Free-Riding and Whitewashing in Peer-to-Peer Systems*

Michal Feldman[1]
mfeldman@sims.berkeley.edu

Christos Papadimitriou[2]
christos@cs.berkeley.edu

John Chuang[1]
chuang@sims.berkeley.edu

Ion Stoica[2]
istoica@cs.berkeley.edu

[1]School of Information Management and Systems
U.C. Berkeley

[2]Computer Science Division
U.C. Berkeley

ABSTRACT

We develop a model to study the phenomenon of free-riding in peer-to-peer (P2P) systems. At the heart of our model is a user of a certain *type*, an intrinsic and private parameter that reflects the user's willingness to contribute resources to the system. A user decides whether to contribute or free-ride based on how the current contribution cost in the system compares to her type. When the societal *generosity* (i.e., the average type) is low, intervention is required in order to sustain the system. We present the effect of mechanisms that exclude low type users or, more realistic, penalize free-riders with degraded service. We also consider dynamic scenarios with arrivals and departures of users, and with *whitewashers*: users who leave the system and rejoin with new identities to avoid reputational penalties. We find that when penalty is imposed on all newcomers in order to avoid whitewashing, system performance degrades significantly only when the turnover rate among users is high.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems; J.4 [**Social And Behavioral Sciences**]: Economics

General Terms

Design, Economics, Performance

Keywords

Cheap pseudonyms, cooperation, exclusion, equilibrium, free-riding, identity cost, incentives, peer-to-peer, whitewashing

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1. INTRODUCTION

Why is free-riding widespread among users of P2P systems? How does free-riding affect system performance? What mechanisms discourage free-riding? How does whitewashing affect the performance of P2P systems?
These are the questions that motivate us.

P2P systems rely on voluntary contribution of resources from the individual participants. However, individual rationality results in free-riding behavior among peers, at the expense of collective welfare. Empirical studies have shown prevalent free-riding in P2P file sharing systems [1, 16]. Various incentive mechanisms have been proposed to encourage cooperation in P2P systems [4, 6, 10, 13, 17]. At the same time, it has been suggested that free-riding can be sustainable in equilibrium and may even occur as part of the socially optimum outcome [12].

We develop a simple modeling framework to help answer these questions. At the heart of our model is a user as a rational agent with a private and intrinsic characteristic called her *type*, a single parameter reflecting the willingness of the user to contribute resources (type can be intuitively thought of as a quantitative measure of decency or generosity).

Each user decides whether to contribute or free-ride based on the relationship between the cost of contribution and her type. We assume that the cost of contributing is the inverse of the total percentage of contributors, because when many people free-ride, the load on contributors increases. Thus, if at present a fraction x of the users contribute, the decision of a rational user with type t_i is:

$$\text{Contribute, if } 1/x < t_i$$

$$\text{Free-ride , otherwise}$$

Even within this minimalistic framework we can already see some interesting implications. In this "free market" environment, the percentage x of contributors is determined as the intersection of the type distribution with the curve $x = 1/t$. Under a uniform type distribution, the two curves intersect at two points (see Figure 1), of which the higher one is the attractor of the natural fixpoint dynamics, i.e., starting at some initial x, users arrive at individual decisions, their aggregate decisions define a new x, and so on. As long as the initial x is above the lower intersection point, the process converges to the upper one. If there is no intersection, i.e., when there are too many selfish rascals around, then x becomes 0 (the other attractor, which always exists) and the system collapses.

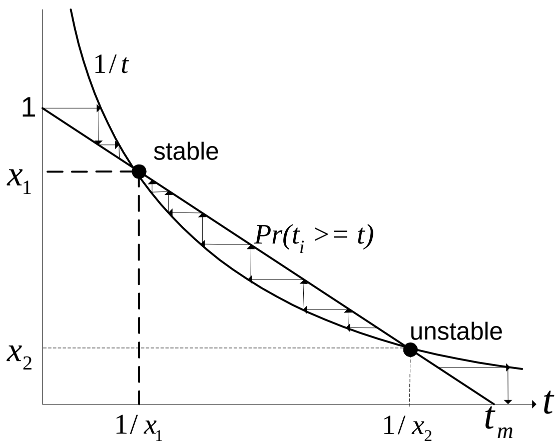

Figure 1: The intersection points of the two curves represent the two equilibria of the system. The curve $x = 1/t$ represents the contribution cost, and $Pr(t_i >= t)$ represents the generosity CDF, assuming $t_i \sim U(0, t_m)$. The higher equilibrium (contribution level x_1) is stable.

To understand system performance, we need to analyze system benefits, as well as costs. What is a user's benefit when the level of contribution is x? We assume that the benefit a user receives from participation in the system (whether or not she contributes), denoted by Q, is a function of the form

$$Q = \alpha x^{\beta}$$

where $\beta \leq 1$ and $\alpha > 0$ are positive constants. Hence user benefit is an increasing function of the number of contributors, but with diminishing returns—a form widely accepted in this context (see, e.g., [2], [3], [15]). Thus, the performance of the system, denoted by W_{system}, is defined as the difference between (1) the average benefit received by all users (including both contributors and free-riders) and (2) the average contribution cost experienced by all users, which effectively include only the contributors (free-riders incur no costs):

$$W_{system} = \alpha x^{\beta} - 1 \tag{1}$$

With this we are ready to tackle more questions:

1. Would excluding low-type users from the system improve performance? The answer seems to be true only if the societal generosity level is low and α is large enough (see Section 3).

2. The exclusion scenario is unrealistic because users' types are private. What if free-riding *behavior* brings some form of penalty, that is, deterioration of benefits by a fraction of $(1 - p)$? We find that the penalty mechanism is effective in discouraging free-riding behavior when the threat is sufficiently high relative to the contribution cost (see Section 4). Moreover, for a sufficiently high threat, no social cost is incurred because no user is effectively penalized, so the optimal performance is achieved.

However, imposing penalties on free-riders require a way to identify free-riders and distinguish them from contributors. Reputation systems [11, 14] may help, but these systems are vulnerable to the whitewashing attack, where a free-rider repeatedly rejoins the network under new identities to avoid the penalty imposed on free-riders [9]. The whitewashing attack is made feasible by the availability of low cost identities or *cheap pseudonyms*. There are two ways to counter whitewashing attacks. The first is to require the use of free but irreplaceable pseudonyms, e.g., through the assignment of strong identities by a central trusted authority [5]. In the absence of such mechanisms, it may be necessary to impose a penalty on all newcomers, including both legitimate newcomers and whitewashers. This results in a social cost due to cheap pseudonyms, as suggested by Friedman and Resnick [9]. We find that performance is significantly affected only for high turnover rates (see Section 5).

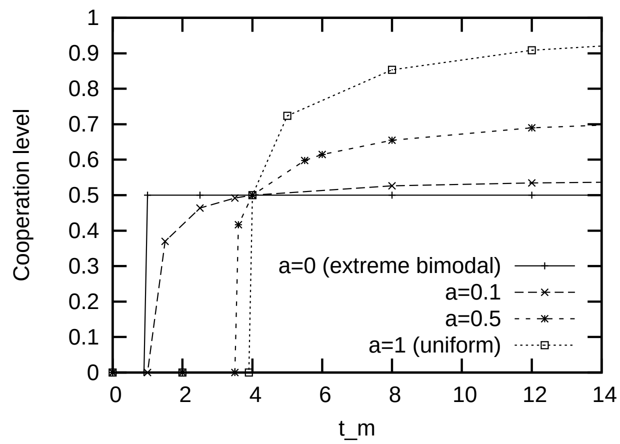

Figure 2: Contribution level as a function of the societal generosity level for different generosity distributions.

2. CONTRIBUTION LEVEL

The contribution level, x, is the fraction of users whose generosity (type) exceeds the current contribution cost, $1/x$. Thus, the fraction of users who contribute is derived by solving the following fixpoint equation:

$$x = \text{Prob}(t_i \geq 1/x) \tag{2}$$

To solve this equation, we need to make assumptions about the type distribution. In this section, we consider the following distribution:

- Fraction a of the users: $t_i \sim U(0, t_m)$
- Fraction $\frac{1-a}{2}$ of the users: $t_i = 0$
- Fraction $\frac{1-a}{2}$ of the users: $t_i = t_m$

The parameter $a \in [0, 1]$ determines the degree of bimodality of the distribution, with $a = 0$ corresponding to an extreme bimodal distribution and $a = 1$ corresponding to a uniform distribution. t_m is the maximum willingness to contribute resources, and the expected type is always $t_m/2$, independent of the value of a. t_m is thus an important parameter of the system, as it reflects the societal "generosity" (it is twice the expected type).

For $a = 1$, a user's type is uniformly distributed between 0 and t_m. Under a uniform distribution, we derive the fraction

General symbols	
t_i	user $i's$ type
t_m	maximal type in population
α	system benefit coefficient
β	diminishing returns coefficient
W	realized performance
Q	individual benefit
R	contribution cost
T	threat level
z	exclusion fraction
p	penalty level
p_m	maximal possible penalty
Static system	
x	contribution level
Dynamic system	
x_s	contribution level of stayers
x_l	contribution level of leavers
x_a	average contribution level
d	turnover rate

Table 1: Model's symbol notations.

of contributors as follows:

$$x = \text{Prob}(t_i \geq 1/x) = 1 - \frac{1}{xt_m} \tag{3}$$

which yields:

$$x_{1,2} = \frac{t_m \pm \sqrt{t_m^2 - 4t_m}}{2t_m}$$

The larger root x_1 is the stable equilibrium (attractor, see Figure 1) while x_2 is unstable. For $t_m < 4$, there is no intersection between the curves, thus the contribution level becomes 0 and the system collapses.

The contribution level varies depending on the type distribution and range (reflected by a and t_m) as shown in Figure 2. It increases in t_m and converges asymptotically to:

$$x_m = \frac{1+a}{2}$$

On the other hand, the contribution level falls to zero when t_m falls below the threshold t_m^{min}, as shown in Figure 3.

$$t_m^{min} = \max\left(1, (16a)/(1+a)^2\right)$$

For a uniform distribution, $t_m^{min} = 4$, whereas for the extreme bimodal distribution, $t_m^{min} = 1$. This means that when the societal generosity level is low, a bimodal type distribution can better sustain the system than a uniform type distribution. On the other hand, when the societal generosity level is high, a uniform type distribution can realize a higher contribution level and system performance. For analytical tractability, we use the uniform type distribution in the remainder of this paper. We leave a more thorough analysis of other type distributions for future work.

3. EXCLUSION MECHANISM

The analysis presented above suggests that when the societal generosity is low, the system cannot be sustained without intervention. In this section, we analyze the effect of intervention in the form of exclusion.

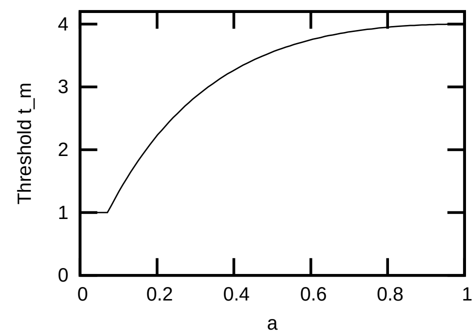

Figure 3: The minimal t_m value as a function of a that achieves positive contribution under a bimodal distribution.

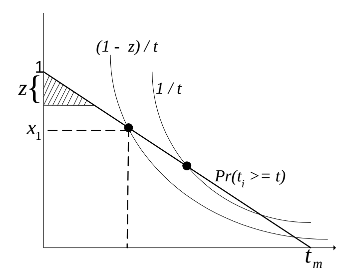

Figure 4: The effect of the exclusion mechanism. The shaded area represents the excluded users, and the (higher) intersection point occurs at a higher contribution level.

If we had perfect information about the type of each individual user, we could *exclude* the users of the lowest type in order to increase the contribution level. This shifts the cost curve downward (see Figure 4), resulting in a higher contribution level. However, exclusion also decreases performance by limiting the number of users who enjoy the system's benefits. The trade-off is optimized at a particular exclusion level.

Suppose a fraction z of users are excluded. The fixpoint equation describing contribution level now becomes:

$$x = Prob(t_i \geq \frac{1-z}{x}) \tag{4}$$

which yields:

$$x = \frac{t_m + \sqrt{t_m^2 - 4t_m + 4t_m z}}{2t_m}$$

Notice that x represents the contribution level in the entire system rather than that in the post-exclusion system; therefore, the effective contribution level is the minimum between this value and $(1 - z)$.

With the exclusion in effect, the system performance becomes:

$$W_{system}^{exclusion} = (\alpha x^\beta - 1)(1 - z)$$

The optimal exclusion level is:

$$z^* = \text{argmax}_z \; W_{system}^{exclusion}$$

Figure 5 presents the system performance as a function of t_m with and without exclusion. We see that intervention is not necessary when the societal generosity is sufficiently high ($t_m >\sim 4.5$). Any performance improvements realized by the high-type users are offset by the loss in benefits for the excluded low-type users. In contrast, for lower t_m values, the exclusion mechanism is effective in preventing a total collapse in cooperation.

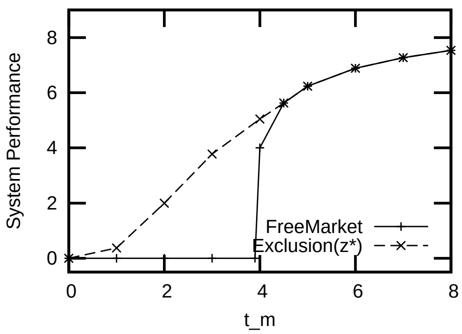

Figure 5: System performance as a function of t_m under free-market and exclusion. $\beta = 0.7$, $\alpha = 10$.

4. PENALTY MECHANISM

The exclusion mechanism that we describe is unrealistic, because it assumes that types are observable. In addition, the exclusion mechanism excludes users based on innate *type* rather than *behavior*. In doing so, it does not allow users to adjust their behavior in response to the imposed threat.

The penalty mechanism assumes that free-riding behavior is observable, even though innate user types may not be; that is, users are labeled as either contributors or free-riders, and being a free-rider entails a penalty – deterioration of a user's benefits by a fraction of $(1-p)$. An example penalty would be exclusion with probability p. Another example penalty, which is mathematically equivalent to the first, is service differentiation, under which free-riders' system benefits are reduced, while contributor benefits are not (see [4], [11], [8] for various mechanisms that have been proposed and analyzed, and which would have this effect). Downgrading the performance of the free-riders has two effects, which both lead to a higher contribution level. First, the penalty reduces the contribution cost, denoted by R, since the load placed on the system is reduced. Second, it introduces a threat, denoted by T; users who free-ride know that they will get reduced service.

Under the penalty mechanism, the realized performance of contributors and free-riders is:

$$W_{contributors} = Q - R = \alpha x^\beta - \tfrac{x+(1-x)(1-p)}{x}$$

$$W_{free-riders} = Q - T = \alpha x^\beta - p\alpha x^\beta$$

Consequently, the contribution level, x, is derived according to the following expression:

$$x = \text{Prob}(t_i \geq R - T)$$

$$x = \text{Prob}(t_i \geq \frac{x+(1-x)(1-p)}{x} - p\alpha x^\beta) \qquad (5)$$

In what follows, we set $\beta = 1$ for tractability and presentation clarity. The solution of this fixpoint equation is:

$$x = \frac{p - t_m + \sqrt{p^2 + 2t_m p + t_m^2 - 4t_m + 4p\alpha - 4p^2\alpha}}{2(-t_m + p\alpha)}$$

System performance now becomes:

$$W^{penalty}_{system} = (\alpha x^\beta - 1)(x + (1-x)(1-p))$$

and the optimal penalty level is:

$$p^* = \text{argmax}_p \; W^{penalty}_{system}$$

While p yields a higher contribution level, it also reduces the benefit to free-riders. However, if p is set high enough, it achieves full cooperation, and no penalty is actually imposed. Based on equation 5, this is achieved when $p \geq \frac{1}{\alpha}$. In this case, we achieve the maximal system benefits:

$$Q_m = Q(x = 1) = \alpha$$

For example, if $Q_m = 10$, we only need a mechanism that can catch and exclude a free-rider with 10% probability, but if $Q_m = 1.1$, we will need to increase the probability to over 90%.

These results suggest that if we impose a high enough penalty, or are able to identify and exclude free-riders with high probability, we achieve optimal system performance. However, in many cases it may be difficult or costly to exclude free-riders with high probability, and p will be restricted by a maximal feasible value, denoted by p_m.

Figure 6 presents the percentile of optimal performance that can be achieved by the penalty mechanism for different p_m values for a given α of 10. As long as $p \geq 1/\alpha$, optimal system performance can be achieved, regardless of the value of t_m. In our example, where $\alpha = 10$, the curve representing $p_m = 0.1$ exemplifies this (For lower values of α, a higher p_m will be required). On the other hand, if the penalty is set too low (e.g., $p = 0.01$), the resulting performance is not significantly better than the free-market ($p = 0$) outcome.

An additional issue is the stability of the equilibrium. It is true that if $p = 1/\alpha$, $x = 1$ is an equilibrium for all t_m values. However, the basin of attraction, $[1-\epsilon, 1]$, varies depending on t_m, and a low t_m value may lead to an extremely small ϵ or even $\epsilon = 0$, which means that the system will never converge to $x = 1$ unless the initial x is 1. The threshold value above which the system converges to $x = 1$, denoted by $t_m^{threshold}$, is a function of α and ϵ as follows:

$$t_m^{threshold} = \frac{1 - 2\alpha + \epsilon\alpha}{\alpha(\epsilon - 1)}$$

$t_m^{threshold}$ increases in ϵ as expected. For the value presented in the figure ($\alpha = 10$), $t_m^{threshold}(\epsilon = 0) = 1.9$, which means that for $t_m < 1.9$, $x = 1$ is not an attractor, and the wider the desired basin of attraction is, the higher $t_m^{threshold}$ becomes.

5. THE SOCIAL COST OF FREE IDENTITIES

In Section 4, we show that a penalty mechanism can discourage free-riding behavior. However, the effectiveness of penalties can be undermined by the availability of cheap pseudonyms. In particular, a free-rider might choose to *whitewash*, i.e., leave and rejoin the network with a new identity on a repeated basis, to avoid the penalty imposed on a free-rider. The lower the cost of acquiring new identities, the more likely a free-rider will engage in whitewashing. Since whitewashers are indistinguishable from legitimate newcomers, it is not possible to single them out for the imposition

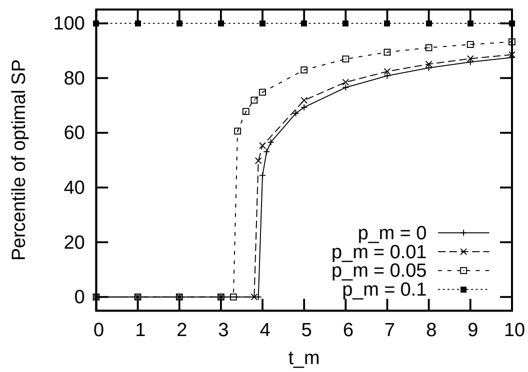

Figure 6: Percentile of optimal performance for different values of p_m. Note that $p_m = 0$ refers to the free-market scenario. $\alpha = 10$.

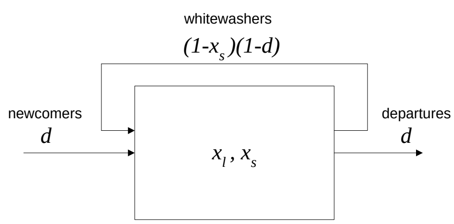

Figure 7: Dynamic system with arrivals, departures, and whitewashers. A fraction d of users depart and are replaced by the same number of newcomers. At the same time, a fraction $(1-d)(1-x_s)$ of users whitewash under FI.

of a penalty. Of course, it is possible to counter the whitewashing strategy by imposing the penalty on all newcomers. However, this results in a social cost, as shown by Friedman and Resnick [9].

In this section, we are interested in quantifying the social cost of cheap pseudonyms in terms of reduced system performance. We do so by extending our model from section 4 into a dynamic model in which users join and leave the system. To quantify the performance reduction due to cheap pseudonyms, we consider two dynamic scenarios: *permanent identities* (PI) and *free identities* (FI).

Under PI, identity costs are taken to be infinity[1], while under FI, they are free. In actuality, identity cost can take any positive finite value, and users decide whether to whitewash depending on how the identity cost compares to the penalty imposed on free-riders and newcomers. In this paper, we focus on the two extreme cases of infinite and free identity costs, as we believe these cases provide important insights while preserving simplicity.

[1]Identity cost refers to the cost of acquiring any additional identity after the first, which is considered to be a sunk cost.

5.1 System Dynamics and Population Mixture

We model a system where some users leave and newcomers join, with a turnover rate of d (Figure 7). We assume that arrivals and departures are type-neutral and therefore do not alter the type distribution [2].

The population at each point in time is composed of the following four groups:

- existing contributors (EC)
- existing free-riders / whitewashers (EF/WW)
- new contributors (NC)
- new free-riders (NF)

The difference between the permanent and free identities scenarios is signified by the members of the second group. While free-riders stay in the system if identities are permanent, they will adopt whitewashing behavior under free identities. However, if penalty is imposed also on newcomers, free-riders are indifferent between staying or whitewashing.

5.2 Contribution Cost, Threat and Contribution Levels

An important property of the dynamic scenarios is that not all users care about the threat. The users who leave the system at the end of each period are not affected by the penalty they would have paid had they stayed in the system. Consequently, we get two separate contribution levels:

x_l: the contribution level of users who leave

x_s: the contribution level of users who stay

The values of x_s and x_l in equilibrium satisfy the following equations:

$$x_l = \text{Prob}(t_i \geq R) \quad (6)$$

$$x_s = \text{Prob}(t_i \geq R - T) \quad (7)$$

(Recall that R and T denote the contribution cost and the threat, respectively).

The average contribution level in the system, denoted by x_a, is:

$$x_a = dx_l + (1-d)x_s$$

The contribution level of users who stay is always greater than or equal to that of users who leave. Unlike the static system, where $x = 1$ can be achieved for a sufficiently high p, dynamic scenarios cannot achieve $x_a = 1$ due to the users who leave.

The user's contribution cost in each period is determined by the ratio between the fraction of users who get the full benefit of the system and those who get the reduced benefit. If only existing free-riders are penalized (feasible only under PI), all other groups get the full benefit. However, if all newcomers are penalized, all groups except for existing contributors get reduced service. The following table presents the fraction of users who get the full and reduced benefit under the two scenarios:

[2]The model can be extended in future work by considering more sophisticated dynamics, as discussed in Section 6.

	NC not penalized	NC penalized
% penalized	$(1-d)(1-x)$	$d+(1-d)(1-x)$
% not penalized	$(1-d)x+d$	$(1-d)x$

Based on this table, the contribution cost under PI, when newcomers are not penalized is:

$$R_{PI} = \frac{(1-d)x + d + (1-d)(1-x)(1-p)}{x}$$

The cost under FI, when newcomers are penalized is:

$$R_{FI} = \frac{(1-d)x + d(1-p) + (1-d)(1-x)(1-p)}{x}$$

The cost is lower under FI because a larger fraction of users are penalized; therefore the demand placed on the system is lower. Nevertheless, the benefits of all users, except for existing contributors, is also reduced. Under PI, if we set p sufficiently high, we can obtain a scenario where p threatens users but no penalty is actually imposed (similar to the static system, see Section 4). In contrast, under FI, imposing a penalty always results in reduced performance, because newcomers are penalized independently of their behavior.

5.3 System Performance

Table 2 presents the fraction in the population and the realized performance level of each group under the two scenarios. System performance is:

$$W_{system} = \sum_j (f_j * W_j)$$

The best strategy is to impose a penalty p^* that satisfies:
$p^* = \text{argmax}_p \quad W_{system}$

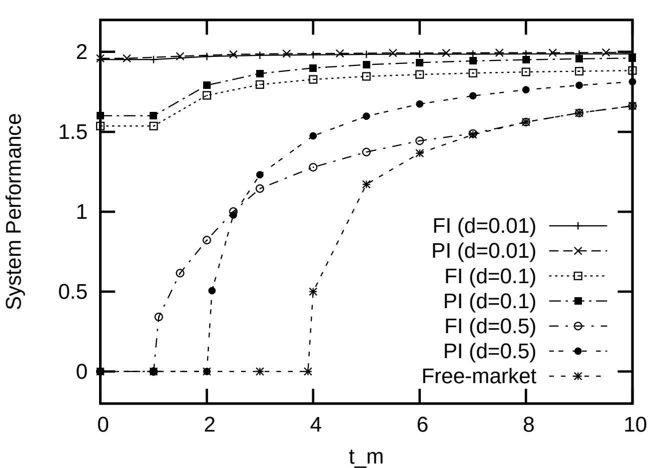

Figure 8: System performance subject to $p = p^*$ under free-identities, permanent identities and free market; $\beta = 1$, $\alpha = 3$.

Figure 8 compares the system performance, W_{system}, subject to a penalty $p = p^*$, under PI and FI as a function of t_m for different turnover rates (d). We make the following observations:

- For very small turnover rates ($d = 0.01$), the system performs close to its optimal level, as the threat is imposed on the majority of the population, and thus a small penalty level is sufficient to achieve a high contribution level. No notable performance gap exists between PI and FI. As turnover increases, a higher penalty is required, which reduces system performance.

- As t_m increases, system performance converges to its optimal level under both scenarios. The performance gap between the two scenarios shrinks.

- Under a high turnover rate ($d = 0.5$) and low t_m values, the system performs better if a penalty is imposed on newcomers even under PI. If societal generosity is low and the turnover rate is high, it is hard to obtain satisfactory contribution levels, and penalties to newcomers may help improve contributions by reducing the load placed on the system.

We conclude that a notable social cost due to free identities is incurred only when a penalty on all newcomers is unnecessarily imposed. In particular, the cost is incurred only under high turnover rates (d) and only in conjunction with intermediate contribution levels (t_m) and low system benefits (α). In contrast, in cases where the system can tolerate the newcomers, the imposition of a penalty on all newcomers incurs a social loss. In what follows, we provide some observations that help explain these findings:

- If the turnover rate is low, the fraction of newcomers in the population is small. Therefore, penalizing newcomers does not significantly affect system performance. In addition, because the population is fairly permanent, a low p imposes a sufficient threat to obtain many contributions.

- If the turnover rate is high and the societal generosity is low, system collapse can only be avoided by reducing the demand placed on the system. Assessing a penalty on all newcomers is one method to limit the demand. In these situations, penalizing newcomers actually helps to sustain the system by reducing system overload.

- If the societal generosity is high, a high contribution level is obtained even in the absence of intervention. Therefore, the best policy under both scenarios is to impose a small penalty or no penalty. Hence, no notable social loss is incurred due to free identities.

- If the benefits of the system (α) are high, even a small p results in a high threat to free-riders. Once again, the optimal p is small, and so no notable gap occurs.

6. DISCUSSION AND FUTURE WORK

We have presented an economic model of user behavior in P2P systems and derived some useful observations. In particular, a mechanism that penalizes free-riders can improve system performance by reducing the cost placed on contributors. This mechanism is especially effective when the societal generosity is low, in which case performance is low or zero in the absence of intervention. Additionally, penalizing all newcomers may be effective in discouraging whitewashing behavior. Newcomer penalties reduce system performance only for high turnover rates.

Group (j)	Group Size (f_j)	Realized Performance (W_j)	
		Permanent identities	Free identities
EC	$(1-d)x$	$Q - R_{PI}$	$Q - R_{FI}$
EF / WW	$(1-d)(1-x)$	$Q(1-p)$	$Q(1-p)$
NC	dx	$Q - R_{PI}$	$Q(1-p) - R_{FI}$
NF	$d(1-x)$	Q	$Q(1-p)$

Table 2: The size and realized performance level of the different groups under the PI and the FI scenarios.

Our model is flexible enough to account for a diverse set of characteristics. For example, we extend our model to account for resource heterogeneity. To do so, we split each *user* into a number of *virtual users*. The number of virtual users is proportional to the amount of the user's resources. We find that users with many resources bear higher costs, and therefore exhibit lower contribution levels. Because contribution from high-resource users is more valuable in terms of system performance, a heterogeneous system results in a lower system performance than a homogeneous system. However, if the resource level and the generosity level correlate, a heterogeneous system may result in better performance than a homogeneous one. Several research questions arise in this context, as discussed next.

In this work, we do not propose a new incentive scheme. Instead, we aim to develop a game-theoretic framework that shows how incentive schemes affect user behavior and system performance, and to obtain a better understanding of the different factors and system parameters relating to the need and effectiveness of these schemes. For this purpose, we have simplified the model with a set of somewhat restrictive assumptions. In future work, we plan to relax or modify some of the assumptions and possibly extend the model in several directions:

- Additional incentive schemes. We plan to analyze the effect of system partitioning on user behavior and system performance. In particular, if the system is partitioned into two or more subsystems that impose different penalties on free-riders, how would this affect the results?

- Additional penalty forms. We plan to consider other newcomer penalties. One possible penalty is an entry fee that can be used as a pure transfer to the system. Some examples of entry fees include monetary payments that can be distributed among the participants or a required contribution of resources. While these mechanisms entail no direct loss in efficiency, they introduce a different set of issues. First, this type of mechanism essentially *forces* contribution at the entering stage, and may therefore prevent some users from participating. Second, contribution of resources from newcomers prior to their participation may be limited, because in many cases the resources are gathered through membership in the system. Third, redistribution of monetary payments may be difficult due to highly dynamic system membership.

- System dynamics (Section 5). In a dynamic scenario, the model can be extended by assuming (1) departure rates that depend on performance, (2) arrival rates affected by p, and (3) dynamics that affect the distribution by postulating type-dependent departures and arrivals. In particular, one could imagine that p would affect the arrival rate in different directions. On the one hand, imposing penalties on newcomers may discourage them from joining the system, which reduces arrivals. On the other hand, users who join a system that penalizes its users may expect higher performance levels. Such a system may be particularly attractive to join. Depending on how p affects the arrival rate, the performance effect of free identities may increase or decrease relative to our results.

- Identity costs. In our analysis, we consider the two extreme cases of infinite and zero identity costs. In future work, we intend to study cases in which the cost of identity, c, is a positive finite value. In this context, performance might benefit from imposing different penalties on free-riders and newcomers (e.g., $p_{newcomers} = p_{free-riders} - c$).

- Additional performance metrics. In this paper, we use the metric of *system performance*. This metric assigns equal weights to the realized performance of all users, whether they are contributors or free-riders. In the future, we plan to consider other performance metrics that might be more appropriate on grounds of fairness. One metric might assign more weight to the performance of contributors than the performance experienced by free-riders.

- Resource heterogeneity. Several interesting directions can be examined in the context of resource heterogeneity. First, how do the results change if users can contribute resources at different levels, as opposed to the binary categorization of contributor or free-rider that we have assumed in this paper. Second, it will be interesting to experiment with alternative contribution cost functions that may be more reflective of the opportunity cost. For example, users with many resources may experience lower opportunity costs even when they contribute more resources [7]. If so, the system may exhibit better performance.

7. REFERENCES

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