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User Selfishness vs. File Availability in P2P File-Sharing Systems: Evolutionary Game Theoretic Approach

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Abstract In a Peer-to-Peer (P2P) file-sharing system, a node finds and retrieves its desired file. If multiple nodes cache the same file to provide others, we can achieve a dependable file-sharing system with low latency and high file availability. However, a node has to spend costs, e.g., processing load or storage capacity, on caching a file. Consequently, a node may selfishly behave and hesitate to cache a file. In such a case, unpopular files are likely to disappear from the system. In this paper, we aim to reveal whether effective caching in the whole system emerges from autonomous and selfish node behavior. We discuss relationship between selfish node behavior and system dynamics by using evolutionary game theory. As a result, we show that a file-sharing system can be robust to file disappearance depending on a cost and demand model for caching even if nodes behave selfishly.

Keywords Peer-to-Peer (P2P) file-sharing system, evolutionary game theory, selfish node behavior

CR Subject Classification C.2.4 Distributed Systems, C.4 Performance of Systems

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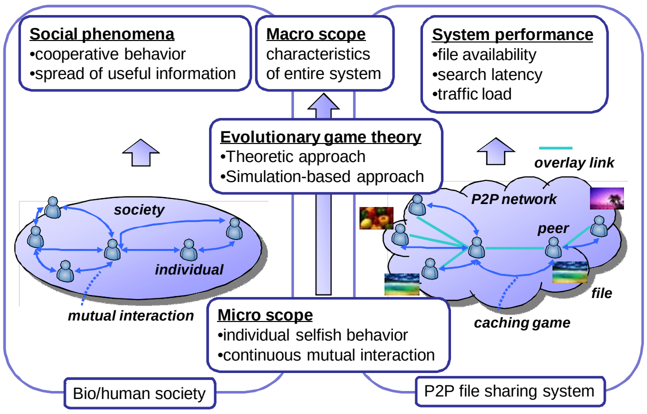


Fig. 1 Similarity between bio/human society and P2P file sharing system, and role of evolutionary game theory.

1 Introduction

In a Peer-to-Peer (P2P) file-sharing system, a node exchanges information and files with other nodes over a logical network, called an overlay network, which consists of nodes and logical links established among them. Each node caches its original or retrieved files into a local storage to share them with other nodes. If multiple nodes cooperatively cache an identical file into their storages, a node can find it with higher probability and retrieve it more quickly. This leads to enhance performance, availability, and dependability of the system [2, 3].

On the other hand, such a self-organizing characteristic also allows nodes to act freely in the P2P file sharing system. Since each node participating in the system is a user's terminal, it is controlled by the user. In general, each user takes an interest in its own benefit rather than the performance of the whole system [4]. If users hesitate to cache files due to the cost required for caching, such as storage consumption, processing load, and bandwidth consumption, unpopular files tend to disappear from the system. It is difficult for the system to monitor and manage all nodes constantly so that the system achieves effective caching, i.e., keeping availability for all files. Thus, it is desirable that selfish and autonomous nodes' behavior leads to the effective caching in the whole system.

A society of organisms is also constructed by selfish and autonomous behavior of lots of individuals. In such a biological society, superior genes with high fitness for the environment are inherited from ancestors to offspring through competition among individuals in the evolutionary process of organisms. Evolutionary game theory is a framework to investigate what kinds of phenomena emerge from the mutual interaction among individuals. In this paper, we focus on the similarity between the biological society and the P2P file sharing system and reveal how the selfish nodes' behavior affects the performance of the whole system by using evolutionary game theory (Fig. 1).

We first model the bargain about caching among nodes as a caching game between two nodes taking into account cost and demand for caching. Then, we evaluate the relationship between the models and the system performance by using evolutionary game theory. Through theoretic analysis, we figure out basic characteristics of the system. We further evaluate the system performance in detail by changing the models and topological structure of the network.

The rest of the paper is organized as follows. Section 2 gives research backgrounds and related works. In section 3, we describe models of caching games with which we deal in this paper. Then, we introduce evolutionary game theory in section 4. We describe theoretic analysis in section 5 and evaluate the system performance through simulation experiments in section 6, respectively. Finally, section 7 gives conclusions and future work.

2 Related works

Users who only download files without caching and sharing any files are referred to as free-riders [4]. There are several studies on reducing the number of free-riders [5–7]. For example, in Ref. [5], each node is assumed to minimize its own costs for using a file. The costs are storage capacity consumed by caching and latency to retrieve the file from its corresponding file holder (provider). Under these assumptions, it was shown that Nash equilibria, i.e., stable states of a system, exist in such a situation by game theory. Furthermore, the authors show an optimum state of the system is equal to one of the Nash equilibria by introducing a payment model in which a node can obtain payments to cache a file from other nodes that retrieve the cache file.

On the other hand, in Ref. [6], the authors discuss cooperative node behavior in a file-sharing system under the framework of Multi-Person Prisoner's Dilemma. If there is no incentive for caching a file, all nodes become free-riders in a Nash equilibrium. Through analyses and simulation evaluations, they show that nodes intend to contribute to caching if they can obtain payments or reputations from other nodes in compensation for caching a file.

The above mentioned approaches in Refs. [5–7] are based on incentive mechanisms in which payments or reputations from other nodes are essential to achieve cooperative caching. However, such incentive mechanisms are not necessarily applicable to a file-sharing system. For example, there is a file-sharing system that hides a provider from nodes requesting the corresponding file so as to improve the anonymity among nodes [8]. In such a system, it is difficult for a provider to obtain payments from the requesting nodes.

As approaches different from the above mentioned incentive mechanisms, there are several studies on how the cooperative behavior emerges from interactions among users using evolutionary game theory [9–12]. Refs [9, 11, 12] aim to investigate what mechanisms lie behind the emergence of the cooperative behavior in the human society where each individual has a temptation to be selfish. They insist that several factors have impacts on the emergence of cooperative behavior, e.g., the topological structure of the human society, users' sense of value to cooperation, etc.

In recent years, several researchers have applied evolutionary game theory to achieve cooperative network systems [10]. Hales proposed SLACER algorithm that controls the topological structure of a P2P network using evolutionary game theory [10]. In SLACER, each node plays a game with a neighboring node and it keeps the connection to the neighbor if the neighbor is cooperative. Otherwise, it disconnects the connection and randomly chooses a node as a new neighbor. As time passes, SLACER can construct multiple groups of cooperators.

Table 1 General payoff matrix.

player 1 \ player 2	cooperator	defector
cooperator	(R, R)	(S, T)
defector	(T, S)	(P, P)

In this paper, we try to figure out the relationship between user selfishness and the performance of P2P file-sharing systems by using evolutionary game theory.

3 System model

3.1 Overview

We first describe the overview of the P2P file sharing system assumed in this paper. Each node obtains a set of providers using one of existing search methods. It then retrieves the desired file from one or more providers in the set. Note that the node can become a new provider of the file. As a result, the providers can construct an overlay network for sharing the file. Because costs accompany caching a file, the node bargains with other providers to decide whether it keeps caching the file. In this paper, we model the bargains among file holders as caching games on the presupposition that the node plays a caching game with another node randomly chosen from the set. Each node determines whether it keeps caching the file or not based on the results obtained after a certain number of games. For simplicity, we deal with the case of a single file in this paper but we can extend our discussion to the case of multiple files by allowing nodes to play multiple caching games in parallel.

3.2 Caching game

To model the caching game, we first define a payoff matrix that determines the relationship between node's behavior (strategy) and payoff obtained by the strategy. Table 1 shows a general payoff matrix between two players used in game theory. A defector exploiting a cooperator obtains T and the exploited cooperator receives S. Both players receive R (P) when they cooperate (defect) each other. Prisoner's dilemma game ($T > R > P > S, 2R > T + S$) and snowdrift game ($T > R > S > P$) are examples of the well-known games.

In the P2P file sharing system, each node has two strategies: caching ($\mathcal{S}_{\rm c}$) and no caching ($\mathcal{S}_{\rm n}$). The node with $\mathcal{S}_{\rm c}$ ($\mathcal{S}_{\rm n}$) corresponds to the cooperator (defector). Since a node satisfies its demand to the file by leveraging the file, we define the benefit obtained by the use of the file as its demand b. On the other hand, a node has to spend cost(s) on caching a file, e.g., processing load c_l caused by self and other node's access to the file and storage capacity c_s consumed by caching the file.

In what follows, we investigate the system performance using two models: processing load model and storage capacity model. In case of the processing load model, the parameters of payoff matrix become $R = b-c_l, T = b, S = b-2c_l, P = 0$. Note that $b-2c_l$

should be greater than 0 to prevent all nodes from selecting the strategy $\mathcal{S}_{\rm n}$. This condition is not necessarily unrealistic because users ordinarily try to avoid the file availability becoming zero. On the other hand, we obtain $R = b - c_l, T = b, S = b - c_l, P = 0$ in case of the storage capacity model. Note that $b - c_s \geq 0$ because of the same reason in the processing load model. Both models can be classified into games with $T > R \geq S > P$. Although there are lots of other possible models for realistic P2P file-sharing systems, the following approaches and results are applicable to them if the condition of $T > R \geq S > P$ is satisfied.

4 Evolutionary game theory

In a society of organisms, various individuals influence each other. Evolutionary game theory [13] originally tries to figure out a mechanism in which optimum behavior comes down to offspring in the evolutionary process of organisms. Suppose that individual behavior defined by genes corresponds to a strategy in game theory and the number of offspring selecting the behavior is proportional to payoff acquired by the strategy. In such a case, various individuals are in strategically mutual dependence relation of game theory. Thus, by using game theory, we can explain the phenomenon that superior behavior spreads over a society of organisms through inheritance from ancestors to offspring. Moreover, in sociology and economics, there are several studies that aim to reveal the phenomena in which valuable information and behavior spread over human societies by using evolutionary game theory [9, 11, 12].

Evolutionary game theory provide us with two kinds of frameworks to reveal the relationship between individual behavior and system behavior: replicator dynamics and agent-based dynamics. Replicator dynamics is a mathematical model in which the ratio of individuals selecting a strategy increases when the strategy can yield more payoff than the average payoff of all strategies [13]. Replicator dynamics is applicable when the number of individuals composed of the society is relatively large and the network among the individuals is mean-field like. Thus, we can reveal the system characteristics when a node has information on all providers through the search process mentioned in section 3.1. In such a case, the overlay network for sharing the file is equivalent to a full mesh network.

On the other hand, agent-based dynamics models a phenomenon that a superior strategy spreads over the network in a hop-by-hop manner. In agent-based dynamics, an individual plays a game once with all neighboring individuals, determines superiority of its own strategy based on the game results, and finally decides the next strategy. Thus, agent-based dynamics is applicable to various network topologies including the full mesh network. If a node obtains only part of providers through the search process due to the limitation of search range, the topology of the overlay network for sharing the file can vary.

5 Theoretic analysis by replicator dynamics

In this section, we theoretically derive the relationship between the above mentioned models and the ratio of cooperators by replicator dynamics [13]. As mentioned above, every node decides whether to cache the file after a certain number of caching games with other nodes. At each game, the node rationally behaves: It compares the expected payoff obtained by strategy $\mathcal{S}_{\rm c}$ and that obtained by strategy $\mathcal{S}_{\rm n}$, and selects a strategy proportional to the payoffs acquired by the strategy. In what follows, we describe the detail of the strategy selection.

We denote the ratio of cooperators, i.e., nodes selecting $\mathcal{S}_{\rm c}$, to the whole nodes by x. The expected payoff $U_i(\mathcal{S}_{\rm c})$ that node i obtains when selecting $\mathcal{S}_{\rm c}$ is given by

$$U_i(\mathcal{S}_{\rm c}) = xR + (1-x)S.$$

We similarly have the expected payoff $U_i(\mathcal{S}_{\rm n})$ that node i obtains when selecting $\mathcal{S}_{\rm n}$ as follows:

$$U_i(\mathcal{S}_{\rm n}) = xT + (1-x)P.$$

The differences between the expected payoffs of cooperators and those of the whole nodes are expressed as

$$U_i(\mathcal{S}_{\rm c}) - \{xU_i(\mathcal{S}_{\rm c}) + (1-x)U_i(\mathcal{S}_{\rm c})\} = \{(R+P-T-S)x + S - P\}(1-x).$$

Finally, replicator dynamics $\dot{x}$ that indicates the transition of x is defined as follows:

$$\dot{x} = \{(R+P-T-S)x + S - P\}(1-x)x. \tag{1}$$

The equilibria of x that satisfy $\dot{x} = 0$ are 0, 1, and $(S-P)/(T+S-R-P)$. Next, we describe the stability of their equilibria. In Eq. (1), $(1-x)x$ is constantly over zero for $0 \le x \le 1$. The remaining part $(R+P-T-S)x+S-P$ becomes positive for $x < (S-P)/(T+S-R-P)$ and negative for $x > (S-P)/(T+S-R-P)$ because of the definition of games in section 3. As a result, x approaches to $(S-P)/(T+S-R-P)$ independently of the initial value of x. Thus, the steady equilibrium is

$$x = \frac{S-P}{T+S-R-P}. \tag{2}$$

Eq. (2) indicates that the ratio of cooperators at a steady state depends on the parameters of the payoff matrix. Based on Refs. [14–16], we first define r as the cost-to-benefit ratio of mutual cooperation. r means a risk that a node should take when it behaves as a cooperator. r ranges (0,1]. The smaller value of r indicates that cooperators increase. In this paper, r is determined by b and c_l or by b and c_s. Therefore, r can be regarded as the ratio of demand to cost for caching.

In case of the processing load model, from Eq. (2), the ratio x of cooperators at a steady state becomes

$$x = \frac{b-2c_l}{b-c_l}.$$

On the other hand, the cost-to-benefit ratio of mutual cooperation r is given as follows:

$$r = \frac{c_l}{b-c_l}.$$

Finally, the relationship between x and r satisfies

$$x = 1 - r. \tag{3}$$

We can also derive the relationship between x and r in case of the storage capacity model as follows:

$$x = \frac{1}{1+r}. \tag{4}$$

From Eqs. (3) and (4), the ratio x of cooperators deteriorates with the increase of the r, namely the decrease of the demand b to the file, independently of the cost models. In this paper, we aim to achieve a file-sharing system with high file-availability that is robust to file disappearance. In case of the processing load model, Eq. (3) denotes that a file disappears from the system when r is close to 1 that means the demand to the file is low. On the other hand, the storage capacity model enhances the file availability by preventing x falling in 0 even if r is 1.

6 Simulation-based analysis by agent-based dynamics

Agent-based dynamics [17] can reveal how much caching based on local interaction among neighboring nodes has impact on the number of cache files in the whole system. Moreover, we can evaluate search latency for a file since we can obtain the strategies of all nodes, namely the locations of cache files.

6.1 Agent-based dynamics

In agent-based dynamics, a node determines its strategy by comparing its own payoffs with those of a neighboring node of the overlay network for sharing the corresponding file. A node initially selects a strategy at random. The initial ratio of cooperators and that of defectors are fifty-fifty in Refs. [14–16]. Once a node i determines its strategy, it plays a game once with all neighboring nodes. This is one generation. At the end of the generation, the node i calculates average A_i of payoffs acquired, then determines the strategy of the next generation as follows.

Step 1: Selection of a neighboring node for comparison of payoffs
The node i randomly chooses a node j from neighboring nodes.

Step 2: Decision of the next strategy based on the comparison of average payoffs
If $A_j > A_i$ is satisfied, the node i imitates the strategy of node j with the following probability:

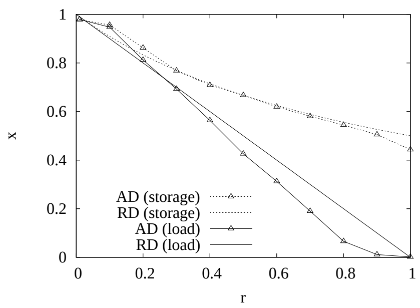
$$P_A(i,j) = \frac{A_j - A_i}{T - P}.$$

Otherwise, it does not change its strategy. The node i tends to imitate the strategy of a node that obtained more payoffs than it. In addition, P_A increases in proportion to the payoff differences.

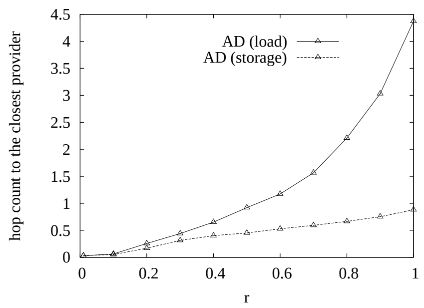
In an actual system, we should consider the overheads incurred by playing games and exchanging payoffs with neighboring nodes. We expect that these processes can be realized by slightly modifying the keep-alive messaging typically used in P2P file-sharing systems.

6.2 Simulation experiments

Through several simulation experiments, we evaluate how the node behavior based on the payoff matrix affects file availability and search latency of the whole system in scale-free and random networks. We evaluate the file availability by the ratio x of cooperators. In the case of the single-file caching, the number of cache files is the same



(a) fraction of cooperators



(b) hop count to the closest provider

Fig. 2 payoff matrix vs. file availability and search latency (scale-free: m=4)

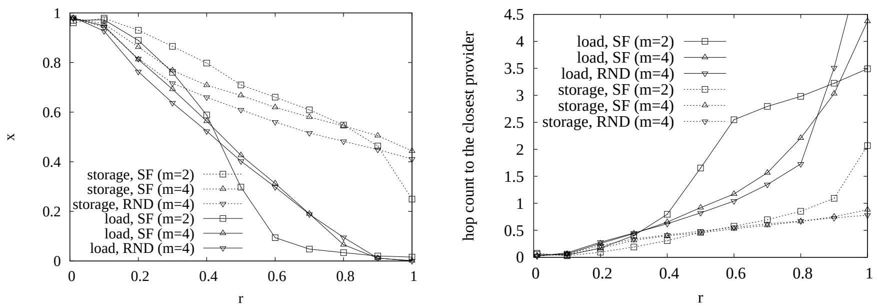
as the product of x and the number of nodes. On the other hand, we define the search latency as the average hop count between a node to its closest provider including itself. Note that we alternatively use the maximum hop count between two arbitrary nodes when a file disappears from the system.

6.2.1 Simulation model

We used NetLogo [18] in our simulation experiments. Based on Refs. [14–16], we set simulation configurations as follows. We generated scale-free and random networks of 1000 nodes by using the topology generator BRITE [19]. The scale-free network was based on Barabási-Albert (BA) model [20] and the random network generated by waxman algorithm [21] with $\alpha = 0.15$ and $\beta = 0.2$. We also set the number m of connections that a newly participating node established to 2 and 4. Table 2 represents the average of maximum hop count between two arbitrary nodes in twenty networks. We set the caching costs c_l and c_s to 1, respectively. Thus, independently of the cost models, $b = (1+r)/r$ was derived. We configured that the initial ratio x_0 of cooperators was 0.5. To investigate the system characteristics in a steady state, we show results when 1000 generations passed. The following results indicate the average of twenty simulations. We abbreviate replicator dynamics to RD, agent-based dynamics to AD, scale-free to SF, and random to RND in the following figures.

6.2.2 Impact of payoff matrix

Figure 2(a) illustrates that the relationship between r and the ratio x of nodes taking the strategy $\mathcal{S}_\mathrm{c}$ that is derived by agent-based dynamics in a scale-free network with $m = 4$. We discover that x deteriorates with the increase of r, namely the decrease of demand, regardless of the cost models. In addition, the processing load model causes the disappearance of files with larger r. On the other hand, the file availability is enhanced by using the storage capacity model even if r is 1. Next, Fig. 2(a) also shows x derived by replicator dynamics. In case of the processing load model, x of agent-based dynamics is lower than that of replicator dynamics excluding the case of smaller r. On the contrary, the storage capacity model enhances the file availability as x of agent-based dynamics achieves almost the same as that of replicator dynamics.



(a) fraction of cooperators

(b) hop count to the closest provider

Fig. 3 impact of network structure (m=2 vs. m=4, scale-free vs. random)

Table 2 maximum hop count between two arbitrary nodes

	$m = 2$	$m = 4$
scale-free network	7.4	5
random network	8.7	6

Figure 2(b) depicts that the search latency increases with the growth of r, independently of the cost models. This is because the number of providers decreases as shown in Fig. 2(a). In case of the storage capacity model, x is higher than 0.4 even for a low-demand file. Consequently, a node can reduce the search latency by finding out a closer provider.

6.2.3 Impact of network structure

Figure 3 illustrates x and the search latency in scale-free networks with $m = 2, 4$. Since the average degree is $2m$, larger m makes a network dense. Figure 3(a) shows that smaller m promotes to increase high-demand files, independently of the cost models. This is due to the effect of high degree nodes. A high degree node tends to acquire more payoffs than other nodes and be chosen for comparison of payoffs by its neighboring nodes. As a result, the strategy of a high degree node is likely to spread over the network. The impact of high degree nodes is accelerated in a network with small m where low degree nodes frequently exist.

On the other hand, Fig. 3(b) presents that the search latency of $m = 2$ is lower than that of $m = 4$ if r is smaller than 0.3 in the processing load model and 0.5 in the storage capacity model. This is because files with smaller r are more cached in the case of $m = 2$ as shown in Fig. 3(a). Since the increase of r results in the decrease of providers, the search latency of $m = 4$ becomes superior to that of $m = 2$. Note that there is slight difference between $m = 2$ and $m = 4$ in the storage capacity model.

Figure 3 also shows that x and the search latency in the random network with $m = 4$. We find that x in the scale-free network is mainly larger than that in the random network as shown in Fig. 3(a). Contrary to our expectation, Fig. 3(b) presents that the search latency in the scale-free network is not so superior to that in the random network despite of its lower diameter of the network (Table 2). This is because

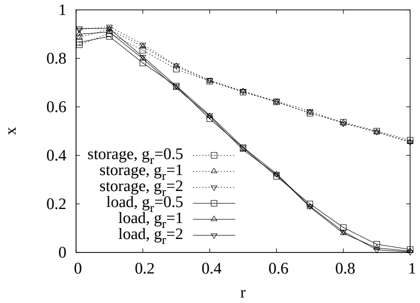


Fig. 4 impact of evolving network (scale-free: $m = 4$)

files tend to be cached at regular nodes rather than high degree nodes in the scale-free network. In other words, we can alleviate load concentration on high degree nodes while suppressing the search latency. We give the detail discussion about the load balancing in section 6.2.5. Note that the difference of degree distribution does not so much affect to the search latency in case of the storage capacity model.

In summary, we can accomplish a file-sharing system with high file-availability and low search-latency by using the storage capacity model independently of the network structures.

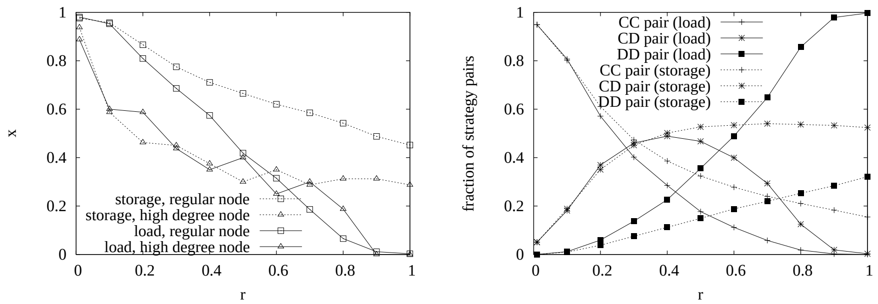
6.2.4 Impact of evolving network

Although we have evaluated the system performance in case of the static networks, actual P2P networks are evolving networks where nodes sequentially participate in the system. In this section, we reveal how the growth of the network affects the system performance. We used BA model ($m = 4$) as an example of the evolving networks. To evaluate the impact of the relationship between the growth rate of the network and the frequency of the caching games, we define a game ratio g_{r} as the number of games per node arrival. Noe that when the game ratio is less than 1, games are conducted every $\lfloor 1/g_{\mathrm{r}} \rfloor$ node arrivals.

Figure 4 illustrates the relationship between r and x for the both cost models when the game ratio is set to 0.5, 1, 2. First, the difference of the game ratio does not have much influence on the system performance. Thus, caching condition is independent of the growth rate of the network. Next, comparing Fig. 4 with Fig. 3(a), we find that the results are similar to those in case of the static networks, which means that we need not to evaluate in case of the evolving networks in more detail.

6.2.5 Load balancing

It is desirable that files are appropriately distributed in the network to cope with disturbances caused by node departures or attacks from malicious users. In what follows, we evaluate the case of the scale-free network with $m = 4$. Figure 5(a) depicts the relationship between r and x for high-degree and regular nodes. Note that a high-degree node is a node whose degree is not less than $k_{\max}/2$ where $k_{\max}$ is the largest degree in the network [22].



(a) fraction of cooperators (regular nodes vs. high degree nodes)

(b) strategy pair

Fig. 5 load balancing (cost: storage, scale-free: $m = 4$)

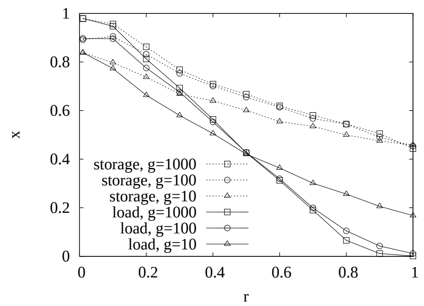


Fig. 6 convergence property (scale-free: m=4)

By comparing Fig. 5(a) with Fig. 2(a), we find that the regular nodes present almost the same results as the whole nodes. This is because the regular nodes are the majority in the scale-free network. On the contrary, the high-degree nodes have different characteristics. Except for the processing load model ($r \geq 0.7$), the high-degree nodes tend not to cache files compared with the regular nodes. Consequently, load concentration on the high-degree nodes can be reduced.

Figure 5(b) illustrates the fraction of strategy pairs between two neighboring nodes. The strategy pair is classified into three types: cooperator-cooperator (CC), cooperator-defector (CD), and defector-defector (DD). The fraction of strategy pairs enables us to comprehend how the network consists of cooperators and defectors. As shown in Fig. 5(b), a cooperator's cluster shrinks with the increase of r in both cost models. In the processing load model, defectors finally overcome cooperators as DD reaches to 1. However, cooperators can coexist with defectors in the storage capacity model even when r becomes large.

These results imply that the storage capacity model contributes to effective load balancing.

6.2.6 Convergence Property

Figure 6 illustrates the relationship between r and x when the generation g is 10, 100, and 1000. We denote x at g as x_g. As mentioned before, x_0 is set to 0.5, independently of r. The results show that the system almost reaches a steady state at $g = 100$ because the disparity between x_{100} and x_{1000} is at most 0.087. Furthermore, the difference between x_{10} and x_{1000} are less than 0.19. We can conclude that the system has relatively high convergence property, despite the fact that it is based on only local interactions between neighboring nodes.

7 Conclusions

In this paper, we revealed the relationship between node behavior and effective caching in the whole system by evolutionary game theory so as to accomplish a file-sharing system with high file availability and low search latency even if nodes behaved selfishly and autonomously. We first made modeling a file-sharing system as two kinds of caching games between two neighboring nodes of the overlay network for sharing the corresponding file. Then, we showed the basic characteristics of the models by analytically deriving the number of cache files in the system based on replicator dynamics. Furthermore, through simulation experiments based on agent-based dynamics, we evaluated how much local interactions among nodes had impact on the system performance. Simulation results showed that the storage capacity model made a file-sharing system robust to fie disappearance independently of the network structures even if nodes behave selfishly.

As future research work, we should examine a caching game that takes into account dynamic costs, e.g., delay and bandwidth. Furthermore, we plan to analyze the dynamics of information networks other than the file-sharing system and propose control mechanisms based on the analysis. For example, information travels along a chain of intermediate nodes toward its destination in the following information systems: information distribution on an overlay network, e.g., application level multicast, and information diffusion and gathering on a sensor network. Since forwarding information takes costs, such as network bandwidth and electricity consumption, an effective forwarding mechanism taking into account the significance of information is needed. Evolutionary game theory can reveal node behavior suitable for such effective information transfer.

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