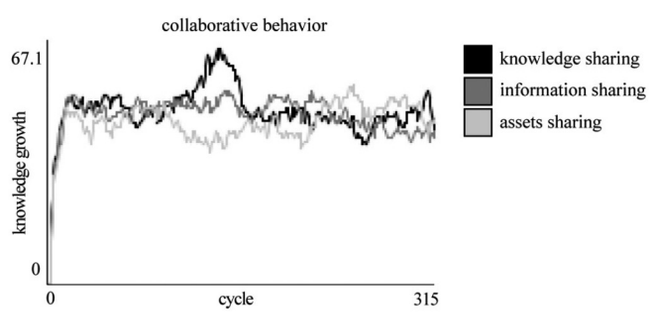


Fig. 6a: The impact of collaborative behavior on knowledge increment (2≤N1<10)

the knowledge gap in a short period of time. Hence, differences in knowledge potential can persist.

5. CONCLUSIONS

Using collaborative theory as its foundation, this study focuses on the influence of collaborative context and collaborative behavior on knowledge growth. More precisely, this paper simulates such a process by applying multi- agent-based modeling. Consequently, the following conclusions are drawn:

(1) Knowledge growth in the distributed innovation network is affected by the specific context of the collaborative R&D among new energy technology firms. Based on the interactions between the contexts, activities and behavioral mechanisms of distributed innovation knowledge flow, knowledge transfer and knowledge sharing among new energy technology firms, new knowledge is constantly being generated, which promotes the growth of knowledge.

(2) R&D collaboration among new energy technology firms is conducive to collaborative R&D activities among firms, as well as knowledge growth in the firms and the entire network.

(3) New energy technology firms can strengthen mutual cooperation through strategic alliance, technological alliance, construction of knowledge innovation platform, establishment of information network and other ways. For example: 1) The Swedish company of Guoneng electric vehicle and Hegang Group signed a strategic cooperation agreement in Shijiazhuang. The two sides will focus on new energy vehicles, combine the automobile industry chain of Guoneng with the iron and steel industry chain of Hegang, and build a new competitive advantage of the whole industry chain cooperation. 2) Hitachi automotive systems, a subsidiary of Hitachi, signed a cooperation framework agreement with WanLiYang, a company headquartered in Zhejiang Province, China. The two companies will work together to develop and sell e-axis new energy vehicle drive systems suitable for the Chinese market.

Given that relevant exploratory research was carried out, certain shortcomings inevitably limit the academic strength of this study. Firstly, when modeling the multi-agent-based knowledge growth process, in order to simplify the model and facilitate the simulation, only the impacts of context and behavior on knowledge growth were considered. Secondly, 150 simulation tests were carried out when the network scale was limited. While such an approach guaranteed control over network scale, it nonetheless failed to show the similarities and differences associated with the influence of network features on knowledge growth for different network scales.Thirdly, This paper does not touch on micro-level variables like senior managers and researchers of all levels. Finally, the function of behavioral space in the Netlogo simulation platform should be taken into consideration in future research for further exploration.

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APPRECIATION

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SUPPLEMENTARY MATERIAL

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