ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Research on Internet of Things Economic Development Model and Strategy Selection under the Perspective of Big Data

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SUMMARY: *The study of the benefit distribution mechanism of the Internet of Things (IoT) industry chain is conducive to the member enterprises to recognize their own positioning, and has a guiding role in the overall layout of the IoT industry. This paper establishes a competitive evolution game model between operators and system integrators, and analyzes the factors affecting the cooperation between the two parties as well as the distribution mechanism of cooperative operating costs and cooperative excess returns. Numerical simulation was carried out using matlab to further verify the relevant conclusions. The probability of the two parties engaging in cooperation to provide services is positively correlated with the coefficient of knowledge learning ability and the benefit of separate R&D, and there exists an excess benefit distribution coefficient* r_1 *=0.5, which makes S reach a great extent. When* $r_1 < 0.5 + \lim_{\delta i \to \infty} \Delta i = 0$ *(*r_1 *=0, and* Δi *is a number close to 0),* W *is certain,* r_1 *and S are positively correlated; when* $r_1 > 0.5 + \Delta i$*, the correlation is negative when* W *is certain. For operators and system integrators and other participating subjects, actively seeking cooperation with an open attitude can make both sides of the cooperation profitable and realize a win-win situation.*

KEYWORDS: *internet of things; operators; system integrators; evolutionary game model; benefit distribution*

1 Introduction

China's Twelfth Five-Year Plan takes scientific development as its theme and main line, and the development of the Internet of Things (IoT) economy is of great significance in accelerating the transformation of China's economic development mode. The development of IoT economy is realized through scientific development in economic, political, social, cultural and other aspects, which involves the application of a variety of advanced technologies, including infrared sensor technology, radio frequency technology, laser scanning technology, global positioning technology, etc., which adopts a variety of technologies to connect the Internet, mobile communication network, etc. with the items, realizing the intelligence of science and technology [1].

From the macroscopic level, the Internet of Things economy has an important impact on the economic structure adjustment, the transformation of the resource allocation mode and the provision of jobs, etc. The development of the Internet of Things economy plays a role to a certain extent in pulling the growth of the national economy and improving the scientific and technological content of economic growth [2-5]. From the meso-level, i.e., industrial

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https://doi.org/10.65102/is2026258
Published: 30 April, 2026

development perspective, the IoT economy drives the development of related industries, including both the optimization of network services, industry and supply chain monitoring, equipment maintenance, and production efficiency improvement, as well as the research and development and production of supporting facilities and software such as IoT network base stations, IoT devices, and applications [6-10]. From the micro level, the establishment of a large network virtual market can change the traditional trading methods, multi-party monitoring of transaction risks, reduce social transaction costs and increase transaction security [11-13].

In recent years, the IoT economic model and strategy has been transformed towards platformization, sharing optimization, service upgrading and other forms of innovation. Guijarro et al [14] constructed a multilateral platform based on sensor services in the IoT, in which the platform brings together three main bodies: users, developers, and sensor networks, and analyzes the business economic model through sensor data to maximize the profit of the platform. Gao et al. [15] built an enterprise digital service and operation platform based on IoT, optimizing the asynchronous and synchronous architectural processing of the service platform to provide personalized services and digital products compliant with national standards for individuals and enterprises. Kliestik et al [16] used AI technology to analyze sensor data of IoT systems for predictive maintenance and combined with algorithmic decision making driven by big data to apply to the industrial IoT economy to optimize maintenance processes and industrial operational efficiency. Eigner and Stary [17] state that IoT drives servitization transformation, transforming a company's traditional marketing model into a customer-oriented marketing model based on advantages such as remote monitoring or remote control and assisting with decision making during the conversion process. Rachman et al [18] combine IoT with MQTT (Message Queuing Telemetry Transport) protocol to design a new distributed bike sharing system, which successfully reduces the response time of the system to 2.91 seconds. H. Assaad et al [19] develops IoT based sensing devices that collect multi-sensor data, fuses them using smart sensor fusion building techniques and quantify the reliability of the sharing economy system in real time, combined with a dynamic pricing model to improve the operational efficiency of the system.

With the globalization of the economy and the internationalization of competition, the development of the IoT economy encounters challenges and opportunities, and it is necessary to promote the high-quality development of the IoT economy from a variety of dimensions, such as resource allocation, productivity improvement, greening, model innovation, and strategy selection. In the era of big data, the combination of IoT and big data is undoubtedly an important technological tool to solve the appealing challenges, to obtain optimization and upgrading in the fields of industrial manufacturing, life application and green development, and to improve the technical support for the IoT economic model and selection strategy. Wan et al [20] proposed new algorithms with the help of cognitive IoT and industrial big data technology to collect data, data hierarchical processing, and information mining for the smart devices through the , and information mining in three stages to provide data reference for device designers for designing smart devices. Lv and Li [21] constructed an intelligent management system in the era of big data by combining technologies such as the Internet of Things, integrated circuit card recognition, radio frequency identification, obstacle and ground sensing, and automated control, which helps to optimize the workflow of the enterprise through data management, analysis, and mining, and improves the efficiency of the enterprise by 30%. Abbas et al [22] deployed IoT sensors in a robot manufacturing industrial environment to collect information such as temperature, humidity, voltage, engine speed, weight, vibration, productivity, and communication status, introduced classifiers to classify the data, and analyzed this information in conjunction with big data analytics to achieve manufacturing process optimization.

Liu et al [23] proposed intelligent traffic flow prediction based on IoT and big data, and analyzed the social benefits gained from this prediction method to help intelligent traffic management and reduce traffic congestion and traffic pressure. Liu [24] used big data technology to optimize the intelligent traffic scheduling algorithms in the Chinese urban IoT platform, which mainly focuses on fusing the multimodal data in the traffic environment, detecting traffic passenger flow, evaluating traffic safety conditions, measuring driver waiting time, and reducing driver waiting time through scheduling algorithms. Babar and Arif [25] performed real-time data processing through big data analytics in an IoT-based smart transportation environment, including data on traffic signals, vehicle speeds, and license plate numbers, to achieve intelligent transportation planning. Maksimovic [26] introduced the green IoT IoT to build a green and sustainable urban living environment, while big data technology mines key information for the data generated in IoT to realize smarter, safer as well as more sustainable cities. Stergiou and Psannis [27] developed a digital virtual twin intelligent system for big data management and analytics for the industrial IoT in a cloud computing environment, which can evaluate the energy consumption of machines and greenhouses and other infrastructures to allocate more energy-efficient resources with reinforcement learning. Sun et al [28] added big data analytics to achieve real-time early warning and monitoring of the logistics chain in a designed cold chain logistics management system based on AI and energy IoT, which allows for energy consumption prediction, optimized resource allocation, and promotes low-carbon and green development of logistics. Adewale et al [29] used the Internet of Things (IoT) and big data analytics to monitor environmental remediation, collect real-time data to manage and optimize environmental remediation projects, improve the efficiency of remediation technology, reduce operating costs, and thus significantly reduce carbon emissions. Therefore, it is an effective approach to promote the innovation of IoT economic development model and strategy selection through big data.

This paper firstly puts forward the basic assumptions of the development and cooperation of the IoT industry chain, and constructs the game analysis model of the IoT industry chain. Based on the perspective of benefit distribution, it analyzes the specific factors affecting the cooperation between operators and system integrators. Construct the IoT industry chain benefit distribution model and deconstruct the influence of many different resource constraints on the competitive and cooperative relationship. Explore the evolution of cooperation strategies between operators and system integrators through theoretical analysis. Take the M2M product application research and development project in a city as an example to carry out numerical simulation experiments. Analyze the impacts of different variables on the cooperation between operators and system integrators in developing IoT products, and propose coping strategies for IoT participating entities.

2 Research on the development and cooperation of IoT industry chain based on evolutionary game

2.1 Evolutionary game modeling

2.1.1 Basic assumptions

(1) Gaming parties. From the perspective of IoT operation, currently there are three main business models for IoT: operator-led operation, system integrator-led operation and service provider-led operation. At present, the main links in China's IoT industry are operators (Mobile, Telecom, Unicom), system integrators (Tongfang Software), communication module vendors

(Huawei, ZTE), and sensing equipment providers (MediaTek, Huadong Technology), etc. The Chinese IoT industry chain lacks important links such as service providers. China's IoT industry chain lacks important links such as service providers, and communication module vendors and sensing equipment providers have limited control over the industry chain. The competition for the dominant position of the industry chain is between operators and system integrators.

Therefore, this paper mainly studies the cooperative evolution game model between operators and system integrators.

(2) Subject strategy. In the strategy selection of this model, each participating subject has two strategy selection options of cooperation and non-cooperation. Moreover, the subject of the game has the ability to learn, and can continuously adjust and improve in the game process to seek better strategies.

(3) Limited rationality assumption. In the fierce market competition environment, the decision-making subject's own cognitive ability is limited, which determines that it is impossible to be completely rational, and its actual behavior is limited rationality. Taking limited rationality as the basis of game analysis will effectively strengthen the conformity between game theory analysis and the real situation, and improve the effectiveness of the analysis conclusions.

(4) The assumption of economic man. The economic man is the main body of economic activities for the purpose of pursuing material interests, people want to pay as little as possible to get the maximum harvest, and for this reason can do whatever it takes. In the highly competitive IoT market, this paper argues that enterprises are always in pursuit of maximizing their own interests or utility, always tend to choose opportunities that can bring them greater economic benefits, and are willing to bear a certain cost of strategic risk.

(5) Information asymmetry. Information asymmetry refers to the incomplete information possessed by the parties in a transaction. In the model, we assume that each participant can not accurately know the strategy choice of another participant, that is, the information is incomplete, the game party due to limited rationality tends not to find the optimal strategy initially, but in the process of repeated games through continuous learning, improvement and adjustment of the strategy, and ultimately find the optimal strategy.

2.1.2 Internet of Things Industry Chain Game Analysis Model Construction

Operators and system integrators have two game options, cooperative and competitive relationships. The cooperative relationship between the operator and the system integrator means that the two are in a principal-agent relationship, and the competitive relationship means that the operator is engaged in the business of system integration in addition to the provision of the network.

(1) Assume a competitive relationship where the operator gain is W_1 and the system integrator gain is W_2;

(2) Assuming a cooperative relationship, the net gain from cooperation is W, where the operator's cooperation gain factor is r_1, the operator's cooperation gain is r_1W, and the system integrator's cooperation gain is $(1-r_1)W$.

(3) If one party cooperates and the other competes, the cooperating party needs to pay the initial cost, assuming that their respective initial costs are C_1 and C_2.

(4) Assume that the ratio of cooperation of the operator is a and the ratio of competition is $1-a$; the ratio of cooperation of the system integrator is b and the ratio of competitive strategy is $1-b$.

The game matrix of operators and system integrators can be obtained by assuming the establishment of the assumptions as shown in Table 1.

Table 1: Game matrix

Telecom operators\System integrators	Cooperation	Competition
Cooperation	$W_1+r_1W;W_2+(1-r_1)W$	$W_1-C_1;W_2$
Competition	$W_1;W_2-C_2$	$W_1;W_2$

The dynamic replication process is a method of solving for partial derivatives, which is better at predicting as well as explaining the behavioral trends of groups, and ultimately can predict the group behavior of individuals. The general differential equation for the dynamic replication process is

$$\frac{1}{x_k}\frac{dx_k}{dt}=[u(k,s)-u(s,s)],k=1,2,3,\cdots\cdots,k \tag{1}$$

where x_k denotes the rate of adopting the k strategy, and the content in parentheses denotes the difference between the fitness of adopting the k strategy and the average fitness. When this equation is greater than 0, it means that the k strategy has a high degree of adaptation, which is also consistent with the survival of the fittest.

According to this differential equation, the dynamic process of replication between operators and system integrators can be listed as:

$$\text{Operators for } \frac{da}{dt}=a*(1-a)*\left(b*r_1*W+b*C_1-C_1\right) \tag{2}$$

$$\text{The system integrator is } \frac{db}{dt}=b*(1-b)*\left(a*(1-r_1)*W+a*C_1-C_1\right) \tag{3}$$

The cooperative and competitive equations between operators and system integrators are finally expressed as the above two equations, and from the differential equations, we can find $O(0,0),A(1,0),B(0,1),C(1,1),D\left(\frac{C_2}{(1-r_1)W+C_2},\frac{C_1}{r_1W+C_1}\right)$. These 5 points are the equilibrium points for the development of operators and system integrators. These five equilibrium points represent different meanings: O represents the competitive strategy adopted by both vendors, A represents the cooperative strategy adopted by the operator and the competitive strategy adopted by the system integrator, B point represents the competitive strategy adopted by the operator and the cooperative strategy adopted by the system integrator, C point represents the full cooperative strategy adopted by the two vendors, and D point represents the state of competitive-cooperative, that is, the current development state. The game state between the operator and the system integrator can be represented as shown in Fig. 1.

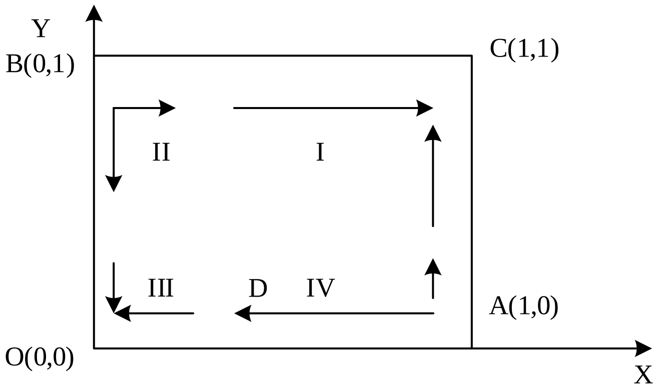

Figure 1: The game map

In Figure 1, the X axis is a, Y axis is b, and the four quadrants represent the four kinds of competitive relationship between operators and system integrators, in which the arrows in the figure indicate the evolution of the relationship between the two, when located in the third quadrant, the operator and the system integrator tends to the O point, i.e., the direction of full competition; when located in the first quadrant the two vendors tend to the C point, i.e., the direction of cooperation, and when Located in the second and fourth quadrant, the competitive relationship depends entirely on the value of the relevant index in the formula $\left(\frac{C_2}{(1-r)W+C_2}, \frac{C_1}{rW+C_1}\right)$.

The game analysis between the operator and the system integrator, it can be known that the two mainly present two kinds of game evolution process, when r is certain, the larger the net benefit, the smaller the initial cost, the smaller the value of D point, the larger the cooperation area, it tends to be a cooperative relationship, otherwise, it tends to be a competitive relationship. In real life, r value determination depends on the scale situation of both parties, the larger the scale, the larger the corresponding r.

The business of each vendor in the value chain of IoT industry is not fixed, for example, chip manufacturers may also be engaged in the business of system integration, and equipment providers may also be chip manufacturers or system integrators, so when considering the development of the value chain of the IoT industry, it is also necessary to consider the game analysis between the vendors, that is, their competition and cooperation, through the game analysis of competition and cooperation relationship can be seen for the Through the game analysis of competitive relationship, it can be seen that for most of the vendors in the value chain of IoT industry, the relationship of cooperation is still greater than competition, and the cooperation can reduce the cost accordingly.

2.2 Analysis of cooperation mechanisms based on benefit distribution

2.2.1 Theoretical analysis of influencing factors

From the analysis in the previous section, it can be seen that the stable strategies of the game between the operator and the system integrator are (cooperative, cooperative), (uncooperative, uncooperative). The probability of which direction the game of both parties evolves is determined by the area of quadrilateral OADB and CADB in Fig. 1. When the initial state falls in the quadrilateral OADB, the system will converge to the point $O(0,0)$, i.e., the operator and the system integrator do not cooperate; when the initial state falls in the quadrilateral CADB, the system will converge to the point $C(1,1)$, i.e., the operator and the system integrator cooperate.

When the two parties cooperate and provide services together, the distribution factor of their costs is r_2. The area S1 of the quadrilateral OADB determines the probability that the two parties converge to non-cooperation. And:

$$S1=\frac{1}{2}\left(\frac{C_2'-C_2}{(1-r_1)W-(1-r_2)C+C_2'-P_2+Q_2}+\frac{C_1'-C_1}{r_1d-r_2C+C_1'-P_1+Q_1}\right) \tag{4}$$

From equation (4), there are 12 factors that affect the probability of cooperation between the parties.

The analysis leads to the following conclusions.

(1) Excess Benefits

The probability of cooperation between operators and system integrators to provide IoT services is proportional to the excess revenue W obtained by the cooperation between the two parties.

Analyzing Equation (4), it can be seen that S_1 is a monotonically decreasing function of W, i.e., the area of S_1 decreases with the increase of the excess benefit W obtained from the cooperation between the two parties, the probability of the two parties to carry out the cooperation will increase, and the likelihood of the equilibrium state to evolve to $(1,1)$ is increased.

(2) Cooperation Cost

The probability of cooperation between operators and system integrators to provide IoT services is inversely proportional to the total cost C paid by both parties to cooperate to provide services.

From equation (4), S_1 is a monotonically increasing function of C, as the total cost of cooperation C increases, the area of S_1 increases, the probability that the two parties do not cooperate will increase, and the probability that they tend to cooperate decreases.

(3) Cost of working independently

The probability that an operator and a system integrator work together to provide IoT services is proportional to the cost C_1, C_2 that both parties pay to provide the services independently.

S_1 is a monotonically decreasing function of C_1, C_2. As the cost of the operator and the system integrator to provide IoT services independently increases, the probability that both parties tend to choose the non-cooperation strategy decreases, and the evolutionary game equilibrium tends to increase the probability that both parties cooperate.

(4) Incremental gain of betraying party

When one party cooperates and the other does not, the larger the incremental gain P_1, P_2 obtained by the non-cooperating party, the smaller the probability that the operator and the system integrator will cooperate to provide IoT services.

S_1 is a monotonically increasing function of P_1, P_2, and as the incremental revenue P_1, P_2 obtained by the non-cooperating party benefiting from the other party's milder market strategy increases, the probability of both parties tending to choose non-cooperative strategies increases, and the probability of the evolutionary game equilibrium tending to cooperation between both parties decreases.

(5) Retaliation and punishment of the betraying party

When one party cooperates and the other party does not, the greater the retaliation and punishment Q_1, Q_2 the non-cooperating party receives from the cooperating party, the greater the probability that the operator and the system integrator will cooperate to provide IoT services.

S_1 is a monotonically decreasing function of Q_1, Q_2, when the non-cooperating party is subjected to the retaliation and punishment of the cooperating party Q_1, the larger Q_2 is, the smaller the area of S_1 is, i.e., the probability that both parties tend to choose non-cooperating strategy decreases, and the more probable it is that the operators and system integrators will cooperate in providing IoT services.

(6) The betrayed party pays the cost

When one party cooperates and the other party does not, the cost paid by the cooperating party C_1', C_2' the larger, the smaller the probability that the operator and the system integrator will cooperate to provide IoT services.

$$\frac{\partial S_1}{\partial C_1'} = \frac{r_1 W - r_2 C - P_1 + Q_1 + C_1}{2(r_1 W - r_2 C + C_1' - P_1 + Q_1)^2}, \frac{\partial S_1}{\partial C_2'} = \frac{(1-r_1)W - (1-r_2)C + C_2 - P_2 + Q_2}{2((1-r_1)W - (1-r_2)C + C_2' - P_2 + Q_2)} \tag{5}$$

When $r_1 W - r_2 C - P_1 + Q_1 + C_1 < 0$, $W_1 + r_1 W - r_2 C < W_2 - C_1 + P_1 - Q_1$, i.e., when the excess revenue allocated to the operator for cooperating to provide the service minus the shared cooperation cost is less than the revenue gained from non-cooperation minus the cost of independent development and penalties from the other party, according to the revenue matrix, the non-cooperation strategy will be selected for the operator regardless of the change of C_1'.

When $r_1 W - r_2 C - P_1 + Q_1 + C_1 > 0$, i.e., the operator's excess revenue allocated from cooperation in service provision minus the shared cooperation cost is greater than the revenue obtained from non-cooperation minus the cost of independent development and the counterparty's penalties, $\frac{\partial S_1}{\partial C_1'} > 0$, i.e., when S_1 is an increasing function of C_1', the larger the cost C_1' that the operator pays as a betrayed collaborator is, the larger the S_1 is, and the smaller the likelihood that both parties will collaborate in the provision of IoT services.

Similarly, when $(1-r_1)W - (1-r_2)C + C_2 - P_2 + Q_2 < 0$, according to the revenue matrix, the non-cooperation strategy will be selected for the system integrator regardless of the change of C_2'. When $(1-r_1)W - (1-r_2)C + C_2 - P_2 + Q_2 > 0$, the larger the cost C_2' paid by the system integrator as a betrayed cooperator is, and the larger the S_1 is, the lower the probability of the two parties cooperating in the provision of IoT services.

(7) Revenue sharing mechanism

When other conditions are certain, there exists an optimal allocation ratio α of excess revenue r_1 that maximizes the likelihood of cooperation between the operator and the system integrator.

$\frac{\partial S_1}{\partial r_1}=\frac{1}{2}W\left(\frac{C_2'-C_2}{((1-r_1)W-(1-r_2)C+C_2'-P_2+Q_2)^2}-\frac{C_1'-C_1}{(r_1W-r_2C+C_1'-P_1+Q_1)^2}\right)$, and S_1 takes the second-order derivative of α with $\frac{C_2'-C_2}{((1-r_1)W-(1-r_2)C+C_2'-P_2+Q_2)^3}+\frac{C_1'-C_1}{(r_1W-r_2C+C_1'-P_1+Q_1)^3}>0$. Let $\frac{\partial S_1}{\partial \alpha}=0$, i.e., when $\frac{C_2'-C_2}{((1-r_1)W-(1-r_2)C+C_2'-P_2+Q_2)^2}=\frac{C_1'-C_1}{(r_1W-r_2C+C_1'-P_1+Q_1)^2}$

when S_1 is extremely small and the possibility of cooperation between the operator and the system integrator is maximum.

(8) Cost sharing mechanism

When other conditions are certain, there exists an optimal allocation ratio β of cooperative operation cost C , which makes the possibility of cooperation between operators and system integrators maximum.

When $\frac{C_2'-C_2}{((1-r_1)W-(1-r_2)C+C_2'-P_2+Q_2)^2}=\frac{C_1'-C_1}{(r_1W-r_2C+C_1'-P_1+Q_1)^2}$ when S_1 is extremely small, and the operator's likelihood of cooperating with the system integrator is greatest.

2.2.2 Construction of the Benefit Distribution Model of the Internet of Things Industry Chain

In this paper, it is assumed that the factors affecting the distribution of benefits among member enterprises of the IoT industry chain include the following: (1) the total revenue of the IoT industry chain is R ; (2) the efforts made by the dominant enterprises of the benefit distribution, operator A_1 and system integrator A_2 , for the revenue of the IoT industry chain, which are denoted as a_1, a_2 ; (3) the dominant vendor (operator) pays the fixed compensation to the system integrator's fixed compensation T ; (4) the profit sharing ratio of A_1 and A_2 in the total revenue of IoT industry chain, denoted as r_1 and $1-r_1$, respectively; and (5) the cost of IoT industry chain member firms, including the fixed cost and variable cost, and the variable cost is denoted as $C(a_1), C(a_2)$. Where the fixed cost is a constant independent of the contribution of each member firm to the industry chain denoted as C_1, C_2 ; the variable cost is the cost related to the effort, which increases with the increase of the effort, and denoted as r_2 and $1-r_2$ are the coefficients of the variable cost of the firms of A_1, A_2 . In order to be able to better study the problem, we make further assumptions that the variable costs of A_1 and A_2 , as well as the total revenue of the IoT industry chain are quadratic functions of the level of effort, and it is worthwhile to note here that the coefficient 0.5 is added to each functional equation for the convenience of the simplification of the later operation, which can be accounted for the cost coefficients by rounding off the square of 0.5, and that the coefficients of each functional equation are reduced to 1, which does not influence the The functional relationship between the variables.

From the above analysis, the total revenue R and profit π of the IoT industry chain can be expressed as follows:

$$R(a_1, a_2) = \frac{1}{2}(a_1 + a_2)^2 + (a_1 + a_2) \tag{6}$$

$$\pi(a_1, a_2) = R(a_1, a_2) - C(a_1) - C(a_2) \tag{7}$$

Meanwhile, the operator's and system integrator's revenues (R_1 and R_2) are respectively:

$$R_1 = r_1 R - T - C(a_1) \tag{8}$$

$$R_2 = T + (1 - r_1)R - C(a_2) \tag{9}$$

The variable costs $C(a_1)$ and $C(a_2)$ of the other operator A_1 and the other member firm A_2 are respectively:

$$C(a_1) = C_1 + \frac{1}{2} r_2 a_1^2 \tag{10}$$

$$C(a_2) = C_2 + \frac{1}{2}(1 - r_2) a_2^2 \tag{11}$$

At different stages of the development of the IoT industry chain, each participant in the IoT industry chain, IoT operators and system integrators of the IoT industry chain, for their own interests, choose the time and manner of the occurrence of the strategy in a flexible way, so that different kinds of gaming behaviors under different strategies will be formed.

2.2.3 Game Analysis of Benefit Distribution of Internet of Things Industry Chain

(1) Distribution of benefits in the IoT industry chain with operators as leaders

There are leaders and followers in the industry chain. According to the study of the leading enterprises in the IoT industry chain, operators act as the leader of the IoT industry, while system integrators are the followers. The game between these two is a sequential dynamic game, and the final result of this game is Stackelberg equilibrium. The game process of the IoT industry chain in the distribution of benefits is as follows: firstly, the dominant enterprise operator determines the profit distribution ratio r_1 by adjusting its own efforts and actions, so as to pursue the maximization of its own benefits, and then the system integrator decides its own efforts according to the determined r_1 to pursue the maximization of benefits. In this process, the operator, the leader of the IoT industry chain, decides the proportion of profit distribution according to the actual situation. At the same time, in the process of pursuing its own profit maximization, it must be subject to the following constraints: other member enterprises of the IoT industry chain must be profitable in the whole industry chain, and each member enterprise has the ability to decide its own efforts and actions, so as to pursue profit maximization.

According to the Stackelberg game reverse induction method, the game should be discussed from the second stage, i.e., the system integrator determines the content of the contract and pursues the maximization of its own interests. To maximize the profit of the system integrator is to make the function convex and the derivative function equal to zero.

$$\frac{\partial R_2}{\partial R_2} = (1-r_1)[(a_1+a_2)+1] - r_2 a_2 = 0 \tag{12}$$

It can be derived:

$$a_2 = \frac{(1-r_1)(a_1+1)}{r_2-(1-r_1)} \tag{13}$$

It can only be a convex function when $\frac{\partial R_2}{\partial R_2} < 0$. From the above equation, it can be concluded that the degree of effort of other IoT industry chain member enterprises is positively correlated with the proportion of their profit distribution, while it is negatively correlated with the coefficient of their variable costs.

After completing the second stage of the game analysis, the first stage of the dynamic sequence game is studied below, that is, the operator adjusts its own efforts and determines s according to the efforts of other IoT industry chain members to pursue the maximization of its own interests. The problem can be expressed as follows:

$$\begin{cases} \frac{\partial R_{a_1}}{\partial a_1} = \frac{(1-r_2)^2 r_1 (a_1+1)}{(r_1-r_2)^2} - r_2 a_1 = 0 \\ \frac{\partial R_{a_1}}{\partial (1-r_1)} = \frac{\begin{array}{c} 2(1-r_2)^2 r_1 (a_1+1)^2 - (r_1-r_2)* \\ [(1-r_2)^2 a_1^2 + 2(1-r_2)^2 a_1 + 2(1-r_2)(1-r_1) - (1-r_1)^2] \end{array}}{2(r_1-r_2)^3} = 0 \end{cases} \tag{14}$$

(2) Distribution of benefits in the IoT industry chain with member enterprises in an equal position

With the gradual strengthening of the core competitiveness of the leading manufacturers and operators, the relationship between operators and equipment manufacturers, software and application developers, system integrators, etc. in the IOT industry chain will undergo a series of corresponding changes. Equipment manufacturers, software and application developers, system integrators, etc. will no longer be satisfied with the operator to determine the profit distribution ratio of enterprises in the industry chain, and the negotiation ability of these vendors has been enhanced to take advantage of this to pursue their own interests to the maximum. The following is a dynamic game in which the operator and other member enterprises are in the same position at the same moment, and the result of this game is the Nash equilibrium. The process of the game is that the operator and its member companies negotiate to determine a mutually agreed profit sharing ratio, and in the case of the determined profit sharing ratio, the participating members use the corresponding strategies to maximize their own profits.

Also from the second stage of the game, in the case of determining the proportion of profit distribution, the operator and other members of the profit optimization problem is:

$$\frac{\partial R_{a_L}}{\partial a_1} = r_1[(a_1+a_2)+1] - r_2 a_1 = 0 \tag{15}$$

$$\frac{\partial R_{a_2}}{\partial a_2} = (1-r_1)[(a_1+a_2)+1] - (1-r_2)a_2 = 0 \tag{16}$$

Joining equations (14) and (15), the optimal effort of A_1 and A_2 firms is known as:

$$a_1^2 = \frac{r_1 r_2}{r_2(1-r_2) - r_1(1-r_2) - (1-r_1)\alpha} \tag{17}$$

$$a_2^2 = \frac{(1-r_1)r_2}{r_2(1-r_2) - r_1(1-r_2) - r_2(1-r_1)} \tag{18}$$

The first stage of the game is to determine the optimal profit sharing ratio through negotiation between the operator and other member firms. This step is actually to determine the optimal behavior or effort of A_1, A_2 firms to pursue the maximum total return of the industry chain.

3 Analysis of Big Data-driven Internet of Things Industry Chain Development Models and Strategies

3.1 Theoretical analysis

The evolution of the cooperation strategy between operators and system integrators is closely related to the saddle point $\left(\frac{Q_2}{(1-r_1)W + Q_2 - P_1}, \frac{Q_1}{r_1 W + Q_1 - P_2}\right)$ position change is closely related. From the above analysis, it can be seen that a variety of factors, such as the total return from cooperation and the coefficient of distribution of cooperative surplus, will affect the value of the saddle point, which in turn affects the positioning of the saddle point on the coordinate axes, and they will all affect the trend of the evolution of the game strategy.

The evolution of the cooperation strategy of the operator and the system integrator in the proposition one scenario is shown in Fig. 2.

Proposition 1: (1) The operator and the system integrator have the same profit and loss, and the cooperative strategy in which the cooperative strategy party gets more loss than the competitive strategy gain, i.e., $Q_1 = Q_2 = Q$, $P_1 = P_2 = P$, and $Q > P$; (2) The coordinates of the saddle point are (x_0, y_0); (3) the area representing the choice of (competitive, competing) strategies is S, then we have $2S = x_0 + y_0$.

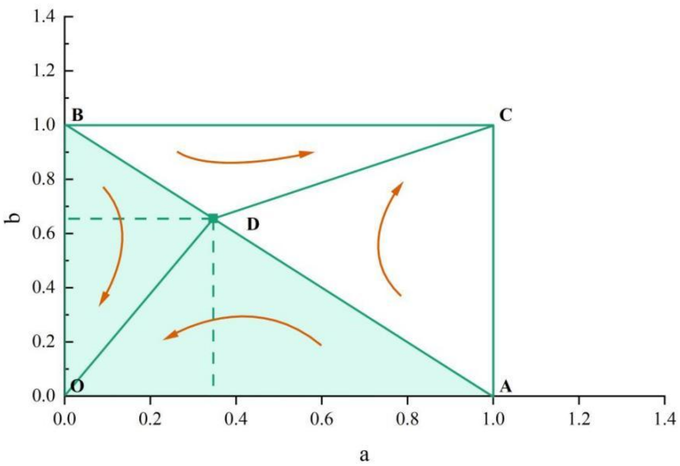

Figure 2: Evolution of cooperative strategies in the case of Proposition 1

The evolution of the cooperation strategy between the operator and the system integrator in the proposition two scenario is shown in Fig. 3.

Proposition 2: The benefit distribution coefficient r_1 is centered around 0.5 and cannot be too biased towards 0 or 1, otherwise it will increase the probabilistic choice of competition. Since $2S = \frac{Q}{(1-r_1)W+Q-P} + \frac{Q}{r_1W+Q-P}$, our partial derivation of the dependent variable S gives us that when $\omega < 0.5$, there is $\frac{\partial S}{\partial r_1} < 0$, i.e., S is monotonically decreasing and $(1-S)$ is monotonically increasing; when $r_1 > 0.5$, there is $\frac{\partial S}{\partial r_1} > 0$, i.e., S is monotonically increasing and $(1-S)$ is monotonically decreasing. Therefore, when $r_1 = 0.5$, S has the minimum value and (x_0, y_0) tends most to $(1,1)$, i.e., the operator and the system integrator have the minimum possibility of competition and the maximum possibility of cooperation. When r_1 gradually deviates from 0.5, both S will gradually increase, and (x_0, y_0) gradually tends to $(0,0)$, i.e., the probability of the operator and the system integrator gradually increases and the probability of cooperation gradually decreases. Therefore, when the proportion of benefit distribution deviates from 0.5, it may have the effect of reducing incentives and intensifying competition, and it is better to control the magnitude of the deviation of the proportion of distribution without changing the other equilibrium factors. We can see from Figure 3 that S is represented by the area of the region constituted by the OADB and $1-S$ by the area of the region constituted by the CADB.

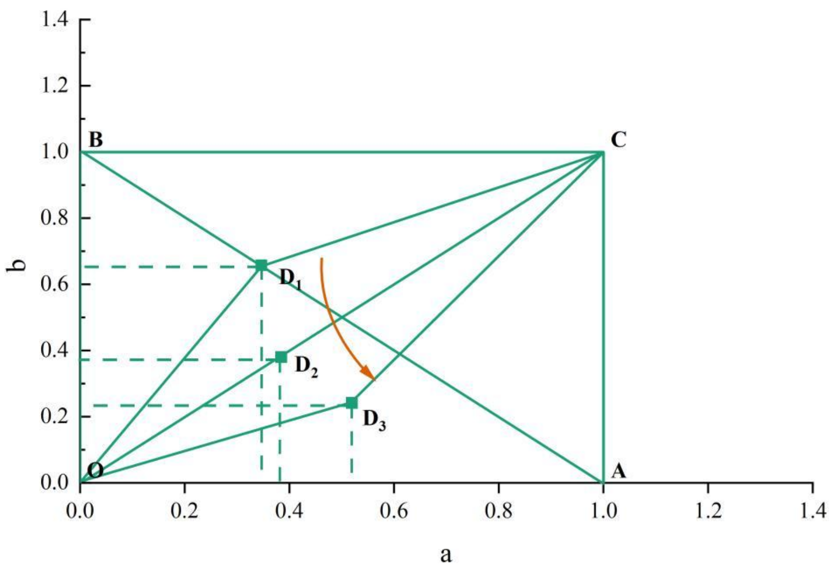

Figure 3: Evolution of cooperative strategies in the case of Proposition 2

The evolution of the cooperation strategy between operators and system integrators under the scenario of Proposition 3 is shown in Fig. 4.

Proposition 3: The larger the value-added gain from cooperation W, the greater the likelihood of cooperation between the operator and the system integrator will be. Since the previous assumption of equal gains for the (competition, cooperation) and (cooperation, competition) scenarios already exists, i.e., $P_1 = P_2 = P$, we now need to make the assumption that the other parameters are also kept constant as the basis for analyzing the impact of the magnitude of value-added gains from the cooperation in the game on the evolutionary path of the system. Since $2S = \frac{Q}{(1-r_1)W+Q-P} + \frac{Q}{r_1W+Q-P}$, we obtain by taking the partial derivation of the dependent variable S : $\frac{\partial S}{\partial W} < 0$ when $W > 0$, i.e., S monotonically decreases and $(1-S)$ monotonically increasing, (x_0, y_0) gradually tends to $(0,0)$, i.e., as the value-added benefits of cooperation in the alliance gradually increase, the greater the likelihood of cooperation between the operator and the system integrator. For ease of understanding, let $r_1 = 0.5$.

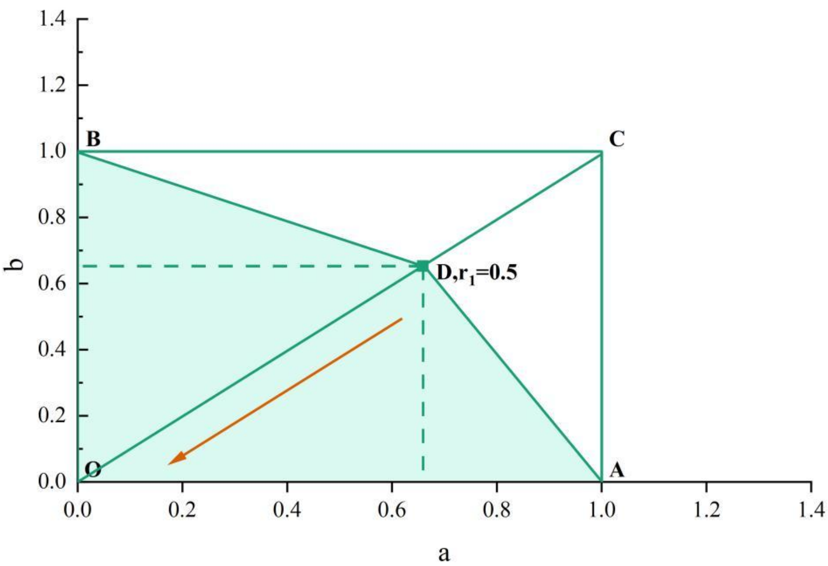

Figure 4: Evolution of cooperative strategies in the case of Proposition 3

The evolution of the cooperation strategy between the operator and the system integrator under the proposition four scenario is shown in Fig. 5.

Proposition 4: The larger the competitive loss Q to the party choosing to cooperate, the smaller the possibility of cooperation between the operator and the system integrator will be. We assume that other parameters remain unchanged to study the impact of the loss to the competed party when a single party chooses to compete in the two-party game on the evolution path of the system. Since $2S = \frac{Q}{(1-r_1)W+Q-P} + \frac{Q}{r_1W+Q-P}$, we take the partial derivation of the dependent variable S to obtain: when $Q > 0$, $\frac{\partial S}{\partial W} > 0$, i.e., S monotonically increases and $(1-S)$ monotonically decreases, and (x_0, y_0) gradually converges to $(1,1)$, i.e., as the loss of the competed party in the coalition gradually increases, the less likely the operator and the system integrator are to cooperate. For ease of understanding, we also let $r_1 = 0.5$.

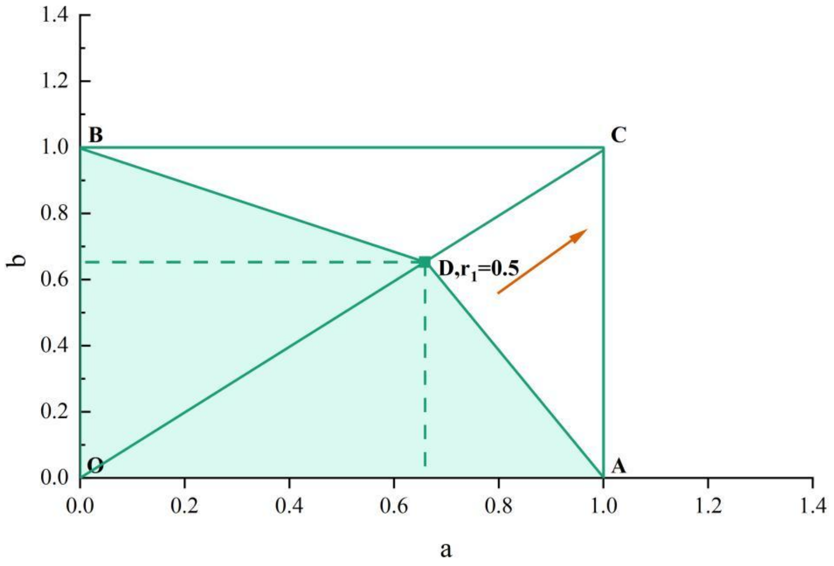

Figure 5: Evolution of cooperative strategies in the case of Proposition 4

3.2 Simulation analysis

Taking the M2M product application research and development project in a city as an example, we analyze the influence of different variables on the cooperation between operators and system integrators to develop IoT products. According to the collected information and the assumptions of the model, it is assumed that the amount of resources invested in the cooperation by the operator a_1 ϵ[8,30] million yuan, the amount of resources invested in the cooperation by the system integrator a_2 ϵ[6,25] million yuan, and the excess return obtained after the successful cooperation W ϵ[40,12] million yuan, and the coefficient of the distribution of the excess returns r_1 ϵ[0.25,0.75], and the coefficients of knowledge learning ability γ_1, γ_2 ϵ[0.25,0.75]. In addition, if one side of the game chooses the betrayal strategy, the maximum amount of betrayal gain it can obtain does not exceed the amount of the other side's resource input, and the betrayal gain is also related to the length of its own participation in the cooperation, so we assume that E_i ϵ[2,6] million dollars, and at the same time, in the event that one side of the game betrays, the other side chooses to develop the gain alone $\triangle W_i$ ϵ[2,600] million dollars.

In the discussion in this section, the relevant parameters given the above parameter values are taken as follows: the amount of resource input of the operator a_1=8 million yuan, the amount of resource input of the system integrator a_2=6 million yuan, the excess return W=70 million yuan if the collaborative research and development is successful and goes to the market, and the coefficient of the distribution of excess return r_1=0.25, in addition, the knowledge learning ability coefficient of the operator γ_1=0.25, and the knowledge learning ability coefficient of the system integrator γ_2=0.25. If one party cooperates and the other does not, we assume that the operator's gain from the separate development $\triangle W_1$=500, the system integrator's gain from betrayal E_2=300; and when the operator's gain from betrayal E_1=400, the system integrator's gain from developing alone is $\triangle W_2$=400. Since the gains when neither party cooperates W_1, W_2 size has no effect on the model results, so their numerical sizes are not considered. According to the values of the above parameters, Matlab programming is used to carry out numerical simulation to analyze the impact of different factors on the choice of IoT business model.

3.2.1 Effect of knowledge learning ability coefficient on game strategy

Assuming that the knowledge learning ability coefficients γ_1, γ_2 of the operator and the system integrator are varied in the interval [0.25,0.75], and the values of the other parameters are taken as described above, the influence of the game parties on the probability of the game strategy at different knowledge learning ability coefficients can be obtained as shown in Figure 6. When γ_1, γ_2=0.75, S reaches 0.8819, 0.8661, respectively.In the given parameters, the operator's individual R&D gain and betrayal gain are slightly higher than that of the system integrator, while the excess gain distribution coefficient is much lower than that of the system integrator, and the level of betrayal gain is inversely proportional to the size of the area of S. Thus, the As the knowledge learning ability coefficient increases, a smaller increase in the separate R&D gain brings about a larger increase in the probability of the operator's cooperative R&D strategy selection.

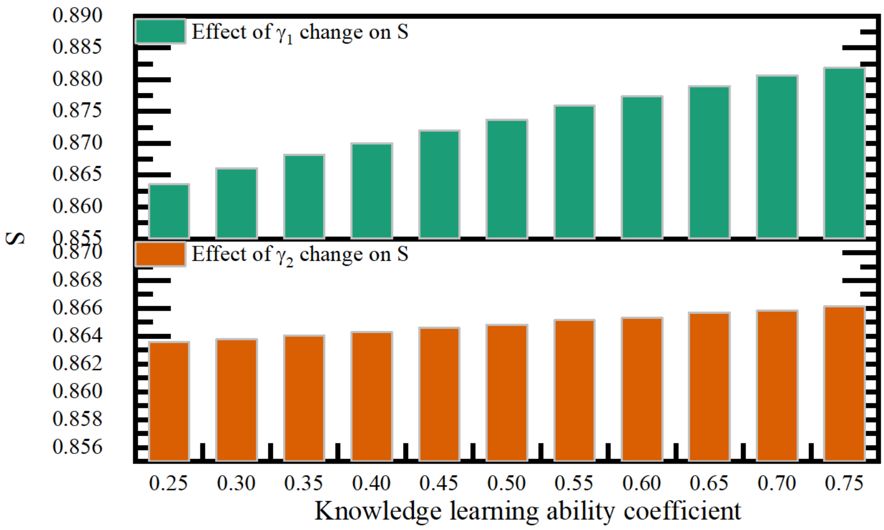

Figure 6: Effects of different knowledge learning ability coefficient

3.2.2 Impact of Individual R&D Gains and Betrayal Gains on Game Strategies

When other parameters are fixed and the operators and system integrators' individual R&D gains $\triangle W_1$, $\triangle W_2$, and betrayal gains E_1, E_2, respectively, are taken to be in the interval of [200, 6] million yuan, the relationship between the individual R&D gains and the Betrayal gains on the probability of collaborative R&D is shown in Figure 7. When $\triangle W_1$, $\triangle W_2$ = 600, S reaches 0.8942, 0.8903, respectively. E_1, E_2 = 600, S reaches 0.8564, 0.8686, respectively. This shows that, when both sides of the game independent R&D may gain, the greater their incentive to invest in R&D, the higher the probability that the two sides conduct cooperative R&D. And due to factors such as the technology spillover of the cooperating parties and the knowledge learning ability of the betraying party, which makes the motivation for opportunistic behavior stronger when the betrayal gain is larger, even though the two parties will choose to cooperate at the initial stage, it will lead to the failure of the cooperation and affect the long-term strategy choices of the two parties of the game.

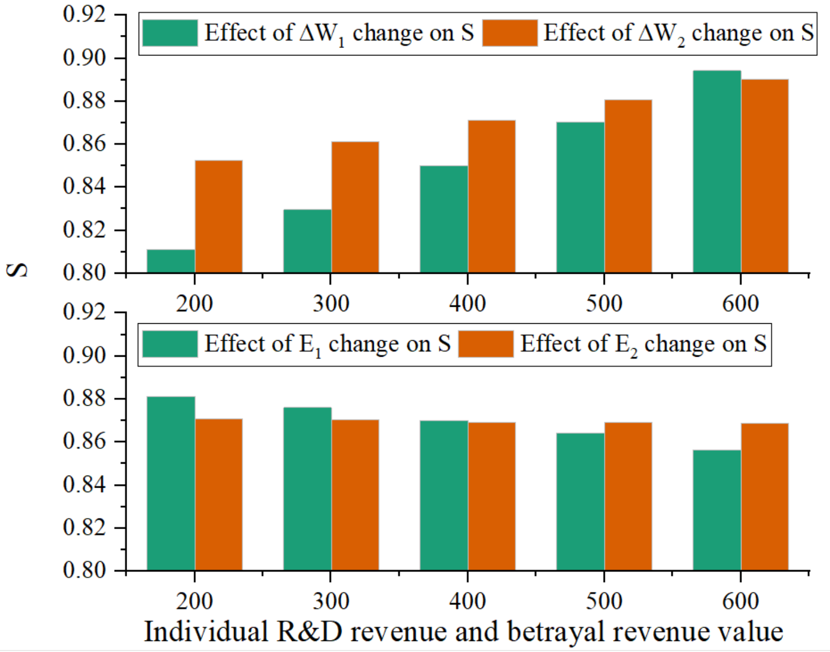

Figure 7: The effect of R&D returns alone versus defections

3.2.3 Impact of Excess Returns and Excess Return Allocation Coefficients on Game Strategies

Fixing other parameters to remain unchanged, so that the excess revenue sharing coefficient r_1 of the operator and the system integrator varies on the interval [0.25,0.75], and at the same time, make the excess revenues take W =4000, 6000, 8000, 10000, 12000, respectively, and get the effect of excess revenues and excess revenue sharing coefficients on the cooperative R&D probability are shown in Fig. 8. When other parameters are certain, S first increases to a great value and then gradually decreases as the excess revenue allocation coefficient r_1 increases. This indicates that there exists a value of r_1 that makes S reach an extreme value, which is consistent with the previous analysis. Meanwhile, fixing the other parameters, the probability of the two parties choosing to cooperate in R&D increases with the increment of excess returns, and S reaches a great value when W = 12000.

Numerical simulations illustrate that the maximum is reached when r_1 is around 0.5. When r_1 <0.5+ $\lim_{\delta i \to \infty} \Delta i = 0$ (r_1 =0, Δi is a number close to 0), and W must be certain, the r_1 is larger then S is larger, which indicates that when the coefficient of excess benefit distribution is higher, the operator gains more from cooperative R&D, its incentive to invest in cooperative R&D is also higher, and the probability of the two parties cooperating in R&D is higher. When r_1 > 0.5 + Δi, the larger r_1 is the smaller S is for certain W .

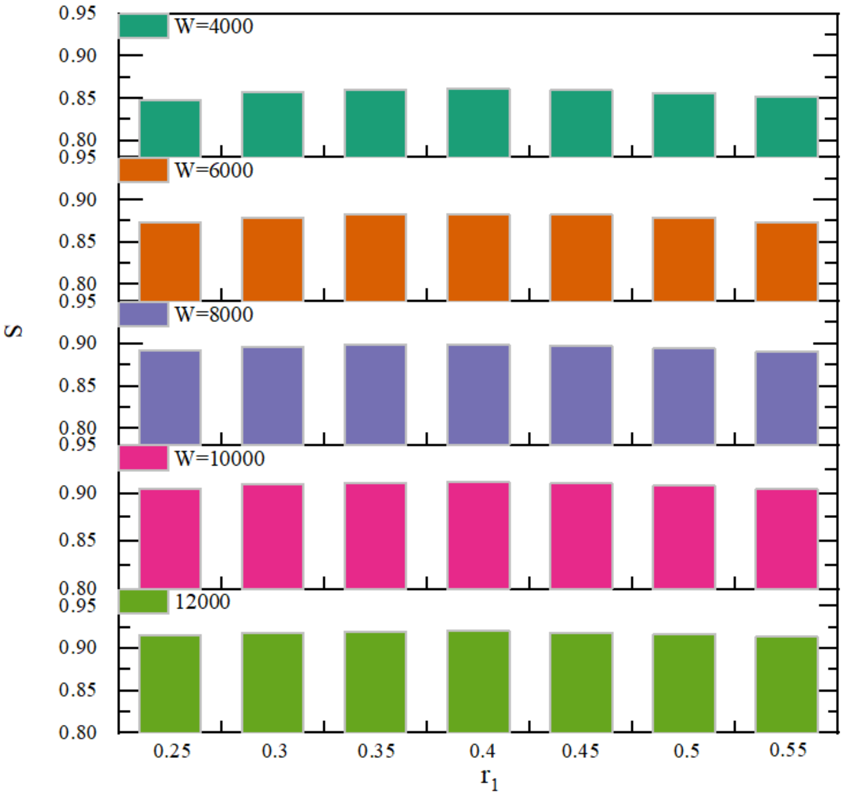

Figure 8: The effect of excess returns on the distribution coefficient of excess returns

Further sensitivity analysis on excess return is done, based on the super-conflict knowledge learning ability coefficient, the expected return fitting curve is shown in Figure 9. When r_1 is located in the interval [0.25,0.75], with the increase of r_1, the knowledge learning ability coefficient of the operator is increasing, and the knowledge learning ability coefficient of the system integrator is decreasing. When r_1 lies in the interval [0.25,0.75], as r_1 increases, the operator's expected revenue R_1 keeps increasing, and the system integrator's expected revenue R_2 profit keeps decreasing.

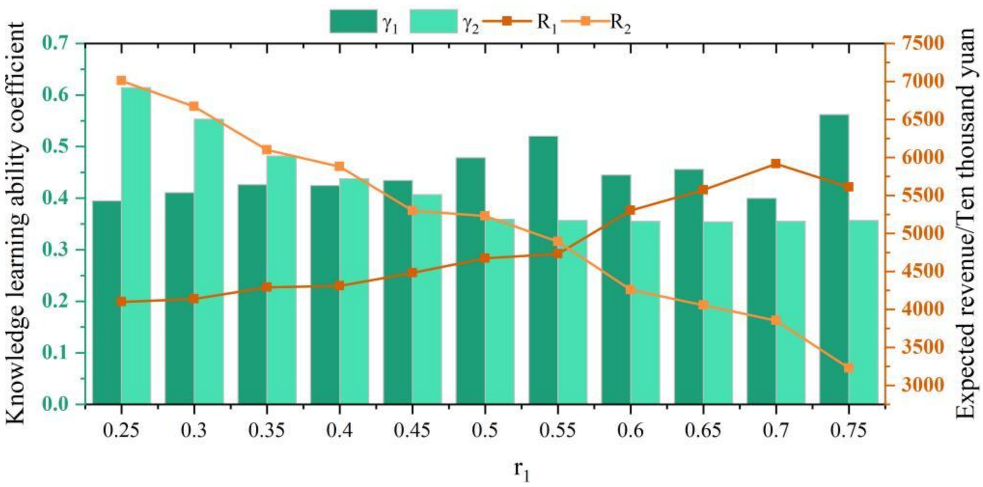

Figure 9: Fitted curves

3.2.4 The effect of the amount of information on game strategy

Finally we consider the effect of the amount of information λ. A suitable revenue sharing contract cannot be generated under the partial revenue structure, when the probability of the system evolving to an efficient solution can only be increased by changing the allocation of the amount of information. The effect of the λ fluctuation interval on S is shown in Fig. 10. It can be seen that S is better when λ is in the range of 0.55 to 0.65.

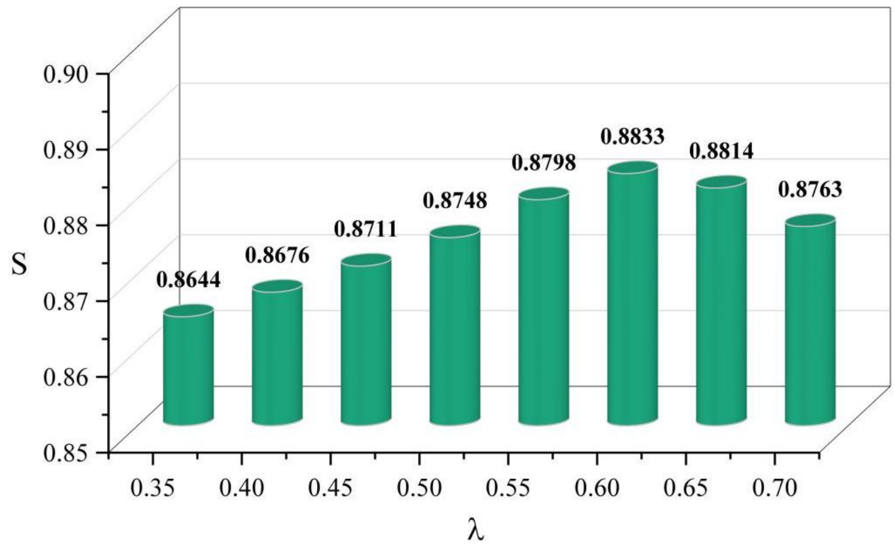

Figure 10: Effect of λ fluctuation interval on S

4 Conclusion

This paper adopts the evolutionary game method to model the cooperation mechanism between operators and system integrators in the IoT industry chain, and analyzes the factors affecting their long-term cooperation.

According to the results of the evolutionary game, S increases with the increase of the knowledge learning ability coefficients γ_1, γ_2 of the operator and the system integrator, and the higher the coefficients of the knowledge learning ability are, the higher the probability of both parties choosing to cooperate. When the operator and system integrator's separate R&D gains $\triangle W_1$, $\triangle W_2$ increase, S keeps rising. When the betrayal gain E_1, E_2 of the two sides of the game increases, S keeps decreasing, and the probability of cooperative R&D between the two sides of the game keeps decreasing. The distribution coefficient of excess returns of the system integrator is getting lower and lower, and its gains from cooperative R&D are getting less and less, and its probability of choosing cooperative R&D is getting smaller and smaller. When λ lies in the interval [0.35,0.6], S increases with the increase of λ.

The findings of this paper have the following implications for the choice of IoT economic development model and strategy.

(1) Reasonable benefit distribution mechanism and cost sharing mechanism will ensure that both parties of cooperation will obtain ideal benefits and realize win-win situation. Therefore, operators and system integrators should look for the optimal benefit distribution ratio and cost distribution ratio to promote the evolution of both parties towards cooperation.

(2) Under the competitive conditions, operators and system integrators should actively seek cooperation and take the initiative to show a cooperative posture, which will help the realization

of IoT industry chain cooperation.

Funding

This research was supported by the:

2025 Shandong Provincial Key Research Project in Arts and Sciences: "Financial Sustainability Study of Shandong Public Cultural Cloud Platform" (Project ID: L2025Z05160667);

2023 Annual General Research Project of Shandong Education Science "14th Five-Year Plan": Research on Curriculum System Construction for "Field Engineer" Training in Vocational Education (Project Number: 2023YB171);

Shandong Vocational Education Teaching Reform Research Project: Research and Practice on the Construction of Efficient Classroom for Core Courses of Big Data and Accounting Major Empowered by Digital (Project Number: 2023082).

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