Scientia Iranica E (2015) 22(6), 2548–2557

SCIENTIA IRANICA

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
www.scientiairanica.com

Analysis of network trust dynamics based on the evolutionary game

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Received 6 December 2012; received in revised form 26 August 2014; accepted 15 November 2014

KEYWORDS
Trust;
Trust dynamics;
Game theory;
Evolutionary game.

Abstract. Trust, as a multi-disciplinary research domain, is of high importance in the area of network security and it has increasingly become an important mechanism to solve the issues of distributed network security. Trust is also an effective mechanism to simplify complex society, and is the source to promote personal or social cooperation. From the perspective of network ecological evolution, we propose the model of the P2P Social Ecological Network. Based on game theory, we also put forward network trust dynamics and network eco-evolution by analysis of network trust and the development of the dynamics model. In this article, we further analyze the dynamic equation, and the evolutionary trend of the trust relationship between nodes using the replicator dynamics principle. Finally, we reveal the law of trust evolution dynamics, and the simulation results clearly describe that the dynamics of trust can be effective in promoting the stability and evolution of networks.

1. Introduction

The P2P network is composed of nodes with different functions, structure and service. These nodes not only involve cooperation but also competition that aggravates the instability and disorder of the network because of the existence of free riders and malicious nodes. How to promote cooperation between nodes is very important in P2P. As known, emergence and maintenance of cooperation are the most interesting and baffling problems in social and ecological networks [1-7]. One way to approach the problem is the possibility of using evolutionary game theory [8-12], in which the game is an interaction model in the competition between micro-individuals. As long as contradiction, competition and cooperation exist between micro-individuals, the micro-dynamics evolutionary mechanism can be described by a game theory model. P2P networks, social networks and ecological networks have striking similarities. Therefore, analyzing the dynamic characteristics of cooperation between the nodes in the P2P network is a challenging subject and also the focus of the proposed research.

In 1961, Lewontin first applied the thought of game theory to biological science [13], describing the interaction between species and the natural environment. In 1973, Smith and Price completed their famous paper "The logic of animal conflict" [14]. With the perspective of individual choice and the application of game theory, this paper further explains why fights between animals are always of limited aggression, and never cause serious damage. This is the first time that game theory has formally been applied to evolution. Game theory is developed based on the understanding

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that all involved individuals are rational. Therefore, the idea of game theory is applied to biological sciences with three key changes:

1. Change of strategy connotation: In evolutionary game theory, "survival of the fittest" becomes the basis of strategy selection for players;
2. Change of Equalization: The Evolutionary Stable Strategy (ESS) [14] proposed by Smith and Price is the "Nash Equilibrium" of the evolutionary game. That is, if all individuals in a population have adopted a certain strategy and, at this time, a handful of any other mutation strategies cannot invade this population, this strategy is called evolutionary stable. This specific strategy is called the evolutionary stable strategy. Each evolutionary stable strategy must be the Nash equilibrium, but only strict Nash equilibrium is an evolutionary stable strategy [15];
3. Changes in connotation of individual interaction: In evolutionary game theory, the game individual interacts by random matching [16], and this interaction of the evolutionary game has been thoroughly studied [1,17-19] in a complex network.

Due to the connotative change of the above three important concepts, evolutionary game theory endows dynamic evolutional ideas with a static decision-making process. This process not only enriches and promotes the development of the theory of biological evolution, but also makes evolutionary game theory into an important theoretical technology in ecological stability analysis and micro-economic analysis. Since then it has been widely applied to economic, social and behavioral sciences [20-22].

The classic game theory is based on players with the assumption of "perfect rationality", demanding that actors should have sound judgment and forecasting capabilities, and always pursue their own interests to the maximum. But, Alchian [23] believes that in the real world, the future is uncertain and information is also incomplete. Therefore, perfect rationality is not common under those constraint conditions. He originally proposed a system evolution model based on the thought of "natural selection", which is a biological evolution. In this model, people adapt to the changing environment and survive through imitative and trial-and-error behavior. In addition, the "replicated dynamic" [14] mechanism assumes that the players are bounded rationally, and decides the behavior strategy through imitation and trial-and-error. The adjustments of the dynamic strategy and evolutionary stability are obtained through the repeated game. Moreover, Smith introduced the concept of the evolutionary stable strategy in [13], and noted that in biological populations, all individuals use a strategy.

Trust is a subject of strong theoretical significance and realistic meaning. It is related to human behavior, which changes due to the uncertainty of the environment. Accurately understanding the change of human behavior in a variety of situations is important to define trust. Trust involves interpersonal interaction strategies, dependent relationships, and game theory. Game theory studies strategy interaction and offers an alternative perspective to profoundly reveal the important role and production mechanism of trust. Therefore, research on trust based on game theory is quite common in sociology, economics, politics, and other disciplines [24-31].

Trust is further an important topic in the area of Online Social Networks (OSNs) in which a number of uncovered and potential problems occurs [32-35]. Several of these issues are highly related to the area of trust in P2P networks and the evolution of future networks in which OSN and the introduction of social interaction has created a way to mimic real human communication using the Internet. For example, by services like Facebook, Twitter and Google+ it is now possible to interact and share feelings and images by flooding your social network with information related to your daily activities in a way not possible before the era of OSNs.

In computer science, game theory mainly concentrates on applied research of the resource sharing incentive mechanism; typically, trust and cooperation. Namely, it is how to make nodes cooperate with each other by taking effective strategies. Previous research is based on the simple pure strategy game and there is little research involving the dynamic, uncertainty trust game [36]. In [37], a model of the "prisoners' dilemma" in the P2P file sharing network is proposed. However, it only proposes some feasible methods of establishing the incentive mechanism, and has not been able to adapt to the self-organization management model. Non-cooperative repeated game theory is applied to the study of incentives in packet routing forwarding by Blanc et al. [38]. The distributed algorithm to adapt to a self-organization management model is also not given. In addition, Buragohain et al. [39] gave a non-cooperative game model in the P2P network resource sharing. Also, a majority of the current research projects are concentrated on Ad Hoc Networks [26-28] and not on P2P networks.

Trust is the vital basis of cooperation. So, this paper is based on evolutionary game theory to analyze the dynamics characteristics of trust and its trends of evolution and evolutionary stability. Moreover, it demonstrates that trust is an important mechanism to reduce network security risks and maintain network stability. First, based on social and ecological networks, we propose the model of the P2P Social Ecological Network. Then, we analyze the strategy choice of the populations, and get the Evolutionary Stable Strategy in the P2P Social Ecological Network.

The rest of the paper is organized as follows. The dynamics model of trust and its analysis is presented in Section 2. Section 3 shows the simulation experiments and also presents the evaluation of the results. Finally, our work is concluded in Section 4.

2. Dynamics model of network trust

2.1. P2P social ecological network

Ecology is a subject studying the relationships between biology, people and the environment, and the functional structure of natural ecological and human ecology systems. The basic principles of ecology can be applied to not only biology but also production activities in which human beings are engaged. From social ecology, network speeding development will lead to a series of questions between various factors within the network, as well as the network and other related social environments. All other social systems that affect network development constitute the ecological environment of network development, i.e. interaction and mutual influence between the ecological environments is analyzed with an eye towards connections and development, which are then formed as a network ecosystem.

In complex and dynamically changing environments, such as P2P networks, the interactions and transfer of information between services are sometimes uncertain and continuously changing, which makes the network system more dynamic. In addition, evolutional results of these long-term processes will make development of the dynamic and organic system much more self-organizing. Eventually, the whole system achieves stability and evolution through interaction and collaboration between nodes.

In our proposed work, we are inspired by mechanisms in ecological and social networks in order to analyze the evolutionary stability of P2P networks. In P2P networks, we put node groups of different types, such as normal, malicious, and free-rider class node groups, as different populations in the ecological network. We can also place a virus as an invasion population, as part of the P2P network social ecology. The following section describes several definitions.

Definition 1. P2P networks are social-ecological networks, expressed as $\mathrm{PSE}_{\mathrm{net}} < G, R >$. Among them, G represents the set of the population in the network, R represents the relationships between the ecological nodes in the population, and the relationships between the populations will emerge by the relationships of the nodes.

Definition 2. The population set is defined as $G = (G_1, G_2, \cdots, G_n)$, where $G_i (i = 1, \cdots, n)$ denotes one population in the ecological network. Viruses or Trojan horses constitute one or more populations.

Definition 3. The same types of ecological node are defined as a population, $G_i = (g_1, g_2, \cdots, g_m)$, and among them, $g_j (j = 1, \cdots, m)$ is an ecological node in the P2P networks.

Definition 4. Relationship sets are defined as $R = (r_{11}, r_{12} \cdots, r_{ij}, \cdots, r_{mn})$ among ecological nodes where $r_{ij} (i = 1, \cdots, m, j = 1, \cdots, n)$ represents the relation between ecological nodes within one or two populations.

The ecological node in the network with people in social networks has limited rationality because of understanding limitations and network knowledge limitation regarding the information of other nodes. At the same time, it is selfish, has opportunistic tendencies, and is determined, by its nature, to pursue its own long-term optimization outcome (such as the degree of safety). The ecological nodes interact with each other according to their strategies, which provide the ecological power for network evolution. As a result, we can consider the behavior of this interaction between nodes as game behavior, and the behaviors of an ecological node occur in order to help it survive in the network and pursue its own interests. The interactive process is the game process driven by the different strategies adopted by the nodes.

Definition 5. $\mathrm{PSE}_{\mathrm{net}}$ is a finite set, $S = (s_1, s_2, ..., s_w)$, in the network eco-node behavior policy set. It is called strategy space in which the nodes randomly select strategy $s_y (y = 1, \cdots, w)$ in order to interact in the games.

A complex social ecological network, such as the P2P network system, is made up of a variety of relationships produced by different species and their interaction. Nodes in multiple or single populations follow dynamic and self-adjustment evolutionary game theory to compete for limited network resources, such as storage resources, computing resources and network bandwidth, which provide the power for the network ecological evolution.

2.2. Trust dynamics model

A social network is formed by interaction between people and organizations. It is their behavior that forces the social development and evolution of the ecological network. Therefore, we use abstract force models and principles to explain and analyze the cooperative evolution and network stability. Both the relationship formed between nodes and the influence from the context nodes are influential properties.

When the nodes of the P2P network interact,

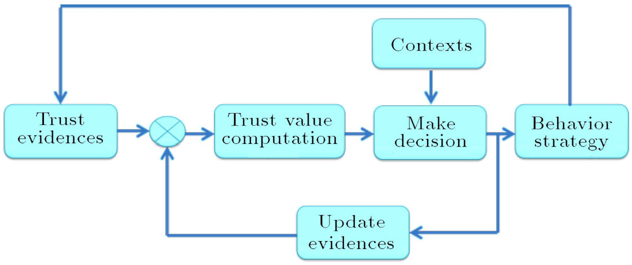

Figure 1. Dynamics model of network trust.

they must consider their safety. Cooperation, the core of P2P, means taking risks. It cannot guarantee the stability of the network. We propose to use the Trust of the Dynamics between the nodes to study the evolution stability and the evolution rule of network ecology. Figure 1 depicts the network trust calculation dynamic model proposed in this article.

The trust dynamics process can be described as follows:

1. Collection and storage of trust evidence;
2. Calculation of trust (taking into account the context);
3. Choice of trust strategy;
4. Evaluation of interaction behavior, namely feedback.

Definition 6. Trust dynamics in the P2P service environment is concerned with network stability and evolution based on node trust strategy, interaction and feedback.

2.3. Trust dynamics analysis

To simplify the discussion on the above model, the evolution game is studied between the nodes in a single population (that is, the same type of node population), where nodes provide or consume services (such as file sharing).

Definition 7. The probability distribution function of interactive strategies adopted by players (Network Ecosystem node) is $P = (p_1, p_2, \cdots, p_w)$ where p_y is the probability of the node selection strategy, s_y, $\sum_{y=1}^{w} p_y = 1$ $(y = 1, \cdots, w)$.

Definition 8. A game is an interaction of two rational nodes. The benefit function of a game is u whose value is related to the strategy used by both sides.

The probability of selecting interactive game strategy, p_i, changes over time, which can be expressed as a function of time $p_i(t)$. For simplicity, it can still be expressed as p_i.

The expected probability of a node, y, to choose pure strategy, s_y, is:

$$u_y = p_y * u(s_y). \tag{1}$$

		Node 1	
		Trust	Distrust
Node 2	Trust	r, r	s, d
	Distrust	d, s	p, p

Figure 2. The Benefit matrix of node 1 and node 2 in game.

The earnings of the p_x selected mix strategy, s_x, as:

$$u_x = \sum_{x=1, x\neq y}^{w} (p_x * u(s_x)). \tag{2}$$

By Eqs. (1) and (2), we understand that the replicated dynamic equation of the node game is:

$$\frac{dp_y}{dt} = p_y * \left(p_y * u(s_y) - \sum_{x=1, x\neq y}^{w} (p_x * u(s_x)) \right). \tag{3}$$

There are various strategies and different types of relationship between nodes. The core of the whole network stability depends on the cooperation during the interaction process. In order to discuss the trend and stability of the evolution, we focus on the trust relationship and assign two values to it; trust and distrust. Figure 2 shows the benefit matrix of both sides in a game. Among them, r denotes the benefit when both parts choose trust strategy in a game. If only one party's strategy is defined by trust, s denotes the benefit of the trusting party and d denotes the benefit of the distrusting party. p denotes the benefit of both parts when they choose the distrust strategy.

In the famous "prisoners' dilemma", the only case, where Nash equilibrium exists, is when both parts choose the distrust strategy. However, when the nodes consider long-term survival in the network, they adopt the mutual trust strategy to continue the game. This is called 'Game Refined Nash equilibrium' in non-cooperative game theory. We introduce cooperative game theory to the P2P network and use it to analyze and solve the trust evolution among nodes. The theory guarantees the strategy equilibrium and the stability of the network evolution.

We also use the "replicated dynamic" mechanism to solve the game model with two nodes. Among them, the nodes choose a strategy with transcendental behavior probability to each game, correct the transcendental probability through imitation, trial and error, and evolve to the posteriori probability.

We assume that the probability of choosing a trust strategy probability at the first stage is x, and the probability of using the distrust strategy is $1 - x$.

Therefore, the node's benefit, u_1, to choose the trust strategy is:

$$u_1 = x * r + (1 - x) * s. \tag{4}$$

The node's benefit, u_2, to choose the distrust strategy is then:

$$u_2 = x * d + (1 - x) * p. \quad (5)$$

Thus, the node average benefit, $\bar{u}$, is:

$$\bar{u} = x * u_1 + (1 - x) * u_2. \quad (6)$$

Here, if we assume $r = 1$, and s, d, and p are zero, the benefit of nodes with the trust strategy is higher than nodes with the distrust strategy. It is also higher than the average benefit, based on the above formula, unless all nodes choose the distrust strategy (the reason is $0 < x < 1$, so $u_1 = x > x^2 = \bar{u} > 0$). This will be discovered by the distrust node, in which it will change its strategy in order to get higher benefit. Therefore, the proportion of nodes with different strategy is changing with time, i.e. the changing rate can then be expressed by the following dynamic differential equation:

$$\frac{dx}{dt} = x * (u_1 - \bar{u}). \quad (7)$$

This differential equation is called the replicated dynamic equation. The reason is that it is consistent with the equation that describes the natural selection process of frequency changing of an individual's specific traits in biological evolution.

$F(x)$ denotes $\frac{dx}{dt}$, and we obtain the next equation from Eqs. (4) to (7):

$$\frac{dx}{dt} = F(x) = x * (1 - x) * (x * (r - d) + (1 - x) * (s - p)). \quad (8)$$

We first obtain the stable solution of the replicated dynamic equation, if we consider the Evolutional Stable Strategy (ESS) of the game. That is, the proportion of nodes with trust or distrust strategies remain unchanged in the calculation process of the replicated dynamic equation. Then, we can analyze the stability of these steady-state fields, i.e. it will maintain the equilibrium state, even with small deviation disturbance. In Figure 3, we can see the evolution rule for two kinds of proportion nodes.

To set $F(x) = 0$, we can obtain the three following solutions:

$$x_1 = 0, \quad (9)$$

$$x_2 = 1, \quad (10)$$

$$x_3 = \frac{p - s}{r - d + p - s}. \quad (11)$$

According to the stability principle of differential equations, we know that the derivative of a function must be less than 0 at the steady state, that is $F(x^*) < 0$, and x^* is the ESS. Therefore, to make the trust strategy become an ESS in the network evolution, we further need to discuss the value of r, s, d, and p.

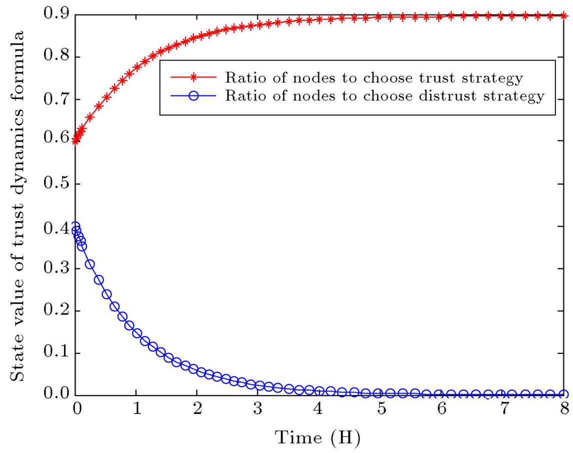

Figure 3. State diagram of trust dynamics equation (assuming $r = 1$, and s, d and p are zero).

2.4. Trust strategy stability analysis

Thus, if the trust strategy becomes an ESS, it should meet the following conditions:

1. $F'(x_1 = 0) < 0$,
2. $F'(x_2 = 1) < 0$,
3. $0 < x_3 = \frac{p-s}{r-d+p-s} < \frac{1}{2}$.

Next, we discuss the parameters, r, s, d, and p, and analyze the trust strategy of how to obtain the ESS in the network evolution:

1. When $p < s$, $r < d$, and $r - d > p - s$, node 2 could select the trust strategy, which then make it beneficial for node 1 to select the distrust strategy. This also holds for when node 2 chooses the distrust strategy and the benefit of node 1 with a distrust strategy and vice-versa. It is then possible to verify that:

$$F'(x_1 = 0) > 0, \qquad F'(x_2 = 1) > 0,$$

and:

$$0 < x_3 = \frac{p - s}{r - d + p - s} < \frac{1}{2}.$$

The phase diagram of the replicated dynamic differential equation is shown in Figure 4.

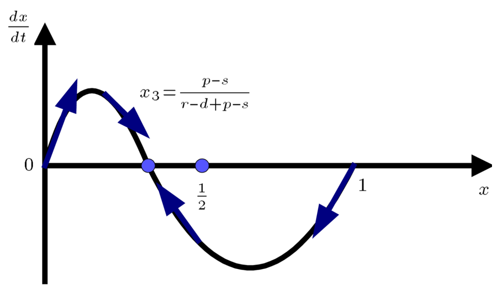

Figure 4. Partial phase diagram of the replicated dynamic equation.

It can be seen from Figure 4 that the tangent slope at $x^* = x_3$ is lower than 0, and the tangent slope at $x_1 = 0$ and $x_2 = 1$ is greater than 0. It can also be seen from Figure 4 that the number of nodes with trust strategy will eventually stabilize around x_3, and the number of nodes with distrust strategy is $1 - x_3$, following that $1 - x_3 > x_3$.

2. When $p < s$, $r < d$, and $r - d < p - s$, it is similar as for case 1. It is then also possible to verify that:

$$F'(x_1 = 0) > 0, \qquad F'(x_2 = 1) > 0,$$

and:

$$\frac{1}{2} < x_3 = \frac{p - s}{r - d + p - s} < 1.$$

The phase diagram of the replicated dynamic differential equation is then shown in Figure 5.

It is further possible to verify (in Figure 5) that a similar tangent slope evaluation is obtained as for case 1 and Figure 4.

3. When $p > s$, $r > d$, and $r - d > p - s$, a trust strategy for node 2 is beneficial, which also makes the trust strategy more beneficial for node 1 compared to a distrust strategy. This also holds for the distrust strategy for both nodes. This is then verified by:

$$F'(x_1 = 0) < 0, \qquad F'(x_2 = 1) < 0,$$

and:

$$0 < x_3 = \frac{p - s}{r - d + p - s} < \frac{1}{2},$$

with a phase diagram presented in Figure 6.

It can be seen from Figure 6 that the tangent slope at x_3 is greater than 0, and the tangent slope at x_1 and x_2 is lower than 0. Therefore, x_3 is not an evolutionary stable strategy, and x_1 and x_2 are. The two strategies of trust and distrust are likely to be used by both sides of the game node, but because:

$$0 < x_3 = \frac{p - s}{r - d + p - s} < \frac{1}{2},$$

it can be seen that the probability of using a trust strategy is greater than the probability of using a distrust strategy.

4. When $p > s$, $r > d$ and $r - d < p - s$, it is similar as for case 3. At this time, there are also:

$$F'(x_1 = 0) < 0, \qquad F'(x_2 = 1) < 0,$$

and:

$$\frac{1}{2} < x_3 = \frac{p - s}{r - d + p - s} < 1,$$

and the phase diagram is shown in Figure 7. The probability of using a trust strategy is then lower than the probability of using a distrust strategy;

5. When $p > s$ and $r < d$, it does not matter if node 1 chooses the trust or distrust strategy. The benefit of node 2 with a distrust strategy is always more than the benefit with a trust strategy. That is, when $F'(x_1 = 0) < 0$ and $F'(x_2 = 1) > 0$ (the phase diagram is shown as in Figure 8), it can be seen that x_1 is the stability strategy, while x_2 is not. So,

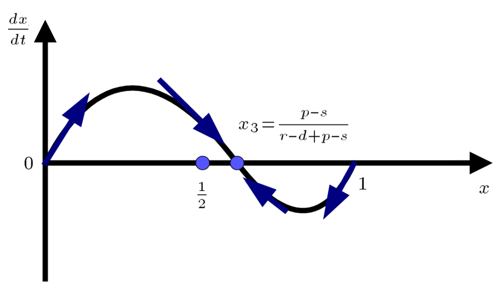

Figure 5. Partial phase diagram of the replicated dynamic equation.

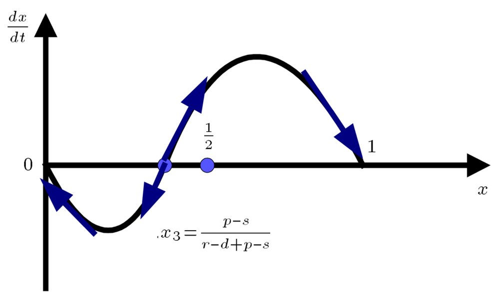

Figure 6. Partial phase diagram of the replicated dynamic equation.

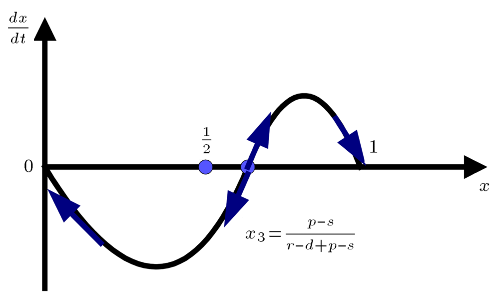

Figure 7. Partial phase diagram of the replicated dynamic equation.

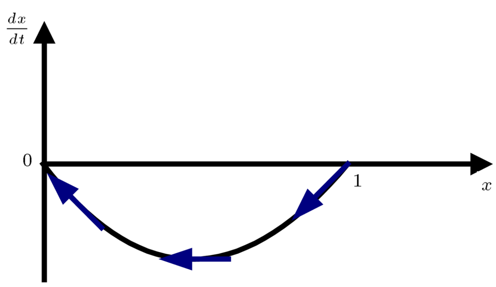

Figure 8. Partial phase diagram of the replicated dynamic equation.

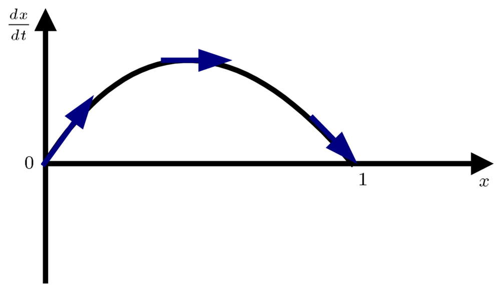

Figure 9. Partial phase diagram of the replicated dynamic equation.

all the players in the game tend to use the distrust strategy;

6. When $p < s$ and $r > d$, it does not matter if node 1 chooses the trust or distrust strategy. The benefit of node 2 with a trust strategy is always more than the benefit of choosing a distrust strategy. That is, when $F'(x_1 = 0) > 0$ and $F'(x_2 = 1) < 0$ (the phase diagram is shown in Figure 9), it can be seen that x_2 is the stability strategy, while x_1 is not. So, all the players in the game tend to use the trust strategy.

   By the above analysis, trust is an evolutionary stable strategy in an ideal situation, when $F'(x_2 = 1) < 0$. In general, it is normal for players in a game to adopt the two strategies. However, making the trust strategy evolve to ESS, by regulating certain mechanisms, is important, while maintaining network stability and security. Therefore, the players will tend to select the trust strategy as long as $p < s$ and $r > d$. In addition, $r - d >>> p - s$ (the meaning of the symbol $>>>$ is much larger than $>$), even though $F'(x_1 = 0) < 0$, in which a stable strategy exists.

With $x_3 = \frac{p-s}{r-d+p-s} \to 0$, the proportion of nodes with a distrust strategy will gradually decrease through continuous imitation, and trial and error. Finally, it will achieve a stable small scale level, as depicted in Figure 7, developed from the state of Figure 4. It can also be observed that it will ultimately tend to the stability of the trust strategy. Even though a small number of nodes occasionally deviate, wherein they choose a distrust strategy, the replicated dynamic mechanism will make it back to a stable level. In this way, trust is the only evolutionary stable strategy.

After analyzing two different strategies of the trust evolution game, from their motivation to punishment mechanism regulations, which change the game matrix parameters, it can be seen that the convergence speed to a stable state of trust strategy is faster than that of a distrust strategy. In the evolutional process of a trust game, the new game strategy depends on the current strategy, and the process also meets the property of a Markov chain. This Markov chain is homogeneous, because the evolutional transition probability does not depend on time in the evolutionary process. Instead, it shows that the evolution of the strategy can converge. It also confirms that the trust strategy will eventually become an evolutionary stable strategy in a network evolution.

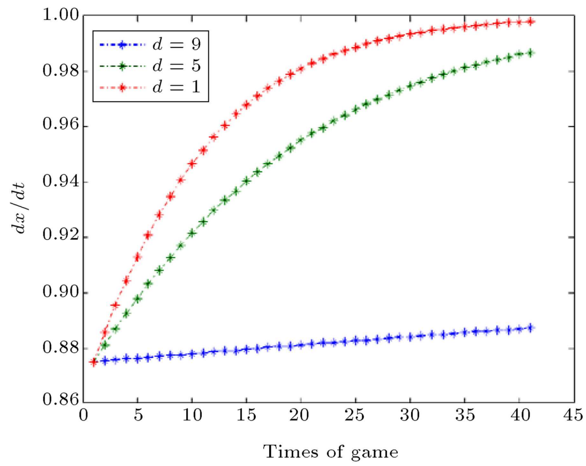

Figure 10. Different $\frac{dx}{dt}$ with d when $r = 10$, $s = 1$, and $p = -1$.

3. Experimental simulation analysis

1. If we assume that $r = 10$, $s = 1$, $p = -1$, and $p - s = -2$ for $d = 9$, $d = 5$, and $d = 1$, the changing curve of $\frac{dx}{dt}$ is then shown in Figure 10. It is observed in Figure 10 that when the gap between $r - d$ and $p - s$ is bigger and bigger, the change of $\frac{dx}{dt}$ is quite obvious. That is, the relative change between the proportion of nodes with a trust strategy is possible to detect, as the adjustment mechanism obviously works. Similarly, as long as $p < s$, $r > d$, and $r - d >>> p - s$, the players constantly adjust their strategy through trial and error, and imitation. Similarly, adjusting the other parameter values, as long as the above conditions are met, will lead to the same results.
2. If we assume that:

   (1) $r = 10$, $s = 1$, $p = -1$, and $d = 1$,
   (2) $r = 10$, $s = -1$, $p = 1$, and $d = 1$,
   (3) $r = 1$, $s = 1$, $p = -1$, and $d = 10$,
   (4) $r = 1$, $s = -1$, $p = 1$, and $d = 10$,

   we can get four different curves, respectively, as shown in Figures 11-14.

In the first case, the trust meets the conditions of the evolutionary stable strategy. So, when x is small, the curve also changes more quickly. In addition, when x is of a bigger number, the curve changes more slowly.

In the second case, when a node chooses the distrust strategy, the best choice of another node is

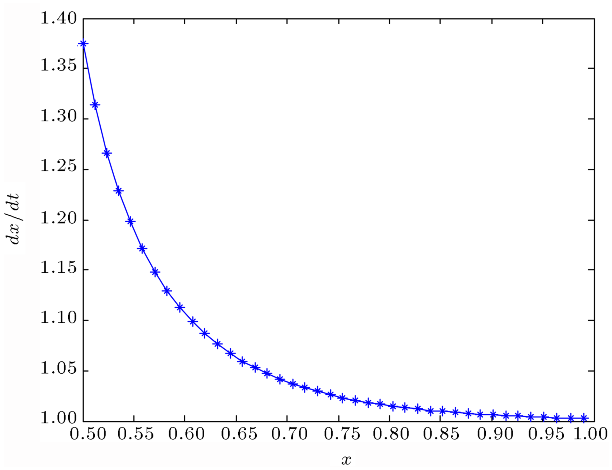

Figure 11. Function picture when $r = 10$, $s = 1$, $p = -1$, and $d = 1$.

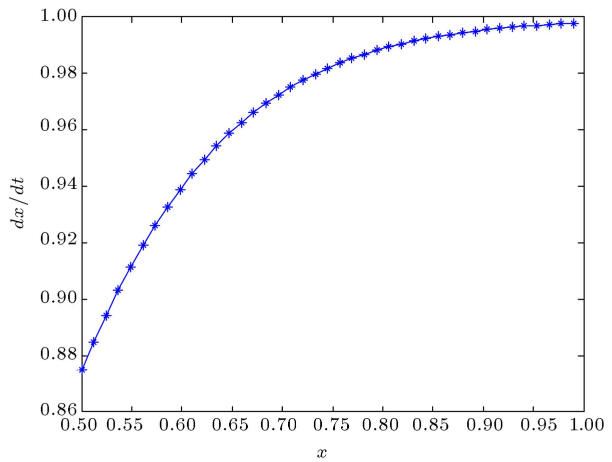

Figure 12. Function picture when $r = 10$, $s = -1$, $p = 1$, and $d = 1$.

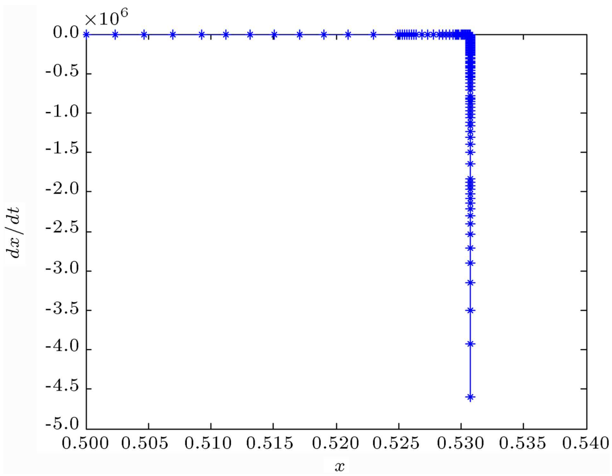

Figure 13. Function picture when $r = 1$, $s = 1$, $p = -1$, and $d = 10$.

then to select the distrust strategy. It can then be seen, from Figure 12, that the change of the curve is relatively smooth.

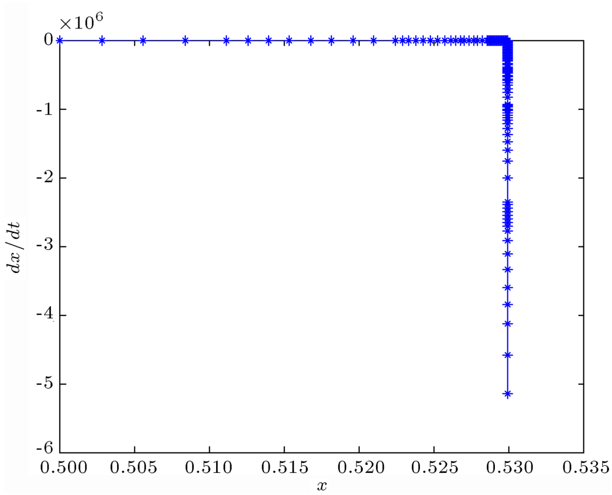

Figure 14. Function picture when $r = 1$, $s = -1$, $p = 1$, and $d = 10$.

In the third case, when the other side chooses the trust strategy, our own strategy is to choose the distrust strategy. Then, when the other side selects the distrust strategy, our own strategy will be the choice of trust, which is completely tit-for-tat.

And in the fourth case, when the other side chooses the trust strategy, our own strategy is to choose the distrust strategy. Then, when the other side selects the distrust strategy, our own strategy will also be the choice of distrust. In Figure 14, the choice of this strategy can be seen. Moreover, before x reaches a certain threshold, the changes of $\frac{dx}{dt}$ cannot be seen.

However, when the threshold is reached (although the function value does not change much), the value of x does not make any significant changes.

From the above simulation, it can be concluded that for the node selection of a trust strategy in the network, and as long as effective control measures are taken, it can make trust the stable strategy of evolution. This will then provide an effective mechanism for network security and stability. Thus, the realization of trust depends on the adjustment of parameters, that is, for the network node to take corresponding incentive measures related to reward or punishment behaviors.

4. Conclusion

This paper is based on the ecological evolution mechanism, and its major contribution is a proposed P2P social ecological network using the evolution game and replicated dynamic mechanism. It analyzes the dynamic evolution tendency and simulates the evolution of a single type of service network. It is further noticed that in order to make the network evolution stable and the service performance optimized for a reliable and trustworthy environment, the network should adjust the income of an interaction strategy in the game and set up a corresponding incentive and punishment mechanism. Thus, nodes in the network could achieve effective cooperation and the trust strategy will become the stable strategy of the interactive nodes. The network will then obtain a service of higher security and trust between the cooperating nodes.

This paper also discusses the maneuverability and feasibility of network trust and security through simplified and proposed trust game model. In future research, multi-group (multi-services) and multi-strategy matching will be further elaborated upon to randomly undertake the feasibility and operability of trust game evolution and provide a reference model for network service optimization and for the stability of the whole network. This will, hopefully, create a perfect trust mechanism of network security and offer more powerful tools for a further stability evolution and optimization service related to P2P networks.

Acknowledgement

This work was supported in part by the National Natural Science Foundation of China (No. 61170038, 61472231), the National Social Science Foundation of China (No. 14BTQ049), the Natural Science Foundation of Shandong Province (ZR2012FM013), and a project of International Cooperation in the Training of Excellent Backbone Teachers for Advanced University in Shandong Province.

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