Int J Parallel Prog (2019) 47:686–708
https://doi.org/10.1007/s10766-018-0559-9

Analysis for Behavioral Economics in Social Networks: An Altruism-Based Dynamic Cooperation Model

Deng Li[1] · Zhujun Chen[1] · Jiaqi Liu[2]

Received: 30 September 2017 / Accepted: 22 January 2018 / Published online: 16 February 2018

Abstract Aiming at uncooperative behaviors such as free-riding, white-washing and sybil attacks, and the lack of rationality hypothesis in the traditional economic models, the paper presents an Altruism-Based Dynamic Model (ABDM) in social networks by introducing views from reciprocal altruistic theory. Considering the initiative of nodes behind reciprocal altruistic behaviors, the ABDM improves the cooperation rate of the network and promotes the propagation of cooperative behavior by using the nodes' inherent ability of reciprocal altruism. Furthermore, based on nodes' bounded rationality, ABDM also perfects models of traditional economic theories. The simulation results show that compared with the traditional model, the proposed ABDM has the higher level of cooperation, the stronger scalability and the better robustness. On this basis, the paper analyzes the ABDM at different scenarios: varying group sizes and population; behavior selection under varying parameter settings (cost-to-benefit ratios of the psychological payoff and etc.). With the more efficient interactions among the nodes, the ABDM model can improve the efficiency of parallel processing.

Keywords Social network · Altruism · Cooperation · Parallel processing

✉ Jiaqi Liu
liujiaqi@csu.edu.cn

Deng Li
d.li@csu.edu.cn

1 School of Information Science and Engineering, Central South University, Changsha 410083, China

2 School of Software, Central South University, Changsha 410083, China

1 Introduction

Social networks have not only been a hot area of complex networks, but also become an advanced research hotspot in the field of parallel processing as one of typical multi-agent systems [1–3]. Methods in social network analysis and modeling can be widely used in data processing and analysis [4–6]. As one kind of relative stable systems, social networks compose of the social relationships among individuals [7]. Social networks focus on the interactions and connections among individuals. Social networks have significant features, including large user scale, dynamics, User Generated Content (UGC) [8], high degree of freedom and flexibility, etc. The challenges of social networks are obvious: the lack of effective supervision from the system [9], the high possibility of a one-time interaction among individuals, and the uncooperative behaviors of individuals (such as free-riding [10,11], white-washing [12,13] and sybil attacks [14,15]) pointed at the maximization of utility. Above behaviors seriously inhibit cooperation and affect the development of social networks. There is no doubt that cooperation is the basis for social networks. How to design the network model and the mechanism to ensure the cooperation of individuals becomes a challenging research topic in social networks.

2 Related Work

2.1 Cooperative Mechanisms in Social Networks

At present, researches on cooperation mechanisms in social networks mainly focus on reducing those behaviors such as free-riding and cheating.

- To solve the free-riding problem, common models are put forward including the micro-payment mechanism [16], the reciprocity mechanism [17] and the reputation mechanism [18]. The micro-payment mechanism uses virtual currency as a transaction certificate to eliminate free-riding behaviors. Ning et al. [19] presented a dynamic payment mechanism, where the reward of each user is determined by the value of the resource or the level of each user. The mutual supervision among nodes is the main characteristic of the reciprocal mechanism , and one node's reciprocal ability is assessed by its neighbors according to parameters such as resource contribution and etc. [20] has proposed an incentive mechanism for equal exchange of data. According to the interests of nodes, the message is divided into the primary message (the higher interest message) and the secondary message (the lower interest message). Thus, one who wants to obtain the primary message should pay a number of secondary messages. Reputation mechanism uses the reputation to evaluate the historical behaviors of nodes and distinguish different services. A mechanism is presented to prevent the free-riding in [21], in which nodes would be ranked by their transaction histories and contributions. So a node with the higher level would have the higher permissions;
- Aim to cheating, white-washing, sybil attacks and other malicious acts, most models use reputation [22], trust [23] and other characteristics of the social status to detect malicious behaviors and to punish malicious nodes. Buttyn et al. [18] and

Barbian [24] proposed a structure of trust for online social networks called SocialTrust. In SocialTrust, the trusts of the users are calculated by both the quality of links and the feedback scores. Thus, it can punish the cheating behaviors. Trifunovic et al. [25] and Fu et al. [26] proposed methods using explicit social trust and implicit social trust to deal with two patterns of sybil attacks. Explicit social trust is obtained from one node's neighbors, and implicit social trust is obtained from the surrounding nodes within two-hop by the similarity and the familiarity. Mtibaa and Harras [27] and Najaflou et al. [28] presented two methods to establish a trusted connection: between the source node and each forwarding node; between any two forwarding nodes. Combined with three trust filters including mutual friends, common interests and social distances, six trusted filters are proposed to establish a trusted connection among nodes. Bigwood and Henderson [29] and Vegni and Loscri [30] proposed a method using existing social information to detect and punish selfish nodes. Social information is obtained by directly accessing records or visiting online social networks (such as Facebook's friends list).

Most of cooperation mechanisms mentioned above are based on the rationality hypothesis of traditional economic models [31–33], which have assumed that individuals have perfect rationality or bounded rationality. The core of social networks is the connections among all the social individuals. In social networks, the behaviors and the connections of individuals are interrelated. More and more researches have proved that people make optimal decisions based on not only the rationality but also the emotion [34,35]. The rationality and the emotion both impact on the behaviors of individuals in human-based systems including social networks. In other words, we can not simply explain the behaviors of nodes in social networks by the rationality hypothesis, which can not effectively guarantee the social network cooperation and security issues.

2.2 The Reciprocal Altruism

It is well known that there is an obvious disagreement over the rationality hypothesis between the traditional economic theories and the reciprocal altruism. The reciprocal altruism can be explained by the behavior that one is willing to pay the cost to promote cooperation although it can not get benefit return immediately [36,37]. Meanwhile, the reciprocal altruism focuses on the fairness so that it is necessary to identify and punish the uncooperative individuals. Current researches on this theory cover economics, sociology, psychology, computer science and many other fields.

- In the field of economics, a relevant study shows that the utility function defined by the social preference model considers the willingness to punish those behaviors that violate the rules of cooperation and fairness [38]. Compared with the self-interest model in traditional economics, this model can explain the actual behavior of people in the more reasonable way.
- In the field of sociology, the German economist Werner Guth found a game called ultimatum [39–41], the rule of the game is following: the game includes a distributor and a recipient; the distributor receives a fixed amount of money and decides

how to allocate the money with the recipient (the recipient's money cannot be zero); the recipient can only accept or refuse the assignment. If the recipient accepts, the money will be allocated according to the rules of the distributor; if the recipient refuses, both of them cannot get paid. The final experimental results show that the distributor will generally allocate 40% of the total to the other (the recipient can get 40% of the total amount of money); if the distributor's proposal is less than 20% of the total (the recipient can get 20% of the total amount of money), the recipient will refuse with a probability of fifty because the assignment is unfair.
– In the field of experimental economics, many scholars have argued that the reciprocal actors are willing to pay for cooperation only if they are expected to receive long-term or indirect benefits in traditional economics. And a lot of laboratory experiments [42,43] have proved the existence of strong reciprocity behaviors that many people will be willing to pay the cost to reward cooperation and punish noncooperation even if they can not get any pay back.
– In the field of physiology, psychology, [44] shows that people have the willingness to punish those who violate fairness and justice. When people find that those who violate social norms still not be punished, they will feel unhappy and even angry; otherwise, once a fair social norm has been established, they will feel satisfied. This result supports the existence of altruistic punishment from the neural basis.
– In the computer field, about 20% nodes in BitTorrent selflessly contribute their resources so that the performance of the system could be guaranteed [45]. Shah et al. [46] had added altruistic punishment to the traditional incentive mechanism and effectively improved the cooperation rate of P2P systems.

Therefore, no matter what kind of domain, there always are strong reciprocal nodes who do not make choices to maximize the utility. Strong reciprocity behaviors mean that the nodes make choices by considering fairness. Thus, the reciprocal altruistic is one of the essential factors that affects the decision-making of people, and it can be used for investigating the individuals' behaviors [47,48].

In this paper, we introduce the reciprocal altruism theory into the incentive mechanism. Based on the bounded rationality, nodes become the smarter and feel the more satisfied with the co-evolution of the individuals' strategies and the underlying interaction network (we adopt the basic dynamic structure proposed by [49]). Furthermore, we define a new utility function to measure nodes' payoffs in social networks, including economic payoffs and psychological payoffs.

The main contributions of this paper are following: 1. The paper proposes an Altruism-Based Dynamic Model (ABDM) in social networks and proves its effectiveness by simulations; 2. The paper redefines some basic terms in traditional economic theories such as human rationality, self-interest, complete information, utility maximization and preference consistency, so that those terms can be more suitable for realized situations.

3 Our Model

The ABDM proposed in this paper is inspired by behavioral economics and sociology. Reciprocal altruism, which is one of the inherent characteristics of an individual with bounded rationality, has been introduced into the ABDM. Therefore, the ABDM can be used to describe the behaviors of individuals in social networks in a more reasonable and a more suitable way.

3.1 Model Description

In the fields of social networks, individuals' behaviors in information communication and resource sharing indicate that individuals in social networks have obvious clustering [50]. Therefore, social networks focus on groups of nodes instead of a single node. The ABDM uses the N-player prisoner's dilemma (NPD) as a framework to investigate the interactions of nodes in social networks [49,51].

Algorithm 1 Model description

Require: system size P , number of iterations i_{max}, group size N, number of groups G
1:**for** i=0 to i_{max} **do**
2:   Grouping ($P/N=G=\{G_0,G_1,\ldots,G_{max}\}$)
3:   **for** G_0 *to* G_{max} **do**
4:     NPDgame(G)
5:     SetLinks (G)
6:     ComputeUtility(G)
7:   **end for**
8:   UpdateStrategy (P)
9: **end for**

The execution cycle of the ABDM is sketched in Algorithm 1: The nodes in each iteration will be divided into G_{max} groups (line 2); The nodes within each group interact with each other at the same time (line 4); When the interactions are completed, the nodes would adjust their own connections based on the actions played (line 5); And then the nodes calculate their utilities in the current interaction (line 6); At last, a number of nodes are chosen for strategy updating (line 8). In the following sections, these steps are explained in detail.

In the ABDM, the opponents of each node are defined as the nodes in the same group except itself. The opponent selection (Grouping) means that each node would be added to a group. The interaction (NPD game) means that a service requestor node sends its requests to its opponents. The behavior selection describes the process of whether the opponents would respond to the service requests after receiving the requests. The connection adjustment (setLinks) describes that after its last interaction, a service requestor node marks the opponents who respond its request with the connection weight so that it can choose a path to send their requests next time.

3.2 Opponent Selection

In each iteration, the system size (population size) P would be divided to several numbers of groups according to the group size N. Thus, the opponent selection means the formation of groups.

Algorithm 2 Opponent selection

Require: System altruistic rate θ , Neighbor selection rate ε, random number: *r1*,*r2*, reciprocal altruistic node *i*, node *j*, the set of *j*'s neighbors :{ Neighbors}, the set of idle nodes: IdleNodes,group size *N*, number of groups $G=\{G_0,G_1,...,G_{max}\}$

for G_0 to G_{max} **do**
  if $j \in$ IdleNodes **do**
    AddGroup (*j*)
    if $r1 < \theta$ and $i \in$ {IdleNodes} **do**
      AddGroup (*i*)
    else do
      AddGroup ({IdleNodes})
    while $r2 < \varepsilon$ and {Neighbors} $\in$ {IdleNodes} and NumbersOfGroup $< N$ **do**
      AddGroup (*j*)
    end while
    while NumbersOfGroup $< N$ **do**
      AddGroup ({IdleNodes})
    end while
end for

There is no doubt that the reciprocal altruistic nodes with high unconditional cooperation rate will punish the uncooperative opponents for fairness in order to force their opponents to cooperate in the interactions of their groups. It is foreseeable that the cooperation rate will be improved because of the reciprocal altruistic nodes in the groups.

Our model introduces system altruistic rate θ and neighbor selection rate ε: The first member of the group with size N is selected randomly from idle nodes who have not been assigned to any group in the current iteration. With probability θ, one of idle reciprocal altruistic nodes is selected to add to the group. With probability $1 - \theta$, one of idle nodes (except the reciprocal altruistic nodes) is chosen. The remaining $N-2$ members are selected randomly from the neighbors of the first member with the probability of ε. With the probability of $1 - \varepsilon$, or in the case where the neighbors of the first member are all assigned, the remaining $N-2$ members are selected randomly from the idle nodes.

3.3 Behavior Selection

3.3.1 The Types of Nodes

The ABDM has three different types of nodes: ALL-C (always plays the cooperative action), ALL-D (always plays the betrayal action, we reward those noncooperation behaviors as betrayal) and Reciprocal altruistic (with a probability to plays the cooperative or betrayal action, see details below).

The inherent parameters of the three nodes are listed:

- Fairness coefficient c: describes the degrees of chasing fairness; the range of c is [0,1]; the fairness coefficient of the ALL-C node: $c=1$; the fairness coefficient of the ALL-D node: $c=0$; the initial value of the fairness coefficient of the reciprocal altruistic node: c_0.

- Average fairness coefficient $\bar{c}$: describes the average fairness coefficient of the nodes in current group; if there is a node i in the current group $G = \{i, j_n(n = 1, 2, N-1)\}$, c_{j_n} is used to decribe the opponents' fairness coefficient where j_n is used to describe the opponents of node i; the average fairness $\bar{c_i}$ of node i in the current iteration can be defined as:

$$\bar{c_i} = \frac{1}{N} * \left(c_i + \sum c_{j_n}\right)(n = 1, 2, \ldots, N-1) \tag{1}$$

- Average connection strength $\bar{w}$: describes the average connection weight among the node and its opponents in the current iteration; if there is a node i in the current group $G = \{i, j_n(n = 1, 2, N-1)\}$; w_{ij_n} is used to describe the connection strength between node i and one of its group members $j_n(n = 1, 2, N-1)\}$; the average connection weight $\bar{w_i}$ of node i in current iteration can be defined as:

$$\bar{w_i} = \frac{1}{N-1} * \sum w_{ij_n}\,(n = 1, 2, \ldots, N-1)\,. \tag{2}$$

3.3.2 Reciprocal Altruistic Node

The ABDM introduces reciprocal altruistic nodes, according to the bounded rationality and the reciprocal altruistic theory from behavioral economics. The behavior selection of each reciprocal altruistic node is influenced by both the connections and the reciprocal altruistic characteristic. In this model, reciprocal altruistic nodes have a certain altruistic willingness including altruistic cooperation and altruistic punishment. At the same time, reciprocal altruistic nodes also have the good cognitive abilities, which can let them make choices based on the information of neighbors when they do not choose unconditional cooperation.

The relevant parameters of the reciprocal altruistic node are defined as follows:

- Altruistic cooperation coefficient λ: expresses the altruistic degree. When the cooperation rate of the group is high, the coefficient of cooperation will increase; when the proportion of cooperation decreases, the coefficient of cooperation will decrease accordingly. In this paper, we use the formula (3) to describe the coefficient of cooperation of the reciprocal altruistic nodes:

$$\lambda = \begin{cases} \lambda_0 + \mu & \left(\frac{n}{N} \geq 0.5\right) \\ \lambda_0 - \mu & \left(\frac{n}{N} \leq 0.5\right) \end{cases} \tag{3}$$

  λ_0 is used to describe the initial altruistic coefficient of cooperation of reciprocal altruistic nodes. μ means the increment (or decrement) of altruistic coefficient, $\frac{n}{N}$ is used to describe the proportion of cooperation nodes within the group, n means the number of nodes which choose cooperation and N means the group size.
- Unconditional cooperation rate P_a: The proportion for reciprocal altruistic nodes to choose the selfless behavior which means that reciprocal altruistic nodes choose cooperation without considering any other information such as the connections and etc. In this paper, we focus on the situation when the reciprocal altruistic nodes

Table 1 Probability distribution of node behavior selection

Node types	Cooperate	Betray
ALL-C	1	0
ALL-D	0	1
Reciprocal altruistic (unconditional cooperation)	P_a	0
Reciprocal altruistic (non-unconditional cooperation)	P_c	$1 - P_c$

do not choose unconditional cooperation. So the unconditional cooperation rate of the reciprocal altruistic nodes is determined by the formula (4):

$$P_a = \lambda_0 \tag{4}$$

– Cooperation rate P_c: According to the decision rules in social networks [48], the reciprocal altruistic nodes will choose to cooperate with the probability P_c as formula (5) defined, and choose to betray with the probability $1 - P_c$ when they do not choose unconditional cooperation:

$$P_c = \frac{(\bar{w} + \bar{c})^{\gamma} + \lambda}{(\bar{w} + \bar{c})^{\gamma} + \lambda + 1} \tag{5}$$

$\bar{w}$ is used to describe the average connection strength among the node and its opponents (group members) in the current iteration. λ is defined in formula (3); $\bar{c}$ is defined in Sect. 3.3.1. The gradient of the probability density function is determined by γ .

3.3.3 The Rules of Behavior Selection

Different types of nodes have different rules of behavior selection. Table 1 has given the rules of behavior selection which are described by probability.

– ALL-C nodes always choose to cooperate, ALL-D nodes always choose to betray;
– Reciprocal altruistic nodes choose to cooperate or betray according to the probability calculated by themselves. There is a certain probability P_a for reciprocal altruistic nodes to choose unconditional cooperation. With the probability $1 - P_a$, the nodes choose to cooperate with the probability P_c, choose to betray with the probability $1 - P_c$. It should be noted that when the reciprocal altruistic nodes choose unconditional cooperation and their opponents choose cooperation at the same time, they will improve their own cooperation coefficient although they do not know the behaviors of their new opponents in the next interactions.

3.4 Connection Adjustment

Social networks focus on the connections among individuals. The connections among individuals will be adjusted according to each individual's historical behaviors.

Table 2 Altruistic node psychological payoff parameters

b_c	Psychological benefits of cooperation
c_p	Psychological loss of being betrayed
b_p	Psychological benefits of giving punishment
c_{tp}	The economic cost of being punished (refer to the theory of loss aversion [53,54], $c_{tp} = 1/2\, c_p$)

For each pair of node i and node j in the group, w_{ij} is mentioned in Sect. 3.3.1. In this paper, the formula (6) is used to describe the connection adjustment rules for nodes:

$$w_{ij} = \begin{cases} w_{ij} + 1 & if\ both\ i\ and\ j\ cooperated \\ w_{ij} - 1 & otherwise \end{cases} \tag{6}$$

If both the node and its opponent cooperate, then the node will strengthen the connection with each other; if one of the nodes in this iteration do not cooperate, then the node will reduce the weight of the connection.

3.5 Payoff Calculation

The traditional NPD utility function has considered only the economic payoff of the nodes [52], which is determined by the formula (7):

$$\Pi^E(i) = \begin{cases} \Pi^E(C) = \frac{b*n}{N} - c & if\ node\ i\ cooperated \\ \Pi^E(D) = \frac{b*n}{N} & if\ node\ i\ betrayed \end{cases} \tag{7}$$

$\Pi^E(i)$ means the utility of node i in this NPD game; and n means the number of cooperative nodes in the group, N means the group size, c means the cost of cooperation and b means the benefit of cooperation. And the following conditions must hold for the NPD game: $c > b/N$(betrayal is always the choice because of the most benefit) and $b > c > 0$ (the individual's active contribution is beneficial to the whole group).

Based on the traditional NPD payoff function as formula (7), this paper presents the psychological payoff function of the NPD game, which is determined by the formula (8):

$$\Pi^P(i) = \begin{cases} \Pi^P(C) & if\ node\ i\ cooperated \\ \Pi^P(D) & if\ node\ i\ betrayed \end{cases} \tag{8}$$

It is obvious that after considering the reciprocal altruistic nodes, the utility function of nodes in traditional economics is unreasonable for the ABDM. Thus, the ABDM presents the parameters as follows (Table 2):

According to the parameters in Table 2 and formula (8), the concrete expression formulas of $\Pi^P(C)$ and $\Pi^P(D)$ are given:

– When node i chooses to cooperate, we use the formula (9) to describe the psychological payoff of the node:

$$\Pi^P(C) = \begin{cases} \frac{n}{N} * b_c + \frac{N-n}{N} * (b_p - c_p - (N-n) * c_{tp}) & altruism\ nodes \\ \frac{n}{N} * b_c - \frac{N-n}{N} * c_p & others \end{cases} \tag{9}$$

where n is the number of cooperative nodes in the group. The proportion of cooperation nodes in the group determines the psychological benefits of the node i, and the proportion of betrayal nodes in the group determines the psychological lost of the node i; $b_p - c_p - (N-n) * c_{tp}$ means that when node i is a reciprocal altruistic node, it will punish the betrayal nodes in its group by paying the economic cost based on its own altruistic willingness.

– When node i choose to betray, we use the formula (10) to describe the node's psychological payoff :

$$\Pi^P(D) = -k * 2 * c_{tp} \tag{10}$$

where k is the number of times that node i has been punished in one iteration (by reciprocal altruistic nodes within the group). When the proportion of reciprocal altruistic nodes in the group increases, the punishment to the betrayal nodes would be much heavier.

In conclusion, the economic payoff and psychological payoff are both the necessary factors in the behavior selection in social networks. In this paper, we use the formula (11) to describe the payoff of the nodes in the ABDM:

$$\Pi = \alpha * \Pi^E + \beta * \Pi^P \tag{11}$$

α is the weight of economic payoff and β is the weight of psychological payoff; $\alpha + \beta = 1$; and Π presents the true utility of a node in social networks when it make decision considering both rationality and emotion. Moreover, α has different values in different situations, the same as β.

3.6 The Comparison of the ABDM and the MIX Model

Rezaei and Kirley [49] has confirmed that the dynamic adjustment model (we regard this model as the MIX) can effectively improve the cooperation rate in social networks. As shown in Table 3, there are significant differences between the MIX and the ABDM on model settings (such as node types, etc.) and the internal mechanisms (such as behavior selection and etc.). Particularly, nodes in the ABDM consider much more information in behavior selection than that in the MIX, and will be more generous when their opponents choose to betray.

It is well known that strategy update is the essential part of a social network evolution model. As shown in Table 3, in the ABDM, an evolution probability δ is used to describe the evolution process. With the evolution probability δ, $P * \delta$ (system size

Table 3 The comparison of the ABDM and the MIX

	MIX	ABDM
The types of nodes	ALL-C, ALL-D, MIX	ALL-C, ALL-D, reciprocal altruistic
Behavior selection	Connections	Connections,fairness coefficient and unconditional cooperation
Opponent selection	Neighbors	Neighbors and reciprocal altruistic nodes
Connection adjustment	Delete the connection	weaken the connection
Strategy update	The lower copy the higher	the lower copy the higher

P) pairs of nodes will compare their accumulated payoff after each iteration. The node with the lower payoff will copy the other's strategy and connections (forming the connections with weight 1). Above mechanism is used to promote the diffusion of successful strategies in social network evolution models.

4 Simulation

The simulation experiments are given in this section in order to prove the validity of the ABDM. At the same time, plenty of systematic Monte Carlo simulations [55] and statistical methods are used for the analysis of results.

4.1 Parameters Setup

The parameter settings used in the simulation experiments are shown in Table 4:

4.2 Results

The following results are averaged over 30 independent trials. The reported results focus on these investigation: (1) how the parameters in Table 4 make a difference to the cooperation rate of the system; (2) the internal causes of how the ABDM facilitates cooperation in social networks.

4.2.1 Group Size Versus Strategy

In this section, the model is examined using different group size to investigate the impacts of N to the cooperation rate. At the same time, the comparison of the ABDM and the MIX under the same conditions is given. In each case, the results of the cooperation rate versus time for increasing values of N are investigated. According to Table 4, $P = 1000$, $\lambda = 0.2$, $\mu = 0.001$, $c_0 = 0.5$, $r1 = 0.6$, and α:β=8:2 are used for this cases. The iterations ($t = 20 * 50, 20 * 300, 20 * 2000$) depend on different cases (the values of parameters are discussed below).

Table 4 The parameters of experiments

Population size: $P = 1000, 2000, 5000$
Evolution probability: $\delta = 0.001$
Group sizes: $N = 2, 4, 5$ (group size which is less than a threshold can facilitate cooperation [49])
The probability of choosing neighbors: $\varepsilon = 0.9$
The probability of choosing reciprocal altruistic nodes: $\theta = 0.9$
The gradient of the probability density function (in formula (5)): $\gamma = 1.5$ (as per[56])
The proportion of different types of nodes: 1:1:1
The initial value of the reciprocal coefficient (in formula (3)): $\lambda_0 = 0.05, 0.1, 0.15, 0.2$
The increment of the reciprocal coefficient (in formula (3)): $\mu = 0.0001, 0.001, 0.005, 0.01$
The fairness coefficient of reciprocal altruistic nodes: $c_0 \in (0, 1)$
The cost-to-benefit ratio of the economic payoff (in formula (7)): r=c/b=0.6
The proportion of the economic payoff α and the psychological payoff β (in formula (9)): α:β = 10:0, 9:1, 8:2, 7:3, 6:4, 5:5
The maximum number of iterations: $i_{max} = 40{,}000$

Figure 1a plots the results of the MIX, and Fig. 1b plots the results of the ABDM under the same iterations ($t = 20 * 2000$). Above results represent the impacts of different group sizes to cooperation rates. In the MIX, the high cooperation rate at equilibrium is consistent with the results of the standard 2×2 PD game using a spatial structure when $N = 2$, and the cooperation rate at equilibrium decreases when N increases. In the ABDM, the proportion of cooperation at equilibrium is equal to 1, no matter which value N takes. Compared to Fig. 1a, b, it is obvious that the ABDM has the higher cooperation rate at equilibrium than the MIX with the same N. Figure 1c plots the results of the ABDM with the iterations ($t = 20 * 50$), in order to investigate the tendency of the cooperation rate with more values ($N = 2, 4, 5, 8, 10, 15$) for N. The cooperation rate grows faster as the value of N increases.

Figure 2 can explain above conclusion by showing the trajectory of the proportion of different node types. The trajectory of different strategy types in the MIX is shown in Fig. 2a–c and that in the ABDM is shown in Fig. 2d–f. As Fig. 2a–c are shown, the cooperation level in the MIX depends on N. When N is less than 5, nodes in the MIX can quickly establish connections with each other; when N is larger than 5, the betrayal behaviors overspread more quickly as N grows. It is because the punishment (by connection adjustment) is limited. As Fig. 2d–f are shown, when N increases, the proportion of reciprocal altruistic nodes in groups relatively increases and the intensity of punishment for betrayal nodes relatively increases, which could result in the higher cooperation rate.

Furthermore, as you can see in Fig. 3, the average node degree of the reciprocal altruistic nodes (or the $All - C$ nodes) is proportional to the iterations, while the average node degree of the $All - D$ nodes is always zero. And obviously, the dynamic adjustment mechanism of the connections among nodes makes sense to the degree distribution in Fig. 3. It is because the nodes who cooperate with each other can

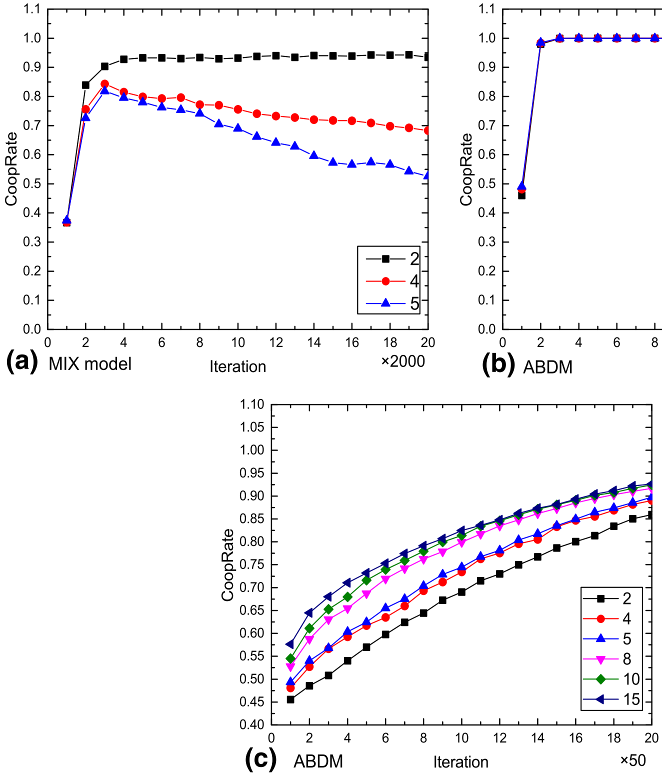

Fig. 1 Cooperation rate versus time for various values of N in different cases

establish or enhance their connections. That can clearly explain the conclusion of Figs. 1c and 2d–f. The results from above three graphs show how the ABDM works dynamically, and also draw a conclusion that the ABDM has a much better effect on facilitating cooperation in social networks.

4.2.2 Fairness Coefficient and Increment of the Reciprocal Coefficient

In this section, the simulations focus on c_0 and μ. In each case, the results of the cooperation rate versus time according to the increasing values of c_0(or μ) are investigated. The iterations($t = 20 * 50, 20 * 300$) depends on different cases. Other parameters are the same as the values in Sect. 4.2.1 except $N(N = 5)$.

Table 5 shows the data of cooperation rate versus time for various values of c_0. It can be found that the cooperation rate will quickly converge to 1 regardless of the values of c_0.

As Fig. 4 is shown, when c_0 increases, the initial cooperation rate increases because of the higher probability that reciprocal altruistic nodes choose to cooperate as formula (5) described. There are no significant differences between each cooperation rate at equilibrium and each c_0.

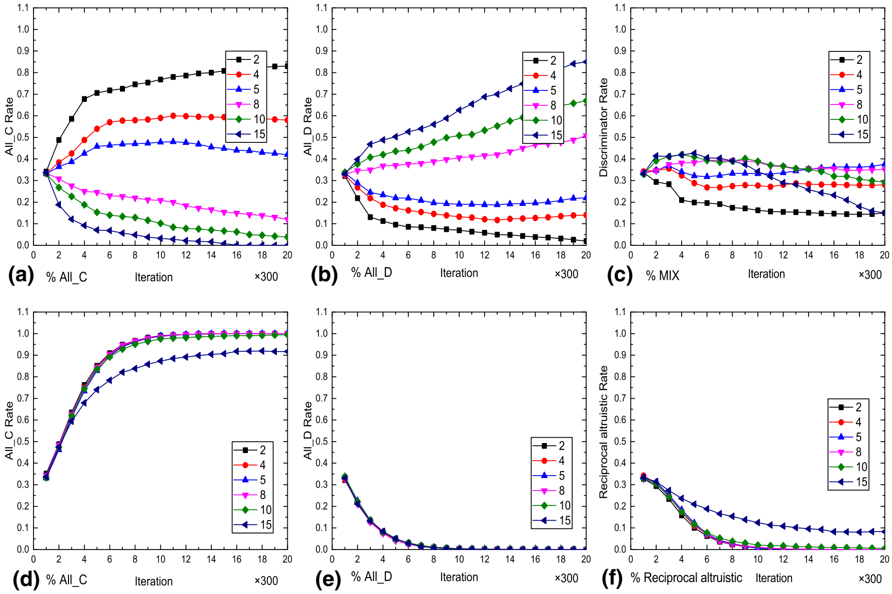

Fig. 2 Trajectory of the proportion of different nodes types versus time for various values of N

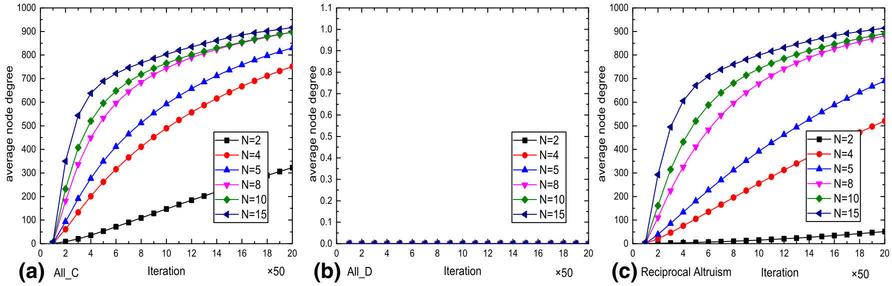

Fig. 3 Trajectory of the average node degree of different nodes versus time for various values of N

Table 5 Cooperation rate versus time for various values of c_0

$c_0/time$	0	1000	2000	3000	4000	5000	6000
0.1	0.4658	0.9016	0.9852	0.997	0.99996	0.9998	1
0.2	0.4782	0.903	0.986	0.9972	0.9996	0.9998	1
0.3	0.4878	0.9042	0.9874	0.9972	0.9996	1	1
0.4	0.4996	0.9042	0.9876	0.9976	0.9998	1	1
0.5	0.5018	0.9086	0.9876	0.9982	0.9998	1	1
0.6	0.503	0.9094	0.9876	0.9984	0.9998	1	1
0.7	0.504	0.911	0.9884	0.9984	0.9998	1	1
0.8	0.5158	0.912	0.9884	0.9986	0.9998	1	1
0.9	0.5206	0.9124	0.9886	0.999	0.9998	1	1

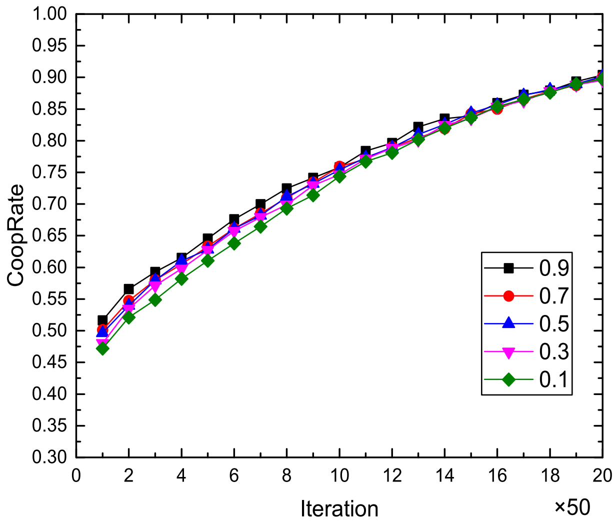

Fig. 4 Cooperation rate versus time for various values of c_0

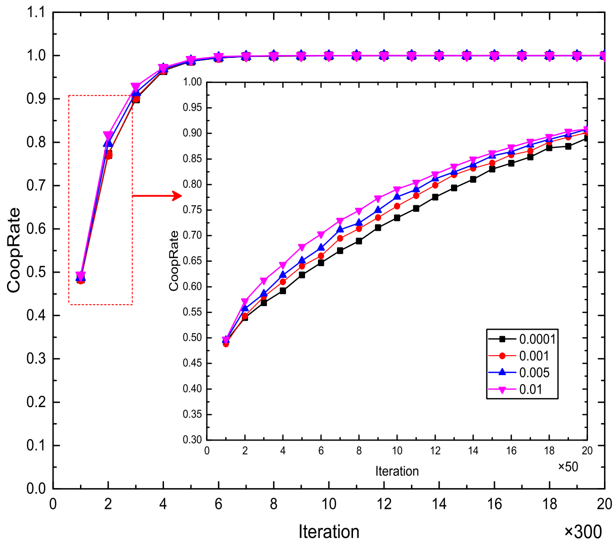

Fig. 5 Cooperation rate versus time for various values of μ

Figure 5 ($t = 20 * 300$) plots the results of the cooperation rate versus time for various values of μ with the iterations ($t = 20*300$), which shows that the cooperation rate will quickly converge to 1 regardless of the values of μ. The results with the iterations ($t = 20 * 50$) are plotted in Fig. 5 ($t = 20 * 50$). When μ increases, the cooperation rate grows faster. It could be explained by the conclusion that the reciprocal altruistic nodes get the higher probability to cooperate with the higher μ as formula (3) and (5) described. When the network has reached its stabilization, the values of μ almost has no effects on cooperation rate.

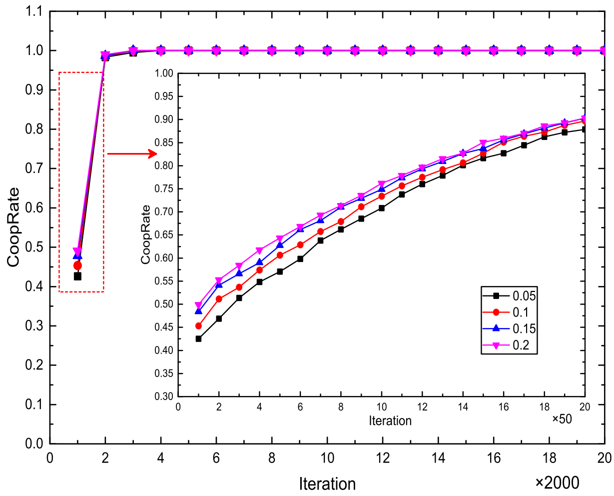

Fig. 6 Cooperation rate versus time for various values of λ_0

According to the two sets of experiments, we will consider $c_0 = 0.5$ and $\mu = 0.001$ in other sets of experiments.

4.2.3 The Initial Value of the Reciprocal Coefficient

As λ_0 means the possibility of unconditional cooperation for reciprocal altruistic nodes, it is meaningful to investigate the relationship between λ_0 and the cooperation rate. $N = 5$ and the iterations ($t = 20 * 50, 20 * 2000$) are used for this cases. The other parameters are the same as the values in Sect. 4.2.1.

Figure 6 plots the results of the cooperation rate versus time for increasing values of λ_0 as formula (3) and (4) described. It is found that the cooperation rate is proportional to λ_0. According to the formula (4), the larger the value λ takes, the greater the chance that the reciprocal altruistic nodes select the unconditional cooperation is.

4.2.4 Cost-to-Benefit Ratio of the Psychological Payoff

In order to investigate the behaviors of the ABDM in more details, the impacts of $r1$ would be studied. $N = 5$ and the iterations ($t = 20 * 50$) are used for these cases. The other parameters are the same as the values in Sect. 4.2.1.

Figure 7 plots the results of the cooperation rate versus time for increasing values of $r1$ as formulas (9) and (10) described. The nodes in the ABDM which choose cooperation will get psychological benefits to make sure that they will not have the lowest utilities. And there is a certain probability for the reciprocal altruistic nodes to choose unconditional cooperation. Therefore, the cooperation rate will grow higher no matter of the values of $r1$. When $r1$ increases, the punishment for the betrayal nodes increases, which means that the betrayal nodes are under the more stringent supervision. When $r1 = 0$, there are significant differences compared with the rest of

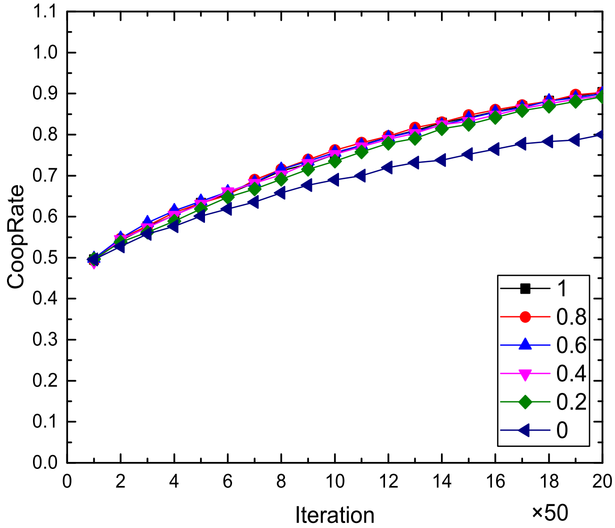

Fig. 7 Cooperation rate versus time for various values of $r1$

values: the payoff of the betrayal nodes has the smaller decrement so that it leads to the slower increment of the cooperation rate. It is concluded that $r1$ plays an important role at the ABDM. In the other sets of experiments, we will consider $r1 = 0.6$ in order to plot the trajectory of the results more obviously.

4.2.5 Proportion of the Economic Payoff and the Psychological Payoff

The ABDM adds the psychological payoff to the utility of the nodes in social networks by considering the decision-making elements. In this section, the results of the cooperation rate versus time for increasing values of α:β are investigated. $N = 5$ and the iterations($t = 20 * 300$) are used for this cases. The other parameters are the same as the values in Sect. 4.2.1.

As demonstrated in Fig. 8, when the psychological payoff is not added to the utility of nodes, the cooperation rate at equilibrium is much lower than those with the psychological payoff. When α:β =10:0, the betrayal nodes can not be punished as formula (11) described. That means the ABDM only has the same ability to facilitate cooperation like the MIX as demonstrated in Fig. 1a. As long as α:β $\neq$10:0, the betrayal nodes will be punished by reducing their utilities so as to make the higher cooperation rate. It can be seen that the use of the psychological payoff is the key to the ABDM. Therefore, we will consider the proportion α:β =8:2 in order to give enough punishments to the betrayal nodes.

4.2.6 Scalability and Stability

The scalability of the ABDM will be investigated in this section. Scalability and stability decide the performance of the ABDM under different conditions: node joining, node exiting, node failure restoring, node capability aggregating and etc. When a part

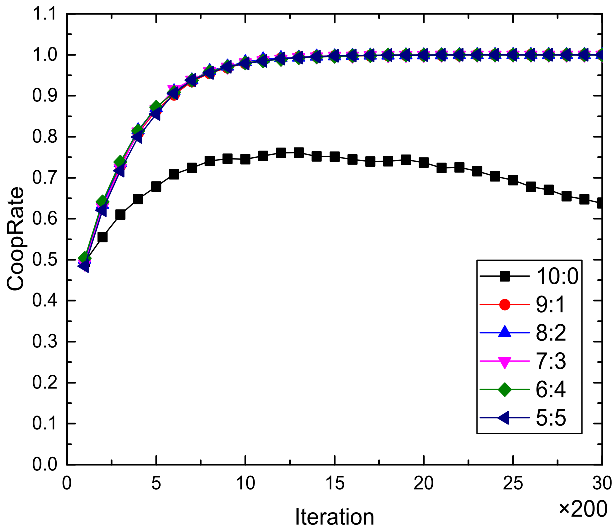

Fig. 8 Cooperation rate versus time for various values of α:β

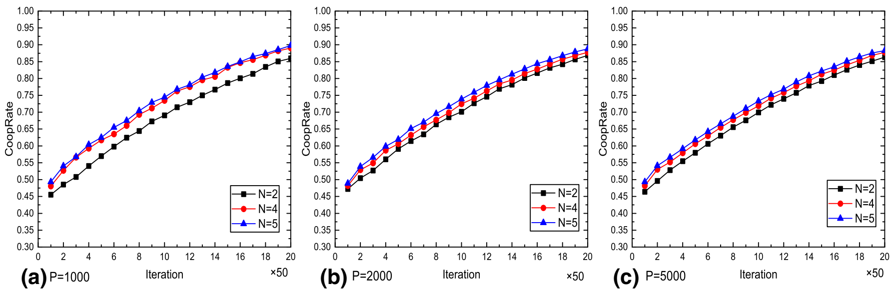

Fig. 9 Cooperation rate versus time for various values of the population size $P(\xi = 0)$

of nodes exited from the network or the population size increased, it is necessary to investigate the impact of the situation above. $\lambda_0 = 0.2$, $\mu = 0.001$, $c_0 = 0.5$ are used for these cases.

As you can see in Fig. 9, population sizes do have a very negligible effect on the behaviors of the ABDM. Figure 10 illustrates the point that when N increases, the proportion of cooperation at equilibrium enhances. According to Fig. 10a, b, it is not hard to find that the higher cooperation rate exists with the higher N when $r1$ has been set. Conversely, if the group size has been set, the situation would be the same as that in Sect. 4.2.4. If the α:β replaces the $r1$, there is no doubt that the higher cooperation rate exists with the higher group size as shown in Fig. 10c, d. Therefore, the cooperation level still stays high although the population increases, or the group size increases, or both the population and group size increase.

In Fig. 11a, we can observe that the cooperation rate of the MIX becomes lower when the more nodes exit. Figure 11b ($t = 20 * 2000$) shows that the cooperation rate of the ABDM will quickly converge to 1 when $\xi \in [0, 0.5]$, and the results have

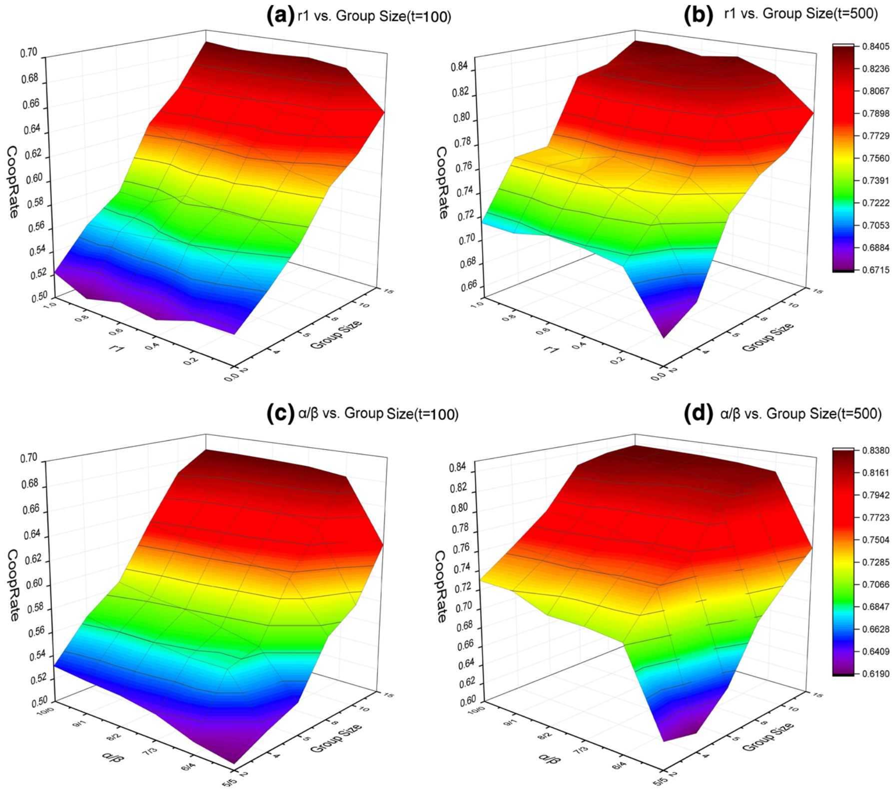

Fig. 10 Proportion of cooperation at equilibrium level as $r1(\alpha : \beta)$ across different group sizes N (please refer to the digital version of the paper for colors)

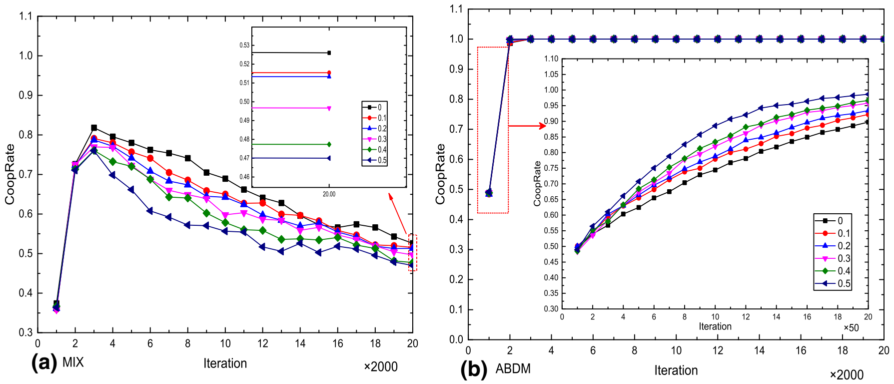

Fig. 11 Cooperation rate versus time for various values of exit rate $\xi(P = 1000)$

confirmed that the ABDM still has a high level of cooperation after part of nodes having exited from the network. As it is demonstrated in Fig. 11b ($t = 20 * 50$), when ξ increases, the initial number of the betrayal nodes in the network relatively decreases, so the network has a higher level of cooperation under the same iterations. In contrast, the poor performance of the MIX is because of its lack of punishments. Above three graphs show that the ABDM has good scalability and robustness. And its scalability makes it practical for using in large social networks, also makes it effective to improve performance of big data processing.

5 Conclusions

Social network is a hotspot in complex networks now, and social dilemma games provide an interesting framework for investigating the co-evolution of cooperation and structure in complex networks. This study has used the NPD game as a framework to investigate how the reciprocal altruistic nodes facilitate cooperation in social networks and how the dynamic social networks improve the efficiency of parallel processing.

The ABDM has its dynamic network structure: nodes which choose to cooperate could strengthen the connections with the opponents, on the contrary, the connections of those who choose to betray could be weakened. We consider the existence of strong reciprocity behaviors and introduce the nodes with bounded rationality into the ABDM. A reciprocal altruistic node can make decisions by considering the information of connections between each opponent and itself. At the same time, a reciprocal altruistic node can punish the betrayal nodes in its group. The ABDM also has put forward a new utility function for the NPD game by introducing the psychological payoff, including the psychological benefits and the psychological loss corresponding to the behaviors of nodes.

The simulation results suggest that the reciprocal altruistic nodes and the psychological payoff both play crucial roles in facilitating cooperation in social networks. It is confirmed that the nodes in the ABDM have high efficiencies of interaction. Therefore, the ABDM can also improve the efficiency of parallel processing. In the meanwhile, the results not only validate our idea of introducing views from reciprocal altruistic but also confirm that the behavior economic theory has provided a new angle of view for researches on the cooperation mechanisms.

There is an opportunity to extend this work in a number of different ways. We have assumed that all the reciprocal altruistic nodes are of the same initial reciprocal coefficient, and all the reciprocal altruistic nodes will punish the betrayal nodes certainly. It is important to investigate these problems in future works.

Acknowledgements This work is supported by the National Natural Science Foundation of China under Grant 61572528.

References

1. Liu, X., Zhou, Y., Hu, C., et al.: MIRACLE: a multiple independent random walks community parallel detection algorithm for big graphs. J. Netw. Comput. Appl. **70**, 89–101 (2016)
2. Meyerhenke, H., Sanders, P., Schulz, C.: Parallel graph partitioning for complex networks. IEEE Trans. Parallel Distrib. Syst. **99**, 1 (2014)

3. Gupta, S., Mittal, S., Gupta, T., et al.: Parallel quantum-inspired evolutionary algorithms for community detection in social networks. Appl. Soft Comput. **61**, 331–353 (2017)
4. Shi, X., Chen, M., He, L., et al.: Mammoth: gearing hadoop towards memory-intensive mapreduce applications. IEEE Trans. Parallel Distrib. Syst. **26**(8), 2300–2315 (2015)
5. Liu, Y.X., Liu, A., Guo, S., et al.: Context-aware collect data with energy efficient in Cyber-physical cloud systems. Future Gener. Comput. Syst. **27**(2), 634–639 (2017)
6. Liu, X., Zhao, S., Liu, A., et al.: Knowledge-aware Proactive Nodes Selection approach for energy management in Internet of Things. Future Gener. Comput. Syst. (2017). https://doi.org/10.1016/j.future.2017.07.022
7. Magnussen, S.: International Encyclopedia of the Social and Behavioral Sciences, 2nd edn. In: International Encyclopedia of the Social Sciences. Macmillan Reference (2015)
8. Ye, Q., Law, R., Gu, B., et al.: The influence of user-generated content on traveler behavior: an empirical investigation on the effects of e-word-of-mouth to hotel online bookings. Comput. Hum. Behav. **27**(2), 634–639 (2011)
9. Crnovrsanin, T., Muelder, C.W., Faris, R., et al.: Visualization techniques for categorical analysis of social networks with multiple edge sets. Soc. Netw. **37**(2), 56–64 (2014)
10. Adar, E., Huberman, B.A.: Free riding on Gnutella. First Monday **5**(10), 134–139 (2000)
11. Izal, M., Urvoy-Keller, G., Biersack, EW., et al.: Dissecting BitTorrent: five months in a torrent's lifetime. In: Proceedings of International Workshop, Passive and Active Network Measurement PAM 2004, Antibes Juan-Les-Pins, France. DBLP, 2017, pp. 1–11 (2004)
12. Saghiri, A.M., Meybodi, M.R.: An approach for designing cognitive engines in cognitive peer-to-peer networks. J. Netw. Comput. Appl. **70**, 17–40 (2016)
13. Wang, Z., Wang, J., Zhao, Y.: The optimization model of trust for white-washing. In: International Conference on Cloud Computing and Security. Springer International Publishing, pp. 169–180 (2015)
14. Alsaedi, N., Hashim, F., Sali, A., et al.: Detecting sybil attacks in clustered wireless sensor networks based on energy trust system (ETS). Comput. Commun. **110**, 75–82 (2017)
15. Ismail, H., Germanus, D., Suri, N.: P2P routing table poisoning: a quorum-based sanitizing ap-proach. Comput. Secur. **65**, 283–299 (2017)
16. Palomar, E., Alcaide, A., Ribagorda, A., et al.: The Peer's Dilemma: a general framework to examine cooperation in pure peer-to-peer systems. Comput. Netw. **56**(17), 3756–3766 (2012)
17. Li, Y., Xu, H., Cao, Q., et al.: Evolutionary game-based trust strategy adjustment among nodes in wireless sensor networks. Int. J. Distrib. Sens. Netw. **2015**, 1–12 (2015)
18. Buttyn, L., Dra, L., Flegyhzi, M., et al.: Barter trade improves message delivery in opportunistic networks. Ad Hoc Netw. **8**(1), 1–14 (2010)
19. Ning, Z., Liu, L., Xia, F., et al.: CAIS: a copy adjustable incentive scheme in community-based socially-aware networking. IEEE Trans. Veh. Technol. **66**(4), 3406–3419 (2016)
20. Tseng, Y.M., Chen, F.G.: A free-rider aware reputation system for peer-to-peer file-sharing net-works. Expert Syst. Appl. **38**(3), 2432–2440 (2011)
21. Martinez-Canovas, G., et al.: A formal model based on game theory for the analysis of cooperation in distributed service discovery. Inf. Sci. **326**, 59–70 (2015)
22. Seo, J., Choi, S., Han, S.: The method of trust and reputation systems based on link prediction and clustering. In: IFIP International Conference on Trust Management. Springer, Berlin, pp. 223–230 (2017)
23. Caverlee, J., Liu, L., Webb, S.: Towards robust trust establishment in web-based social networks with socialtrust. In: International Conference on World Wide Web, WWW 2008, Beijing, China. DBLP, pp. 1163–1164 (2008)
24. Barbian G. Assessing Trust by Disclosure in Online Social Networks[C]// International Con-ference on Advances in Social Networks Analysis and Mining, Asonam: Kaohsiung, Taiwan, 25–27 July. DBLP **2011**, 163–170 (2011)
25. Trifunovic, S., Legendre, F., Anastasiades, C.: Social trust in opportunistic networks. In: IN-FOCOM IEEE Conference on Computer Communications Workshops, pp. 1–6 (2010)
26. Fu, H., Li, H., Zheng, Z., et al.: Optimal system maneuver for trust management in social networks (2016, preprint). arXiv:1604.07139
27. Mtibaa, A., Harras, KA.: Social-based trust in mobile opportunistic networks. In: Proceedings of International Conference on Computer Communications and Networks, pp. 1–6 (2011)
28. Najaflou, Y., Jedari, B., Xia, F., et al.: Safety challenges and solutions in mobile social net-works. IEEE Syst. J. **9**(3), 834–854 (2015)

29. Bigwood, G., Henderson, T.: IRONMAN using social networks to add incentives and repu-tation to opportunistic networks. In: Passat, socialcom: Privacy, Security, Risk and Trust. DBLP 2011, pp. 65–72 (2011)
30. Vegni, A.M., Loscri, V.: A survey on vehicular social networks. IEEE Commun. Surv. Tutor. **17**(4), 2397–2419 (2015)
31. Zhai, C., Zhang, W., Mao, G.: Cooperative spectrum sharing between cellular and ad-hoc networks. IEEE Trans. Wireless Commun. **13**(7), 4025–4037 (2014)
32. Syue, S.J., Wang, C.L., Aguilar, T., Gauthier, V., Afifi, H.: Cooperative geographic routing with radio coverage extension for SER-constrained wireless relay networks. IEEE J. Sel. Areas Commun. **30**(2), 271–279 (2012)
33. Lu, H.C., Liao, W.I.: Cooperative strategies in wireless relay networks. EEE J. Sel. Areas Commun. **30**(2), 323–330 (2012)
34. Mullainathan, S., Thaler, R.H.: Behavioral economics. International Encyclopedia of the Social and Behavioral Sciences vol. 76, pp, 1094–1100 (2001)
35. Hursh, S.R., Roma, P.G.: Behavioral economics and the analysis of consumption and choice. Manag. Decis. Econ. **37**(4–5), 224–238 (2016)
36. Milinski, M., Lling, D.K., Kettler, R.: Tit for Tat: sticklebacks (Gasterosteus aculeatus) trusting' a cooperating partner. Behav. Ecol. **1**(1), 7–11 (2017)
37. Takano, M., Wada, K., Fukuda, I.: Reciprocal altruism-based cooperation in a social network game. New Gener. Comput. **34**(3), 257–272 (2016)
38. Yamamura, E., Tsutsui, Y., Ohtake, F.: Altruistic and selfish motivations of charitable giving: case of the hometown tax donation system. Iser Discussion Paper (2017)
39. Guss, W., Schmittberger, R., Schwarze, B.: An experimental analysis of ul-timatum bargaining. J. Econ. Behav. Organ. **3**, 367–388 (1982)
40. Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., Mcelreath, R.: In seach of homo economicus: behavioral experiments in 15 small-scale societies. Am. Econ. Rev. **91**(2), 73–78 (2001)
41. Camerer, C.F.: Behavioral Game Theory: Experiments on Strategic Interaction. Princeton University Press, Princeton (2002)
42. Fehr, E., Simon, G.: Cooperation and punishment in public goods experiments. Am. Econ. Rev. **90**(4), 980–994 (2000)
43. Guth, W., Tietz, R.: Ultimatum bargaining behavior:a survey and comparison of experimental results. J. Econ. Psychol. **11**, 417–449 (1990)
44. de Quervain, D.J., Fischbacher, U., Treyer, V., et al.: The neural basis of altruistic punishment. Science **305**(5688), 1254–1258 (2004)
45. Qiu, D., Srikant, R.: Modeling and performance analysis of bittorrent-like peer-to-peer networks. In: The 2004 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications (SIGCOMM'04), Portland, pp. 367–378 (2004)
46. Shah, V., Veciana, G.D., Kesidis, G.: A stable approach for routing queries in unstructured P2P networks. IEEE/ACM Trans. Netw. **24**(5), 3136–3147 (2016)
47. Cox, J.C.: How to identify trust and reciprocity. Games Econ. Behav. **46**(2), 260–281 (2004)
48. Brosig-Koch, J., Riechmann, T., Weimann, J.: The dynamics of behavior in modified dictator games. PLoS ONE **12**(4), e0176199 (2017)
49. Rezaei, G., Kirley, M.: Dynamic social networks facilitate cooperation in the N-player prisoner's dilemma. Physica A **391**(23), 6199–6211 (2012)
50. O'Riordan, C., Cunningham, A., Sorensen, H.: Emergence of cooperation in n-player games on small world networks. In: S. Bullock, J. Noble, R. Watson,M.A. Bedau (Eds.), Artificial Life XI: Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems, MIT Press, Cambridge, pp. 436–442 (2008)
51. Kalaignanam, K., Kushwaha, T., Swartz, T.A.: The differential impact of NPD make/buy choices on immediate and future product quality: insights from the automobile industry. Social Science Electronic Publishing (2017)
52. Boyd, R., Richerson, P.: The evolution of reciprocity in sizeable groups. J. Theor. Biol. **132**, 337–356 (1988)
53. Kahneman, D., Tversky, A.: Loss aversion risk less choice a reference-dependent model. Quart. J. Econ. **106**(4), 1039–61 (1991)
54. Kahneman, D., Tversky, A.: Prospect theory: an analysis of decision under Risk. Econo-metrica **47**(2), 263–91 (1979)

55. Arellano, M., Bond, S.: Some tests of specification for panel data: monte carlo evidence and an application to employment equations. Rev. Econ. Stud. **58**(2), 277–297 (1991)
56. Ellis, T.S., Yao, X.: Evolving cooperation in the non-iterated prisoners dilemma: a social network inspired approach. In: IEEE Congress on Evolutionary Computation, pp. 736–743 (2007)