How does user heterogeneity affect performance of P2P caching?: Evolutionary game theoretic approach

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ABSTRACT

Ubiquitous information societies enables us to freely obtain information anytime and anywhere. Beyond this concept, achievement of ambient information societies has been expected in recent years, in which we can retrieve desired information in accordance with current conditions of surrounding environments. In this paper, we focus on Peer-to-Peer (P2P) file sharing systems as an example of such ambient information sharing systems. We try to figure out the system performance when all users behave selfishly and autonomously according to their surrounding situations. In P2P file sharing systems, file availability is improved by users cooperatively caching and sharing files. However, many users may hesitate to cache files cooperatively due to the cost for caching, such as storage consumption, processing load, and bandwidth consumption. In such a case, unpopular files are likely to disappear from the system. In this paper, we reveal how the selfish user behavior affects the system performance using evolutionary game theoretic approach. Specifically, we focus on situations where users are heterogeneous in terms of aggressiveness in cooperative caching. Analytical results show that the user heterogeneity contributes to the stability of file availability.

Keywords

Evolutionary game theory, P2P file sharing system, performance, user heterogeneity

1. INTRODUCTION

Ubiquitous information societies enables us to freely obtain information anytime and anywhere. Beyond this concept, achievement of ambient information societies has been expected in recent years, in which we can retrieve desired information in accordance with current conditions of surrounding environments. In this paper, we focus on Peer-to-Peer (P2P) file sharing systems as an example of information sharing systems.

In the P2P file sharing system, all nodes establish at least one logical link with other nodes and a logical network, called a P2P network, is constructed. They share information and files among other nodes without mediation of servers, differently from the client-server file sharing systems. Thus the P2P file sharing system is robust to the deterioration of the system performance arising from the load concentration on a specific node and the single point of failure. These are potentially critical issues in the client-server architectures.

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. 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). Since there are a large number of nodes participating in the P2P file sharing system, it seems that nodes have different sense of value to a specific file. We therefore investigate how such user heterogeneity affects the system performance.

We first model the bargain about caching among nodes as a caching game between two nodes. We then investigate the relationship between the user heterogeneity and the file availability through theoretic analysis based on evolution-

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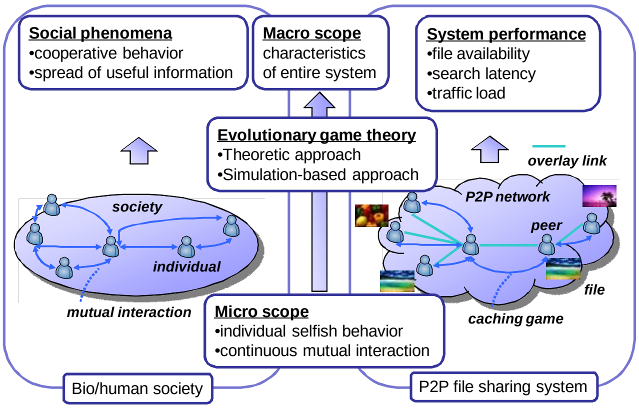

Figure 1: Similarity between bio/human society and P2P file sharing system, and role of evolutionary game theory.

ary game theory. Although we will discuss P2P file sharing systems in this paper, the evolutionary game theoretic approach is expected to be applicable to other autonomous distributed systems constructing the ambient information society and can reveal their system performance when every node acts by taking account of not only its own sense of value but also other nodes' behavior.

The rest of the paper is organized as follows. In section 2, we introduce several research backgrounds and related works. We explain the system model in section 3 and show the performance evaluation through evolutionary game theory in section 4. Finally, section 5 gives the conclusion and future work.

2. RELATED WORKS

Users who only download files without caching and sharing any files are referred to as free-riders [1]. There are several studies on reducing the number of free-riders [2, 9, 11, 13]. For example, in Ref. [2], 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, i.e., 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. [9], 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. [2, 9, 13] 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 [3]. 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 [4, 6, 8, 10, 11]. Refs [4, 8, 10] 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 [6, 11]. Hales proposed SLACER algorithm that controls the topological structure of a P2P network using evolutionary game theory [6]. 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.

Sasabe et al. tackled the problem of cooperative caching in P2P file sharing systems [11]. They modeled the file sharing system as a set of caching games among nodes by taking account of benefit and cost for caching, and they evaluated the system performance through the model. They found that cooperative caching can be accomplished under a situation where the benefit and the cost for caching are uniform among nodes. In practical, however, the benefit and cost for caching can vary from node to node. Thus we investigate how this heterogeneity affects the cooperative caching in this paper.

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 file holders, i.e., nodes that have the desired file, using one of existing search methods. It then retrieves the desired file from one or more nodes in the set. Note that the node can become a new holder of the file. Because costs accompany caching a file, the node bargains with other file holders 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. Next, we describe how the node selects its strategy based on the payoff matrix and the surrounding condition, i.e., the strategy distribution.

Table 1: General payoff matrix.

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

Table 2: Payoff matrix with user heterogeneity ($T_k > R_k \geq S_k > P_k$ $(k = i, j)$).

player j / player i	cooperator	defector
cooperator	(R_i, R_j)	(S_i, T_j)
defector	(T_i, S_j)	(P_i, P_j)

3.2.1 Strategy and payoff

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). According to the discussion in Ref. [11], we obtain the condition $T > R \geq S > P$. It has been pointed out that cooperative caching can be accomplished under this condition [11].

However, the parameters of the payoff matrix can vary from node to node in practical because an unspecified number of nodes join the P2P file sharing system and the sense of value to a specific file is different among users. We can extend Table 1 to Table 2 which is the model of a caching game with user heterogeneity. Here, $T_k > R_k \geq S_k > P_k$ $(k = i, j)$ is satisfied. As a future work, we also plan to investigate the situation where some nodes are more selfish, which means the nodes satisfy the condition of $T_i > R_i \geq P_i > S_i$.

In what follows, we use Table 2.

3.2.2 Strategy selection

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 the strategy which acquires more payoffs. 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 at time t by $p(t)$. The expected payoff $U_i(\mathcal{S}_{\rm c})$ that node i obtains when selecting $\mathcal{S}_{\rm c}$ is given by

$$U_i(\mathcal{S}_{\rm c}) = p(t)R_i + (1 - p(t))S_i. \tag{1}$$

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

$$U_i(\mathcal{S}_{\rm n}) = p(t)T_i + (1 - p(t))P_i. \tag{2}$$

Node i selects the strategy with higher expected payoff after comparing $U_i(\mathcal{S}_{\rm c})$ and $U_i(\mathcal{S}_{\rm n})$. If $U_i(\mathcal{S}_{\rm c}) = U_i(\mathcal{S}_{\rm n})$, node i selects $\mathcal{S}_{\rm n}$ so that we can evaluate the system performance under a situation with less number of cached files. As a result, the next strategy at time $t+1$, $X_i(t+1)$, is given by

$$X_i(t+1) = \begin{cases} \mathcal{S}_{\rm c}, & U_i(\mathcal{S}_{\rm c}) > U_i(\mathcal{S}_{\rm n}), \\ \mathcal{S}_{\rm n}, & U_i(\mathcal{S}_{\rm c}) \leq U_i(\mathcal{S}_{\rm n}). \end{cases} \tag{3}$$

From Eqs. (1)–(3), we find that the strategy $X_i(t + 1)$ is determined depending on $p(t)$ and threshold θ_i composed of the parameters of Table 2:

$$X_i(t+1) = \begin{cases} \mathcal{S}_{\rm c}, & p(t) < \theta_i, \\ \mathcal{S}_{\rm n}, & p(t) \geq \theta_i. \end{cases} \tag{4}$$

Here,

$$\theta_i = \frac{S_i - P_i}{T_i - R_i + S_i - P_i}. \tag{5}$$

3.3 User heterogeneity

In practical P2P file sharing systems, it is natural that each node should have different sense of value to a specific file. In what follows, we explain how to model this user heterogeneity.

θ_i ranges from 0 to 1 based on the condition of $T_i > R_i \geq S_i > P_i$. The larger θ_i is, the more cooperative node i is. We can model the user heterogeneity by introducing a density function $f(\theta)$ of the threshold θ_i.

It is reasonable to assume that uncooperative nodes constitute the majority of the system because caching requires costs. In this paper, we suppose that the density function $f(\theta)$ follows Zipf's law, which is an empirical law appearing in various statistics. Zipf's law implies that out of a population of K elements, the frequency $f(x; \alpha, K)$ of elements of rank x is given by

$$g(x; \alpha, K) = x^{-\alpha} \Bigg/ \sum_{k=1}^{K} k^{-\alpha}, \tag{6}$$

where K ($K > 1$) and α ($\alpha > 0$) denote the number of elements and the exponent characterizing the distribution, respectively. In this paper, both parameters determine the degree of the user heterogeneity: K determines the number of varieties of the threshold and α determines the degree of the bias of the threshold. In our model, Eq. (6) indicates that the number of nodes with the smallest threshold is K^α times as large as that with the largest threshold. The larger K and α are, the more heterogeneous the users' sense of value is.

Although Eq. (6) is a discrete function, we need a continuous density function in using micro-macro dynamics (see section 4.2). We thus model Zipf's law as a continuous density function whose domain is $1 \leq x \leq K$:

$$f(x; \alpha, K) = x^{-\alpha} \Bigg/ \int_1^K y^{-\alpha} dy. \tag{7}$$

We further conduct transformation of variable, $x = K\theta$, and normalization to Eq. (7). Finally we obtain a continuous density function whose domain is $1/K \leq \theta \leq 1$ as follows:

$$f(\theta) = \begin{cases} \dfrac{1}{\log K} \cdot \theta^{-1}, & \alpha = 1, \\ \dfrac{\alpha - 1}{K^{\alpha-1} - 1} \cdot \theta^{-\alpha}, & \alpha \neq 1. \end{cases} \tag{8}$$

4. PERFORMANCE ANALYSIS USING EVOLUTIONARY GAME THEORETIC APPROACH

In this section, we reveal the relationship between the user heterogeneity and the system performance using the system model described in section 3 and evolutionary game theory.

4.1 Evolutionary game theory

In a society of organisms, various individuals influence each other. Evolutionary game theory [12] 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 [4, 8, 10].

4.2 Micro-macro dynamics

Micro-macro dynamics [5] tries to figure out dynamic behavior of a micro-macro loop that defines interactions between micro behavior and macro behavior: micro behavior and macro behavior are regarded as actions of heterogeneous individuals and the collective behavior resulting from mutual interactions among the individuals, respectively. Thus we can reveal how the bargains about caching among nodes affect the caching condition of the whole system using micro-macro dynamics.

Micro-macro dynamics gives us the transition of the ratio $p(t)$ of cooperators to the whole nodes as a difference equation. In what follows, we describe the derivation process of the equation. From Eq. (4), each node determines the next strategy according to the current $p(t)$ and its threshold θ_i. In other words, Eq. (4) determines $p(t+1)$. To obtain $p(t+1)$, we first define the cumulative distribution function $F(\theta)$ as

$$F(\theta) = \int_{1/K}^{\theta} f(x)dx. \tag{9}$$

Note that $p(t+1)$ is given by the ratio of nodes with $p(t) < \theta_i$ to the whole nodes. Because the ratio $1 - p(t+1)$ of nodes with $\theta_i \le p(t)$ to the whole nodes is given by $F(p(t))$, we finally obtain

$$p(t+1) = 1 - F(p(t)). \tag{10}$$

4.3 System performance and stability

In this section, we evaluate the system performance and stability through the analysis using Eq. (10). We define the system performance as file availability that is defined as the ratio of nodes with S_c. If there is the steady state of the system, the file availability in the steady state can be regarded as the equilibrium p^* of Eq. (10). The larger p^* is, the higher the file availability is. p^* can be obtained by solving the following equation.

$$p^* = 1 - F(p^*). \tag{11}$$

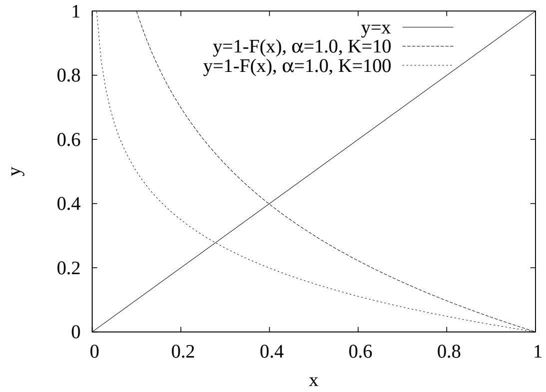

Figure 2: Relationship between equilibrium p^* and complementary cumulative distribution function $1 - F(p^*)$.

Note that p^* is equivalent to the intersection point between $y = x$ and $y = 1 - F(x)$.

Before deriving p^* from Eq. (11), we discuss the stability of the equilibrium. If the equilibrium is stable, $p(t)$ converges to p^* once it reaches the vicinity of the equilibrium. Otherwise, $p(t)$ continues to oscillate forever even if it reaches the vicinity of the equilibrium. Thus, the stability of the equilibrium is significant for the system to achieve effective caching stably.

The stability of the equilibrium depends on the parameters K and α, which determine the degree of the user heterogeneity. We can derive the condition for the stable equilibrium from Eq. (10). The equilibrium is stable if the absolute gradient of $1 - F(p(t))$ at the equilibrium p^* is less than one, that is,

$$\left| \frac{d}{d\theta}[1 - F(\theta)] \right|_{\theta = p^*} < 1, \tag{12}$$

where, from Eqs. (8) and (9), we obtain $1 - F(p(t))$ as follows:

$$1 - F(\theta) = \begin{cases} -\dfrac{\log \theta}{\log K}, & \alpha = 1, \\ 1 - \dfrac{\theta^{-\alpha+1} - K^{\alpha-1}}{1 - K^{\alpha-1}}, & \alpha \neq 1. \end{cases} \tag{13}$$

Because Eq. (11) is a non-linear equation, we will numerically obtain the solution p^* with Newton's method [7]. As shown in Fig. 2, $y = x$ is a function that monotonically increases from 0 to 1 in the range of $0 \le x \le 1$ and $y = 1 - F(x)$ is a function that monotonically decreases from 1 to 0 in the range of $1/K \le x \le 1$, where we assume $K \ge 2$. Thus there is only one intersection point between $y = x$ and $y = 1 - F(x)$ in the range of $1/K \le x \le 1$, so that Newton's method works well.

Figure 3 illustrates the equilibrium p^* when $K \ge 2$ and $\alpha = 0.8, 1.0,$ and 1.2. In all cases, p^* steeply drops in the range of $2 \le K \le 10$ and converges to a value depending on α. We also find that high user heterogeneity, i.e., large K and α, leads to low value of p^*. The reason of this phenomenon is that the number of uncooperative nodes increases with K and α (see Eq. (8)). The most important result for the caching system is that p^* is always greater

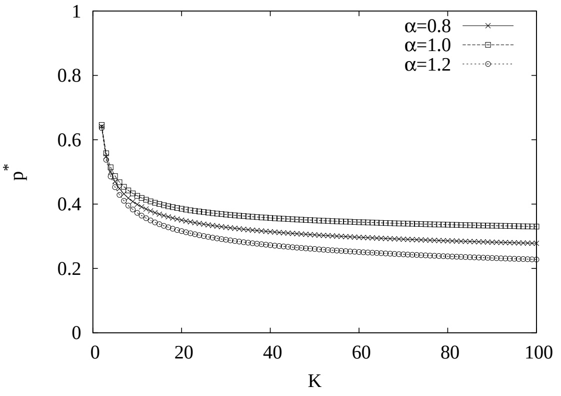

Figure 3: Relationship between K and p^* ($\alpha = 0.8, 1.0, 1.2$).

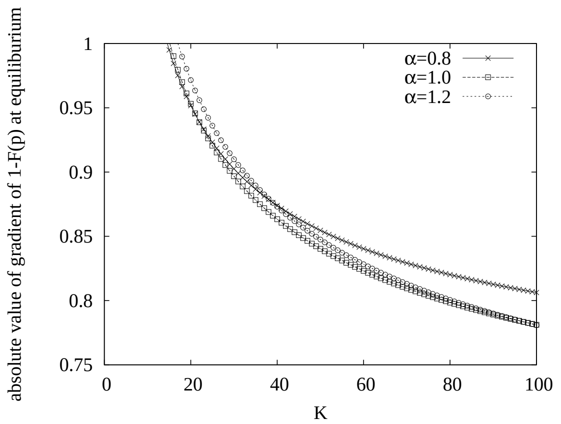

Figure 4: Relationship between K and the left hand side of Eq. (12).

than zero; there is at least one cached file in the network.

Next, we investigate the stability condition of the equilibrium. In case of $\alpha = 1$, we obtain

$$\left|\frac{d}{d\theta}[1 - F(\theta)]\right|_{\theta=p^*} = -\frac{1}{\log(p^*)}.$$

From Eq. (12), the following condition must be satisfied so that the equilibrium is stable:

$$p^* < e^{-1}.$$

Recall that the function $1 - F(x)$ monotonically decreases from 1 to 0 in the domain of $1/K \leq x \leq 1$. Therefore, the following equation should be satisfied for stability:

$$1 - F(e^{-1}) < e^{-1}. \tag{14}$$

Manipulating Eqs. (13) and (14), we finally obtain the stability condition of the equilibrium for $\alpha = 1$.

$$K > e^e. \tag{15}$$

Because $e^e \approx 15.2$ and K increases in proportion to the system scale, the stability condition does not seem to be severe. On the other hand, in case of $\alpha \neq 1$, we obtain

$$\left|\frac{d}{d\theta}[1 - F(\theta)]\right|_{\theta=p^*} = \left|\frac{\alpha - 1}{1 - K^{\alpha-1}}\left(\frac{1 - (p^*)^{-\alpha+1}}{1 - K^{\alpha-1}}\right)^{-\alpha}\right|.$$

Since this equation is too complicate to analyse, we proceed the discussion with numerical examples. Figure 4 depicts the left hand side of Eq. (12) when $K \geq 2$ and $\alpha = 0.8, 1.0$, and 1.2. We find that the minimum integer K that satisfies Eq. (12) is equal to 15, 16, and 18 for $\alpha = 0.8, 1.0$, and 1.2, respectively. Note that when $\alpha = 1$, the minimum integer $K = 16$ satisfies Eq. (15).

Next, we focus on the convergence property. The higher the convergence property is, the shorter the time required for determining whether caching or not is. We demonstrate how $p(t)$ changes according to Eq. (10) in Fig. 5 ($K = 30$) and Fig. 6 ($K = 100$). In both cases, we set α to be 1.0, and the initial value $p(0)$ to be 0.2 and 0.5, respectively. Comparing these figures, we find that the larger K, the shorter the convergence time, independently of $p(0)$. The reason of this phenomenon is that the slope at the vicinity of the equilibrium becomes gradual with the increase in K (Fig. 2). This result indicates that high user heterogeneity contributes to fast decision-making for caching. We obtained similar results when $\alpha \neq 1$.

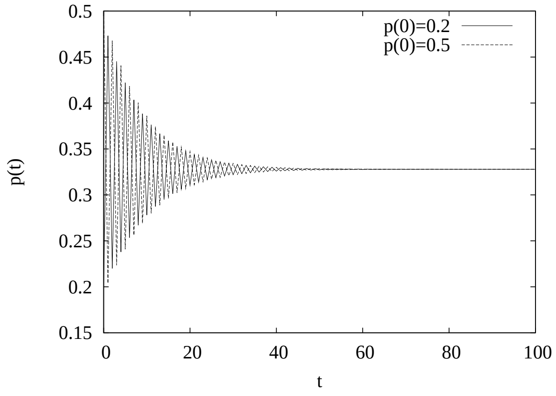

Figure 5: Convergence property ($K = 30$, $\alpha = 1.0$).

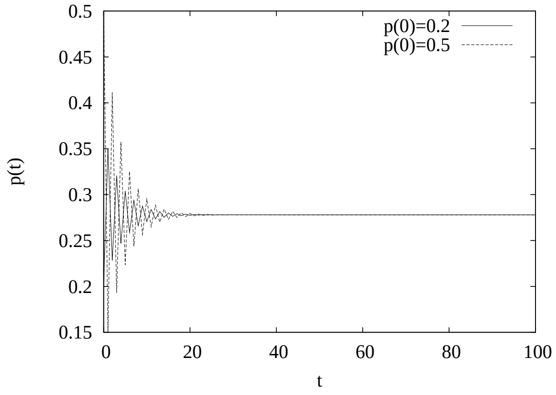

Figure 6: Convergence property ($K = 100$, $\alpha = 1.0$).

We also show the case that the equilibrium does not con-

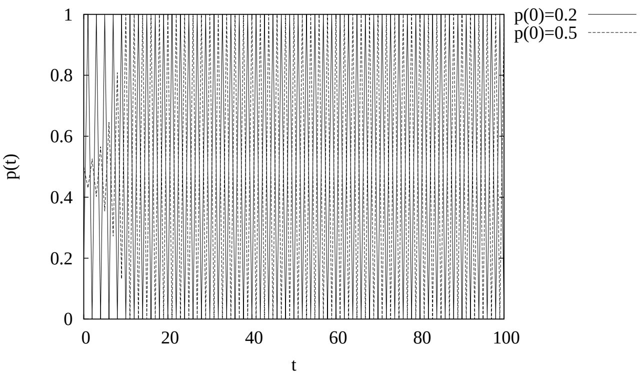

Figure 7: Convergence property ($K = 5$, $\alpha = 1.0$).

verge ($K = 5, \alpha = 1.0$) in Fig. 7. In this case, $p(t)$ permanently oscillates between 0 and 1 after a certain period depending on $p(0)$. Therefore, we cannot achieve effective caching due to the unpredictable file availability. We confirmed that this property can emerge when $\alpha \neq 1$ through numerical experiments.

From the above results, we can conclude that high user heterogeneity leads to achieving a stable caching system keeping file availability.

5. CONCLUSIONS

In this paper, we revealed how the selfish and autonomous users' behavior in the P2P file sharing system affects the system performance, in terms of file availability, under heterogeneous users' sense of value to caching by using evolutionary game theory. We first modeled the bargains about caching among file holders as the caching games between two nodes. We then investigated the relationship between the user heterogeneity and the file availability through theoretic analysis based on micro-macro dynamics. Analytical and numerical results demonstrated that high user heterogeneity leads to achieving a stable caching system keeping file availability.

The following issue is remaining. The analysis based on micro-macro dynamics assumes that each node can know the ratio $p(t)$ of cooperators to the whole nodes. Since $p(t)$ is a global parameter, each node has to exchange information on its strategy with all other nodes. As a future work, we plan to investigate the relationship between the user heterogeneity and the system performance through agent-based dynamics. 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 then decides the next strategy. Consequently, we can find out the system characteristics in the case that nodes selfishly behave based on their local information in various network topologies.

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