Study of Self-adaptive Strategy Based Incentive Mechanism in Structured P2P System

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Abstract. P2P systems provide peers a dynamic and distributed environment to share resource. Only if peers are voluntarily share with each other can system stably exist. However, peers in such systems are selfish and never want to share even with tiny cost. This can lead to serious free-riding problems. Incentive mechanisms based on evolutionary game aim at designing new strategies to distinguish defective peers from cooperative peers and induce them to cooperate more. Nevertheless, the behavior patterns of peers are versatile. Using only one certain strategy to depict peers' behaviors is incomplete. In this paper, we propose an adaptive strategy which integrates advantages of 3 classic strategies. These 3 strategies form a knowledge base. Each time a peer with this strategy can select one adjusting to system status according to the adaptive function. Through experiments, we find that in structured system, this strategy can not only promote cooperation but also the system performance.

Keywords: Adaptive function · Incentive mechanism · Evolutionary game

1 Introduction

Autonomous systems, such as P2P system have been widely used due to their openness and anonymity. The stability of such systems severely relies on the selflessness of peers and cooperation among peers. But peers participate in the system are rational. These selfish peers in P2P system tend to deny service request in order to maximize their own profit. Without any incentive, free-riding problem arises and performance of system declined. So promoting cooperation in P2P system becomes significant.

To encourage peers to voluntarily share in the system, incentive mechanisms are brought in. The essence of incentive is that through providing transaction history to help peers know the service requester and have a better decision on service granting. In this way, peers with poor history can hardly get service from others. To get better service in the following transactions, peers have to voluntarily make contributions, so that cooperation among peers promoted. Incentive mechanism can be divided into different types: micro-payment based [1], reputation based [2–4], genetic algorithm based [5], global trust based [6], market mechanism based [7], social norm based [8], etc.

Normally, peers in P2P system are treated as rational and strategic. They try to maximize their utility by participating the system but never want to cost anything. So evolutionary game [9] is a suitable tool to model the peers and interactions among

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them. It can reveal the pattern of evolution of the system. So many studies propose new incentive strategies to distinguish cooperative peers and promote cooperation among peers. By far, incentive mechanism based on evolutionary game mainly focus on designing reciprocative strategy. Peers with reciprocative strategy make decisions according to transaction history. Although these strategies can promote cooperation in certain scenarios, there're still limits of them. Wang Yuf. proves through theoretical and experimental analysis that without considering cost of getting transaction history, defecting is the only evolutionary stable strategy (ESS) [10].

Nevertheless, peers may behave differently and versatilely when confront same opponent in different environment. So, only one strategy to depict peers behaviors is not suitable. Reference [11] provides us a novel thinking of designing a new strategy. Inspired by Ye, in this paper, we propose a new adaptive strategy. We integrate classic incentive strategies into a knowledge base. Each time a peer interacts with another one, this peer can select one suitable strategy according the surroundings. Through simulation, we find that with adaptive strategy in the system, cooperation is promoted in different network structures as well as system performance.

2 Model P2P System with Evolutionary Game

2.1 Basic Assumptions

Most incentive mechanisms based on evolutionary game consider peers to be bounded-rational. Peers in the system want to maximize their utilities, so to get a better utility they tend to learn from peers with better utility than their own. However, peers may make mistakes for emotional, moral or other unknown reasons. That is why we call it bounded-rational. Besides, peers in the system are strategic. Strategies describe the decision making under various scenarios.

2.2 P2P Evolution Model

P2P evolution model as described in Algorithm 1, each round of transactions consists of three phases: transactions, payoff calculation and strategy update.

(1) Initialization

Before simulation, initialize network structure and all attributes of peers.

(2) Processing transactions

In this phase, each peer randomly sends a service request to their neighbors. Peers who receive requests decide whether to grant the service or not according to their own strategy and transaction history. The transaction history is provided by the system. Each peer will perform m requests and peer behaviors are recorded by the system.

(3) Payoff calculation

Calculate each individual's payoff and the average system performance.

(4) Strategy update

We carry a synchronized update method. At the end of each round, each peer decides whether to change their strategy or not by the same function.

Algorithm 1. Evolution Framework

```
Initialization;
for each round do
    for each peer i do
        for k=0 to m do
            Randomly select neighbor j;
            Peer i send a request to j;
            Peer j responses the request;
            if j is adaptive then
                Peer j implements adaptive function;
            end if
        end for
    end for
    Strategy update;
end for
```

2.3 Network Structure

In many previous studies, the P2P system is depicted as a well-mixed population. However, in real network environment, such a well-mixed population doesn't exist. So, besides a well-mixed population, we have chosen 3 common network structure square lattice, scale-free network and small-world network to better simulate P2P system.

Well-mixed Population. In a P2P system, we consider there to be no central server. Each peer can perform as a server as well as a client. So, in this structure each peer can interact with any other peer in the system.

Square Lattice. Square Lattice is a simple network structure. Peers are located on the vertices with von Neumann neighborhood and periodic boundary conditions. This ensures each peer has the same degree (<k> = 4).

Small-World Network. Small-world network was proposed by Watts and Strogatz in 1998 based on the structure of human society [12]. The formulation of small-world network starts from a circle. Then each node connects other K nodes with probability p. So the average degree of each node is K + 2. In this paper we consider a small-world network with average degree <k> = 4.

Scale-Free Network. In real networks, few nodes have many connections, and most nodes have only a few connections. To describe this attribute, scale-free network [13] is widely used. It's always used to describe the Internet, social networks, etc. In this paper, we use a scale-free network with average degree $\langle k \rangle = 4$.

2.4 Strategy Description

Nodes can be typically divided into 3 types:

ALLC: Always Cooperate. Provides services to other peers unconditionally.
ALLD: Always Defect. Denies requests from other peers unconditionally.
Reciprocator: Incentive strategy. Takes transaction history into consideration when responding to service requests.

2.4.1 Incentive Strategy

In transactions, a server decides whether to grant a service or not according to its strategy. Traditionally, two strategies are considered. ALLC (Always Cooperate), always grants a service unconditionally and neglects the requesters' transaction history; ALLD (Always Defect) never grants a service. However, to distinguish defectors from cooperators and implement incentive mechanism, a third strategy, reciprocity, is needed. Reciprocators, agents with a reciprocal strategy, will grant a service according to the requesters' transaction history. However, in a real system a reciprocator may follow different rules (reciprocal policy) to decide on a response. In this paper, we mainly consider 3 different classic reciprocal policies.

Mirror Policy. The mirror reciprocal policy is described as ones serving the requester with the same probability that the requester serves others. The probability is the ratio of the number of a requester serving others (N_{j_serve}) to the number being served by others ($N_{j\_get\_request}$).

$$p_{mirror} = \frac{Nj\_serve}{Nj\_get\_request} \tag{1}$$

Proportion Policy. Proportion policy can be described as one serving others according to the requesters' history of receiving service [14]. The probability is the ratio of the number of sending service to others (send_service) to the number of getting service from others (get_service).

$$p_{prop} = \min\left(\frac{\text{send\_service}}{get\_service}, 1\right) \tag{2}$$

Upstream Indirect Reciprocity Policy. This policy is proposed by Nowak in 2006 [15]. Peers with this policy may consider the last transaction when it was a service requester. If it got service last time, it will provide service to the other peer this time.

The calculation of serving probability relies on transaction history. But there exists a bootstrapping problem. When no transaction occurs, a reciprocator does not know to grant the service or not. To solve this problem, we adopt a tolerant policy. A reciprocator always serves when confronted with a requester with no transaction history.

2.4.2 Adaptive Strategy

Peers using an adaptive strategy have a knowledge base with three aforementioned incentive strategies. Each time they perform a transaction, peers will select one strategy with a certain probability, and adjust the probabilities through an adaptive function [11]. The adaptive function is described as Algorithm 2. The parameter $Q(S_i)$ is the intermediate value when determining the value of $\pi(S_i)$. $\pi(S_i)$ stands for the probability that strategy S_i is chosen for its following strategy. And $S_i \in S\{\text{Mirror}, \text{Prop}, \text{Indirect}\}$.

Payoff of peer j is denoted by p_j and $\bar{P}_j$ is the average payoff of peer j's neighbors (except itself). The strategy for choosing is influenced by its own payoff (effected by parameter α), neighbors average payoff (effected by parameter γ) and payoff gap (effected by parameter β). This function means the strategy with a lower payoff has a lower probability of being selected next time.

Algorithm 2. Adaptive function

```
For each peer j with adaptive strategy
```

$Q(S_i) \leftarrow (1-\alpha) \cdot Q(S_i) + \alpha \cdot p_j$

$\pi(S_i) \leftarrow \pi(S_i) + \beta \cdot (Q(S_i) - \gamma \cdot \overline{p_j})$

$\text{Normalise}(\pi(S_i))$

2.5 Payoff Calculation

In this paper, we consider the average payoff for each peer. While receiving a service, a peer will have a B bonus and a C cost while providing a service. The total payoff is calculated as (3). As for a well-mixed population, we consider that each peer with same strategy share a common payoff.

$$payoff_i = B * \frac{get\_service}{send\_request} - C * \frac{send\_service}{get\_request} \tag{3}$$

2.6 Learning Model

2.6.1 Learning Best Neighbor (LBN)

As described in Algorithm 3, after each round, each node will consider whether to change its strategy with the probability γa, which is called the adaptive rate. A peer will change to the neighbors' strategy whose payoff is best in its neighborhood (strategy with highest average payoff in well-mixed population) with probability as the sensitivity γs to payoff gap as shown in (4).

$$p_{i \to best} = \gamma s * (payoff_{best} - payoff_i) \tag{4}$$

Algorithm 3. LBN

```
For each peer i
   If randf() < γa
      p_{i→best} ← γs * (payoff_best  − payoff_i)
      If randf() <  p_{i→best}
         Peer I change strategy of best
      else
         Maintain its strategy
   else
      Maintain its strategy
```

2.6.2 Opportunistic Learning Model (OLM)

As shown in Algorithm 4, after each round, each node will randomly choose a teacher from its neighborhood with probability as the sensitivity γs.

Algorithm 4. OLM

```
For each peer i
    Randomly select a teacher peer j

     If i.strategy != j.strategy and i.payoff<j.payoff

       If randf() < γs
           Change strategy to j.strategy
       Else
           Maintain its own strategy
```

3 Simulation

3.1 Experiment Settings

We carry out our experiments in a well-mixed population, square lattice, scale-free network and small-world network, respectively. All these structures contain 2500 peers and the same average degree <k> = 4 (except well-mixed population). Initially, the fraction of cooperative peers (ALLC and R) and defective peers (ALLD) are equal, and the specific fraction is (ALLC, R, ALLD) = (0.4,0.1,0.5). Without special emphasis, we use the parameter listed in Table 1.

Table 1. Parameters

Symbol	Definition	Value
N	Size of population	2500
$<k>$	Average degree of network	4
B	benefit when getting a service	3
C	cost when providing service	1
α	how individual payoff influences strategy choosing	0.2
β	how payoff gap influences strategy choosing	0.3
γ	how neighbors' average payoff strategy choosing	0.85
steps	steps of evolution	5000
m	transactions per node	100
γ_s	sensitivity	0.04
γa	adaptive rate	0.1

3.2 Influence of Network Structure

The well-mixed population is the most widely used structure when studying incentive mechanisms in a P2P system. However, without considering cost when checking transaction history, ALLD is the only ESS. In a real network, due to the network structure, there're always some cooperators that survive. In this group of experiments, we consider the influence of network structure on cooperation and compare the results of three classic strategies in 4 different network structures.

Under the CBLM model in a well-mixed population (Figs. 1 and 5), the only surviving strategy is ALLD, whatever the incentive strategy is. But the situation changes when we add a network structure to it. For Mirror and prop strategies, with the influence of network structure the proportion of cooperators and reciprocators promoted and defectors are well restricted (see Figs. 2, 3, 4, 6, 7 and 8). However, the indirect strategy is a weak incentive strategy. When there are only defectors and indirect reciprocators, they never provide service to each other. It may seem like all peers are defectors in the system so they can co-exist in the system, but the system performance remains very low. We can get similar results under OLM.

To test the effectiveness of the adaptive strategy, we carry out simulation in three network structures and compare the results with other three strategies. Figures 9, 10, 11, 12, 13, 14, 15 and 16 show that an adaptive strategy can promote cooperation under both the CBLM and OLM learning models. Such cooperation is not only the promotion of the total proportion of cooperators and reciprocators, but also the fraction of cooperation. That means with an adaptive strategy, more and more peers are willing to share unconditionally so that the system performance can be promoted and the system can be continuously stable.

In addition to the evolution of cooperation, we also consider the system average payoff at ESS as a measurement of system performance. As shown in Fig. 17, with an adaptive strategy, the system performance cannot reach the highest possible level among all these strategies. The main reason for that is due to the probability of a reciprocator getting service from others and serving others that may not be equal to 1. When an adaptive strategy is brought in, the more cooperators are in the system, and a

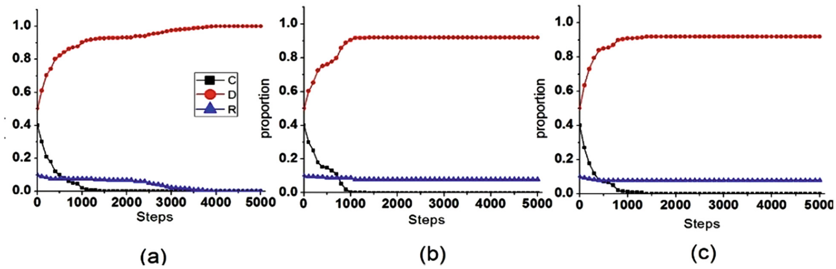

Fig. 1. Evolution under CBLM in well-mixed population; (a) Mirror (b) Prop (c) Indirect.

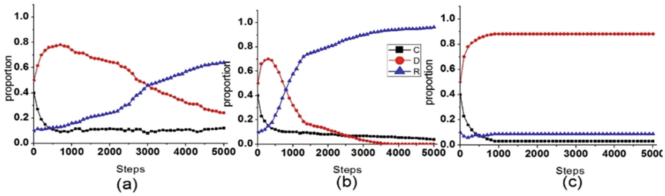

Fig. 2. Evolution under CBLM on square lattice; (a) Mirror (b) Prop (c) Indirect.

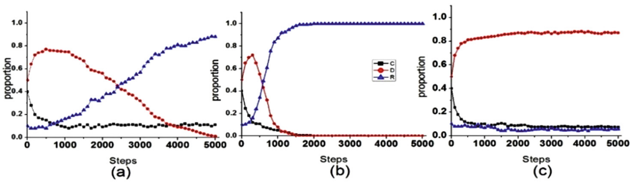

Fig. 3. Evolution under CBLM in scale-free network; (a) Mirror (b) Prop (c) Indirect.

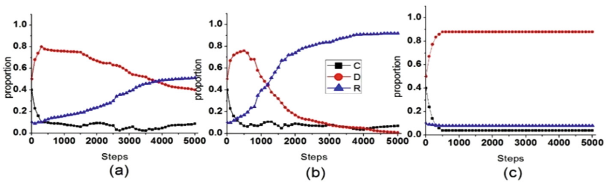

Fig. 4. Evolution under CBLM in small world network; (a) Mirror (b) Prop (c) Indirect.

relatively large cost is incurred. Therefore the system with an adaptive strategy doesn't yield the highest payoff. However, the performance of an adaptive strategy can reach high levels in different networks. This attribute helps an autonomous network maintain better stability. So, the adaptive strategy is still meaningful to the autonomous system design. Also, we can see that the system performance when using an indirect strategy is fairly low. When there are only peers with indirect strategy in the system, once a peer

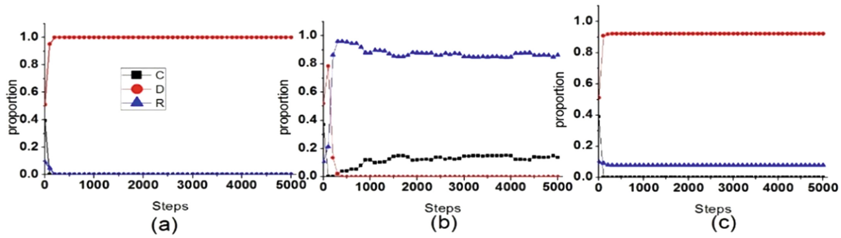

Fig. 5. Evolution under OLM in well-mixed population; (a) Mirror (b) Prop (c) Indirect.

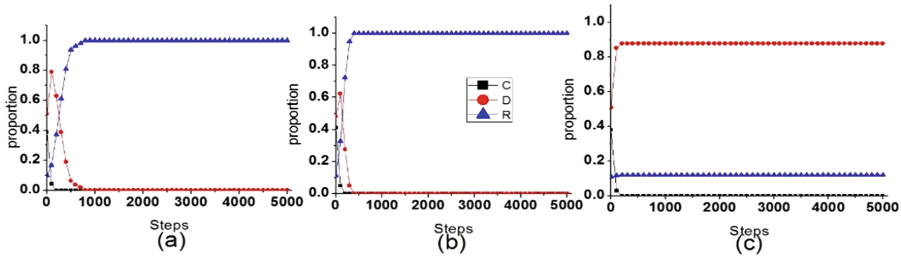

Fig. 6. Evolution under OLM on a square lattice; (a) Mirror (b) Prop (c) Indirect.

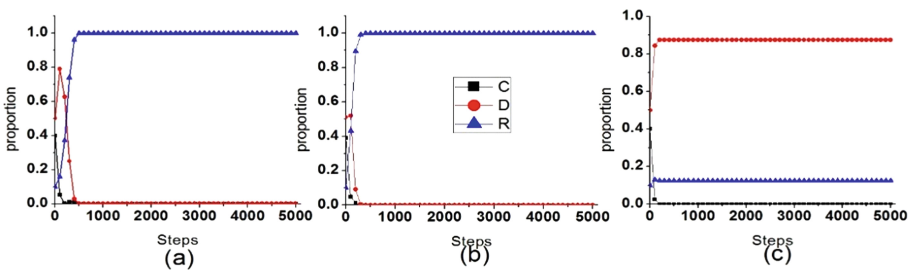

Fig. 7. Evolution under OLM in scale-free network; (a) Mirror (b) Prop (c) Indirect.

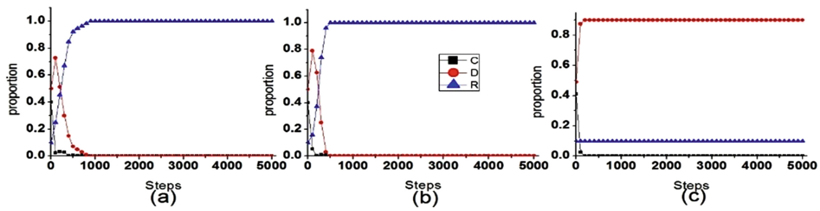

Fig. 8. Evolution under OLM in small world network; (a) Mirror (b) Prop (c) Indirect.

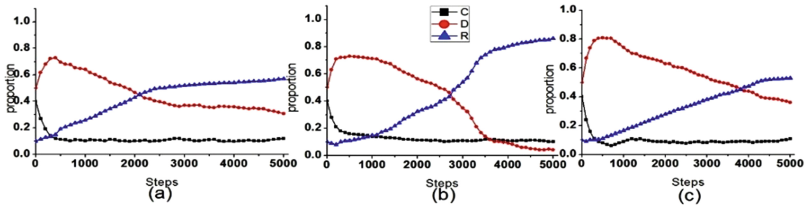

Fig. 9. Evolution under CBLM with mirror strategy; (a) Lattice (b) Scale-free (c) Small World.

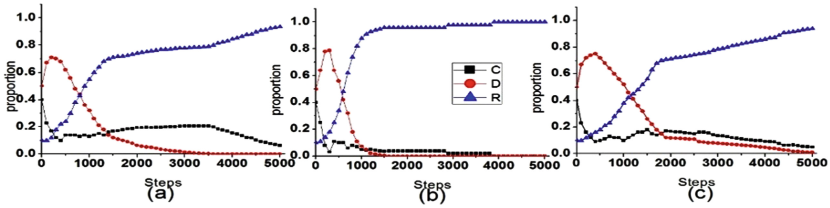

Fig. 10. Evolution under CBLM with prop strategy; (a) Lattice (b) Scale-free (c)Small World.

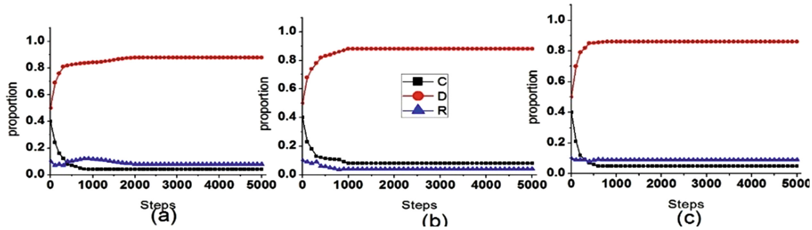

Fig. 11. Evolution under CBLM with indirect strategy; (a) Lattice (b) Scale-free (c) Small World.

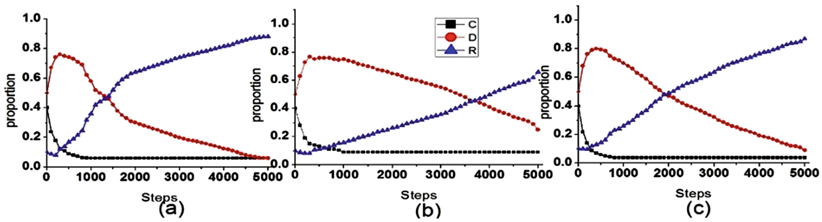

Fig. 12. Evolution under CBLM with adaptive strategy; (a) Lattice (b) Scale-free (c) Small World.

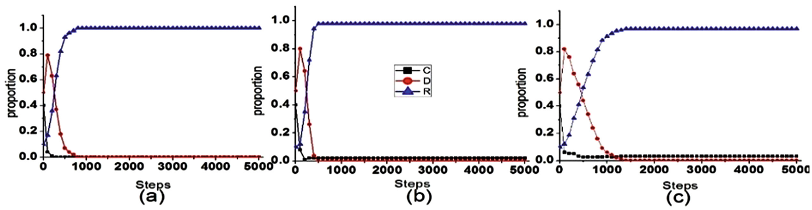

Fig. 13. Evolution under OLM with mirror strategy; (a) Lattice (b) Scale-free (c) Small World.

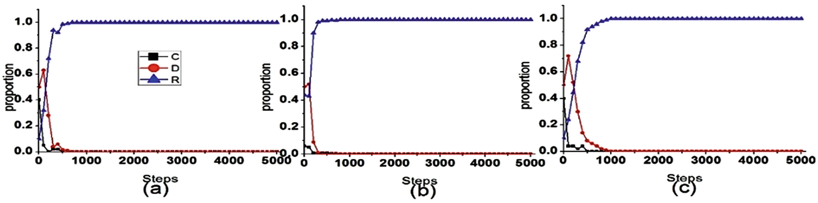

Fig. 14. Evolution under OLM with prop strategy; (a) Lattice (b) Scale-free (c) Small World.

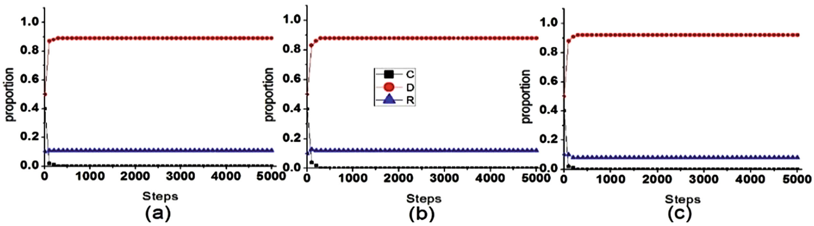

Fig. 15. Evolution under OLM with indirect strategy; (a) Lattice (b) Scale-free (c) Small World.

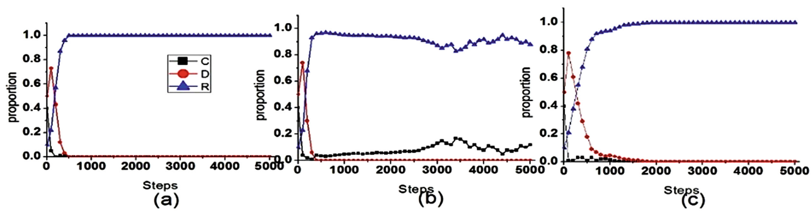

Fig. 16. Evolution under OLM with adaptive strategy; (a) Lattice (b) Scale-free (c) Small World.

defects, then the defecting peer won't cooperate next time. So the cooperation rate is quite low in such system, and the system performance is low. This also proves that indirect strategy is a weak incentive strategy.

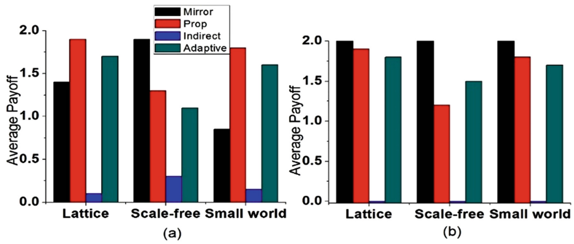

Fig. 17. Average payoff at ESS; (a) CBLM (b) OLM (Color figure online)

4 Conclusions

In this paper we mainly bring in an adaptive strategy into the P2P system. Through simulation under evolutionary game framework, we have reached conclusions as follows:

(1) Cooperation promoted through network structure

We carried out experiments in well-mixed population, square lattice, scale-free network and small-world networks. The experimental results show that with the influence of network structure, the proportion of cooperators and reciprocators rises. It shows that network structure can promote cooperation.

(2) Cooperation promoted through adaptive strategy

To test the effectiveness of adaptive strategy, we carried out experiments in three different networks and compared the results with other three incentive strategies. The results show that in a system with an adaptive strategy, cooperation emerges. Besides, no matter what the network structure is, a system with an adaptive strategy has better robustness and higher performance. So, in summary, the introduction of adaptive strategy has significance as an incentive mechanism to promote not only cooperation but also improve system performance.

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