Research on the Cooperative Behavior in Cloud Manufacturing

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Abstract. With the development of information and network technology, a new type of manufacturing paradigm Cloud Manufacturing (CMg) is emerged. In the CMg environment, geographically distributed various manufacturing resources (MgSs) and manufacturing capabilities managed by different companies are encapsulated as different manufacturing services under the support of cloud computing, Internet of Things and virtualization technologies. CMg can provide on-demand MgSs for the manufacturing tasks (MgTs) of different customers in the network manufacturing environment. One MgT usually needs different MgSs owned by different companies to form a coalition for working together to finish it. However, being an autonomous entity, each MgS generally makes decisions in light of its own interests, so it is difficult to maximize the collective interests of the coalition. The cooperation among the MgSs in the same coalition is an effective way to maximize the collective interests. Hence, how to motivate MgSs to cooperate mutually is been paid more attention in cloud manufacturing environment. In the paper, the evolutionary game theory and the learning automaton are employed to model the decision-making process of MgSs. And a punishment mechanism is introduced to incentivize the mutual cooperation of MgSs. Furthermore, the Blockchain as a data storage structure is adopted to record the behaviors of the MgSs to prevent from falsifying their feedback. At last, the agent-based modeling is used to model and simulate the process of MgSs working together. The simulating results reveal that the punishment mechanism is effective in promoting the cooperation among MgSs from various perspectives.

Keywords: Public good game · Incentive mechanism · Learning automaton Agent-based modeling and simulating

1 Introduction

Cloud manufacturing (CMg) as an emerging service-oriented manufacturing paradigm has been applied in many fields accompanied by the coming of the industrial 4.0, which encapsulates MgSs and manufacturing capabilities into manufacturing services. Due to the complexity of the MgT and the limitation of capacity of MgSs, one MgT usually needs geographically separated MgSs owned by different companies to form a coalition for working together to finish it with less time, less cost and higher quality [1–3]. To

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realize the popularization and efficiency of CMg, the cooperation among the MgSs is emphasized. However, the MgSs are usually selfish to avoid the cost of cooperation and get the profits at the cost of others, which is difficult to maximize of the collective interests. Hence, the cooperation among the MgSs is quite significant. Relevant references have mentioned the importance of cooperation [1–3] but deeply studied the cooperation among the MgSs are scant. The cooperation among rational and intelligent individuals still remains a great challenge. The paper concentrates on the cooperation among the MgSs by employing the tool of agent-based modeling and simulating [4].

The interests of each individual are not only depending on its own behavior but also on the others' behaviors in the same coalition. A suitable theory to analyze the conflict of interests is evolutionary game theory, which has been a popular mathematical model to analyze the problem from an evolutionary perspective [5]. The public good game is multiplayer game in which several individuals decide simultaneously to choose the behavior whether cooperation or noncooperation. The collected interests are multiplied by a factor and equally distributed to every individual no matter what the behavior is taken. It provides an effective theoretical framework for the dynamic and uncertain cloud manufacturing environment to analyze the conflicts of interests among the MgSs.

In generally, the decision-making is performed with the stochastic imitation of the more successful behavior [6–9]. The learning automaton [10] is a type of decision-making method, which the individual learns the optimal behavior from the unknown stochastic environment. The learning automaton has many applications, such as the clustering [11], the prediction [12] and so on. In the paper, the learning automaton [10] is applied to update the psychology of MgSs according to the response from the environment and in turn to update the probability distribution of the behavior using the response and the learning algorithm.

As a solution to the dilemma of cooperation, many aspects of punishment are already investigated. The cooperators punish defectors based on the tolerance threshold [13]. Reference [7] found that individuals tend to follow the strategy of majority and put forward that the individual with the majority strategy will punish the minority individual. Reference [9] referred that the conditional punishment and unconditional punishment. Reference [8] introduced the third party supervision. On the one hand, most of the previous literatures address the problem of cooperation on the regular network (i.e., grid network) or on the irregular network (i.e., small-world network). In the paper, the research is extended into the specific circumstances. The network is dynamic and uncertain in the CMg, which brings the challenge to the research. On the other hand, the strength of the punishment based on the historical behavior is rarely considered in the existing literature. In the paper, the historical behavior recorded in the blockchain that based on the time-effect is taken into consideration in CMg.

The following of the paper is organized as follows. In Sect. 2, the network model is built to describe the relationship among the MTs and MgSs. And then the evolutionary game theory is applied to analyze the conflicts of interests among MgSs. Next, the incentive of the punishment is designed to promote the cooperation among the MgSs. Finally, the learning automaton is used to decision-making for MgSs. In Sect. 3, the results of the simulation and performance analysis are presented. Lastly, some concluding remarks and further research works are pointed out in Sect. 4.

2 The Model and Problem Formulation

The simulation model can be divided into three parts: (1) Network model; (2) Game model; (3) Behavior model. The model can be described as $\Gamma = (G, B, U)$, where $G = (T, S, E)$ means the network, T is the agents of the MgTs, S is the agents of the MgSs and E are the edges that represent the relationship between the MgSs and the MgTs. B denotes the behavior space of the MgSs. U defines the rules of decision-making among the MgSs.

2.1 Network Model

The MgTs and MgSs form the relationship of service, which forms the complex connections among them [2]. The relationship can be described using the bipartite network [14] in Fig. 1, which is a branch of complex network [15]. $T = (T_1, T_2, \cdots, T_n)$ denotes a set of the MgTs, each of which is accomplished by a coalition of MgSs $S = (S_1, S_2, \cdots, S_m)$. One MgT has its own property $T_j = (t_j,\ g_j, r_j)$ and the concert annotations are showing in Table 1. The $S_\mathrm{i} = (Mind_i, ca_i, b_i, c_i, ct_i)$ represents the properties of the MgSs and the specific meaning of which shows in Table 2. The decision-making of S_i changes dynamically with the MgTs' completion. For the T_j, the S_i has to undertake the cooperation cost c_i when taking the behavior of cooperation to make the maximize the interests of coalition but costs nothing when adopting the behavior of noncooperation to maximize own interests.

Table 1. The properties of the MgT

$T_j = (t_j,\ g_j, r_j)$	Description
t_j	Completion time
g_j	Complexity of the MgT, which represents how many MgSs are need for MgT
r_j	The profit ratio

Table 2. The properties of the MgS.

$S_\mathrm{i} = (p_i, ca_i, b_i, c_i, ct_i)$	Description
P_C	Cooperative belief, locating in [0, 1]
ca_i	Capacity, which represents that can handle how many MgTs simultaneously
b_i	Behavior: 0(Cooperation) or 1(noncooperation)
c_i	Cost of cooperation
ct_i	Contribution value, which holds 0 or 1

Specifically, the formation of the network has the following four stages. Firstly, the network is initialized with $m_0 = 1000$ MgSs and $n_0 = 0$ MgTs. n tasks entering the

CMg each time. Secondly, the service selection is mentioned by using the method of the bet wheel of selection based on the number of the historical connections. And the algorithm of the selection is as following:

Step 1: Calculate the number of historical transactions of the MgS:

$$p'(S_i) = d(S_i) \tag{1}$$

Step 2: Calculate the cumulative transactions of the MgS:

$$pp(S_i) = \begin{cases} \sum\limits_{i \in m} (p'(S_i) + a), d(S_i) < \mathrm{ca}_i \\ \sum\limits_{i \in m} (p'(S_{i-1}) + a), d(S_i) = ca_i \end{cases} \tag{2}$$

where a denotes the initial reputation value of the MgS and assuming as 2 in the paper considering that every MgS has a chance to participate in the coalition of MgT. When the number of the MgTs that the MgS is handling attains the maximum limit, the algorithm ignores it and hence promotes the traversal of the MgSs.

Step 3: Calculate the cumulative probability:

$$p(S_i) = \frac{pp(S_i)}{\sum\limits_{j=1}^{m} pp(S_j)} \tag{3}$$

The probability of the MgS selected is proportional to the cumulative probability.

Thirdly, the relationship of service between the MgSs and the MgTs is mapped to the relationship among MgSs, which is facilitated to analyze the behaviors of MgSs. If the MgSs have joined the same MgTs, there exists connection among them. Lastly, the accomplish time of the MgT decreases to zero gradually and then the MgT exits the CMg.

2.2 Game Model and Punishment Mechanism

Once the network is constructed, the game model is constructed based on the game theory. A realization of high-quality MgT requires the successful coordination of efforts by multiple MgSs. However, the non-cooperators are widespread since the MgSs are rational and selfish expecting to maximum their own interests but cost anything. So each MgS has a tendency to take noncooperation behavior [19].

Evolutionary game theory in behavioral economics provides adequate evidence to analyze social dilemmas and it has been a suitable model for studying the conflicts of interests among the MgSs [16].

The public good game is a multiplayer game that meets the requirements of the group action of MgSs in the same coalition, which is facilitated to analyze the conflicts of interests. Hence, the paper adopts the pubic good game to analyze the problem. The public good game is a model that the MgSs joining for the same MgT to form a coalition as showing in Fig. 1. The interests of the coalition collected by the effort of each individual are multiplied by a profit ration r, with $1 < r < N$ and then divided equally among the individual irrespective of their effors. So the profit of the MgS according to different behaviors can be given as:

$$\begin{cases} \prod_C' = \frac{r \times n_c}{N} - c \\ \prod_D' = \frac{r \times n_c}{N} \end{cases} \tag{4}$$

where c denotes the cost of the cooperation. N represents the number of the MgS participating in the same coalition. n_c denotes the number of MgSs in the same coalition that adopts the cooperative behavior. In generally, the $\prod_C'$ and $\prod_D'$ mean the corresponding profits of the cooperator and non-cooperator. The total payoff of the MgS is accumulated from all the coalitions it participates.

Due to the existing of the conflicts of the interests, the non-cooperators is wide-spread. Hence, the incentive mechanism is required to exerted to the non-cooperators. The paper adopts the mechanism of the punishment. Most existing punishment mechanisms fail to consider the timeliness of historical behavior and the corresponding strength. To handle the change of punishment strength over the historical information, an time decay index inspired by the forgetting curve [17] is added to the calculation in Eq. (5).

$$\beta_{\mathrm{i}} = \begin{cases} 1, & j = k \\ e^{(-1/j)}, & 1 \leq j < k \end{cases} \tag{5}$$

The time decay index gives a higher weight to the current behavioral performance than the past. Then, the calculation method of the strength of the punishment based on the effect of time can be described as:

$$tru = \begin{cases} \frac{\sum_{j=1}^{k-1} tr_i^j \beta_j}{\sum_{j=1}^{k-1} \beta_j}, & k \neq 0 \\ 0, & k = 0 \end{cases} \tag{6}$$

where the tr_i^j is the historical transactional behavior, which is the number of the cooperation divided by the total transactions. k indicates the number of the transactions.

Combining the punishment mechanism, the profit of each MgS is readjusted as:

$$\begin{cases} \prod_C = \prod_C' \\ \prod_D = \prod_D' - \partial(1 - tru) \end{cases} \tag{7}$$

where ∂ is the strength of the punishment.

In the process of recording historical transactions, the transaction information often faces risks such as being tampered, which affects the trustworthiness of the data and the effect of punishment. In addition, it is also necessary to consider how to acquire the historical transaction information. The blockchain is a data structure that combines blocks together in a chain and holds the properties of decentration. The hash value of each block is attained by the contents of the block and the hash value of the previous block. And each block contains the hash value of its previous hash value. And The hash value has the property of changing a bit of content to cause the hash value to change a lot. Hence, it provides a data storage structure and guarantees the irreversibility and transparency of the data. In the paper, the feature of the blockchain is employed to record the historical transaction information and keep the information transparency. The Fig. 1 illustrates the specific diagram of the manufacturing and the record of transaction information.

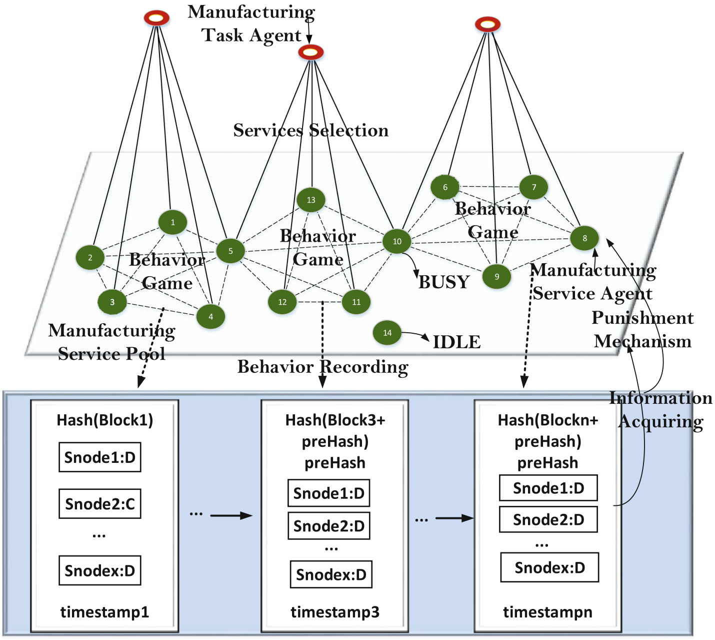

Fig. 1. Illustration of the cloud manufacturing

2.3 Decision-Making Based on the Learning Automaton

The scale of the CMg is getting larger and the collaboration among the MgSs is getting more frequent. The behavior of one MgS may affect its neighbors and one non-cooperative behavior will spread through the connection among the MgSs, which results in a cascading effect. Meanwhile, the MgS is an autonomous individual, which can be treated as an agent. Agents try to make decisions to maximum own interests [18]. However, the agents are bounded-rational, which incurs some mistakes in decision-making. Hence, the decision-making of the agents is of great importance and depends on many factors. These factors essentially reflect the psychology of the agents. The happiness of the agent increases when the payoff of the agent is higher than other agents or higher than itself and the probability of the corresponding behavior increases. Learning automaton is based on the response of the unknown stochastic environment to update the probability distribution of behavior to learn the optimal behavior [10]. Hence, the learning automaton is suitable for the process of decision-making [10] and the according principle is showing in Fig. 2.

The learning automaton can be represented as a six-tuple $<\mathrm{B}, \beta, \mathrm{P}, \mathrm{A}, \mathrm{F}, \mathrm{G}>$. For the convenience of analyzing, the behaviors of the agents are regarded as two types of behaviors that is the cooperation or noncooperation. $\beta \in [0, 1]$ represents the environmental signal. P stands for the probability of the behavior. A is the learning automaton algorithm. $F : S(\mathrm{t}) \times \beta \rightarrow S(t+1)$ is the state transition map. $G : B(P)$ map the current state as a function of the behavior and the probability of the behavior.

At each interaction, the agent updates the behavior from the behavior sets B using the probability distribution of behavior P. The behavior is acted on the environment to generate a stochastic environmental response β in turn to act on the agent to choose its next behavior.

Based on the learning process described above, the probability of the agent's behavior adjusting at time $t+1$ can be described as:

$$\begin{cases} P_C(t+1) = P_C(t) + v\beta(t)(1 - P_C(t)) \\ P_D(t+1) = P_D(t) - v\beta(t)P_D(t) \end{cases} \tag{7}$$

where $P_C(t) + P_D(t) = 1$, v is the learning rate and represents the learning ability of the agent. $P_C(t)$, $P_D(t)$ is the corresponding probability of the behavior.

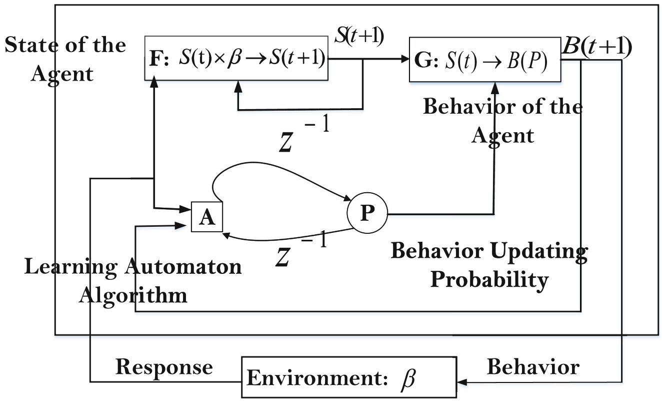

Fig. 2. The principle of the learning automaton

The agents often influence others and are influenced by others in their social environment. In order to maximum their own profits, the agents have to make decisions to coordinate their own behaviors with other agents. Considering the imperfect information, the agent can not only know its own profit, but also know partial information from the individuals who is familiar with it. Here, the average payoff from the neighbors is adopted as the information from others considering the imperfect information. And the w represents the learning weight and can be seen as the information transparency. The w is larger, indicating that the information transparency is smaller since the more information is from themselves. Hence, the environmental signal can be defined as following:

$$\beta(\mathrm{t}) = w \times \frac{(\overline{\prod(t)} - \overline{\prod(t-1)})}{\max\{\overline{\prod(t)}, \overline{\prod(t-1)}\}} + (1-w) \times \frac{(\overline{\prod(t)} - \overline{\prod_n(t)})}{\max\{\overline{\prod(t)}, \overline{\prod_n(\mathrm{t})}\}} \tag{8}$$

where $\overline{\prod(t)}$ and $\overline{\prod(t-1)}$ are the corresponding average payoff of the agent accumulated from all the transactions at the current and last transaction. $\overline{\prod_{\mathrm{n}}(t)}$ represents the average payoff accumulated from all the neighbors at the current transaction.

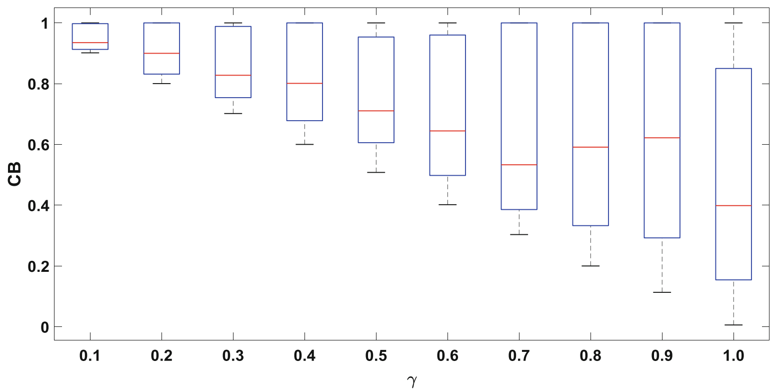

Fig. 3. The distribution of the cooperative belief. And the CB is the $P_c(0)$, which represents the initial behavior probability namely the initial cooperative belief.

Considering the society diversity and the individual heterogeneity, the agents often have a prior cooperative belief to update their behaviors to cooperation or noncooperation. Hence, the cooperative belief is elicited in the paper and the specific cooperative belief of agents is adopted as in [17].

$$P'_C(0) = 1 + \gamma(\chi^{-1/2} - 2) \tag{9}$$

where χ obeys the uniform distribution, that is $\chi \sim U[0,1]$. The γ represents the heterogeneity of the cooperative belief. Considering that the belief of cooperation is generally between 0 and 1, so the scope of it is scaled as following and the curve of corresponding distribution is shown in Fig. 3.

$$P_C(0) = \begin{cases} 1, & P'_C(0) > 1 \\ P'_C(0), & 0 \le P'_C(0) \le 1 \\ 0, & P'_C(0) < 0 \end{cases} \tag{10}$$

3 Simulation

Agent-based modeling and simulating is a suitable tool to study the complex system [19]. By combining the multi-agents and evolutionary simulation, the paper studies the behaviors among the agents of MgSs. Meanwhile, the effectiveness of the learning mechanism and punishment mechanism has been compared through evolutionary simulation based on the Repast Simphony-2.4.

In the paper, the effects of the punishment on pubic good games in which interactions are driven by the complex topologies on the environment of CMg are explored. For the sake of simplicity but without loss of generality, all the simulations are performed with $t_j = 3$, $g_j = 5$, $ca_i = 5$, $c_i = 1$, $ct_i = 1$ and $m = 1000$.

After building the simulation model in Repast, the probability of the behavior of each agent is sequentially updated when a full interaction ends. The average cooperative belief of the MgSs characterizes the level of the willingness or difficulty to cooperation, which is the key factor to evaluate the effectiveness of the simulation. Hence, the response measuring the average cooperative belief presenting at the steady state is investigated.

Based on the above model, the effectiveness of the punishment is verified from various perspectives. Firstly, in Fig. 4, the characteristic average cooperative belief is showed for different values of the strength of the punishment ∂. And then the simulations are extended for higher value of learning weight w and the learning rate v, which may shed light on the channels how the mechanism works.

In Fig. 4, one can see that the non-cooperators prevail with a slightly small value of ∂ and the cooperators continually expand while the non-cooperators gradually shrink for the appropriate degree of punishment as time evolves. For a fixed value of v, the threshold of the punishment attaining the stable state of cooperation decrease with the increase of w. For example, as $v = 0.2$, the threshold of the strength of punishment is required of 1 to achieve stable cooperation state when the $w = 0.2$ and is corresponding 0.8 and 0.7 when $w = 0.6$ and $w = 0.8$. Actually, this is in line with what one could expect. The information of transparency is lower with the larger w, indicating that the agents have less information about the others and learn more about its own historical transactional information. On the one hand, the more information the agent could attain from others, which means that it has more learning signal for making decisions and more chance to learn the signal of noncooperation to make own benefits maximization. On the other hand, the agent learning by itself can be blind and cannot hold the global information, which is more difficult for it to make the rational decisions.

For a fixed value of w, the higher the learning rate, the stable cooperation state is achieved by lesser punishment. The learning rate represents the learning ability for the agents. The most prominent scenario is when $w = 0.8$. For $v = 0.2$, the frequency of the average cooperative belief starts boosting when $\partial = 0.8$. The cooperative belief stands on a plateau of high value when $\partial = 0.7$ for $v = 0.5$ and appears the same phenomenon when $v = 0.8$. However, there is a bit difference in the time to attain the stable state, which $v = 0.8$ is more faster than $v = 0.5$ at $\partial = 0.7$.

In conclusion, the more information the agents can attain, the much easier for the agents to learn the noncooperation signal. The better the learning ability of the agents, the more promptly it leads to a plateau of cooperation with less strength of the punishment.

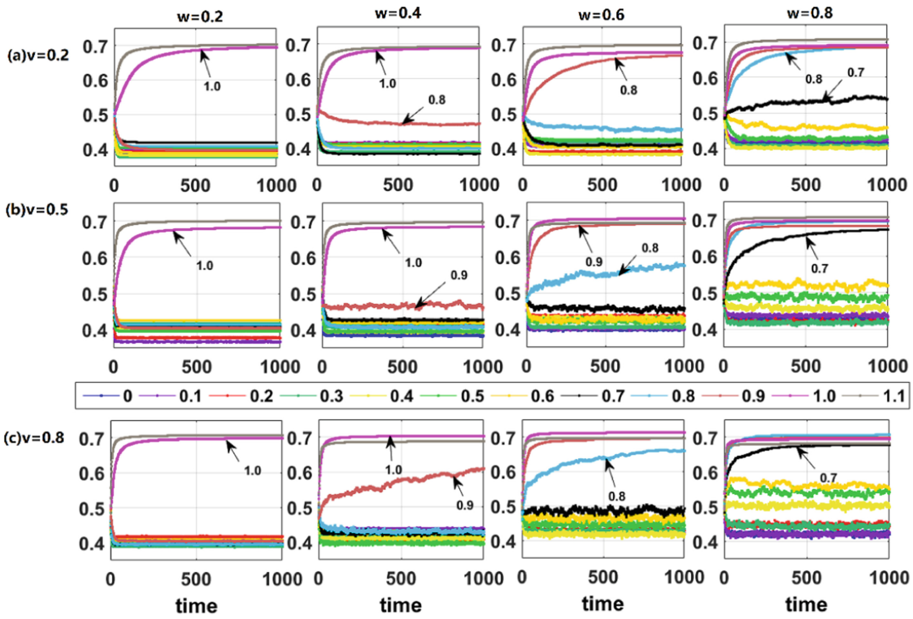

Fig. 4. Time evolution of the fraction of the average cooperative belief. (a) when $v = 0.2$; (b) when $v = 0.5$; (c) when $v = 0.8$. Every colored line describes how the parameters evolve in 1000 times with the number of MgTs is 100, $r = 2$. (Color figure online)

Next, in order to intuitively understand why the stable state is not in complete noncooperation or cooperation as the classic public good game, the average cooperative belief as a dependence of the number of MgTs is investigated with stationary $w = 0.5,\ v = 0.5, r = 2$ showing in Fig. 5. It can be observed that the average cooperative belief initially vibrates along with time and reaches the equilibrium after a long time in the end. The different number of MgTs reflects the different relationship of supply and demand in CMg. Obviously, it can be seen that the higher the number of MgSs demanded, the stable state of the cooperation level is lower. On the contrary, the stable state of the cooperation level is relatively higher. It is not hard to understand the phenomenon. Since the CMg is demand driven network model and the network is built by the preference mentioned above, there exists many idle MgSs when the demand for MgSs is lower. So the chance for MgSs to participate the MgT and the probability of interaction with other MgSs is small. These reasons drive them to keep the initial cooperative belief unchanged. For the number of the MgTs is 200, the maximum supply-demand ratio is 5:3 and the minimum is 5:1. So the average is 5:2, which leads to the almost 30% of the cooperative MgSs in the manufacturing service pool and is almost coincide with the simulation.

Finally, Fig. 6 shows that how the fraction of the cooperative belief *CB* is evolved with the changing of the initial cooperative belief and the strength of the punishment at different profit ratio. The results is calculated by doing 330 independent runs for 1000 times and take the average value of the last 20 stable states with fixed values of $w = 0.5,\ v = 0.5$ and $n = 100$.

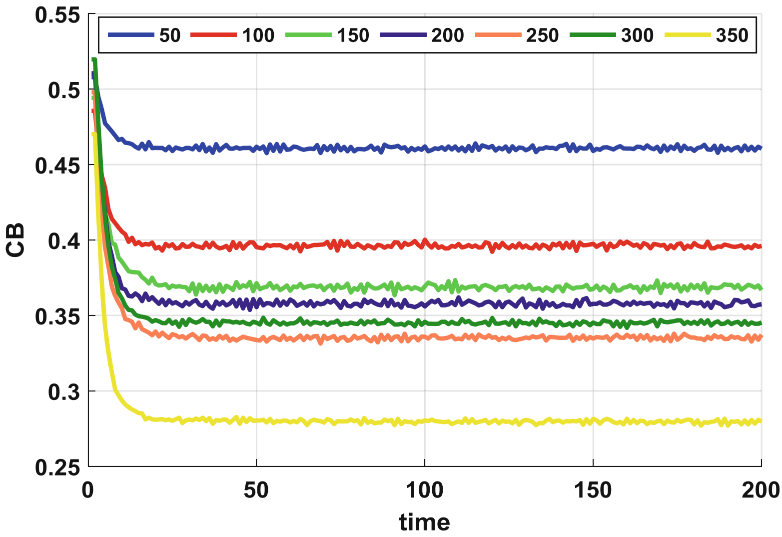

Fig. 5. Frequency of the cooperative belief with $w = 0.5$, $v = 0.5$, $\partial = 0$ and $r = 2$. Every colored line represents for different number of MgTs in 200 times. (Color figure online)

The turning point of the cooperative belief is different contrasting the three figures in Fig. 6. The turning point is $\partial = 0.8, 0.7, 0.6$ in sequence when the average cooperative belief starts to rise. When r is larger, the agent is much easier to learn the behavior from the coalitions with more cooperators. That is to say, the behavior of the agent from the coalition with more cooperators spreads much faster comparing with less cooperators since the cooperation can attain more interests than noncooperation. On the contrary, the behaviors from the coalition with less cooperators are more conductive to maximize their own interests when r is smaller. Moreover, the band is much wider to reach a high level of cooperative belief when r is larger. When $r = 2$, the band is narrow which is only from 0.9 to 1. When $r = 3$ and $r = 4$, it becomes wider from 0.7 to 1 and 0.6 to 1, which means that achieving the same average cooperative belief when reaches the equilibrium requires less strength of punishment as the r increases. Hence, the larger r is more conductive to help the cooperators to resist the invasion by non-cooperators. The result also conforms to the instinct of the real life, which the individual is more willing to cooperate when the profit ratio of the MgT is larger.

In addition, the initial reputation of the environment γ also has some impact to some degree. From the Fig. 6 (a–c), it can conclude that the γ is inversely proportional to the average cooperative belief, which is not hard to understand the phenomenon. The larger the γ is, the more widely distributed the initial cooperative belief is. That is to say, the median of the initial cooperative belief is relatively lower when γ is larger from Fig. 3. Hence, the different distribution of the initial cooperative belief leads to different point of equilibrium. Moreover, it also can attain high level of cooperative belief when appropriate punishment is exerted, which proves the effectiveness of the punishment from another aspect.

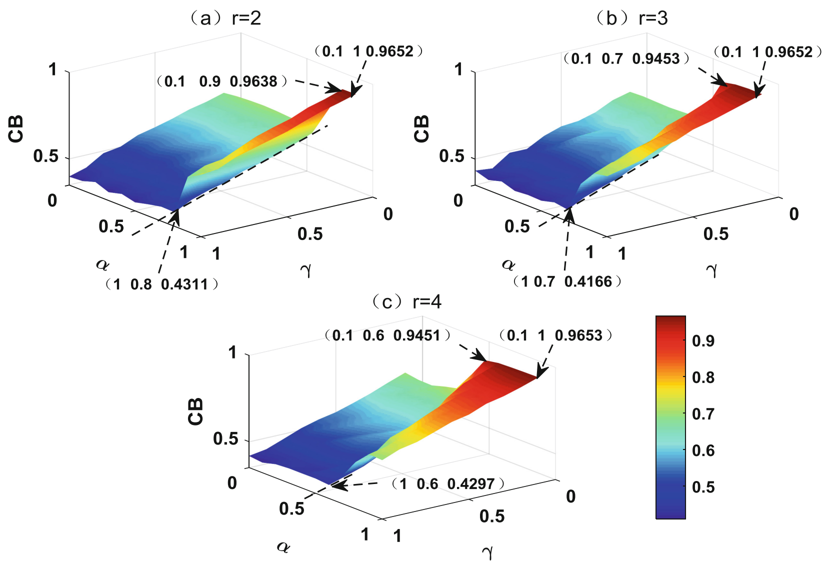

Fig. 6. The fraction of the average cooperative belief in dependence on γ (the initial distribution of the cooperative belief) and ∂ (the strength of the punishment). (a) when $r = 2$; (b) when $r = 3$; (c) when $r = 4$

In conclusion, by means of theoretical analysis and simulations, it has good performance when adopting suitable strength of punishment.

4 Conclusion

The phenomenon of the noncooperation widely exists among MgSs in CMg. In order to promote the cooperation among MgSs, the incentive mechanism of punishment is exerted to the MgSs. Unlike previous works, the historical transactional behaviors acting as a strength of the punishment is adopted to the paper. The process of the decision-making is essentially the changing of psychology of the agents caused by the environment. Hence, the learning automaton is proposed to update the psychology of the agents according to the signal of the environment and in turn to make decisions according to the psychology.

The paper verifies that such incentive mechanism of punishment has good performance in promoting cooperation in some degree from multiple perspectives. Firstly, different information transparency can have different thresholds of the punishment. The more information the agents can attain from the environment, the higher threshold of punishment the stable average cooperative belief requires. In addition, the learning ability of the agents has some influence on the final evolution but relatively smaller compared to the parameter of information transparency, which is much easier to learn the signal of cooperation with fast learning ability. Moreover, the profit ratio of the MgT is larger, the more conductive to boost the cooperation and less strength of punishment it requires to maintain the cooperation. Lastly, the initial reputation of the environment has some impacts on the point of equilibrium to some degree. Even if the initial environment is terrible, it can attain the high level of cooperation when applied appropriate punishment. In a word, the effectiveness of the proposed incentive mechanism is verified from multiple perspectives, which can significantly reduce the number of the non-cooperators when the proper strength of punishment is exerted.

As future works, more complex issues will be considered into the model to deeply understand of the impact of the evolution of the behavior in cloud manufacturing environment.

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