Evolutionary Game Analysis of Manufacturing Resource Sharing Among Symmetric Enterprises in Cloud Manufacturing Environment: Postprint

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Abstract

To address the challenges of manufacturing resource sharing and collaborative cooperation in complex manufacturing industries, an evolutionary game model for manufacturing resource sharing in cloud manufacturing environments is constructed. The model reveals the evolutionary interaction relationship in manufacturing resource sharing between resource service providing enterprises and resource service demanding enterprises. Based on system dynamics software, an SD model is established to conduct comparative analysis of the impact of different parameter variations on evolution outcomes. Research demonstrates that initial sharing proportion, platform management capability coefficient, resource transformation capability coefficient, resource synergy capability coefficient, informatization benefit coefficient, technology loss risk coefficient, channel cost coefficient, penalty cost coefficient, trust level coefficient, and incentive coefficient all exert significant influence on the strategy evolution outcomes of both game-playing enterprises. To promote enterprise information interoperability and resource sharing in cloud platforms, management improvements must be implemented in the aforementioned aspects.

Full Text

Preamble

Game Model Analysis of Symmetrical Enterprises' Manufacturing Resource Sharing Under Cloud Manufacturing Environment

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Abstract: To address the challenges of manufacturing resource sharing and collaborative cooperation in complex manufacturing industries, this paper constructs an evolutionary game model for manufacturing resource sharing in a cloud manufacturing environment. The model reveals the evolutionary relationship between resource service provider enterprises and resource service demander enterprises in manufacturing resource sharing. Based on a System Dynamics (SD) model built using system dynamics software, the paper comparatively analyzes the influence of different parameter variations on evolutionary outcomes. Research shows that the initial sharing ratio, platform management capability coefficient, resource transformation capability coefficient, resource collaboration capability coefficient, information efficiency coefficient, technical loss risk coefficient, channel cost coefficient, penalty cost coefficient, trust coefficient, and incentive coefficient all exert significant influence on the strategic evolutionary outcomes of both game parties. To promote information exchange and resource sharing among enterprises in the cloud platform, improvements must be made in these aforementioned aspects.

Keywords: cloud manufacturing; manufacturing resource sharing; evolutionary game; system dynamics

0 Introduction

Driven by the application of high-tech in the 21st century, the pace of manufacturing industry development has gradually accelerated, moving steadily toward globalization, specialization, and servitization. To cope with the challenges of the knowledge economy and manufacturing globalization, and to rapidly respond to market demands and enhance market competitiveness, networked manufacturing models such as agile manufacturing, Manufacturing Grid (MGrid), and Application Service Provider (ASP) have emerged. Despite more than a decade of development, the manufacturing grid model has achieved certain results in different fields, yet bottlenecks remain in service models, manufacturing resource sharing and allocation technologies, and security issues. Therefore, Li Bohu et al. [1] pioneered a service-oriented networked manufacturing model—cloud manufacturing. This model should not only embody the concept of "concentrated use of distributed resources" but also effectively realize the concept of "distributed service of concentrated resources." Since the proposal of cloud manufacturing theory, academia has widely focused on its hierarchical structure [2], typical characteristics [3], key technologies [4], resource virtualization [5,6], and operation models [7], achieving substantial theoretical research and practical application results. However, compared with these achievements, research on supply chain performance allocation after manufacturing resource sharing remains limited, with existing literature only proposing some targeted ideas and methods. Jin Ying et al. [8] proposed establishing a virtual organization cooperation system for cloud manufacturing service platforms that introduces penalty factors, based on the analysis of virtual organization cooperation informatization service platform requirements, laying important theoretical and practical foundations for virtual organization cooperation research in cloud manufacturing environments. Jia Guozhu et al. [9] used system dynamics methods to analyze shared resource conflict problems and proposed a shared resource usage rights grading and exchange mechanism based on simulation model results, specifically addressing internal enterprise shared resource conflicts. Li Fang et al. [10] studied the sharing effectiveness and mechanisms of cloud manufacturing platforms by establishing a sequential game model to analyze technology and service transactions on cloud manufacturing platforms. Su Kaikai et al. [11] established a non-cooperative game model using a multi-objective optimization function of service quality indicators and flexibility indicators as the payoff function for both game parties, effectively solving the manufacturing resource optimization allocation problem in cloud manufacturing environments. Argoneto et al. [12] proposed a capability sharing structure in cloud manufacturing environments, employing cooperative game algorithms based on the Gale-Shapley model and fuzzy engine tools to select capability allocation strategies considering relevant enterprise benefit functions, verifying the high performance of cloud manufacturing capability sharing structures through case simulations.

The above research on manufacturing resource sharing and supply chain performance analysis shows that current analyses of manufacturing resource sharing in cloud manufacturing environments are primarily conducted under the assumption that all sharing parties are "completely rational," requiring participants to always maximize their own benefits under any circumstances. However, the cooperation intentions of participants in cloud manufacturing environments are long-term. Manufacturing resource sharing parties integrate their respective advantageous resources and enter the cloud platform to cooperate upon agreeing to the cloud platform management agreement. Their enterprise behaviors in resource sharing are often constrained by other cloud platform cooperation parties and thus cannot achieve maximum self-benefit goals. The "bounded rationality" assumption of evolutionary game theory fits this research background perfectly. Therefore, this paper adopts evolutionary game theory methods to conduct trend analysis on the cooperation process of enterprise manufacturing resource sharing in cloud manufacturing environments, considering the benefits of both game parties and measuring the influence of different factors on enterprise manufacturing resource sharing equilibrium strategies based on introducing the marginal scale benefits brought by cloud platform management capabilities.

1 Problem Description

The cloud manufacturing platform constructs a virtual resource pool, primarily composed of manufacturing resources, manufacturing services, manufacturing demands, and several other components. To efficiently achieve resource sharing and better serve the public, the cloud platform requires access from a large number of manufacturing resource provider enterprises and manufacturing resource demander enterprises, striving to realize the actual scale benefits of the cloud platform as soon as possible. The manufacturing industry is a complex systematic project, particularly in large-scale complex manufacturing industries such as automotive manufacturing, shipbuilding, and electrical machinery and equipment manufacturing, all of which require collaborative cooperation between manufacturing enterprises and numerous component suppliers at various levels. To realize the cloud manufacturing model in the domestic manufacturing field, manufacturing enterprises and component suppliers at all levels must abandon traditional supply chain systems, upgrade basic networks and information infrastructure, complete the virtual encapsulation of manufacturing resources, jointly access the cloud platform, and achieve optimal allocation of manufacturing resources in the cloud, thereby forming an advanced supply chain operation management system for manufacturing enterprises in the cloud manufacturing environment. However, the access of manufacturing enterprises and component suppliers to the cloud platform is a dynamic game process. In the process of realizing resource sharing, numerous technical and non-technical issues such as benefit distribution and resource allocation are involved. Whether these problems are solved directly affects the acceptance of the cloud manufacturing platform by various enterprises and concerns the theoretical construction and practical application of the cloud manufacturing platform. Therefore, this paper focuses on studying the manufacturing resource sharing relationship between resource provider enterprises (component suppliers at all levels) and resource demander enterprises (production enterprises) in large-scale complex manufacturing fields under the cloud manufacturing environment, analyzing the influence of different factors on manufacturing resource sharing.

2 Evolutionary Game Model Construction

2.1 Model-Related Variables

Model-related variables are shown in Table 1 .

Table 1. Related Variables

Variable Symbol	Variable Name
θ	Trust coefficient
I	Cloud platform management capability coefficient
C_1, C_2	Channel cost coefficients for RSP and RSD enterprises
r_1, r_2	Information efficiency coefficients
T	Technical loss risk coefficient
Q_1, Q_2	Sharable manufacturing resource quantities for RSP and RSD enterprises

Variable Symbol	Variable Name
u_1, u_2	Resource collaboration capability coefficients for RSP and RSD enterprises
z_1, z_2	Resource transformation capability coefficients for RSP and RSD enterprises
α, β	Penalty cost coefficients
x, y	Initial sharing probabilities for RSP and RSD enterprises
λ	Incentive coefficient
π_0	Basic benefit when both enterprises choose not to share

2.2 Game Model Construction Assumptions

a) Resource Service Provider (RSP) enterprises primarily provide various manufacturing equipment and material resources used in the component manufacturing process (hard manufacturing resources), while Resource Service Demander (RSD) enterprises primarily provide various software tools, product models, professional knowledge, and process data necessary for component manufacturing activities (soft manufacturing resources).

b) A certain RSP enterprise A and RSD enterprise B both access the cloud platform. The strategy space for both parties is either manufacturing resource sharing or manufacturing resource non-sharing. Both enterprises are bounded rational and can independently adopt strategies.

c) The cloud platform management capability is unlimited and can accommodate an unlimited number of RSP enterprises, with the population quantities of both types of enterprises being uniformly mixed.

d) Let θ be the probability that enterprise A chooses manufacturing resource sharing (which can also be understood as the proportion of RSP enterprises choosing manufacturing resource sharing in the population; this interpretation applies hereafter without further elaboration), where $\theta \in (0,1)$, and $1-\theta$ be the probability that enterprise A chooses manufacturing resource non-sharing. Let y be the probability that enterprise B chooses manufacturing resource sharing, where $y \in (0,1)$, and $1-y$ be the probability that enterprise B chooses manufacturing resource non-sharing.

e) When both enterprises A and B choose manufacturing resource non-sharing, the basic benefit of enterprise A is π_1, and the basic benefit of enterprise B is π_2.

f) When enterprise A chooses manufacturing resource sharing while enterprise B chooses manufacturing resource non-sharing, enterprise A must invest substantial channel costs to purchase, upgrade, or replace existing material sensing equipment and cyber-physical system equipment to establish databases and information systems that interface with the cloud platform, as the hard manufacturing resources provided by enterprise A require identification and access through IoT and cyber-physical systems to be transformed into virtual resources of the cloud platform. These channel costs are denoted as C_1. Meanwhile, due to improved production and management informatization, enterprise A' s benefits also change. The enterprise' s information efficiency coefficient is denoted as r_1, so the information efficiency benefit is $r_1\pi_1$, while enterprise B' s basic benefit remains π_2.

g) When enterprise A chooses manufacturing resource non-sharing while enterprise B chooses manufacturing resource sharing, since enterprise B shares soft manufacturing resources and the enterprise itself has a high degree of informatization, the soft manufacturing resources provided do not require identification and access through IoT and cyber-physical systems, thus requiring less investment than enterprise A. Enterprise B' s channel cost is denoted as C_2. However, because the soft manufacturing resources shared by enterprise B primarily consist of various manufacturing software tools, product models, professional knowledge, and process data—core technical advantages of the enterprise—once open for sharing, the enterprise must bear technical loss risks. Enterprise B' s technical loss cost is denoted as T, while enterprise A' s benefit remains the basic benefit π_1.

h) When both enterprises A and B choose manufacturing resource sharing strategies, the benefits from manufacturing resource sharing include the following components in addition to the aforementioned channel costs, information efficiency benefits, and technical loss costs:

a) Resource collaboration benefit. The value created through resource sharing collaboration benefits when both enterprises access the cloud platform. This benefit is related to the enterprise' s own informatization degree and its ability to absorb shared resources. The collaboration benefit of enterprise A is denoted as $u_1\pi_1$, and the collaboration benefit of enterprise B is $u_2\pi_2$.

b) Resource transformation benefit. The benefit brought by transforming and integrating shared manufacturing resources to create new value. This benefit is directly related to the enterprise' s own R&D level and innovation capability. The transformation benefit coefficient is denoted as z, introducing the transformation benefit factor λ. The transformation benefit factor resulting from cloud platform and resource transformation is a nonlinear function of the actual sharable manufacturing resource quantity. As the actual sharable manufacturing resource quantity increases, the transformation benefit factor increases accordingly. However, when the sharable manufacturing resource quantity increases to a certain extent, the expected benefit factor from resource transformation will approach the saturation point, reaching the theoretical maximum value. The resource transformation benefit of enterprise A is denoted as z_1Q_1, and the resource transformation benefit of enterprise B is denoted as z_2Q_2.

c) Marginal scale benefit. The cloud platform management capability coefficient I is defined as the number of RSP enterprises that the cloud platform can accommodate. As the number of enterprises continues to increase, the types of manufacturing resource sharing also increase, thereby forming scale benefits for RSP enterprises in the cloud manufacturing platform. The scale benefit brought by one RSP enterprise entering the cloud manufacturing platform for all RSP enterprise groups is denoted as I. According to scale benefit and marginal benefit theory [17-18], when the number of RSP enterprises entering the cloud platform is small and the cloud platform management capability is strong, the scale benefits of the cloud platform increase rapidly. When the number of RSP enterprises entering the cloud platform is large, even exceeding the scope of cloud platform management capability, the marginal scale benefits they can bring become increasingly smaller or even negative. Based on the above definitions and analysis, when both RSP and RSD enterprises choose to share manufacturing resources, the marginal scale benefit of RSP enterprise A can be expressed as a function of sharing probability: $I\theta$.

d) Social additional benefit. The cloud manufacturing platform is a social network where all manufacturing resources are concentrated in the virtual resource pool. Manufacturing resource sharing leads to improved social relationships and increased social capital. This social relationship or network connection is also part of the benefits from manufacturing resource sharing for both enterprises. The social additional benefit is denoted as λ.

e) Penalty cost. During the manufacturing resource sharing process, both parties agree through contracts or agreements in the cloud platform to impose corresponding penalties on cloud platform enterprises that do not follow the sharing agreement, thereby forming penalty costs. The penalty cost of enterprise A is denoted as α, and the penalty cost of enterprise B is denoted as β.

2.3 Evolutionary Game Model Construction

Standard uniformly mixed evolutionary game theory requires that the population contains infinitely many individuals uniformly mixed (any two individuals in the population are equally likely to engage in the game), and does not consider uncertain factors in the decision-making environment [19]. Based on the variable assumptions in the above scenarios, the game payoff matrix for two types of symmetrical enterprises conducting manufacturing resource sharing in the cloud manufacturing environment is obtained, as shown in Table 2 .

Table 2. Evolutionary Game Payoff Matrix for Symmetrical Enterprise Manufacturing Resource Sharing in Cloud Manufacturing Environment

	RSD Enterprise B	
	Share (y)	Not Share ($1-y$)
RSP Enterprise A		
Share (θ)	$\pi_1+u_1\pi_1+z_1Q_1+I\theta-C_1-\alpha(1-y)$, $\pi_2+u_2\pi_2+z_2Q_2+I\theta-C_2-T-\beta(1-\theta)$	$\pi_1+r_1\pi_1-C_1$, π_2
Not Share ($1-\theta$)	π_1, $\pi_2+r_2\pi_2-C_2-T$	π_1, π_2

The expected benefits for RSP enterprise A choosing resource sharing and resource non-sharing are respectively:

$$\pi_{1s} = y[\pi_1 + u_1\pi_1 + z_1Q_1 + I\theta - C_1 - \alpha(1-y)] + (1-y)(\pi_1 + r_1\pi_1 - C_1)$$

$$\pi_{1n} = y\pi_1 + (1-y)\pi_1 = \pi_1$$

Similarly, the expected benefits for RSD enterprise B choosing resource sharing and resource non-sharing are respectively:

$$\pi_{2s} = \theta[\pi_2 + u_2\pi_2 + z_2Q_2 + I\theta - C_2 - T - \beta(1-\theta)] + (1-\theta)(\pi_2 + r_2\pi_2 - C_2 - T)$$

$$\pi_{2n} = \theta\pi_2 + (1-\theta)\pi_2 = \pi_2$$

Therefore, the expected average benefit for RSP enterprise A is:

$$E_1 = \theta\pi_{1s} + (1-\theta)\pi_{1n}$$

The expected average benefit for RSD enterprise B is:

$$E_2 = y\pi_{2s} + (1-y)\pi_{2n}$$

According to the Malthusian dynamic equation, the rate of strategy change equals its fitness [20]. Therefore, the differential equations for the gene replication dynamic process of the evolutionary game of the two types of enterprises are respectively:

$$\frac{d\theta}{dt} = \theta(\pi_{1s} - E_1) = \theta(1-\theta)(\pi_{1s} - \pi_{1n})$$

$$\frac{dy}{dt} = y(\pi_{2s} - E_2) = y(1-y)(\pi_{2s} - \pi_{2n})$$

Let $\frac{d\theta}{dt} = 0$, we can obtain $\theta^* = 0$, $\theta^* = 1$, or:

$$y^* = \frac{r_1\pi_1 - C_1 + \alpha}{u_1\pi_1 + z_1Q_1 + I\theta + \alpha y}$$

Similarly, let $\frac{dy}{dt} = 0$, we can obtain $y^* = 0$, $y^* = 1$, or:

$$\theta^* = \frac{r_2\pi_2 - C_2 - T + \beta}{u_2\pi_2 + z_2Q_2 + I\theta + \beta\theta}$$

Since θ and y represent the probabilities of strategy selection for the game parties, we have $0 \leq \theta \leq 1$ and $0 \leq y \leq 1$. Based on this, the constraint conditions are shown in equation (8).

The five equilibrium points generated by the evolutionary game dynamic process are: $O(0,0)$, $A(1,0)$, $B(0,1)$, $C(1,1)$, and $D(\theta^*, y^*)$. According to the stability determination method of the Jacobian matrix proposed by Friedman [21], the local stability analysis can be obtained. Taking partial derivatives of equation (7) with respect to θ and y respectively yields the following Jacobian matrix (denoted as J):

$$J = \begin{bmatrix} \frac{\partial\dot{\theta}}{\partial\theta} & \frac{\partial\dot{\theta}}{\partial y} \\ \frac{\partial\dot{y}}{\partial\theta} & \frac{\partial\dot{y}}{\partial y} \end{bmatrix}$$

The local stability analysis results for the five equilibrium points are shown in Table 3 . Through stability analysis results, it can be seen that among the five equilibrium points, there are two evolutionary stable strategies, respectively satisfying conditions for $O(0,0)$ and $C(1,1)$, corresponding to the evolutionary stable strategy combinations (Not Share, Not Share) and (Share, Share). Points $A(1,0)$ and $B(0,1)$ are unstable points, and point $D(\theta^*, y^*)$ is a saddle point.

Table 3. System Equilibrium Point Stability Analysis Results

Equilibrium Point	det(J)	tr(J)	Stability
$O(0,0)$	+	-	ESS
$A(1,0)$	-	+	Unstable
$B(0,1)$	-	+	Unstable
$C(1,1)$	+	-	ESS
$D(\theta^*, y^*)$	+	0	Saddle point

Through analysis, it can be known that this dynamic game process will eventually converge to the strategy equilibrium point O where both types of enterprises choose not to share and the strategy equilibrium point C where both choose to share. The direction in which the saddle point moves is jointly affected by influencing factors such as initial sharing probability, platform management capability coefficient, resource transformation capability coefficient, resource collaboration capability coefficient, information efficiency coefficient, technical loss risk coefficient, channel cost coefficient, penalty cost coefficient, trust coefficient, and incentive coefficient. The dynamic variation process of the game is shown in Figure 1 [Figure 1: see original paper].

3 SD Model and Simulation

3.1 SD Model Construction

The SD model for the evolutionary game of symmetrical enterprise manufacturing resource sharing in cloud manufacturing environments is built based on Vensim software. Its structure is shown in Figure 2 [Figure 2: see original paper]. The SD model consists of 4 level variables, 2 rate variables, and 19 auxiliary variables. The sharing probability rate variables for the two types of enterprises are represented by VarA and VarB respectively, with their value formulas derived from the gene replication dynamic process differential equations mentioned above. Other variable names are largely consistent with those in the evolutionary game model.

3.2 Instance Simulation Experiment Scenario

1) Resource Type Description

Based on the manufacturing resource situation of a Shanghai automotive group and its component suppliers, the manufacturing resources involved in this instance simulation are mainly divided into two categories: hard manufacturing resources and soft manufacturing resources. Hard manufacturing resources primarily include manufacturing equipment required in product production activities (specialized equipment necessary for manufacturing activities such as machining centers, CNC machine tools, experimental equipment, and simulation equipment), computing equipment (various computing system hardware facilities such as arithmetic units, storage devices, and I/O terminals), and materials required for products (finished products, semi-finished products, and raw materials). Soft manufacturing resources mainly refer to professional software tools required in production activities (various large-scale professional software such as AutoCAD, Matlab, and ProE), manufacturing models (various empirical models used for mechanical, thermal, dynamic, and control analysis), domain knowledge (multidisciplinary and multi-domain knowledge used in various stages of manufacturing activities), and process data (large amounts of process data accumulated from previous manufacturing activities).

2) User Demand Description

Manufacturing resource provider enterprises achieve interconnection, identification, perception, and information transmission of manufacturing resources through the Internet of Things (IoT), Cyber-Physical Systems (CPS), and computing system virtualization, thereby realizing the virtualization of physical manufacturing resources and completing the construction of virtual manufacturing resource pools. Manufacturing resource demander enterprises publish single manufacturing resource demand tasks or combined resource demand tasks on the cloud platform according to their own needs. The cloud platform operator mainly bears the risks that may arise during the manufacturing resource allocation service process, while ensuring the smooth progress of manufacturing resource allocation services by constraining manufacturing resource provider enterprises.

3) Instance Simulation Analysis
Based on the financial statements, performance assessments, and information engineering diagnostic models of a Shanghai automotive group and its component suppliers, effective initial parameter values were obtained through requirement analysis, cost budgeting, risk control, comprehensive diagnosis, quality tracking, and other approaches. The SD model initial values are set with initial time = 0, final time = 100, and time step = 0.25.

The simulation process in this paper fixes most variable initial values while separately changing parameter initial values from ten aspects: initial sharing probability, platform management capability coefficient, resource transformation capability coefficient, resource collaboration capability coefficient, information efficiency coefficient, technical loss risk coefficient, channel cost coefficient, penalty cost coefficient, trust coefficient, and incentive coefficient, to conduct comparative analysis of different parameter changes on system evolution results.

1) Influence of Initial Sharing Probability on Evolution Results
With the initial sharing probability value of type B enterprises fixed at 0.2, the initial sharing probability values of type A enterprises are set to 0.1, 0.4, 0.7, and 0.9 respectively to observe the changes in sharing strategy selection for both types of enterprises. The simulation results are shown in Figure 3 [Figure 3: see original paper] and Figure 4 [Figure 4: see original paper].

The simulation results show that when the initial sharing probability value of type B enterprises is fixed, the evolution trend of type A enterprises' sharing probability is significantly affected by its initial sharing probability value, showing a positive correlation. That is, when the initial sharing probability value of type A enterprises is larger, the speed at which its sharing probability converges to 1 is relatively faster. At the same time, the sharing probability of type B enterprises also shows a positive correlation with the initial sharing probability value of type A enterprises. When the initial sharing probability value of type A enterprises is larger, the speed at which type B enterprises' sharing probability converges to 1 is faster, and vice versa. According to evolutionary game theory, the probability of a single enterprise choosing manufacturing resource sharing within a population is the same as the proportion of enterprises choosing manufacturing resource sharing within that population. Therefore, whether an enterprise chooses a sharing strategy is influenced by the participation level of most enterprises in the industry. Specifically, when leading enterprises in the industry gradually enter the cloud manufacturing platform for manufacturing resource sharing, other enterprises will follow suit and use the cloud manufacturing platform, forming an industry scale effect. Similarly, fixing the initial sharing probability value of type A enterprises and changing the initial sharing probability value of type B enterprises will produce similar phenomena, with the simulation process omitted here.

2) Influence of Platform Management Capability Coefficient on Evo-

lution Results

With the initial sharing probability value of type B enterprises fixed at 0.2, the platform management capability coefficient values are set to 0.1, 0.4, 0.7, and 9 respectively to analyze the changes in sharing strategy selection for both types of enterprises under type A enterprise initial sharing probability values of 0.1, 0.4, 0.7, and 0.9 (since the simulation results are similar, only the simulation results for platform management capability coefficient equal to 0.1 and 0.7 are shown in Figure 5 [Figure 5: see original paper] and Figure 6 [Figure 6: see original paper]).

The simulation results show that the evolution trend of type A enterprises' sharing probability is significantly affected by the platform management capability coefficient. When the I value is larger, the speed at which type A enterprises' sharing probability converges to 1 is faster, and vice versa. However, as the initial sharing probability of type A enterprises increases, the influence of the platform management capability coefficient on the evolution trend of its sharing probability becomes smaller. Therefore, the cloud platform management capability coefficient has a significant positive influence on enterprise manufacturing resource sharing strategy selection. When the cloud platform management capability coefficient is larger, enterprises are more inclined to choose the cloud platform to implement sharing strategies. Similarly, the sharing probability of type B enterprises is also affected by the platform management capability coefficient in a similar manner, with the simulation process omitted here.

3) Influence of Resource Transformation Capability Coefficient on Evolution Results

With the initial sharing probability value of type B enterprises fixed at 0.2, the resource transformation capability coefficient of type A enterprises is set to 0.5 and 0.9 respectively, with evolution results shown in Figure 7 [Figure 7: see original paper] and Figure 8 [Figure 8: see original paper].

Compared with Figure 3, it is found that as the resource transformation capability coefficient of type A enterprises gradually increases, the speed at which its sharing probability converges to 1 accelerates, indicating that the resource transformation capability coefficient is an important guarantee for promoting cooperation among enterprises. Similarly, the sharing probability of type B enterprises is also affected by the resource transformation capability coefficient in a similar manner, with the simulation process omitted here.

4) Influence of Resource Collaboration Capability Coefficient on Evolution Results

With the initial sharing probability value of type B enterprises fixed at 0.2, the resource collaboration capability coefficient of type A enterprises is set to 0.4 and 0.7 respectively, with evolution results shown in Figure 9 [Figure 9: see original paper] and Figure 10 [Figure 10: see original paper].

Through comparative analysis with Figure 3, it is found that as the resource collaboration capability coefficient of type A enterprises gradually increases, the speed at which its sharing probability converges to 1 accelerates, indicating a positive correlation between the resource collaboration capability coefficient and the evolution trend of sharing probability. Similarly, the sharing probability of type B enterprises is also affected by the resource collaboration capability coefficient in a similar manner, with the simulation process omitted here.

5) Influence of Information Efficiency Coefficient on Evolution Results
With the initial sharing probability value of type B enterprises fixed at 0.2, the information efficiency coefficient of type A enterprises is set to 0.45 and 0.85 respectively, with evolution results shown in Figure 11 [Figure 11: see original paper] and Figure 12 [Figure 12: see original paper].

At this time, the convergence speed of type A enterprises' sharing probability to 1 is significantly accelerated compared with Figure 3. It can be discovered that enterprises promoting informatization construction can not only improve their own production, service, and management efficiency but also promote cooperation among enterprises.

6) Influence of Technical Loss Risk Coefficient on Evolution Results
With the initial sharing probability value of type A enterprises fixed at 0.3, the initial sharing probability of type B enterprises is set to 0.1, 0.4, 0.7, and 0.9 respectively to observe the evolution results of type B enterprises' sharing probability when the technical loss risk coefficient of type B enterprises is 0.4 and 0.9 respectively, with simulation results shown in Figure 13 [Figure 13: see original paper] and Figure 14 [Figure 14: see original paper].

Comparing Figure 13 and Figure 14, it is evident that the increase in the technical loss risk coefficient significantly reduces the speed at which type B enterprises' sharing probability converges to 1. More notably, in Figure 14, when the initial sharing probability value of type B enterprises is 0.1, the initial sharing probability of type B enterprises actually converges to 0. This indicates that the probability of type B enterprises choosing the sharing strategy decreases with the increase of the technical loss risk coefficient. When this coefficient increases to a certain level, enterprises will undoubtedly choose the manufacturing resource non-sharing strategy.

7) Influence of Channel Cost Coefficient on Evolution Results
With the initial sharing probability value of type B enterprises fixed at 0.2, the channel cost coefficient of type A enterprises is set to 0.6 and 0.9 respectively, with evolution results shown in Figure 15 [Figure 15: see original paper] and Figure 16 [Figure 16: see original paper].

Comparing Figure 15 and Figure 16, it is clear that when the channel cost of type A enterprises increases, the probability of its sharing probability converging to 1 decreases and the decreasing speed slows down. Specifically, when the channel cost coefficient of type A enterprises is 0.8 or 1, type A enterprises with an initial sharing probability of 0.1 will eventually converge to 0, indicating that type A enterprises will choose the manufacturing resource non-sharing strategy when channel costs are excessively high. Therefore, if the cost for enterprises to enter the cloud platform far exceeds the benefits it brings, no matter how advanced the manufacturing technology is, it will not prompt enterprises to change their production models. Thus, low cost and high efficiency should be made the absolute advantage of the cloud platform. Similarly, the sharing probability of type B enterprises is also affected by channel costs in a similar manner, with the simulation process omitted here.

8) Influence of Penalty Cost Coefficient on Evolution Results

With the initial sharing probability value of type B enterprises fixed at 0.2, the penalty cost coefficient of type A enterprises is set to 0.4 and 0.6 respectively, with evolution results shown in Figure 17 [Figure 17: see original paper] and Figure 18 [Figure 18: see original paper].

Through comparative analysis with Figure 3, it is not difficult to find that as the penalty cost coefficient gradually increases, the probability of type A enterprises' sharing probability converging to 1 decreases and shows a slowing trend. Specifically, when the penalty cost coefficient increases to a certain level, such as the initial value of 0.6 set in this paper, type A enterprises will eventually converge to 0 regardless of their initial sharing probability value, indicating that type A enterprises will choose to abandon manufacturing resource sharing under the premise of excessively high penalty cost coefficients. However, in the evolution process of sharing strategies, some enterprises often choose to share some low-value, non-core manufacturing resources, which allows them to save channel costs, avoid technical loss risks, and still obtain shared manufacturing resources from the cloud platform. To stimulate enterprises to share core manufacturing resources and increase the cost of such free-riding behavior, a penalty mechanism must be established. If the penalty cost coefficient is too low, it cannot achieve the goal of promoting enterprises to choose manufacturing resource sharing. Conversely, if the penalty cost coefficient is too high, it will inevitably increase enterprises' psychological risk costs, causing them to abandon manufacturing resource sharing. Therefore, the penalty cost coefficient must be set reasonably. Similarly, the sharing probability of type B enterprises is also affected by penalty costs in a similar manner, with the simulation process omitted here.

9) Influence of Trust Coefficient on Evolution Results

With the initial sharing probability value of type B enterprises fixed at 0.2, the trust coefficient is set to 0.55 and 0.85 respectively, with evolution results for type A enterprises' resource sharing shown in Figure 19 [Figure 19: see original paper] and Figure 20 [Figure 20: see original paper].

Through comparative analysis with Figure 3, it is found that when the initial sharing probability value is larger, as the trust coefficient increases, the probability of type A enterprises' sharing probability converging to 1 increases. However, when the initial sharing probability value is very small, such as when the initial sharing probability of type A enterprises is fixed at 0.1 and 0.3, the trust coefficient shows a negative correlation with enterprise sharing probability, even converging to 0. This indicates that when the initial sharing probability is too low, a higher trust coefficient will instead increase mutual suspicion between the sharing parties, ultimately leading enterprises to choose the manufacturing resource non-sharing strategy. This shows that when the enterprise sharing probability initial value is high, full mutual trust between enterprise parties helps the continuation of resource sharing, and platform incentives will also promote the in-depth development of resource sharing. Conversely, if the enterprise sharing probability initial value is too low, an excessively high trust coefficient will instead make enterprises suspicious of each other and increase distrust of the cloud manufacturing platform, which will inevitably affect the continuation of manufacturing resource sharing. Therefore, a reasonable trust coefficient must be established. Since the incentive coefficient and trust coefficient belong to the same type of variable in the mathematical model, the simulation results are consistent, and the simulation process is omitted here.

4 Conclusion

This paper establishes an evolutionary game model for symmetrical enterprise manufacturing resource sharing strategies in cloud manufacturing environments from the perspective of evolutionary game theory. Based on the system dynamics method, the software Vensim is used to conduct dynamic simulation of the system, and the influence of different factors on evolution results is comparatively analyzed. The following conclusions and recommendations are drawn from the perspectives of cloud manufacturing service providers and manufacturing enterprises:

a) For cloud manufacturing service providers: The cloud platform management capability coefficient has a significant positive influence on enterprise manufacturing resource sharing strategy selection. When the cloud platform management capability coefficient is larger, enterprises are more inclined to choose the cloud platform to implement sharing strategies. As providers of manufacturing resource services, cloud manufacturing service providers should strengthen the construction of management capabilities. Additionally, if the cost for enterprises to enter the cloud platform far exceeds the benefits it brings, no matter how advanced the manufacturing technology is, it will not prompt enterprises to change their production models. Therefore, low channel costs and high information efficiency should be made the absolute advantages of the cloud platform. The setting of the penalty cost coefficient is an important guarantee for the healthy development of enterprise resource sharing models in cloud environments. Reasonably setting the penalty cost coefficient is an important issue that cloud manufacturing service providers need to consider. The information efficiency coefficient and technical loss risk coefficient are key factors in the evolution process of enterprise sharing strategies. Cloud manufacturing service providers must strengthen risk control in terminal access, system operation, electronic payment, and other collaborative businesses while ensuring basic information efficiency benefits for enterprises, improve the reliability of resource interoperability and sharing, and simultaneously integrate enterprise manufacturing resource types, formulate reasonable incentive coefficients, and provide effective guarantees for the stable operation of the cloud manufacturing resource sharing model.

b) For enterprises: As economic entities on the cloud platform, their population sharing proportion will affect the evolution process of sharing strategies to a certain extent. Whether an enterprise chooses a sharing strategy is influenced by the participation level of most enterprises in the industry. Specifically, when leading enterprises in the industry gradually enter the cloud manufacturing platform for manufacturing resource sharing, other enterprises will follow suit and use the cloud manufacturing platform, forming an industry scale effect. To a certain extent, the trust coefficient also affects the results of sharing strategy evolution. When the enterprise sharing probability initial value is high, full mutual trust between enterprise parties helps the continuation of resource sharing. The resource collaboration capability coefficient and transformation capability coefficient put forward higher requirements for enterprise informatization improvement and innovation R&D capabilities in cloud manufacturing environments. Therefore, enterprises must enhance their own informatization degree and increase investment in R&D and innovation to promote the in-depth development of resource sharing.

This paper is based on the premise of bounded rationality in evolutionary game theory, breaking through the complete rationality hypothesis of classical game theory to solve practical problems more scientifically and reasonably. Moreover, combining the system dynamics method with evolutionary game theory to study the problem of symmetrical enterprise manufacturing resource sharing in cloud manufacturing environments is also a new attempt. The research in this paper is conducted under certain reasonable assumptions. Although reality is often more complex, the research conclusions have certain theoretical guiding significance for the development of enterprises and cloud manufacturing service providers. In subsequent research, we will further optimize the model based on practical realities to deepen its practical significance. Additionally, this paper does not involve more complex multi-party cooperative collaborative manufacturing scenarios, which will also be the focus of our subsequent research.

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Note: Figure translations are in progress. See original paper for figures.