International Journal of Industrial Engineering Computations 16 (2025) 1025–1038

Contents lists available at GrowingScience

International Journal of Industrial Engineering Computations

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Environmental preference utility and evolutionary game of collaborative innovation of asymmetric technology enterprises based on complex networks

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C H R O N I C L E

Article history:
Received June 1 2025
Received in Revised Format June 28 2025
Accepted August 10 2025
Available online August 10 2025

Keywords:
Simulation Algorithm
Asymmetric evolutionary game
Technology enterprises
Collaborative innovation
Environment preference utility
Complex network

A B S T R A C T

Based on complex networks, the innovation strategies of enterprises or governments are analyzed by using asymmetric evolutionary games. The evolutionary game model is considered to be a better way to promote collaborative innovation between large and small enterprises. First, a model is established based on the replicator dynamic equations. Then, based on complex network and computer simulation technology, a network evolutionary game model with improved strategy update rules including environmental preference utility is designed. The results show that the conclusions of the mathematical and network models of evolutionary stable strategies (ESS) are the same. The complex network model can provide more detailed information on the evolutionary processes of enterprises, and the parameter values can be adjusted to analyze the evolution sensitivity. In a uniform or non-uniform environment, the effect of environmental preference on evolution is weak, indicating that the effect of collaborative innovation on asymmetric enterprises is weak. The initial probability of enterprise collaborative innovation is the key to ESS. A dynamic model of asymmetric replication factor and an evolutionary game model composed of two participants of large technology enterprises and SMEs are established. Complex networks and environmental preferences are involved in evolutionary games to better analyze the ESS.

1. Introduction

Collaborative development and sharing economy have become international trends in socio-economic development. In recent years, scientific research intermediaries such as scientific and technological parks, entrepreneurial parks and incubators have sprung up. These facilities provide companies, universities and research institutions with a broad platform for mutual learning and collaborative innovation. The government has conducted extensive research on enterprise technological innovation policies. Some studies have sought to draw lessons from foreign policies and explored how these experiences can be adapted and applied in China (Liang, 2020; Zheng & Liu, 2021). Geng et al. (2025) took China's innovation policies in promoting the development of the new energy vehicle industry as a case study, examining the implementation process, pathways, and theoretical logic of the "establishment and breakthrough" strategy combination in innovation policies. Additionally, using panel data from Chinese listed companies and regional macroeconomics from 2008 to 2019, they tested the impact of local industrial policies on corporate innovation activities (He et al., 2022), and empirically analyzed the relationship between government incentives, green industrial policies, and enterprise technological innovation (Zhang & Lei, 2023).

In recent years, the structural characteristics, dynamic evolution of innovation networks, and their mechanisms of influence on corporate innovation performance have become key research foci. From a network structure perspective, scholars have identified centrality, relationship strength (Wang et al., 2024), and structural holes (Li et al., 2024; Xu & Zhang, 2024) as core features. Among these, centrality and relationship strength significantly enhance corporate innovation performance by improving knowledge transfer efficiency (Wang et al., 2024), while structural hole positions strengthen disruptive innovation

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ISSN 1923-2934 (Online) - ISSN 1923-2926 (Print)
2025 Growing Science Ltd.
doi: 10.5267/j.ijiec.2025.8.002

capability through the mediating mechanism of knowledge flow (Xu & Zhang, 2024). Notably, network content characteristics exhibit nonlinear effects: partner diversity and technological diversification demonstrate a U-shaped impact on corporate innovation efficiency, moderated by structural holes and centrality (Lu et al., 2025; Li et al. 2023).

At the dynamic capability level, digital orientation emerges as a critical pathway through which innovation networks drive corporate transformation. Research indicates that expanding the breadth and intensity of innovation networks reinforces digital orientation, thereby promoting digital transformation, with the heterogeneity of executive teams positively moderating this mechanism (Liu et al., 2024). Digital trust, as a core element of Industry 4.0, has also been shown to significantly improve open innovation performance by enhancing technological absorptive capacity (Mubarak & Petraite, 2020). Institutional environments and spatial factors play equally important roles. Environmental regulation not only directly fosters corporate technological innovation but also amplifies the positive impact of structural holes and centrality on innovation performance (Li et al., 2024). A case study of the Yangtze River Delta further reveals a dual diffusion mechanism in innovation networks— peripheral cities receive contagious diffusion through production networks from neighboring areas while embedding themselves in hierarchical diffusion networks of core cities via venture capital linkages (Cheng & Zeng, 2023). This spatial spillover effect is equally pronounced in digital transformation, where regional digital industrialization levels exert a "competitive effect" on the innovation efficiency of adjacent firms (Li et al., 2023).

Research on the application of evolutionary game theory in collaborative innovation mechanisms among technology enterprises remains relatively limited. Some studies have employed replicator dynamic evolutionary game equations, while others have constructed evolutionary simulation models based on static or regular networks (Zhou et al., 2021). Studies such as "Research on collaborative innovation behavior of enterprise innovation ecosystem under evolutionary game" (Yuan & Li, 2024) and Wang et al. (2025) have analyzed the influence of firm heterogeneity and network size on outcomes, proposing a novel technology diffusion model based on evolutionary game theory. Other studies on evolutionary game models related to the government and nascent entrepreneurs have also been discussed (Mohammad-Ali et al., 2022; Ru et al., 2022). Calderini et al. (2023) introduced transformative innovation policies that can provide systemic solutions to socio-environmental challenges because of their "experimental", "reflexive" and "inclusive" character. de Souza João-Roland and Granados proposed (2023) a framework that in-dicates the what, why, and when of the social innovation strategy, highlighting the essential role of community, universities, and embeddedness of users throughout the whole innovation process.

From the above, scholars have conducted many researches on the collaborative innovation of science and technology enterprises or related countermeasures. However, few studies have used complex network based asymmetric evolutionary games to analyze the innovation strategies of enterprises or governments. In general, and according to various sources, it can be said that the most common criterion used to distinguish SMEs is the number of their employees (SMEs have fewer employees). Other criteria include total capital, total assets, annual cash flow or sales, and type of ownership. In this paper, a dynamic model of asymmetric replicator composed of large technology enterprises and SMEs are established. Based on complex networks, the influences of some important parameters of evolutionary games and the influence of environmental factors on enterprise decisions are also discussed. The evolutionary stable strategies (ESS) for evolutionary games are introduced. The related research covers three aspects: the policies, networks, and evolutionary games of collaborative innovation of science and technology enterprises.

Two evolutionary game theory based models are presented to explore the strategies for collaborative innovation promotion: (1) a mathematical model with replicable dynamic equations and a Jacobian matrix; (2) a complex network programming model that incorporates environmental preferences to observe evolution at the micro-level. The model innovatively introduces a complex network and environmental preferences. The results show that the key to collaborative innovation is the initial probability of enterprise collaborative innovation, and the effect of environmental preference is weak (Chaudhari & Sinha, 2021). A higher initial collaborative innovation ratio can promote the willingness of both parties to collaborate.

2. Evolutionary Game Model of Asymmetric Enterprises

2.1 Assumptions

In this paper, there are two participants in the evolutionary game model: large technology enterprises and SMEs. For model tractability, the following assumptions are made:

Assumption 1: Each participant is an asymmetric technology enterprise group. Individual members of a group do not play games with each other, but fully-connect with members from other groups. According to the update rules, evolution proceeds step by step.

Assumption 2: Each participant can use two strategies, namely collaborative innovation and independent innovation.

Assumption 3: Information asymmetry. Individual members with bounded rationality are uncertain about the strategies of others and may sometimes choose unfavorable strategies.

Assumption 4: Government departments may or may not encourage scientific and technological innovation. In our model, the cost(c) of science and technology indirectly reflects the government's choice to innovation strategies. The higher the cost, the weaker the incentive.

2.2 Payoff matrix

Based on the above assumptions, the payoff matrix for both participants are shown in Table 1.

Table 1
Payoff matrix

Payoffs		Large enterprises	
		Collaborative innovation	Independent innovation
SMEs	Collaborative innovation	$R_1(e_1+e_2)p-c_1$, $R_2(e_1+e_2)p-c_2$	$e_1p_1-a-c_0$, $e_2p_2-c_0$
	Independent innovation	$e_1p_1-c_0$, $e_2p_2-b-c_0$	$e_1p_1-c_0$, $e_2p_2-c_0$

In the above, e1 and e2 denote the core completeness of SMEs and large enterprises, respectively; R1and R2 denote the profit distribution ratios of collaborative innovation between SMEs and large enterprises, respectively, R1+ R2=1 and R1<R2.p is the probability of successful collaborative innovation between two individuals (also known as the collaborative innovation rate or collaborative efficiency). p1and p2(p >p2 >p1) are the probabilities of successful independent innovation of SMEs and large enterprises, respectively. Assuming that a and b are the costs paid by SMEs and large enterprises, respectively when only one participant agrees to collaborate. Also, c0, c1 and c2 are the costs of independent innovation and collaborative innovation of SMEs, and the costs of collaborative innovation of large enterprises, respectively. Suppose thatc1<c2<c0.

3. Replicator Dynamic Equations

Let x and y be the respective percentages of SMEs and large enterprises that choose collaborative innovation, respectively. The following replicator dynamic equations are used to derive the strategy update ratios of both participants:

$$F_1 = {d_x}/{d_t} = x(1-x)[y(R_1(e_1+e_2)p - c_1 - e_1p_1 + a + c_0) - a] \quad (1)$$

$$F_2 = {d_y}/{d_t} = y(1-y)[x(R_2(e_1+e_2)p - c_2 - e_2p_2 + b + c_0) - b] \quad (2)$$

According to the equilibrium theory, F1=0, and its solutions are three equilibrium points: x=0, x=1, or y*=$a/[(R_1(e_1+e_2)p - c_1 - e_1p_1 + a + c_0)]$. Similarly, F2=0 and its solutions are: y=0, y=1, or x*=$b/[(R_2(e_1+e_2)p - c_2 - e_2p_2 + b + c_0)]$.

In this way, five equilibrium points of (0,0), (0,1), (1,0), (1,1) and (x*, y*) are obtained. The last point is a mixed strategy equilibrium point, whereas the remaining points are pure strategy points. Following Friedman, the Jacobian matrix J in Eq. (3) can be used to evaluate the local stability of each point in the four cases described in Table 2 (Dai & Yao, 2023):

$$J = \begin{bmatrix} \frac{\partial F_1}{\partial x} & \frac{\partial F_1}{\partial y} \\ \frac{\partial F_2}{\partial x} & \frac{\partial F_2}{\partial y} \end{bmatrix} = \begin{vmatrix} (1-2x)[y(R_1(e_1+e_2)p - c_1 - e_1p_1 + a + c_0) - a] & x(1-x)R_1(e_1+e_2)p \\ y(1-y)R_2(e_1+e_2)p & (1-2y)[x(R_2(e_1+e_2)p - c_2 - e_2p_2 + b + c_0) - b] \end{vmatrix} \quad (3)$$

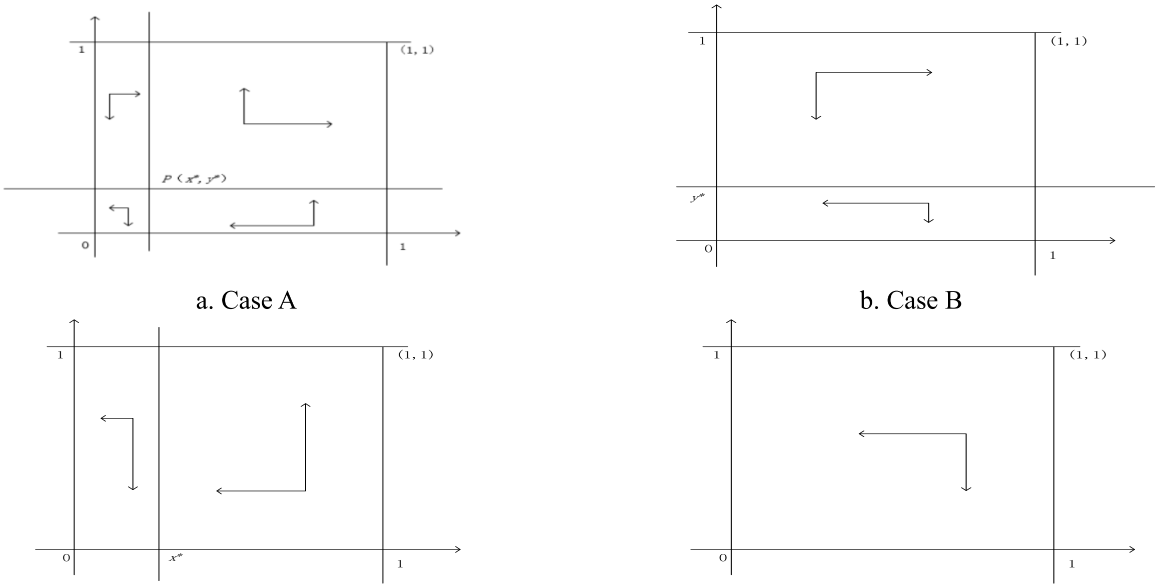
$$Det.J = (1-2x)[y(R_1(e_1+e_2)p - c_1 - e_1p_1 + a + c_0) - a] * (1-2y)[x(R_2(e_1+e_2)p - c_2 - e_2p_2 + b + c_0) - b] - x(1-x)R_1(e_1+e_2)p * y(1-y)R_2(e_1+e_2)p \quad (4)$$

$$Tr.J = (1-2x)[y(R_1(e_1+e_2)p - c_1 - e_1p_1 + a + c_0) - a] + (1 - 2y)[x(R_2(e_1+e_2)p - c_2 - e_2p_2 + b + c_0) - b] \quad (5)$$

The possible values of x and y are 0 and 1, respectively, which can be substituted into Eq. (4) and Eq. (5) to obtain the polarities of Det.J and Tr.J, respectively. The results of the four cases are shown in Table 2.

Table 2
ESS analysis

Case	Evolutionary equilibrium	Det.J	Tr.J	Local stability
$R_1(e_1+e_1)p+c_0$	x=0, y=0	+	-	ESS
$> c_1+e_1p_1$	x=0, y=1	+	+	Unstable
$R_2(e_1+e_1)p+c_0$	x=1, y=0	+	+	Unstable
$> c_2+e_2p_2$	x=1, y=1	+	-	ESS
Case A	$x=b/[\begin{pmatrix}R_2(e_1+e_2)p-c_2\\-e_2p_2+b+c_0\end{pmatrix}]$, $y=a/[\begin{pmatrix}R_1(e_1+e_2)p-c_1\\-e_1p_1++c_0\end{pmatrix}]$	-	0	Saddle point
$R_1(e_1+e_1)p+c_0$	x=0, y=0	+	-	ESS
$> c_1+e_1p_1$	x=0, y=1	+	+	Unstable
$R_2(e_1+e_1)p+c_0$	x=1, y=0	-	Uncertainty	Unstable
$< c_2+e_2p_2$	x=1, y=1	-	Uncertainty	Unstable
Case B	$y=a/[\begin{pmatrix}R_1(e_1+e_2)p-c_1\\-e_1p_1++c_0\end{pmatrix}]$ F_2<0always holds.	-	Uncertainty	Unstable
$R_1(e_1+e_1)p+c_0$	x=0, y=0	+	-	ESS
$< c_1+e_1p_1$	x=0, y=1	-	Uncertainty	Unstable
$R_2(e_1+e_1)p+c_0$	x=1, y=0	+	+	Unstable
$> c_2+e_2p_2$	x=1, y=1	-	Uncertainty	Unstable
Case C	$x=b/[\begin{pmatrix}R_2(e_1+e_2)p-c_2\\-e_2p_2+b+c_0\end{pmatrix}]$, F_1<0always holds.	-	Uncertainty	Unstable
$R_1(e_1+e_1)p+c_0$	x=0, y=0	+	-	ESS
$< c_1+e_1p_1$	x=0, y=1	-	Uncertainty	
$R_2(e_1+e_1)p+c_0$	x=1, y=0	-	Uncertainty	
$< c_2+e_2p_2$	x=1, y=1	+	+	Unstable
Case D	F_1<0 always holds. F_2<0 always holds.	None	None	None



a. Case A

b. Case B

c. Case C

d. Case D

Fig. 1. The phase image corresponding to each case

Only Case A has a stable point (1,1), indicating that all enterprises have chosen the collaboration strategy. From Fig. 1, the following conclusions can be drawn:

(i) Figs. 1(a) and (d) show that only Case A with $R_1(e_1+e_2)p+c_0 > c_1+e_1p_1$ and $R_2(e_1+e_2)p+c_0 > c_2+e_2p_2$can evolve into an ESS point(1,1).As an ESS, point (0,0) can easily evolve in the four cases. When R1+R2=1, R1<R2, p>p2>p1and c1<c2<c0, the conditions of Case A are more easily satisfied. There is a possibility of dissatisfaction due to the key factor R. When R1 is too large and R2 is too small, at least one of the equations in Case A is impossible. Another key factor is e, which

also influences the constraints of the equations. A longer distance between e1 and e2 may change > to <. Other parameters also have some influence on the equations.

(ii) In Fig. 1(a), if the proportion of initial collaborative innovation enterprises is lower than the saddle point, the development trend of collaborative innovation would be weakened. When the proportion is higher than the saddle point, the number of enterprises participating in the collaborative innovation would increase until all enterprises choose collaboration. Therefore, the key to fully collaborative innovation is to increase the initial collaborative proportions of SMEs. This in turn depends on promoting the core competence e2 and the distribution of profits R2, while reducing the collaborative innovation costs c2 or c0.

(iii) ESSs in Figs. 1(c) and (d) are both (0, 0), which means that all enterprises eventually choose independent innovation. This choice is clearly harmful to economic development, and it must be avoided. However, according to the conditions shown in the first column of Table 2, the probability of Case A is actually the highest. For this reason, as long as the measures are adapted to local conditions and guided correctly, the enterprises are more willing to choose collaborative innovation, and the environment will become more conducive to collaborative innovation.

The limitations of replicator dynamic equations are: (1) The system is unrealistic because it is a fully connected network in which everyone gambles; (2) The results of ESSs are more important than their formation, and the formation is also quite crucial; (3) Only the bounded rationality is considered, while the individual learning ability and the derivation of learning environmental to reality are ignored. An evolutionary game simulation model based on complex networks is established. The following points supplement the results of replicator dynamic equations.

(i) Business-to-business interactions between enterprises are geographically restricted in reality, and not every enterprise interacts with each other. The real interactive network is more of a BA scale-free network, which should be taken into account in the ESS analysis. Previous studies have found that this complex network could promote collaboration between enterprises in symmetrical evolutionary games. In unsymmetrical enterprises, the complex network based evolutionary games would be different. These two key factors are discussed in the following subsections.

(ii) The effects of the core parameters in Table 1 on the evolutionary process are discussed in Section 5.

(iii) An environment preference utility factor should be joined in the evolution, because strategy update rules under environmental preference would accelerate or decelerate the evolutionary processes.

4. Design of the BA Network

A node in a complex network represents a scientific and technological enterprise (or participant), while an edge connecting two nodes represents the possibility of collaborative innovation between two enterprises. A game between two participants should follow the payoffs in Table 1. An edge means that the two associated nodes should play the game once per cycle. The replicator dynamic equation only provides the final result (ESS). However, in a complex network where a game occurs between two associated nodes in each cycle, the change in the observable value is also measurable. Thus, ESSs and some observations could be obtained from the network evolutionary games.

Because we are examining an asymmetrical evolutionary game, the node degree is set to be an enterprise scale. The node represents a large enterprise if its degree is higher than d; otherwise, it represents a SME.

4.1 BA network structure

Fig. 2 is a general example of a BA network for this study.

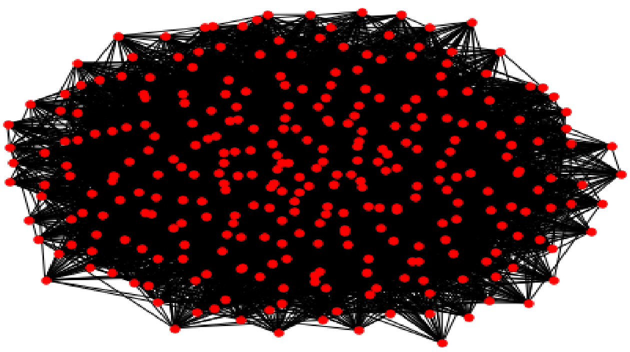


Fig. 2 BA network

(i) The innovation network of enterprises is composed of a BA scale-free network model. The mathematical representation of the network is G(V，E), where V is the set of all nodes (individuals or participants) and E is the set of all edges. eij=1indicates a direct connection between i and j, and eij=0 means no connection.

(ii) Innovation networks are static, i.e., the nodes and edges do not change as they evolve.

4.2 Strategy update and environment preference utility

Since each participant updates the strategy in each repeated game, the micro-strategy update modes and rules make the group behaviors show discrete dynamic features from the macro-level.

(i) Strategy update mode

There are two common update modes: synchronous and asynchronous. Synchronous update indicates that each participant must learn a strategy per time step. Nowak et al. pioneered the introduction of spatial games with synchronous update. The asynchronous update generates a random sequence [1, N] by random sampling, and the strategy update is completed by the participants in the sequence. To update the strategy, each participant has an average of one chance per time step. The asynchronous update is adopted in the study.

(ii) Strategy update rules

Commonly used updating strategies include imitating the best, imitating the winner, pairwise comparison (Fermi update rule), and stochastic processes based on game matrices. The Fermi updating rule is adopted and combined with an environment preference utility based on a utility function proposed by Charness and Rabin (2002) (the CR model):

$$W\left[s_i(t+1) \leftarrow s_j(t)\right] = \frac{1}{1+e^{\{[f_i(t)-f_j(t)]/k\}}} \tag{6}$$

where *W* is the probability formula, its value is the probability of strategy update at time *t*+1. The probability of strategy update at time *t*+1 is only affected by the strategy at time t, and has nothing to do with the strategy before time *t*. f is the fitness, which is usually taken as the cumulative income of an individual after the games and all its neighbors have been played at each step:

$$f_i = U_i = \sum_{j\in\Omega_i} m_{ij} \tag{7}$$

where fi is the fitness of the i-th individual; Ui is the accumulated income of the i-th individual in a cycle; Ωi is the set of all neighbors of the i-th individual, and mij is the income after a game between *i* and *j*, which is calculated according to the payoff matrix in Table 1. The influence of the environment on the enterprise innovation process forms a positive-going or negative-going environmental preference. The following utility function is used to improve the fitness formula:

$$f_i = U_i + \theta\left(\frac{\sum_{j\in\Omega_i} U_j}{n_i} - U_i\right) \tag{8}$$

where $\frac{\sum_{j\in\Omega_i} U_j}{n_i}$ is the average of accumulated incomes of all neighbors of individual i; fi is the fitness of individual i,$\theta\left(\frac{\sum_{j\in\Omega_i} U_j}{n_i} - U_i\right)$is the environmental preference utility, and θ is the preference coefficient. When 0 <θ< 1, individual i has an environmental competition preference. If $\frac{\sum_{j\in\Omega_i} U_j}{n_i} > U_i$, individual i obtains a positive preference utility; Otherwise, they obtain a negative one. When -1 <θ< 0, individual i has an altruistic preference. If $\frac{\sum_{j\in\Omega_i} U_j}{n_i} < U_i$, individual i will obtain a positive preference utility; Otherwise, they obtain a negative one. When θ=0, individual i is not affected by the environment. There are two environmental preference utility modes: homogeneous and inhomogeneous. The former has the same degree of environmental preference for each individual, while the latter can set different environmental preference coefficients through distribution (Indrawati et al., 2020).

5. Evolutionary Game Simulation of the Complex Network

5.1 Simulation steps

Monte Carlo simulation is a method that uses random numbers (or, more commonly, pseudo-random numbers) to solve many computational problems. Through associating a solved problem with a certain probability model, the computer implements statistical simulation or sampling to obtain an approximate solution. The steps of Monte Carlo simulation (MCS) (Zhou et al., 2021) are as follows:

Step 1: A collaborative innovation network is generated for asymmetrical science and technology enterprises. Then, the nodes with 90-degree or more are selected for large enterprises and other nodes for SMEs. Before playing the game in the first cycle, parameters should be initialized, and the initial strategy granted to each individual randomly according to the appropriate probability. SMEs are awarded a collaborative strategy with an initial probability of ps1 and an independent innovation strategy with a probability of 1-ps1. Large enterprises are awarded a collaborative strategy with a probability of ps2 and an independent innovation strategy with a probability of 1-ps2.

Step 2: Selected individuals in the network play games between every two connected players through asynchronous updates. The accumulated income of each participant in this cycle is calculated according to the payoff matrix in Table 1.

Step 3: Strategies are updated by environment preferences and Fermi rulers. Individual j connected to individual i is randomly selected, and the fitness is calculated. The strategy of individual i is confirmed by Eq. (6).

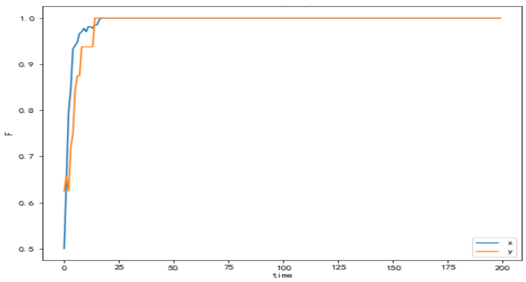
Step 4: Step 2 and step 3 are repeated until the predetermined time step is reached. The time step is the maximum time required to reach dynamic equilibrium.

Step 5: Each random experiment runs 20 times with the same input parameters, and the changes of x and yin each cycle are observed. The averages of these changes are denoted as pf1 and pf2, respectively.

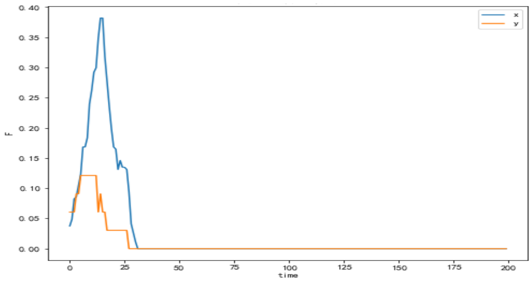
5.2 Sensitivity analysis and Monte Carlo simulation

5.2.1 Comparative analysis of results

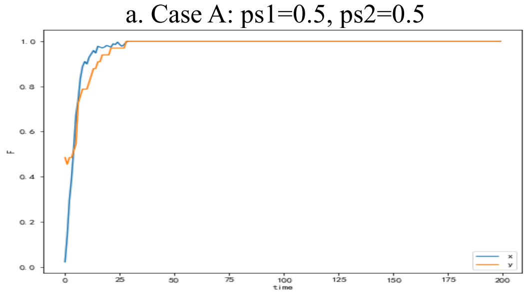
The replicated dynamic equations and Jacobian matrix analysis show two stability strategies in Case A, but there is only one such strategy in B, C, and D.



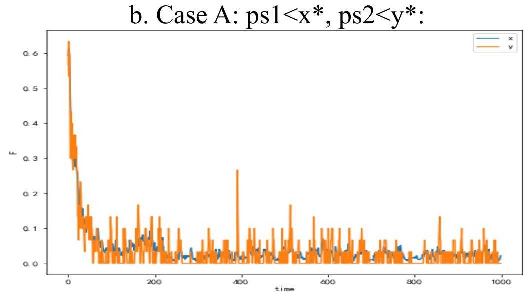
a. Case A: ps1=0.5, ps2=0.5



b. Case A: ps1<x*, ps2<y*:



c. Case A: ps1<x*, ps2>y*



d. Cases B, C and D: ps1=0.5, ps2=0.5

Fig. 3. Evolution of x and y in random process

Fig. 3 shows that the networks played an active role in promoting the formation of evolutionary stability strategies. The main results are as follows:

(i) The replicating dynamic equations show that only when ps1>x* can Case A evolve into a stable state in which both participants adopt cooperative strategies. The stable state is independent of y. In a complex network environment, the same result can be obtained when ps1<x* and ps2>y*, as shown in Fig. 3(c). In the complex network model, SMEs and large enterprises are connected to their neighbors (as in reality). It is quite different from the replicating dynamic model where the participants are interconnected.

(ii) The probabilities of Cases B, C and D are lower than Case A, and their ESSs are (0,0), indicating that all participants finally adopted independent innovation. However, Fig. 3(d) shows no ESS, and a small number of enterprises willing to participate in collaborative innovation all the time. This indicates that a complex network structure can promote collaborative innovation.

5.2.2 Analysis of homogeneous preference utility

The experiment was conducted 20 times with θ = 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0, 0.1. 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9, respectively. The values of pf1 and pf2 are recorded each time.

(1) Sensitivity analysis of initial probability ps1

Fig. 3(b) shows that the ESS of Case A is (0, 0) when the initial probability ps2 is small. Thus, an initial small value of y is allowed in the experiment. The initial valueps1 of x follows the different values shown in Fig. 4.

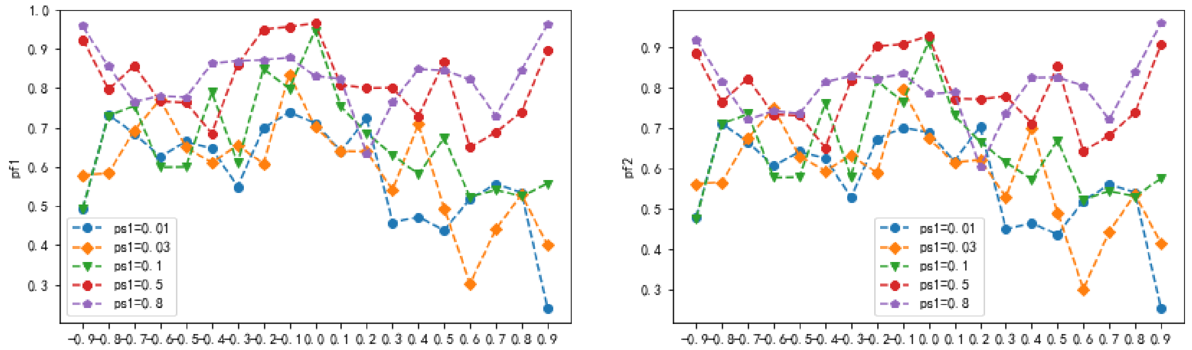


Fig. 4. Sensitivity of ps1

Regardless of the outcome of replicator dynamic equations or complex network models, ps1 has a strong impact on the ESS of evolutionary games. Fig. 4 shows the function of the initial value of *x*. The curves are clearly rising and falling, and the values of pf1 and pf2are not kept at high levels. A detailed analysis is as follows:

When ps1=0.01 or 0.03, the two curves belong to the case of $x<x^*$ and slope slightly downward, and the pf value is the lowest when θ=0.6 and 0.9. When ps1=0.5 or ps1=0.8, the curves belong to the case of $x>x^*$ and slope slightly upward, and the pf value is close to 1 when θ=0 and ±0.9. Therefore, the higher the initial proportion of collaborative innovation for SMEs, the higher is the probability of collaborative innovation among all enterprises in a stable state.

The preference coefficient θ has a certain influence on evolution. According to the overall trend, the values of pf1 and pf2 at θ<0are slightly better than those at θ>0. The altruistic preference is slightly stronger than the competitive preference in promoting collaboration. When θ=0, pf1 and pf2 are relatively high on all curves, i.e., when there is no environmental preference, the synergistic ratio will be high. When θ=±0.9, the utility of competitive or altruistic preference is more obvious.

(2) Sensitivity analysis of profit distribution coefficients

For profit distribution coefficients, R1 and R2 are the distribution ratios, and the sum is 1. Therefore, the analysis of replicator dynamic equations is also important. These experiments were conducted by adjusting R1 (R2 changed accordingly), and other parameters were not changed.

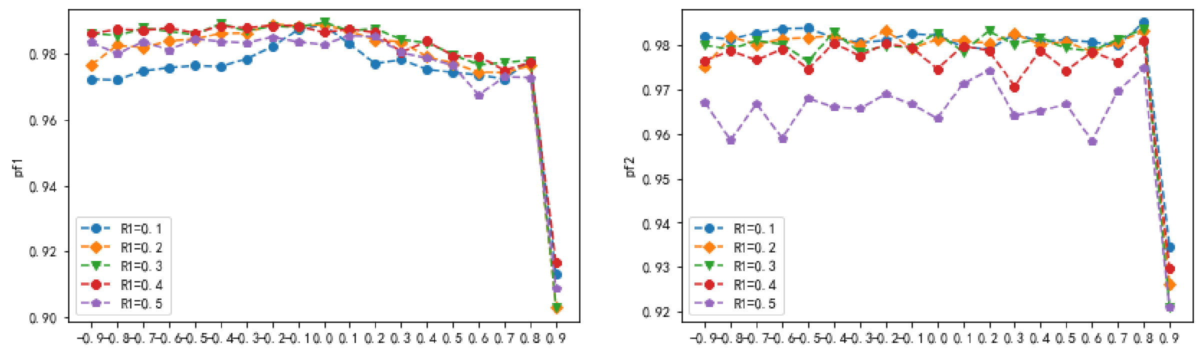


Fig. 5. Sensitivity of R (i)

Fig. 5 shows that the profit distribution has different effects on SMEs and large enterprises. The following conclusions can be drawn:

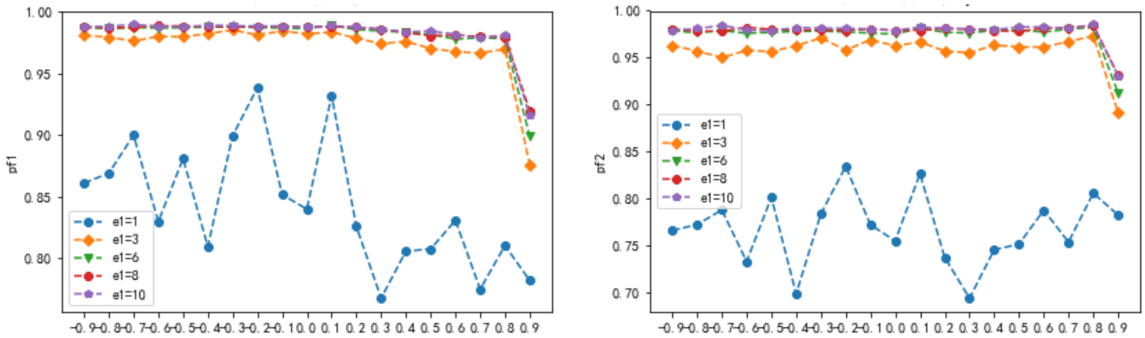
i. The pf1 curves show that, regardless of whether there is collaborative innovation, the effect of profit distribution coefficient is small. When R1=0.1, pf1 is slightly smaller than in other cases. When θ>0.7, the synergistic ratio drops sharply, indicating that the collaborative innovation will be low when the competitive preference is high.

ii. The pf2 curves show that, when R1=0.5, large enterprises and SMEs share the profits equally, which is not conducive to the collaborative innovation of large enterprises. The curve is lower than other curves, and the values of pf2are small. Large enterprises must obtain higher returns than SMEs in profit distribution to promote collaborative innovation. In addition, similar to the left figure, when the environmental preference coefficient θ>0.7, the synergistic ratio drops sharply. The higher the competitive preference, the lower the collaborative innovation.

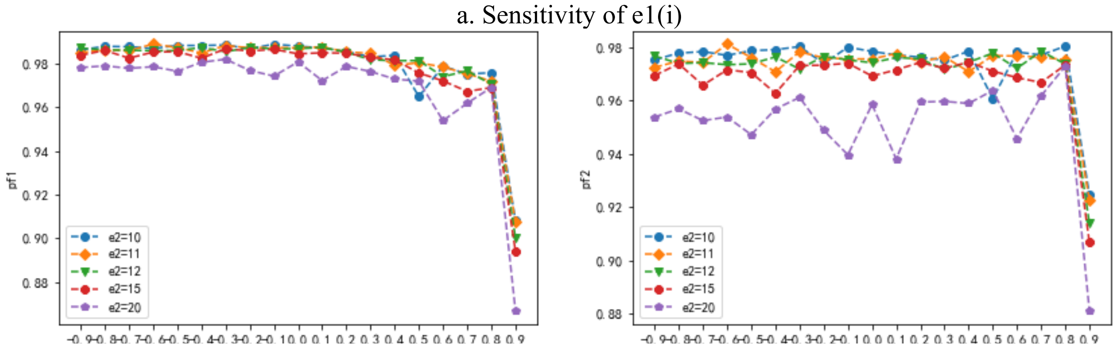
The profit distribution coefficient R1 should be given an appropriate value. Too low value is bad to SMEs, and a profit split equally between SMEs and large enterprises would not be conducive to large enterprises. A larger R1 value has a stronger effect on collaborative innovation. However, a higher environmental competitive preference would significantly reduce the willingness to cooperate.

(3) Sensitivity analysis of core competitiveness

The core competitiveness is represented by two parameters: e1 and e2. Two cases were applied in the experiments: (1)e1=1,3,6,8 and 10, and e2=10; (2)e1=6, and e2=10,11,12,15 and 20. The results are illustrated in Figs. 6(a) and (b).



a. Sensitivity of e1(i)



b. Sensitivity of e2
Fig. 6. Sensitivity of e

The core competitiveness has a certain influence on collaborative innovation, and the core competitiveness of SMEs has a slightly greater impact. The following conclusions can be drawn:

i. When e1=1, there is a big gap between the core competitiveness of SMEs and large enterprises. The weak innovation strength of SMEs hinders collaborative innovation. In Fig. 6(a), the values of pf1are obviously small. When e1>1, although there is a gap, there is little difference in the efficiency of collaborative innovation. As long as SMEs have certain core competitiveness, they can promote collaborative innovation.

ii. When e1 remains unchanged and e2 increases, the core competitiveness of large enterprises improves. Fig. 6(b) shows that this improvement cannot further promote collaboration of enterprises. On the contrary, when the core competitiveness of large enterprises is too high, pf2 will decrease and hinder the collaboration. Therefore, only when there is a moderate gap in the core competitiveness of large enterprises and SMEs can the synergy be promoted in a park or an area.

iii. According to Fig. 6, when the environmental preference coefficient θ<0, the environmental truism can slightly promote collaboration. When θ>0.7, the synergistic ratio drops sharply, and the competitive preference hinders the collaboration.

(4) Sensitivity analysis of the probability of successful collaborative innovation

The probabilities of successful independent innovation are p1=0.1 and p2=0.5, (p>p2>p1). Let p=0.5, 06, 0.7, 0.8 and 1, the results are shown in Fig. 7.

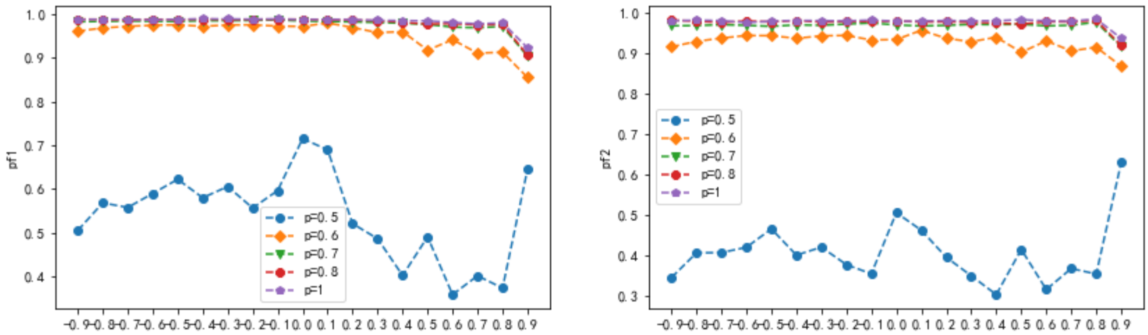


Fig. 7. Sensitivity of p (i)

Fig. 7 shows that when p=0.5 and 0.6, the collaborative innovation ratio shows a downward trend, especially when p=0.5. When the probability of successful collaborative innovation is low, the willingness to stimulate large enterprises to participate in collaborative innovation will not be enough, and the collaborative innovation ratio will decline. When θ<0, the altruistic preference of the environment can slightly promote collaboration. When θ>0.7, the collaborative innovation ratio drops precipitously, indicating that the competitive preference of the environment hinders collaborative innovation (opposite to p=0.5). The competitive preference can promote collaborative innovation, but it is still a counterforce.

(5) Sensitivity analysis of collaborative costs of SMEs

The independent innovation costs of large enterprises arec2 =0.3, and the collaborative innovation costs are c0=0.4 (c1<c2<c0). Letc1 = 0, 0.1, 0.2 and 0.3, the results are shown in Fig. 8.

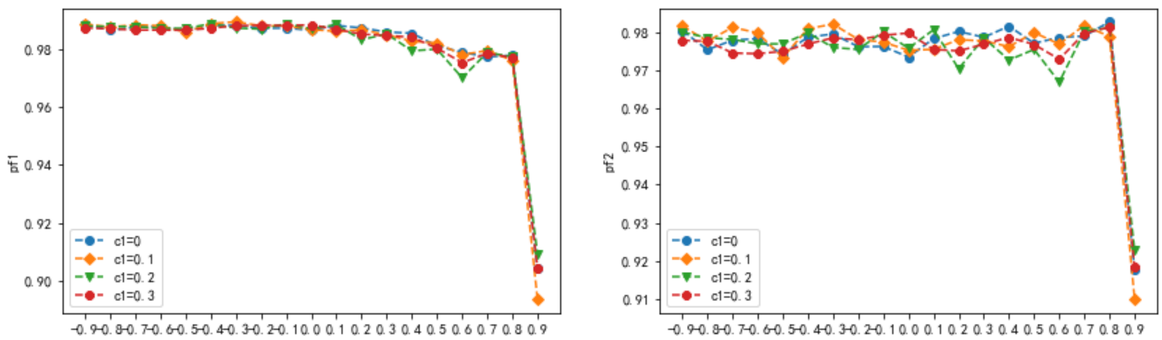


Fig. 8. Sensitivity of c1

The costs of independent innovation of SMEs do not affect the trend of collaborative innovation. As long as the costs are lower than those of collaborative innovation, they will not affect the collaborative ratio. In most cases, the technology enterprises in the network could stably adopt a collaborative strategy.

5.2.3 Analysis for inhomogeneous preference utility

Inhomogeneous preference considers two methods. The first one is completely random. Each individual has a different preference in the environment, and θ is randomly generated for each individual. The second one has a certain proportion μ, and θ is fixed. i individuals with μ use θ, and individuals with 1-μuse -θ. Let θ=0.3, μ=0.1, 0.2, 0.6 and 0.9, the second method is used to observe the effects of μ on evolution (Figs. 9-11.).

i. Sensitivity analysis of coefficients of profit distribution (R1=0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9)

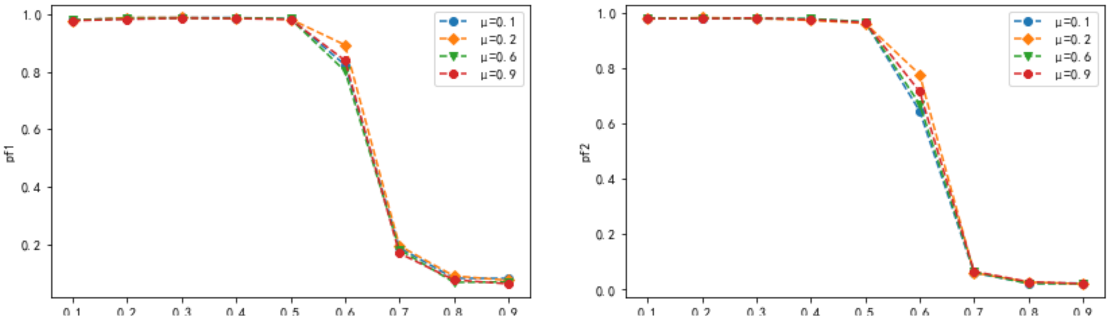


Fig. 9. Sensitivity of R (ii)

ii. Sensitivity analysis of core competitiveness (e1=1, 2, 3, 4, 5, 6, 7, 8, 9 and 10)

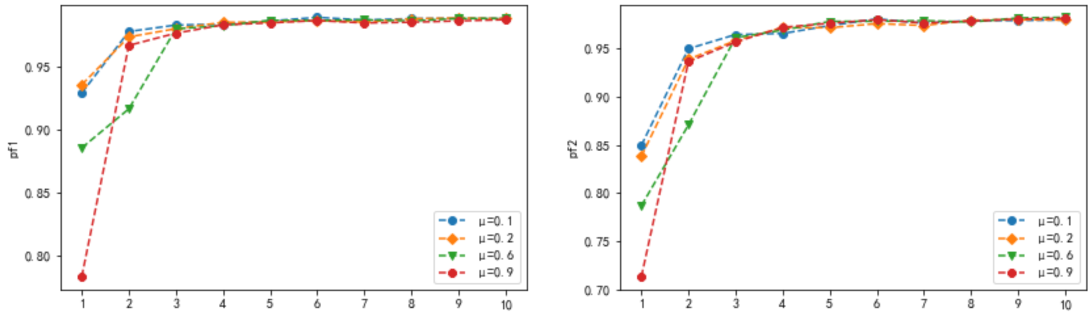


Fig. 10. Sensitivity of e1(ii)

iii. Sensitivity analysis of the probability of successful collaborative innovation (p=0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0)

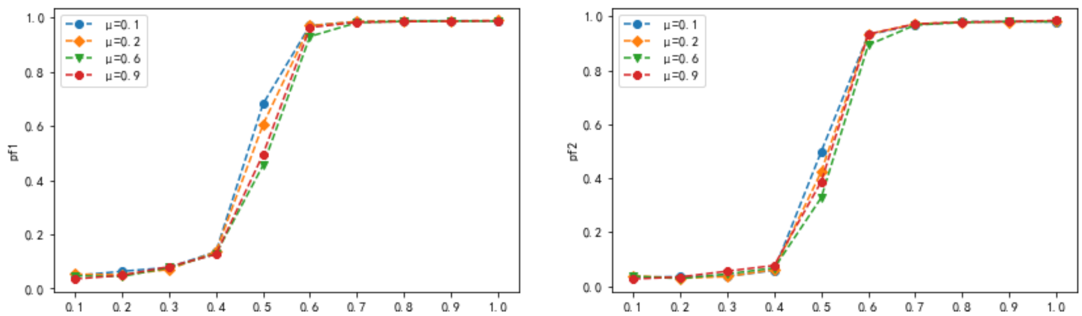


Fig. 11. Sensitivity of p (ii)

Comparing the inhomogeneous with homogeneous preferences, i.e., comparing Figs. 9 with Fig. 5, Fig.10 with Fig.6, and Fig.11 with Fig.7, it can be seen that the evolution results of the environmental inhomogeneous and homogeneous preferences are consistent. In homogeneity does not affect the random process of complex networks. Environmental judgment has little effect on the game evolution of science and technology enterprises. The only judgment ($\theta>0.7$) that is excessively resistant to the environment may hinder the development of collaboration. When $\theta<0$, the decision is optimized with reference to the environment, and the collaboration is only slightly promoted. When $R1>0.5$ in Fig. 9, $e1>0.3$ in Fig. 10, and $p>0.5$ in Fig. 11, the collaborative innovation ratio increases, which is consistent with the conclusions drawn from Figs. 5, 6 and 7.

6. Conclusion

This paper discusses the game evolution of collaborative innovation strategies of asymmetric science and technology enterprises. First, replicated dynamic equations and the Jacobian matrix are used for a mathematical analysis. Then, using the complex network, the process of evolutionary game is simulated according to the game profit matrix, and the strategy update rules are proposed based on the environmental preference utility. A conclusion similar to that drawn by the mathematical analysis is arrived at.

6.1 Discussion of results

After simulation verification, a single-factor analysis method was used for repeated tests. The conclusions are summarized as follows:

(i) The effects of environmental preference are limited. Environmental altruistic preference has positive effects, and competitive preference has negative effects.

(ii) The ESS of collaborative innovation of science and technology enterprises is sensitive to the initial probability of the collaborative innovation. The replicator dynamic equations showed that the evolution is only affected by the initial collaborative probabilities of SMEs. However, the simulation results of complex networks show that the initial collaborative probability of large enterprises also has certain influences.

(iii) The probability of successful collaborative innovation and the proportion of profit distribution also affect ESS. As long as the probability is slightly higher than that of successful independent innovation, as well as the profit distribution is not an extreme value, the ESS of collaborative innovation strategy can be achieved.

(iv) If the core competitiveness gap is too large, SMEs are too weak, or large enterprises are too strong, effective coordination cannot be achieved, which will eventually lead to the ESS of independent innovation.

6.2 Theoretical contributions

Replicated dynamic equations and Jacobian matrices are used for a mathematical analysis. In Case A, the profits obtained by enterprises in collaborative innovation are greater than those obtained in independent innovation. In Case B, only SMEs can gain more profits from collaborative innovation than independent innovation. On the contrary, in Case C, only large enterprises gain more profits from collaborative innovation than independent innovation. Case D indicates that neither of them can obtain more profits from collaborative innovation than from independent innovation. Our basic understanding is that collaborative innovation can complement advantages, reduce costs and improve benefits. Case A is a relatively normal situation, but it is not excluded that due to the exceptional cases, the return of collaborative innovation is lower than that of independent innovation. As such, Cases B, C and D may also occur. However, in cases B, C and D, none of the ESSs are cooperative. So, it is of little significance to discuss the collaborative innovation of Cases B, C and D.
Case A is a normal situation, which could promote the collaboration under certain conditions.

6.3 Practical contributions

Based on the above conclusions, the following countermeasures and suggestions are put forward for the development and construction of science and technology parks or enterprise networks:

(i) At the beginning of the construction of science and technology projects or networks, the government should properly guide and encourage enterprises to innovate collaboratively. This could be achieved through tax cuts, incentives, and more to reduce the costs of collaborative innovation. Moreover, the government can increase the initial proportion of collaborative innovation, or lower the benchmark of the initial proportion to create better initial conditions for collaborative innovation.

(ii) SMEs should be encouraged to develop their own core competitiveness, so that the gap between SMEs and large enterprises in the network is not too large. To accelerate the collaborative process, policies should support enterprises or products with strong competitiveness.

(iii) The collaborative innovation mechanism and innovation system among enterprises should be standardized and improved to ensure effective collaborative innovation and reasonable collaborative profit distribution, so as to improve the probability of successful collaborative innovation.

(iv) Collaborative innovation environments should be further optimized, and altruistic environmental preference should be cultivated as much as possible to promote the development of collaboration.

Based on the mathematical model and simulation method of a complex network, this paper studies the ESS and evolution path of asymmetric collaborative innovation of science and technology enterprises. However, only two participants are involved in the evolution. Only five factors (initial probability, profit distribution coefficients, core competitiveness, the probability of successful collaborative innovation and collaborative costs of SMEs) are discussed in the simulation model and compared with the real network, the complex network is still too ideal. Follow-up studies will consider three-party or multi-party evolutionary games, two-layer or multi-layer network models, further optimized policy update rules which make the enterprise's strategy more in line with its personalized characteristics, etc.

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