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Service Pricing Decision in Cyber-Physical Systems: Insights from Game Theory

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Abstract—In Cyber-Physical Systems (CPS), Service Organizers (SOs) aim to collect service from service entities at lower price and provide better combined services to users. However, each entity receives payoffs when providing services, which leads to competition between SOs and service entities or within internal service entities. In this paper, we first formulate the price competition model of SOs where the SOs dynamically increase and decrease their service prices periodically according to the number of collected services from entities. A **g**ame based **s**ervices **p**rice **d**ecision (GSPD) model which depicts the process of price decisions is proposed in this paper. In the GSPD model, entities game with other entities under the rule of "survival of the fittest" and calculate payoffs according to their own payoff-matrix, which leads to a Pareto-optimal equilibrium point. Numerous experiments demonstrate that the GSPD model can explain the price dynamics in the real world, and also can help decision makers a lot under various scenarios.

Index Terms—Cyber-Physical Systems, game theory, price decision, cooperation rates

1 Introduction

Cyber-Physical Systems (CPS), integrate a vast variety of static and mobile resources, including computing devices [1], crowd sensing networks, sensor/actuator networks [2], and so on, it has better performance than the capabilities of existing systems. In CPS, each device can sense and collect information from the surrounding environment and provide services through exchanging information, those services are called communication services (CS) [3]. Generally, devices which directly sense information from the surrounding environment are called Cyber-Physical Systems entities (called service entities or entities). For example, the crowd sensing networks (CSNs), which leverage the ubiquity of sensor-equipped mobile devices to collect information and provide a new paradigm for solving the complex sensing applications from the significant demands of people's lives [4]. the CPS Organizers (SO) collect some services(referred to as the simple Service, SS) from entities, then composite these services and provide the public (or user) with a higher level of combined services (CoS), such as VTrack [5] for providing omnipresent traffic information and NoiseTube [6] for making noise maps [6].

In CPS, there exist complex interactions among SOs, entities and users. Price competition between SOs and users was previously studied by Walrand [7]. Maximizing profit is the primary concern for SOs, which might be achieved by having high price level for users and low investment on the infrastructure. On one hand, users wish to maximize their utility by consuming high QoS with low service price. The main price competition models are Cournot and Bertrand competition models [8]. In the Cournot model, SOs decide the extent of investment on their infrastructure through competing with each other. On the other hand, in the Bertrand model, SOs engage in price competition to attract more subscribers for a given infrastructure capacity. An important question for SOs is how much of the network capacity should be provisioned and how high the service price should be. In summary, these studies mainly focus on the pricing decision problems between SOs and users. SOs play a decisive role in the price competition through increasing and decreasing the price according to their investment and payment. Price competition between the provider and service consumers first aroused people's concern, and there are many related researches on it [9-12].

However, this paper is mainly concerned about price competition between SOs and entities as well as internal entities. In fact, the two competitions play a vital role in the new service model. With the development of the CPS, traditional service model and the traditional price competition have had a fundamental change. In the traditional service model, SOs provide the user with a service by investing in a certain infrastructure, all provided services in this system belong to the SOs, and the types of services and service ability are limited. In the CPS, services are not only produced by SOs. The system can provide better services for users than the traditional service model. The service interactions are completed by adopting the communication service, which enables the ubiquitous CPS entities to play its great potential, so as to form a new generation of service system model.

In the CPS, there are price competition relationships between SOs and entities. Each SO makes an investment

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in the collection and organizing services, SOs want to receive more service at lower price to improve the quality of combined service for the user (or customer) to maximize its profit. In general, the more simple service (SS) collected by SOs, the better of the quality of combined services provided by SOs. For example, when VTrack collects traffic information services, the incomplete collected traffic information will definitely affect the use of the users. On the contrary, the more information collected by SOs, the better quality of service provided by the VTrack and the more detailed traffic information can be received by users. However, it is not good for SOs to collect too much information, because gathering information require payments, and the quality of QoS is difficult to improve by increasing the amount of information. The number of received services is controlled by adjusting service price dynamically. SOs will raise the service price to stimulate entities provide more services when the number of collected services is little; thereby, in order to obtain maximum profits, when the collected services are too much, SOs will reduce the price so as to decrease the number of collected services and acquisition cost. In general, because the information collection comes with a certain price (or services), entities want to sell their services at a higher price, and hope to buy the services at the lowest price (such as λ). Therefore, there exists an equilibrium points for the service price between SOs and Entities.

Theoretically, finding such equilibrium points is not easy. The situation becomes even more complicated when competition is among entities. In CPS, entities compete not only with SOs, but also with other entities. In the CPS, there are two ways for getting the information by entities (or simple service, SS). (1) through sensing the surrounding environment (i.e. SS); (2)through the information interaction among entities, for example, in the traffic information service system, if the entity A and the entity B mutually exchange information, both entities will respectively get two items of information. In Delay Tolerant Network (DTN) [16], the entity A and the entity B can game with each other; both players help their opponent to relay information and also get information from their opponent. The entities will obtain payoffs when they sell the information (or services) to SOs at calibration price. In the reality, the behaviors of each entity are naturally selfish, each entity hopes to receive service at the minimum cost and receive payoff λ after submitting to SOs. In the CPS, interaction between the two entities can be regarded as a game. If the two entities cooperate with each other in an interaction, it can be seen as a cooperative game. In a cooperative game, entities give certain payment to others and get service from others. However, entities don't always cooperate with others in a cooperator-defector pair. So the game between the entities is very complicated and has a great deal of uncertainty in the CPS model.

The complexity and uncertainty of game between entities have effect on price competition, which leads to price decision becoming extremely difficult. First of all, in the real world, each entity adopts different strategies when interacting with different entities; some entities can adopt the win-stay, lose-shift (WSLS) strategy [11, 13], and some entities can adopt the Tit-for-tat (TFT) strategy. Entities with different strategies play the game with others based on the rule of "survival of the fittest". Some entities will die because of competition failure in the game, and some entities can gain competitive advantage in the competition and occupy the dominant position. The dynamic game process between the entities makes the number of collected services change, which results in changing the price and the game situation between entities in turn. The game between SOs and entities or internal entities forms a complicated system. The price competition among entities is rarely seen in the traditional service model. To find price equilibrium points become extremely complex and difficult in the complicated system.

Researching on the complex price competition rule can help the SOs and entities to choose the appropriate competition strategy and the optimal price so as to occupy the dominant position in the competition. For a long time, the researchers want to establish a suitable model to describe the complex price competition system. The main problems of concern are: for the SOs, (a) the pricing problem of SOs. Considering the number of services received by SOs is ω, for a given network, how much the price λ should be set by SOs when the user provides a service? If the price λ is too high, the more services provided, and the more prices need to be paid by SOs, therefore the efficiency may be lower. (b) When the system is to reach stability, how much are the total expected payment and payoff? (c) How is the number of services provided by entities with different strategies? When SOs are facing the dynamic market, according to the different strategies, entities adopting effective pricing strategy have the most important significance.

For entities, the key issue of concern is: (a) the pricing problem of entities. Entities' price refers to the payment γ promised to give to the other entities which provides the service. SOs offer payment λ to entities when entities report services to SOs. The price λ is relatively stable in a short period of time; the entity obtains little payoff if the service price γ of the entity is too high, which can cause death to the entity. While the service price γ of the entity is too low, other entities have no desire to interact with them, which leads to the entity being at a disadvantage to competition. Thus, setting a reasonable price is the first condition of ensuring an entity's survival. (b) In the game of entities, whether the lower service price or the higher price is better for entities? Which price competition is the dominant factor in the game? (c) Whether the service price of entities with different strategies will finally reach the same state in the evolution of the game? (d) What kind of strategy should be adopted in the game to make an entity win in the competition?

Although there are a lot of studies on price competition model [9-11], most of the researches are mainly aimed at the price competition pattern between service providers and service Consumers (Service Provider VS Services Consumers, SP-SC). A **g**ame based **s**ervices **p**rice **d**ecision (GSPD) model is proposed to depict price competition phenomenon of the CPS on the principles of game theory in economics. The main contributions of our work in this paper are as follows:

(1) A **g**ame based **s**ervices **p**rice **d**ecision (GSPD) model is proposed to depict price competition in Service Organizer VS CPS Entities (SO-E) and Entities VS Entities (E-E). In the GSPD model, each entity has its own payoff matrix, increasing the payoff can stimulate entities to game in order to get more payoffs. Entities will also reduce the number of game when reducing the payoffs of entities; this is consistent with the characteristics of the CPS. The entity is glad to provide more services if the entity obtains more payment in the game. On the contrary, the entity will weaken its participation degree if the entity obtains negative payoffs in the process. The GSPD model reflects the actual situation of CPS. In the GSPD model, the entity will reduce the service price if the total payoffs of the entity grow in the process of game. SOs control the number of received services within the scope of the intended target through adjusting the price unit. The results of theory and experiments show that the proposed GSPD model can dynamically depict the price competition process of SO-E as well as E-E. The GSPD model can also reach the equilibrium points for the service price of SOs and entities at initial price, the number of entities, and the number of services.

(2) The issues which the manager concerned can be answered through the GSPD model. For the manager, they can get the optimized price λ before they put their service into market through the proposed GSPD model; payoff and payment can be predicted under the price λ. The income contributions to the system of population with different strategies can get. Optimize the price λ, payment and payoff by investigating the distribution and density of population and the frequency of the game, such as network structure, which provides valuable decision-making support for managers. For the Entity, GSPD model can give the service price γ of an entity with different strategies and what strategies can make an entity obtain more payoffs in competition. The GSPD model can also reveal that the service price γ of entities with different strategies will not be equal, and the entities with the lowest price γ are not always the biggest payoff. And the biggest payoffs of entity are not necessarily the lowest price γ.

(3) Through our extensive simulation study, we demonstrate that the GSPD model can reach equilibrium points for the service price in various network parameters and under different network structure. The change of system payoffs in different network structure and the price of different network parameters of the system will be given, which help the manager and the entity to obtain the optimal price. Through the analysis of a large numbers of experimental results, it demonstrates that the GSPD model is more suitable to reflect the services pricing competition phenomenon in CPS, which contributes to the theoretical development of literature.

The rest of this paper is organized as follows: In Section 2, the related works are reviewed. The system model is described in Section 3. In Section 4, a **g**ame based **s**ervices **p**rice **d**ecision (GSPD) model for services price decision in CPS is presented. Section 5 is experimental results and comparison. We conclude in Section 6.

2 Background and Related Work

Many competitive models have been used to describe price competition between the user and SOs, and SOs and entities. The relevant researches can be seen in the Ref. [3, 9-12]. The Stackelberg game is a strategy which describes the game between the user and SOs [17]. The Stackelberg game consists of two stages. In the first phase, different SOs declare the price strategy p, and tell the price to all users. Users formulate their own service consumption plan q according to the received pricing strategy p. After determining the price strategy, there are non-cooperative game problem about competition for network resources; Nash equilibrium is a game method to solve this problem. In the second phase, SOs adjust their prices to further obtain the optimal utility after SOs get the strategy of service consumption of the user.

The price war in communication service is observed in Ref. [3, 18]. In such scene, if SOs reduces its price to increase revenue or to monopolize the entire market, then the other operators will also reduce their price or increase the capacity of the network to match the price leader, the reason is that network capacity is directly related to the QoS of users. However, lower price and higher QoS under the same price level have great effect on users. The price down competition will occur repeatedly among all SOs, eventually every SO's revenue will decrease and reach a new equilibrium [3].

The above price competition game can't describe the game relationship among entities. When John Maynard and George R Price proposed that use the method of the "strategy" and mathematics to predict the biological group competition phenomenon in 1973, Evolutionary game theory were originated [19]. Evolutionary game theory is different from the classical game theory which is to highlight change dynamics of the strategy–it influences the balance of the whole system not only through the quantity of the strategy, but also through the density or frequency of the different strategies in the population [20]. Evolutionary game theory is important to explain lots of complex challenges in biological systems. The rule of "Survival of the fittest" is the basic laws of evolutionary game. The payoffs in the game theory are converted to fitness in the evolutionary game (fitness) [20]. It is different from the classical game theory, one important part of evolutionary game theory is replicator dynamics [20]; this rule mainly describes how to reproduce the next generation of individuals with high fitness in the competition group, while the individual with low fitness will die from the group.

In Ref. [20], we show that it is not always true that remembering history for the entity can promote currency in evolutionary games. The participant can remember the last game history (that is, 1-step memory), it is enough for games. So this work adopts the 1-step memory mechanism to code the game history and strategy [20]. In the 1-step memory, all entities only remember the last game history. Cooperative is coded into "1" and defection is coded into "0", There are totally 4 types of historical interactions with 1-step memory: 00 (the sponsor player defects and the opponent defects), 01 (the sponsor player defects and the opponent cooperates), 10 (the sponsor player cooperates and the opponent defects), 11 (the sponsor player cooperates and the opponent cooperates). Though this work can not directly apply in the GSPD model，it gives us some deep thought for game model.

3 The system model and Problem statement

3.1. System model

The adopt system model in this paper is similar to Ref. [3]. We use Fig. 1 to illustrate a Cyber-Physical Systems (CPS). The system consists of three parts：(a) Users i.e. consumers. Users get provided services by giving corresponding payment to SOs. (b) Service Organizers (SOs) collect simple services (SS) from entities and obtain payoffs by providing more comprehensive and better services to users. At the same time, it needs to pay corresponding payment to entities which provide simple services. (c) N CPS entities, i. e. entities. Entities are source gatherer of simple services in the CPS [21-24]. All services are come from entities in the SOs. Entities gain most of primitive simple services (SS) through sensing their surrounding environment. An Entity needs to pay a certain cost for collecting SS and obtain payoffs by submitting SS to SOs. In addition, Entities can also get more SS or benefits through the interaction among entities (game).

There are many researches on price competition between the user and SOs. This article mainly focuses on the more complex price competition between SOs and the entity and among entities.

The main purpose of SOs is to provide more comprehensive and better services to users. But in order to collect those simple services, SOs publish some service gathering tasks to the area of interest (AoI) for the application, for example, traffic information collection can be regarded as a simple service gathering task. Entities in the AoI receiving the service gathering task determine whether to participate in service gathering. If an entity decides to conduct the service gathering, it will collect services and submit the collected simple services to SOs and obtain given payoffs according to the service price set by the SOs. At last, the SOs publish their available composite services for users and get some payoffs from users. It is same as Ref. [3], we only consider one service application in CPSs, which requires continuous service gathering (traffic jam alter, environmental monitoring and protection such as noise, smog/haze detection, citizen-journalism, tourist query, etc.) [3].

Fig. 1. The game based services price decision framework in CPS

There are N entities in the system $\{e_1, e_2, e_3, ..., e_N\}$, each entity represents a person or a mobile device. Game among entities can be conducted to make their own profit maximization, such as environmental monitoring, the traffic networks monitoring. After entity e_1 and entity e_2 receive the service gathering task from the SOs, they sense the surrounding environment and get some simple services respectively. If e_1 and e_2 gave services to each other when entity e_1 games with entity e_2, a cooperative game is formed in this way. In this situation, e_1 and e_2 not only have its own services, but also receive each other's services. Thus they can report more services to their own SOs and obtain more payoffs. At the same time, e_1 and e_2 need to pay the payments for the received services. In Fig. 1, e_1 requests services from e_4, e_4 gives services to e_1, while e_1 doesn't pay corresponding payments to e_4, resulting in e_4 only bearing the cost in the game, and e_1 can receive services without any payments, this is the half cooperation game where e_1 defects and e_4 cooperates. On the contrary, e_1 provides services to e_3, but e_3 don't provides promised payments to e_1; that is, e_1 cooperates and e_3 defects. Finally, e_4 and e_5 don't provide services with each other, so these two entities don't obtain payoffs in the game.

The system model can be adopted for many applications such as from Machine-to-Machine (M2M) communication to Device-to-Device(D2D) communication. For example, Device-to-Device (D2D) communication refers to a radio technology that enables devices to communicate directly with each other [25-26]. The terminal users will be able to benefit from the number of services in D2D. In the D2D communication, it may even allow users to experience benefits in terms of smaller communication latency, increased data rate and reduced energy consumption [22, 23, 25-26]. In a Device-to-Device (D2D) network, each device can be regarded as entity which can collect simple services, it can also transfer the services from the other entity to a certain location under the condition that the payment can be given. If each entity is trusted, the D2D network will run smoothly. In such situation, each entity helps the other entity relay services and obtains the payoff in cooperation with each other. But in the open D2D networks, it does not guarantee that every entity is credible. Some selfish entities don't want to transfer other entity's services and hope other entities to help him transfer services. All of above phenomenon can be described by using the game based services price decision (GSPD) framework in this paper. GSPD model encourage entities to collaborate in the game and promote the exchange of services, maximize the payoff of the entities. Price competition mechanisms are adopted in the GSPD model, which lead the entities to be willing to cooperate with the other entities in the game and relay services, while the others don't want to play with the selfish entities because of the low collaboration ratio. This model is designed to make the D2D network run smoothly.

3.2. Game Strategy

In this paper, we adopt the same game strategy we discussed in Ref. [20], as shown in the Table 1. Considering the total number of entities is m in crowd sensing network, There are n =16 kinds of different game strategy. Each entity adopts one strategy from the 16 kinds of game strategy. One population refers to the entities with the same game strategy. The number of entities in the same population is $\{v_1, v_2, v_3, ...v_n\}$, $\sum_{i=1}^{n} v_i = m$. The ratio of population reflects the situation of different entities adopting different game strategy in real life, while the composition and the proportion of entities with different strategies are different in different regions, and different times. So the real world can be reflected in our model.

Table 1: The coding of 16 strategies

Game history of Two entities	The next step of the first one							
00(defect, defect)	1	1	1	1	1	1	1	1
01(defect, cooperate)	1	1	1	1	0	0	0	0
10(cooperate, defect)	1	1	0	0	1	1	0	0
11(cooperate, cooperate)	1	0	0	1	1	0	1	0
00(defect, defect)	0	0	0	0	0	0	0	0
01(defect, cooperate)	1	1	1	1	0	0	0	0
10(cooperate, defect)	1	1	0	0	1	1	0	0
11(cooperate, cooperate)	1	0	1	0	1	0	1	0

3.3. Problem statement

In order to provide the composite services with a certain Quality of service (QoS) to users, SOs need to collect the simple services from entities. SOs attracts entities to collect and submit SS by issuing the purchase service price. The required numbers of SS υ_e are certain in a small period. SOs can provide composite services with a certain QoS as long as simple services υ_e are collected. The higher the service price λ of SOs is, the more simple services collected by SOs due to the high enthusiasm of the entity. In order to make its quantities reach to υ_e , SOs will reduce the price λ when the number of collected services is bigger than the expected value υ_e . On the contrary, if the number of simple services is below υ_e, SOs stimulates entities to take an active part in the collection by raising price λ , which makes the entity provide more simple services. SO's goal is to ensure receives a certain numbers of simple services by using the price competition mechanism. In this paper, the basic units of time is a fixed service collection cycle, the length of time of the cycle is T , if the current time is t , the current time belongs to $i = \lceil t/T \rceil$ time slot. SOs expects to collect $\upsilon_e(i)$ simple services in the i th time slot, and in the time slot of i , SOs collect $\upsilon(i)$ simple services. Thus the SO's goal is to make the difference υ_Δ between $\upsilon(i)$ and $\upsilon_e(i)$ is minimize, that is.

$$Min(\upsilon_\Delta) = \min \sum_{i \in t} \left| \upsilon_e(i) - \upsilon(i) \right| \quad (1)$$

And the total payments need to be paid by SOs are:

$$\mathrm{M} = \sum_{i \in t} \left(\upsilon(i) \lambda_i \right) \quad (2)$$

For entities, m entities can adopt different strategies in order to get maximize payoffs after SOs publishes service gathering tasks. This situation is complex for different entities to choose different game strategies in the price competition process [12]. For entities, an entity obtains payoffs λ when it reports services to SO. Considering the obtained payoffs $\zeta_{A,j}$ of the entity A when playing game with others in the j_{th} game, the payments are $\vartheta_{A,j}$. The net benefits in the game are $\varpi_{A,j}$ = $\zeta_{A,j}$ - $\vartheta_{A,j}$. After n time games, entity A's total payoffs in a time slot are

$$\varpi_A^{total} = \lambda - q + \sum_{j=1}^{n} \left(\varpi_{A,j} \right) \quad (3)$$

$\lambda - q$ is the net income when entity A reports services to SOs, q is the cost when entity A senses service. The aim of entity A is to maximize ϖ_A^{total} .

Considering entity A plays game with other entities with cooperative strategy in the j_{th} game， entity A can get a service. On the contrary, the number of services is 0. $\upsilon_{A,j}$ represents the number of received services of entity A in the j_{th} game. So the cooperation times of entity A after n times games in a time slot, that is, the number of services is

$$\upsilon_A^{total} = \sum_{j=1}^{n} \left(\upsilon_{A,j} \right) \quad (4)$$

And the received services are the total services received by all entities involved in the service collection tasks in a time slot:

$$\upsilon = \sum_{X\in E} \upsilon_x^{total} = \sum_{X\in E}\sum_{j=1}^{n}\left(\upsilon_{X,j}\right) \quad (5)$$

where X means an entity, and E is the set of all entities. We can know the purposes of GSPD model are

$$\begin{cases} optimize\ \lambda,\ \lambda_x \\ \quad Make \\ \quad Max(\varpi_X^{total}) = Max\left(\lambda - q + \sum_{j=1}^{n}\left(\varpi_{x,j}\right)\right) \quad (6) \\ \quad Min(\upsilon_\Delta) = \min\sum_{i\in t}\left|\upsilon_e(i) - \upsilon(i)\right| \end{cases}$$

SO formulates reasonable price to minimize the difference υ_Δ. The entity determines the service price λ_x to make the price ϖ_x^{total} maximization.

The price decision process of λ and λ_x are very complex through analysis of above researches. Therefore, the pricing problem of dynamic evolution of CPS equilibrium points has never been studied. The main purpose of this paper is to find a game based price decision model which can depict the price decision process for CPS. For SOs, through GPSD model, once the total numbers of services are given, the GSPD model can quickly evolve into robust and equilibrium points. Each entity dynamically adjusts the price λ_x in order to obtain the biggest payoffs. What's more, the following questions can be solved through the GPSD model. For the manager, they can predict the service price λ of SOs as well the price λ_x of each entity at equilibrium points in advance. What kind of population (i. e. the set of entities with same strategy entities is called population) will be involved in the game, how is the price of different population, and different entities in the same population. How much payoffs does each entity get? What's the cooperate rate of the system?

4 GAME BASED PRICE DECISION MODEL

There are many researches about the price competition between the service provider and service consumer in Cyber-Physical Systems, while there are few researches on service pricing between SOs and entities or among entities. The price competition of the SO-E and E-E become the main way of Cyber Physical Systems. Therefore this paper proposes a new model to depict the new price competition process of the CPS.

4.1. Game matrix

Table 2 shows the payoff matrix of a traditional 2×2 game [19]. In CPS, the entity A plays game with the entity B, where both players obtain $\lambda - \vartheta$ if they are in cooperation with each other, both players obtain 0 if they both defect, the cooperator obtains $-\vartheta$, and the defector λ is in the cooperator-defector pair

Table 2: The classic game matrix

		entity B	
		cooperation	non-cooperation
entity A	cooperation	$\lambda-\vartheta,\lambda-\vartheta$	$-\vartheta$, λ
	non-cooperation	λ, $-\vartheta$	0, 0

In the traditional game, the game matrix of each entity is the same. But this does not reflect the actual situation of the Cyber-Physical Systems. In a real Cyber Physical Systems, each entity does not adopt the same game matrix when play with another entity, but the best game matrix should be make maximum profit. In addition, an entity does not give services to other entity without any payoff when playing game with others. In a classic game matrix, the entity does not obtain payoffs when the entity plays game with other entity, but only obtains payoffs when the entity reports services to SOs. The little payoffs make other entities don't want to play with the entity. It also doesn't conform to the actual CPS.

In the GSPD model, a improved game matrix is proposed. In the GSPD model, each entity publishes their payoff matrix when playing game with others; some payoffs can be obtained from the other entity if it reports services to the entity. Entity A can give the price ζ_A to another entity which provides services, and the entity A will obtain payoff λ when reporting the services to SOs. And the entity A needs to pay the price q, thus server price ζ_A of the entity A should meet the following relations:

$$\lambda - \zeta_A - q \ge \varsigma \quad | \; \varsigma \ge 0 \quad (7)$$

Only under the condition of $\varsigma \ge 0$, the entity can obtain payoffs when it receives services. The entity always wants to set ζ_A as low as possible, so as to make the profits as high as possible. However, in the actual market price competition, the low price does not always improve the competitiveness of the entity. The entity prefers to play game with entity for high price to obtain more payoffs. But the low price does not always improve the competitiveness of the entity. The higher the price is, the lower the income obtained by the entity. In the game, if the entity A cooperates and Entity B defects, the entity A gives a service to entity B and doesn't get any payment ζ_B from the entity B, which results in the entity A lose the price q and obtain little payoffs. If the entity A obtains little payoff ς in a cooperator game, and loses the price q in a defector game, the payoffs can be lower than the payment, which leads to the payoffs are 0 or even negative. So it is necessary to set an appropriate price for the entity.

In GSPD model, ζ_A be set:

$$\zeta_A = \partial(\lambda - q) \quad (8)$$

∂ is a high coefficient in the initial state, the entity gradually reduces the value of ζ_A in order to gain more benefits in the process of the game. The entity's total revenue increased with the decrease of price ζ_A, that is, the entity can gain competitive advantage when reducing the price ζ_A, so reduce the price ζ_A until the price reaches balance. In the GSPD model, the way of calculating the price of an entity is: if the entity obtains payoffs respectively are ϖ_{i-1}^{total}, ϖ_i^{total} in the i - 1 and i time slot, the price ζ of the entity needs to be adjusted according to the following function.

$$c(.) = 1 + \frac{1}{\chi}\left(\frac{\varpi_i^{total} - \varpi_{i-1}^{total}}{\varpi_i^{total}}\right) \tag{9}$$

In the equation (9), χ is the velocity correction of ζ, $\varpi_i^{total} - \varpi_{i-1}^{total}$ means that the difference between the payoffs of the current time slot and the payoffs of the previous time slot, which is divided into χ parts. The less χ, the greater speed of evolution, the bigger χ, the speed of evolution is more stable.

Unlike the previous game matrix, service payoff is not fixed when the entity reports services to SOs, it is also change as the process of game. Therefore, it also needs to reflect the situation in the GSPD model. But the price λ is determined by SOs. In our model, we also correct the service price λ in order to make the difference small between actual collection service quantities and the desired services, namely $\min \sum_{i \in t} |\upsilon_e(i) - \upsilon(i)|$. The total received services are $\upsilon(i)$ in i th time slot. The service prices λ of SOs need to be adjusted according to following function.

$$f(.) = 1 + \frac{1}{\upsilon_e(i)}\left(\frac{\upsilon_e(i) - \upsilon(i)}{\mathrm{K}}\right) \tag{10}$$

In equation (10), K is the velocity correction of λ, $\upsilon_e(i) - \upsilon(i)$ means the difference between the expected received services quantities and the current actual received services quantities, which is divided into equal K parts. This means that it expects to achieve the expected service number $\upsilon_e(i)$ after K generations of evolution. The lower the value of K, the greater the speed of evolution, while the bigger K, the speed of evolution is more stable. We put forward the payoff matrix of evolutionary strategy through the above analysis, as shown in table 3.

Table 3: The game matrix of the GSPD model

		Entity B	
		cooperation	non-cooperation
Entity A	cooperation	$f(.)\lambda - c(.)\zeta_A - q$, $f(.)\lambda - c(.)\zeta_B - q$	$-q$, $f(.)\lambda - q$
	non-cooperation	$f(.)\lambda - q$, $-q$	0, 0

4.2. Game strategy

Though game matrix is a model to depict the main part of CPS price competition, it also needs to deal with the game model in detail to depict the price competition process between SO-E, and E-E better in CPS. In practical context, the evolution of the system is also related to the cooperation ratio as well as the density and frequency of different strategies in the population.

(1) Cooperation ratio: In the real world, the entity would be glad to play game with the entity when an entity offers high payments and the cooperation ratio is also high in interaction. For the entity with relatively low payments, the cooperation rate drops when playing game with others and the betrayal ratio rises. The GSPD model reflects the reality phenomenon, a method proposed in the model, that is, to remedy the cooperation ratio on the basis of the entity service price ς in the game. Table. 1 gives the 16 kinds of game strategies with 1-step memory, in the traditional 1-step memory game, where the next step is certain according to the strategies of table. 1. In the GSPD model, the next step does some correction based on the model of our paper, the way is that let the entities run the reverse strategy at some probabilities. And correct probability is based on the degree of ζ_A deviation λ.

$$\varphi = \varepsilon\left(\frac{\lambda - \zeta - q}{\lambda}\right) \tag{11}$$

(2) The frequency of the game. The frequency of the game is the game times of the entity in a generation game (in a time slot). Obviously, the entity has little impact on the payoffs of the system if it doesn't participate in the game. While the game times of the entity has serious effect on the system. The model should encourage those behaviors which can promote the system evolution and impose restrictions on those behaviors which block system evolution. Therefore, in the GSPD model, we adopt the following incentive strategy.

After a round of games, each entity calculates its payoffs. If the payoffs are higher than the other entities of the system or higher than the average payoffs of its neighbors, the system increases the game times to promote its evolution in the next generation of game. Conversely, if an entity's payoff is lower than average payoffs of the system or below the average payoffs of its neighbors in a generation of game, this means that the entity is at competitive disadvantage in the competition, so the obtained payoffs are lesser. Based on the theory of evolution, the game times should be reduced for the decrease of payments in the next generation of game. We call this way that increases game times of the advantaged of population and reduces game times of the disadvantaged of population the "winner increases and loser decreases" strategy.

The "winner increases and loser decreases" strategy is consistent with the CPS. In CPS, the enthusiasm to participate in game can be increased if the payoffs are above the average in the process of game, which results in gaining more payoffs and becoming more active and positive. For that reason, those entities want to increase game times to increase their payoffs. And while for those entities whose payoffs is less than the average in the game, this will reduce the enthusiasm for the game or even cause them don't involved in the game. Therefore, in the GSPD model, g_{i+1} in the formula below means the game times of entity A in $i+1$ th generation.

$$g_{i+1}^{A} = g_{i}^{A}\left(1+\frac{\varpi_{i,A}-\overline{\varpi_{i}}}{\varpi_{i,A}}+\frac{\varpi_{i,A}-\overline{\omega_{i,A}}}{\varpi_{i,A}}\right) \quad (12)$$

g_{i+1}^{A} indicates the number of game in the last generation of game (i th generation), g_{i+1}^{A} means the number of game in the next generation of game ((i + 1)th generation). $\varpi_{i,A}$ denotes the payoffs of the entity in the i th game, $\overline{\varpi_i} = \varpi^{total}/m_i$ said that the average payoffs of the system in the i th generation of game, m_i means the total number of entities in the i th generation of game. $\overline{\omega_{i,A}} = \sum_{B\in N_k}\left(\varpi_{i,B}/N_A\right)$ said that the average payoffs of all the neighbors of entity k, N_k are the number of neighbors of the entity k.

4.3. Evolutionary strategy

In the CPS, in order to survive, the entity with different strategies constantly adapts to the environment in the process of game. So each entity updates their strategy with a certain probability in the game. Replicator rule is adopted in the GSPD model. Replicator rule is also named as proportional imitation rule [24]. When a round of games finished, entity A imitates a random neighbor B with a probability as described in the following equation (13).

$$P\left(S_A \to S_B\right) = \begin{cases} \varepsilon\left(\omega_B - \omega_A\right)/\overline{\omega}, & \omega_B > \omega_A \\ 0, & \omega_B \le \omega_A \end{cases} \quad (13)$$

S_A and S_B are the strategy of entity A and B, ω_A, ω_B are the accumulated payoffs of the entity A and the entity B in a round, $\overline{\omega}$ is the average payoff in the system. ε means adjustment coefficient.

4.4. The game based services price decision (GSPD) algorithm

In the GPSD model, there are 2 kinds of game, one is the game between SOs and entities, and another is the game among entities. The main idea of game between SOs and entities is: SOs set expected purchase service quantity $\upsilon(i)$ in i time slots, and then SOs receive $\upsilon_e(i)$ number of services in i the time, SOs adjusts the purchase price λ based on the difference $\upsilon_e(i)-\upsilon(i)$. The algorithm is as follows:

***Algorithm 1**: game based services price decision algorithm of SOs*

Algorithm 1: service price decision algorithm of SOs
Input: Predict the number of services $\upsilon(i)$ to be collected of SOs
Output: the price λ

1) i =1; *// i is the generation of game*
4) Do while ($i \le \Theta$ & system is unstable)
    For each SO π_s Do
        Computing $\upsilon_e(i)$ after a generation
        Set $f(.) = 1+\frac{1}{\upsilon_e(i)}\left(\frac{\upsilon_e(i)-\upsilon(i)}{K}\right)$
        Set $\lambda = f(.)\ \lambda$
    End for
5) End Do

The game among entities is more complicated. The entity e_A determines their initial price ζ_A based on determined price λ and adjusts the price ζ_A based on their earnings on the equation (9). But the difference from algorithm 1 is that the game among entities needs to adjust the parameters of several other aspects. This mainly includes: (a) Cooperation ratio, the entity chooses different cooperation ratio based on the equation (11); (b) the entity determines the game times according to the results of the last game, such as the equation (12). (c) The entity is in evolution on the basis of the probability in equation (13). This algorithm description is given in the form of pseudo code below.

***Algorithm 2**: services price decision algorithm of entity*

Algorithm 2: **S**ervices price decision algorithm of entity
Input: the price λ
Output: the price ζ of entity

1) i =1; *// i is the generation of game*
2) Do while ($i \le \Theta$ & system is unstable)
    For each entity e_A Do
        $\varpi_{A,i}^{total}$ =0; *//the payoff of entity A is 0*
        For (k =1; $k \le \hbar$; k ++)
            For (j =1; $j \le g_i^A$; j ++)
                $\varpi_{A,i}^{total} = \varpi_{A,i}^{total} + \lambda - q + \zeta_{A,i} - \vartheta_{A,i}$
            End for
        End for
        $c(.) = 1+\frac{1}{\chi}\left(\frac{\varpi_{A,i}^{total}-\varpi_{A,i-1}^{total}}{\varpi_{A,i}^{total}}\right)$
        $\zeta_A = \lambda - c(.)\zeta_A - q$ *//update price if entity A*
    End for
    For each entity e_A Do *//modify game parameters*
        $\varphi = \varepsilon\left(\frac{\lambda-\zeta-q}{\lambda}\right)$ *//update the Cooperation ratio*
        $g_{i+1}^{A} = g_{i}^{A}\left(1+\frac{\varpi_{i,A}-\overline{\varpi_{i}}}{\varpi_{i,A}}+\frac{\varpi_{i,A}-\overline{\omega_{i,A}}}{\varpi_{i,A}}\right)$
        // update the number of the next generation of game
        $P\left(S_A \to S_B\right)$;
        //according to certain probability evolution
    End for
5) End Do

5 THE EXPERIMENTAL RESULTS AND ANALYSIS

5.1. Experimental parameters settings

The experimental parameters are by default: There are 500 entities in this system, λ = 100, ζ =100, q =5. Each entity plays game with 9 randomly chosen neighbors for 90 times in the beginning of the experiment. Calculate the number of received services, if the quantity is lower than the expected value, SOs will increase the value of λ to motivate the entity to receive more services. Each entity determines their own service price ζ based on their income. The average payoffs are calculated according to the payoff matrix when the entity games with its' neighborhood. Each entity calculates the total payoffs after rounds of games, and then calculates the game times in the next generation of game according to their payoffs and the average payoffs of neighbors. If the game time is zero, the entity exits the game (or death).

In this experiment simulation, entities play game for 1000 rounds, each entity plays game with the other neighbors in each round of experiments, the number of game is calculated for the entity after each round of game according to their own earnings, each entity modifies the payoff matrix and adjusts the game strategy after each round of game.

5.2. The stability of the GPSD model

The model stability is test firstly under different network parameters. Steady state refers to the number of entities involved in the game, the cooperation ratio, the collected services, and the density of entity with different strategies no longer change along with the advance of evolution (or a very small change). We can see from Fig. 2-Fig. 10: the proposed model in this paper can smoothly reach the stable state under different network parameters.

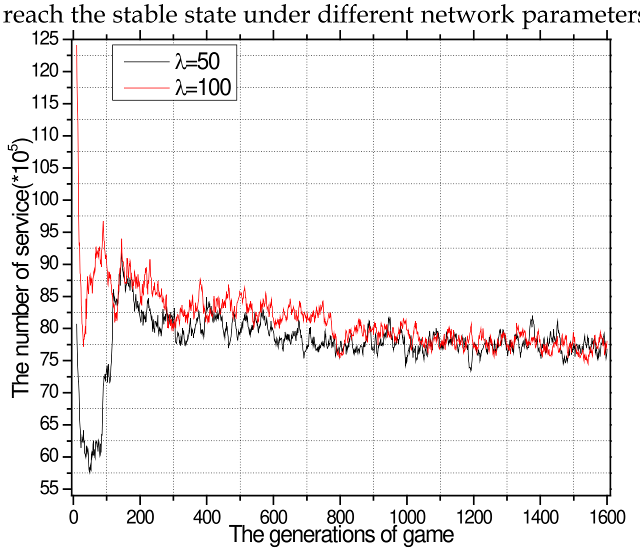

Fig. 2 equilibrium state at the given number of services

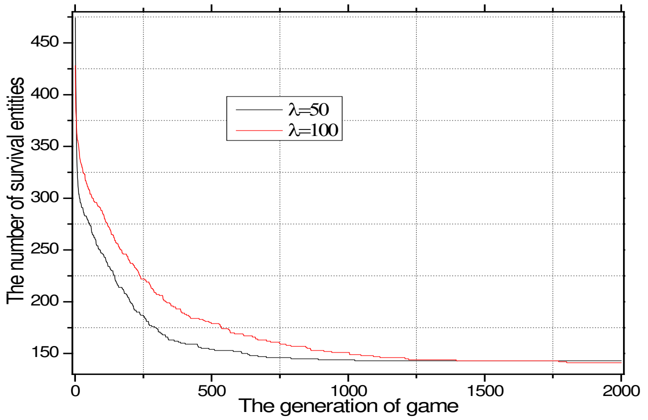

Fig. 3 The number of surviving entities

Fig. 2 shows the case of the number of services through the evolution of the system. We can see from Fig. 2, the overall trend is that the number of services is declining with the evolution of the system at first, and than the number of services increase slowly. The reason is that the payments ζ is high when an entity receives a service at first, the others are glad to play with the entity, and the more services can be received by the SOs. But at the same time because of the high price ζ, the entity obtains low price when reporting the service to SOs. In order to increase their income, the entity must decrease the price ζ, leading to the other entities unwilling to play with the entity with cooperative strategy, so the collected services are less. Sometimes, the lower service price may have bad effect on the entity. At last, the entity improves the service price ζ to reach the stable state. Fig. 3 reflects the case of the surviving entities in the process of the evolution of the game, the number of surviving entities is declining until it reaches stability. Some entities died due to the low total payoffs.

Fig. 4 reflects the case of the price λ of SOs in the process of evolutionary game. The price λ is rising until it reaches stable. Due to the initial price λ is too low, which leads the entities to be unwilling to participate in the game and the received services are low. In order to make the service reach to the expected value, improve the price λ to stimulate the entity interaction with others.

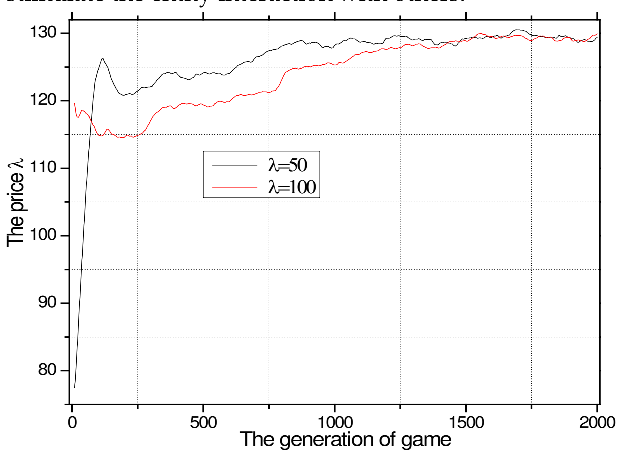

Fig. 4 The price λ can reach equilibrium state

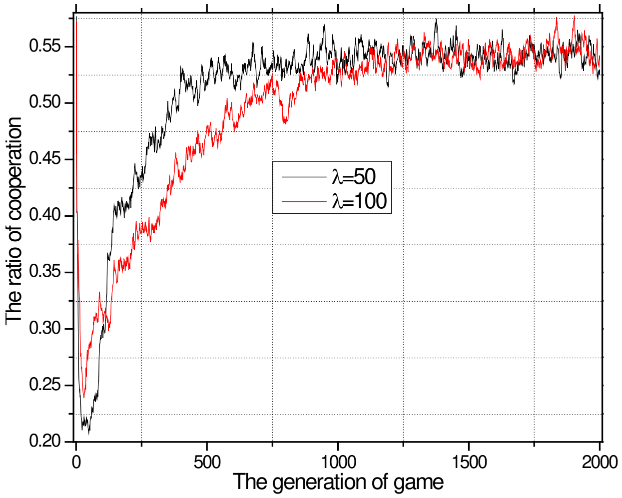

Fig. 5 The ratio of cooperation can reach equilibrium state

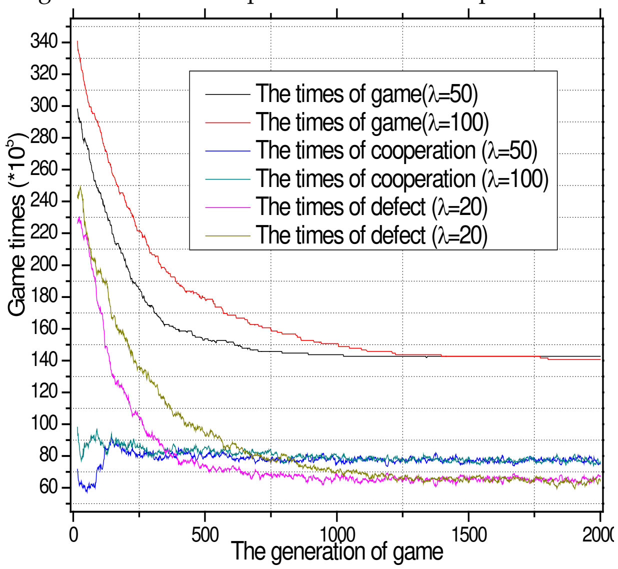

Fig. 6 The total game times, cooperation times, defect times in equilibrium state

Fig. 5 reflects the case of the cooperation ratio in the evolution of game, where the cooperation ratio is rising until it reaches stable. In order to receive more services from entities, SOs constantly increases the service price λ to stimulate the entity interaction with others. When the service price λ is increased, the entity is glad to play with others, so SOs can get more services, that is, the cooperation ratio is grown (Fig. 5). In Fig. 6, the times of game are declining with the evolution of game; the reason is that some entities died due to without any payoffs. Though some entities can increase the number of game, it is slowing and unobvious, the trend is declining (Fig. 6).

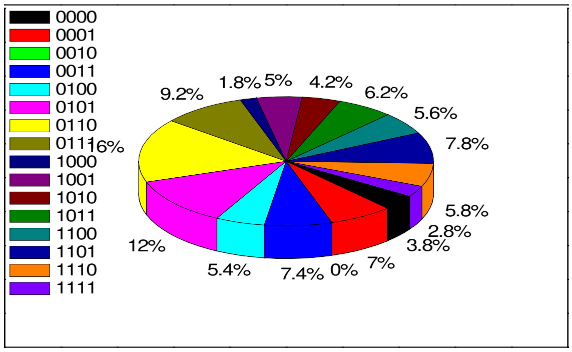

Fig. 7 the number of surviving entities for difference strategies (λ=50)

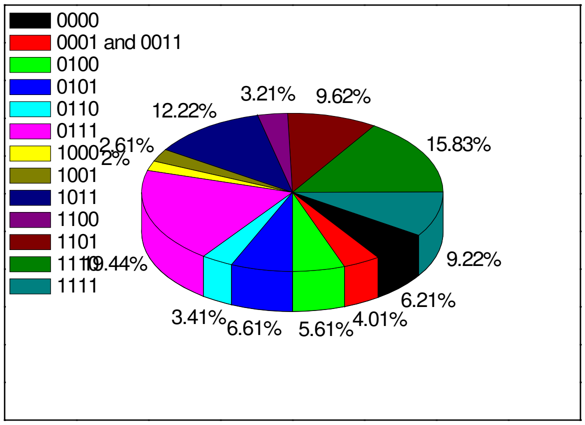

Fig. 8 the number of surviving entities for difference strategies (λ=100)

Fig. 7 reflects the case of the number of surviving entities for difference strategies when the price ζ is 50. "0110" is the best strategy in the service price ζ is 50, which means the entity with "0110" can have more survival than others. Fig. 8 reflects the case of the number of surviving entities for difference strategies when the price ζ is 100. "0111" is the best strategy in the service price ζ is 50, which means the entity with "0111" can have better survival than others. Comparing the results of above, we can obtain that the best strategy is different when the service price λ is different.

Fig. 9 illustrates how the difference of the average unit price of entities between different strategies, but the average unit price is falling when the system reach stability at fast speed in the evolutionary game, as shown in Fig. 10. The main reason is that the service price ζ of the entity is high when the entity receives a service, so the entity's average unit price is high; the entity must reduce the price in order to get higher payoffs during the evolution of system, so the entity gives little payments to the other entity which provides the service. The SOs gives higher payoffs to the entity, so the entity obtains high payoffs. Secondly, some entities died because of the little payoffs, which lead to the total entity unit price low.

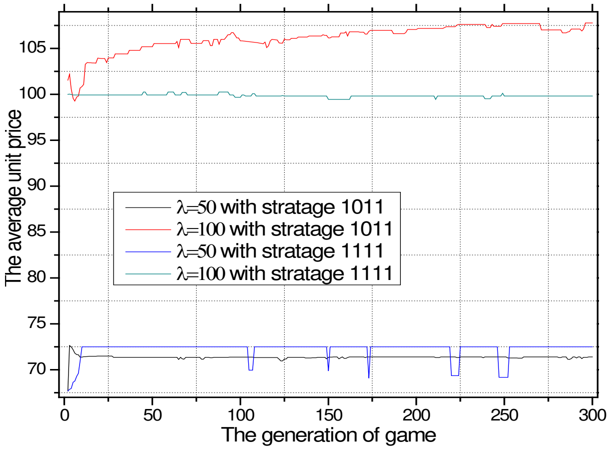

Fig. 9 The average price of each species

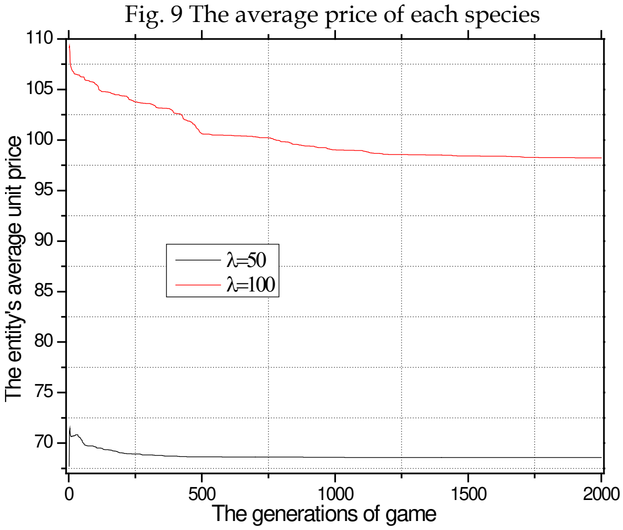

Fig. 10 The average price of entity

5.3. The network parameters effect on price

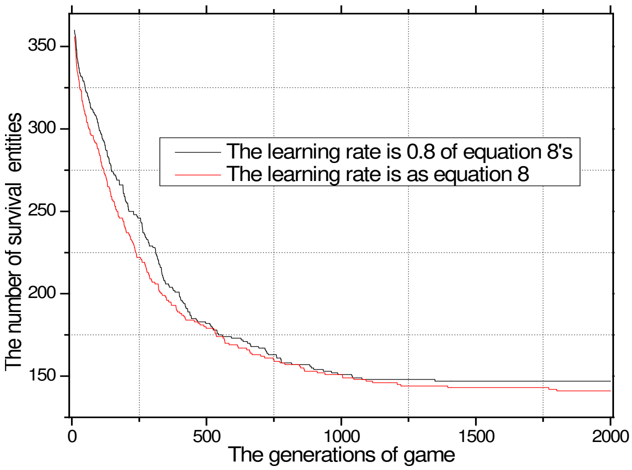

Fig. 11 The number of surviving entities

Fig. 11 shows the different evolution game speed have effect on the model. From the result of the experiment, when the evolution velocity is adopted as equation 8, In terms of the number of surviving entities, the larger the evolution velocity is, the less the number of surviving entities (Fig. 11)is. The reason is that the strategy with the competitive advantage will dominate the network at faster velocity when the evolution velocity is big, and the other disadvantaged strategies will die at faster velocity, which leads to fewer surviving entities (see from Fig. 11). Fig. 12 shows the different cost have effect on the model. It does not affect the speed of reach a stable state when using different payoffs (Fig. 12).

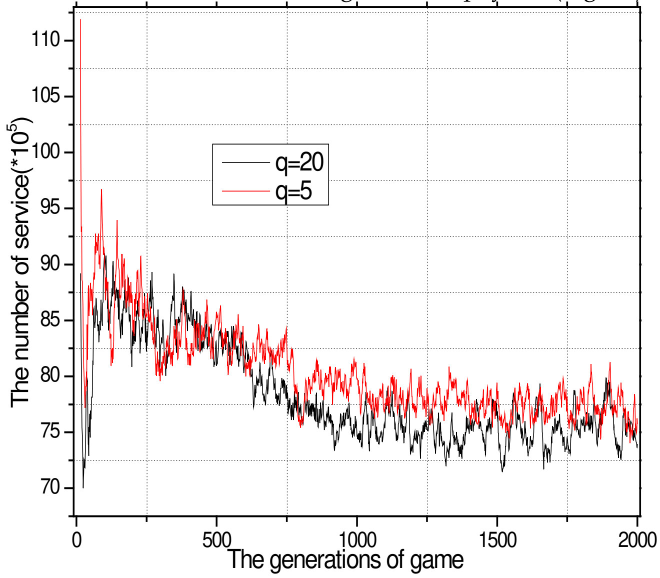

Fig. 12 The total payment with difference cost $-q$

5.4. The result of GPSD model

Whether the number of entities involved in the game have influence on the proposed model is also an interesting topic. We investigate this issue through a series of experiments (Fig. 13 - Fig. 15). First, when the number of entities increases, the cooperation ratio for the system significantly decreased due to the increase of competition, but it is still higher than payments in the condition of insufficient payments (Fig. 13). Second, the number of cooperation games in the system, the total number of games will rise as the system increases the total number of entities (Fig. 14), and the number of defect games in the system grows faster, so as to make the system cooperation ratio decline. Third, the number of surviving entities will also grow with the growth of the total number of entities involved in the game at very great degree (Fig. 15). Fourth, the given price λ has an obvious relationship with the number of entities; the more entities involved in the game is, the lower the price λ is (Fig. 16); the more the total number of services is, the higher the price λ is (Fig. 16). This shows that our model reflects the situation better. The average price of the entity has the same situation; the more entities involved in the game are, the lower the average price λ of the entity (Fig. 16) is, and the more the total number of services is, the higher the average price λ of the entity is(Fig. 16).

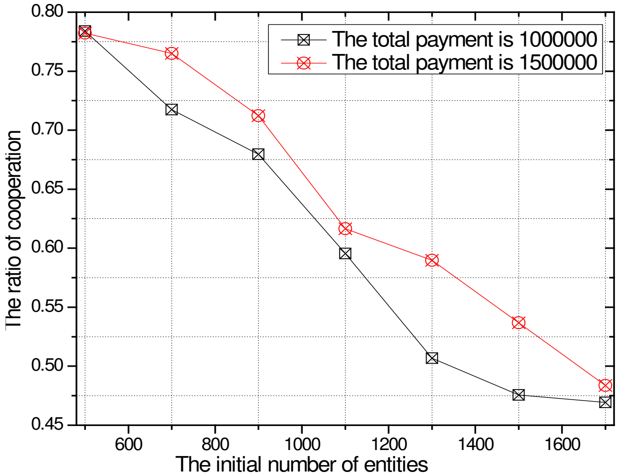

Fig. 13 The ratio of cooperation in stability state under difference initial entities

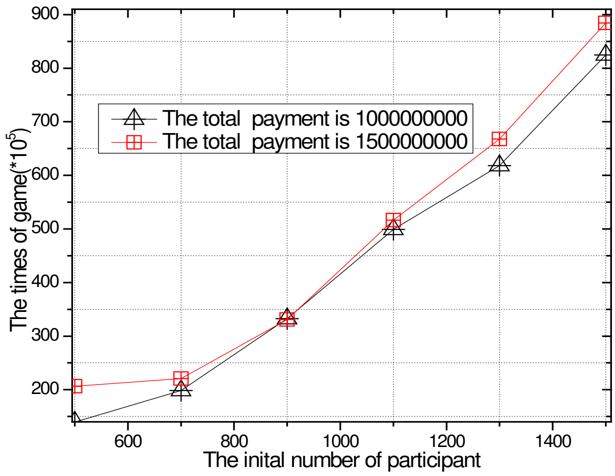

Fig. 14 The times of game in stability state under difference initial entities

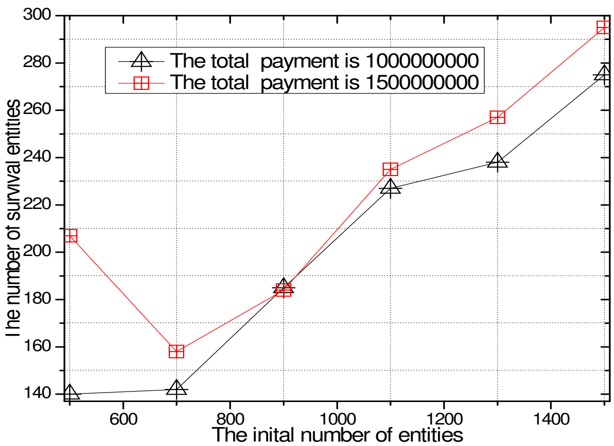

Fig. 15 The number of survival entities in stability state under difference initial entities

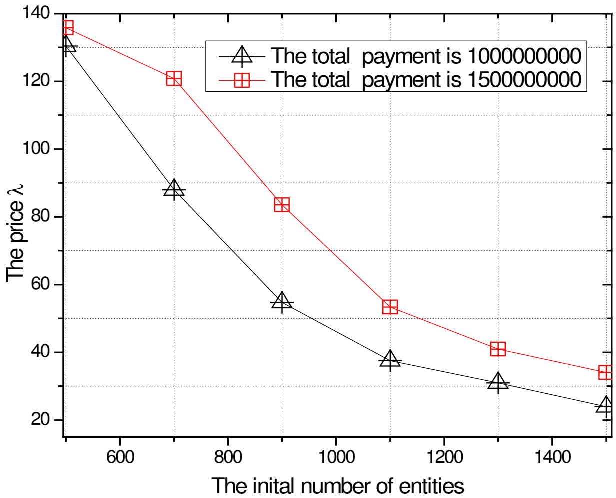

Fig. 16 the price λ of SOs in stability state under difference initial entities

6 Conclusion

In this work, we study how to depict the price decision process between SOs and service entities, and among entities. A game based services price decision (GSPD) model is proposed to depict the phenomenon of price competition in Cyber-Physical Systems (CPS). We demonstrate that proposed model can better depict the process of price competition in CPS, especially the price competitive relationship among entities which is ignored in previous studies. Through a lots of experiments, it is found that the game model can reach rapidly to a stable state under the condition of any given parameters for the system, and entities with difference strategies have different optimal price, even the entity with same strategy have different optimal price when the system reach to stable. All of these are consistent with the looser price competition situation in the actual CPS, it explain that GSPD model can better reflect the diversity and complexity of this kind of price competition in the CPS .Through the model, we can predict in advance what price is optimization for SOs, the average payoffs for each entity, each entity's game times, and cooperation ratio for the system, which provide a good decision support for decision makers.

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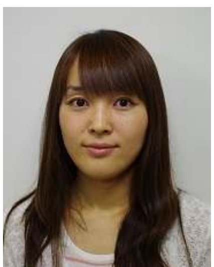

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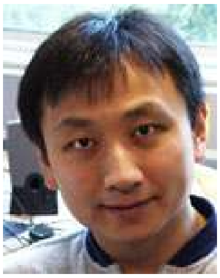

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