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# Discovering Multiple Resource Holders in Query-Incentive Networks

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**Abstract**—In this paper, we study the problem of discovering multiple resource holders and how to evaluate a node’s satisfaction in query incentive networks. Utilizing an acyclic tree, we show that query propagation has a nature of exponential start, polynomial growth, and eventually becoming a constant. We model the query propagation as an extensive game, obtain nodes’ greedy behaviors from Nash equilibrium analysis, and show the impairment of greedy behaviors via a repeated Prisoner’s Dilemma. We demonstrate that cooperation enforcement is required to achieve the optimal state of resource discovery.

**Index Terms**—query-incentive network, P2P media streaming, game theory, resource discovery

## I. INTRODUCTION

Incentive has been a popular topic in online question-answer systems, such as resource query in P2P content-sharing applications [1] [2], and information seeking in social networking services [3] [4]. In the literature, incentive mechanisms for resource discovery have been studied [5] [6] [7], but they only consider the retrieval of a single resource holder. However, we may need multiple resource holders in a realistic network [8], and the conventional mechanisms may not be effective. For example, peers in P2P multimedia streaming networks need multiple neighbors to achieve a reasonable streaming rate. In this work, we study the query propagation and interactions among nodes for the discovery of multiple resource holders in query incentive networks, aiming at achieving optimal state of query propagation and reducing communication overhead (i.e, the number of query-forwardings in the system).

### A. Query process

We dynamically abstract the query propagation as an acyclic tree,  $\mathcal{T}$ . Consider a node  $v^*$  in demand of a resource as the root of  $\mathcal{T}$ . It sends the query to a subset of its neighbors and offers a reward,  $r^*$ , which it will pay when it finds the resource. If a child node (i.e., node receiving a query) is not the resource holder, it checks whether its parent offers a large enough reward and, if so, propagates the query to a subset of its neighbors and offers a smaller reward. These neighbors will handle the query likewise. In this way, the query is propagated in  $\mathcal{T}$  until it reaches the resource holders. To prevent redundant propagation of a query, a node only establishes an edge with the first node sending it this query and becomes this node’s child in  $\mathcal{T}$ .

### B. Related work

The recent study in [5] proposes a branching process [9] model for query incentive networks. The breakpoint structure and growth rates of rewards are thoroughly analyzed. Along

the same lines, [6] studies the transition behaviors through the branching process itself and the failure probability. However, they only consider the scenario of a single resource holder, and due to the complexity of constructing the generating functions, the branching process may not be suitable for modeling query propagation in a network with multiple resource holders. In [7], an incentive mechanism based on subgame perfect equilibrium (SPE) approximation is demonstrated to give better performance than breadth-first-search. They show that the incentive decreases with the number of hops along the propagation path, thus automatically avoiding the flooding problem and the pyramid effect. Again, this mechanism only considers one resource holder. Our study is based on a similar query propagation model – acyclic tree, and examines the scenario with multiple resource holders. We also analyze the system performance w.r.t. the communication overhead.

### C. Our contribution

Targeting the discovery of multiple resource holders, we first conduct an in-depth study of the query propagation pattern in query incentive networks, based on which we propose a model to evaluate a node’s satisfaction. By satisfaction we mean whether a node has enough incentive to propagate a query, or whether a node can find enough resource holders. Further, based on the sequential structure of the query propagation, we model the query propagation as an extensive game, and study the greedy behaviors of immediate neighbors (i.e, they may impair the system performance in order to maximize their own utilities). Our contributions are two-fold:

- We mathematically answer three fundamental questions: (i) What is the node population growth pattern in the propagation tree? (ii) How do we evaluate satisfaction level of different nodes in query incentive networks? (iii) Can we achieve an optimal state in query incentive networks?
- Utilizing game theory and mechanism design, we show that the query propagation reaches a Nash equilibrium in which immediate neighbors exhibit greedy behaviors. To illustrate the impairment of greedy behaviors in query incentive networks, we abstract interactions among immediate neighbors into a repeated Prisoner’s Dilemma, and point out the necessity of cooperation enforcement.

We study the propagation-tree growth pattern and model node satisfaction in Section II, followed by the game theoretic analysis in Section III. Then, we present the simulation results in Section IV, and finally, the conclusion in Section V.

## II. MODELING: TREE GROWTH PATTERN AND NODE SATISFACTION

In this section, we propose a model to evaluate the satisfaction of a node in the propagation tree. This requires a thorough understanding of the query propagation process. Thus, we first study the growth pattern of a propagation tree and then present the evaluation model.

### A. Tree growth pattern

We first look at the discovery success probability. Denote by  $\mathcal{N}$  the size of the network. Let  $p = \frac{n}{|\mathcal{N}|}$  be the *resource popularity* of a resource  $c$ , where  $n$  is the number of resource holders. Suppose that Node  $v$  receives a query with offered reward  $r_v$ . If it is not the resource holder, it will offer reward of  $\phi_v(r_v)$  to its children, which is no larger than  $r_v - C_v$ , where  $C_v$  is the cost function (e.g., charging for the forwarding effort). Let  $\phi$  denote the set of incentive functions  $\{\phi_v(r_v) : v \in \mathcal{T}\}$ . Suppose  $v$  fails to find the resource with probability  $\eta_v(\phi, r_v)$ . Let  $\mathcal{T}_v$  be the subtree rooted at  $v$  in the propagation tree, and denote by  $N_v$  the number of nodes in the subtree,  $\mathcal{T}_v$ . Thus the subtree of  $\mathcal{T}_v$  finds the resource with probability  $\mu_v(\phi, r_v) = 1 - \eta_v(\phi, r_v)$ . To find  $c$ ,  $v$  either holds  $c$  or retrieves resource holders of  $c$  through  $\mathcal{T}_v$ . We can recursively show that a non-resource holder  $v$  fails to find the resource with probability

$$\begin{aligned} \eta_v(\phi, r_v) &= 1 - \mu_v(\phi, r_v) = \prod_{w \in \mathcal{W}} (1 - p)\eta_w(\phi, r_w) \\ &= (1 - p)^{N_v} \end{aligned} \quad (1)$$

where  $\mathcal{W}$  is the set of node  $v$ 's children since only when each child  $w$  of  $v$  and each subtree of  $\mathcal{T}_w$  do not hold the resource, will the subtree of  $\mathcal{T}_v$  receive unsuccessful returns. A non-resource holder  $v$  retrieves  $k$  resource holders with probability

$$\mu_v^k(\phi, r_v) = \binom{N_v}{k} p^k (1 - p)^{N_v - k}. \quad (2)$$

Based on Eqns. (1) and (2), in the following we explore the growth pattern of the propagation tree.

**PROPOSITION 1.** The growth of the node population  $N_{v^*}$  in the propagation tree  $\mathcal{T}$  exhibits the exponential start property with respect to the depth of the propagation tree.

*Proof.* Define the overlapping probability  $p_o^h$  in the propagating hop  $h$  as the probability of sending a query to nodes receiving this query already. We assume that the maximum number of hops in the query propagation is  $H$  and the number of nodes joining the propagation tree in hop  $h$  is  $N(h)$ . Thus,  $p_o^h$  is determined by the number of nodes who have already received queries, namely,

$$p_o^h = \frac{\sum_{h=1}^{h-1} N(h)}{|\mathcal{N}|}, \quad h = 1, \dots, H.$$

For ease of analysis, we define  $\mu = \frac{N_{v^*}}{|\mathcal{N}|}$ . Obviously,

$$p_o^h = \frac{\sum_{h=1}^{h-1} N(h)}{|\mathcal{N}|} \leq \mu, \quad h = 1, \dots, H. \quad (3)$$

Suppose that on average each node in the propagation tree  $\mathcal{T}$  sends the query to  $k$  of its neighbors. One node in hop  $h - 1$  will further forward the query only if it is not a resource holder and this is the first time it receives the query. Thus, we obtain the following recurrence formula:

$$N(h + 1) = k(1 - p)(1 - p_o^h)N(h), \quad h = 1, \dots, H \quad (4)$$

the initial condition of which is  $N(1) = k(1 - p)$ . Combining Inequality (3) and the above recurrence formula, we obtain

$$\begin{aligned} N(h) &> k(1 - p)(1 - \mu)N(h - 1) \\ &> N(1)[k(1 - p)(1 - \mu)]^{h-1} \\ &= \frac{[k(1 - p)(1 - \mu)]^h}{1 - \mu}. \end{aligned}$$

Thus, the node population in the propagation tree  $\mathcal{T}$  is determined by

$$\begin{aligned} N_{v^*} &= \sum_{h=1}^H N(h) \\ &> \sum_{h=1}^H \frac{[k(1 - p)(1 - \mu)]^h}{1 - \mu} \\ &= \frac{1}{1 - \mu} \left( \frac{\tau^{H+1}}{\tau - 1} + \frac{\tau}{1 - \tau} \right) \propto k^H, \end{aligned}$$

when  $H \leq H^*$  and consequently  $\mu$  is small enough so that  $\tau = k(1 - p)(1 - \mu) \approx k$ . Hence, the growth of  $N_{v^*}$  exhibits exponential start w.r.t. the propagation tree depth  $H$ .  $[H^*]$  is the critical point after which  $N_{v^*}$  does not exhibit the exponential start property any more. Denote by  $N_{v^*}(x)$  the continuous fitting curve of  $N_{v^*}$  w.r.t.  $H$ . Then,  $H^*$  can be approximated by

$$\left. \frac{\partial^2 N_{v^*}(x)}{\partial x^2} \right|_{x=H^*} = 0.$$

□

### B. Node satisfaction evaluation

In a practical network, for example, P2P network, a node may discover a substantial number of resource holders (especially for popular resources), and this node only needs a modest number of resource holders to maintain a satisfactory downloading or streaming rate. This means that nodes on the propagation path are not guaranteed to obtain the rewards offered by the root. This results in two problems, namely, how to fairly distribute the rewards among these discovered resource-holding paths, and how to determine whether or not to forward a query.

*Reward division.* As offered, the root only pays rewards to nodes on  $m$  resource-holding paths. These paths are chosen according to the claimed quality of resources offered by the resource holders. To focus our analysis on the resource discovery, we simply assume that the root node randomly chooses  $m$  retrieved resource holders with equal probability. Since we assume  $m$  is a constant for a specific network, this

does not affect our analytical results for the resource discovery mechanism.

*Forwarding decision.* Denote by  $Y$  the event that a node finds one resource destination,  $Z$  the event that this node receives rewards as offered. We denote by  $p_r = \text{Prob}\{Z|Y\}$  the conditional probability of eventually receiving the offered rewards. With higher  $p_r$ , a node has stronger motivation to further propagate the query. Before we discuss  $p_r$ , we suppose that through the discovery mechanism described above the root node eventually discovers  $M(r^*, p)$  resource holders. When we strive to obtain a statistical and holistic perspective of the resource discovery,  $M(r^*, p)$  is only determined by  $p$  and  $r^*$ . In the following, we utilize the conditional probability  $p_r$  to evaluate the satisfaction of the resource holders.

**DEFINITION 1.** The *satisfaction index of the retrieved resource holder* is defined as

$$p_r \triangleq \begin{cases} \frac{m}{M(r^*, p)}, & \text{if } M(r^*, p) \geq m \\ 1, & \text{if } M(r^*, p) < m \end{cases}$$

where the conditional probability  $p_r$  partially reflects one node's willingness to retrieve resource destinations for its parent.

**DEFINITION 2.** The *happiness index of the root* is defined as

$$\rho \triangleq \begin{cases} \frac{M(r^*, p)}{m}, & \text{if } M(r^*, p) \leq m \\ 1, & \text{if } M(r^*, p) > m. \end{cases}$$

Further, we derive the optimal state as follows.

**PROPOSITION 2.** Provided that the root node offers strong enough incentives, for the overall system performance and the satisfaction of all nodes in the system, the *optimal state* of resource discovery is

$$M(r^*, p) = m.$$

*Proof.* This ensures that we do not retrieve redundant resource holders, thus limiting the propagation overhead to the minimum under the condition of providing desirable reliability for the root node (i.e.,  $\rho = 1$ ). As a result, optimal system performance is guaranteed. At the same time, the average reward of each node in the propagation path is maximized in that the total number of rewards offered by the root node is not reduced while  $p_r$  is increased. Therefore, both the root node and the retrieved resource holders are satisfied according to indices defined above.  $\square$

Moreover, how to quantitatively determine  $M(r^*, p)$  is another open problem. The node  $v$  in the propagation tree  $\mathcal{T}$  broadcasts to a subset of its neighbors with  $k_v$  nodes. Denote by  $\delta_v = \frac{k_v}{D_v}$ , the *relative effort strength* of  $v$  in helping its parent. Suppose that nodes in one propagation tree possess uniform relative effort strength and the same node degree, i.e.,  $\delta_v = \delta$  and  $D_v = D$ . We contend that  $M(r^*, p)$  is linearly proportional to  $p$  in that we consider a randomly formed neighborhood relationship. However,  $M(r^*, p)$ 's marginal increase decreases w.r.t. increasing root node incentive after the exponential start of  $N_{v^*}$ , namely, when  $H > \lfloor H^* \rfloor$ .

In the exponential-start stage of  $N_{v^*}$ , we model  $M(r^*, p)$  as

$$M(r^*, p) = \alpha(\delta D)^a p \quad (5)$$

where  $\alpha > 0$  is a weight parameter and  $a = H$  is the exponent determining the marginal increase of  $M(r^*, p)$ . The propagation hop  $H$  is further determined by the root node incentive. Then,  $p_r$  can be reformulated as

$$p_r = \frac{m}{\alpha(\delta D)^H p}$$

when  $N_{v^*}$  exhibits the exponential-start property. Since  $\lfloor H^* \rfloor$  increases w.r.t. decreasing  $k$ , we can control  $p_r$  through both  $k$  and  $H$ . When  $H > \lfloor H^* \rfloor$ , for the exhaustive search of the network,  $M(r^*, p)$  increases in a polynomial form. After the polynomial growth, the node population becomes constant since all nodes in the network have been visited.

### III. UTILITY-FUNCTION-BASED PROPAGATION

In order to provide incentives for query propagation and achieve the optimal system performance at the same time, we establish an extensive game to illustrate the sequential query propagation and derive the greedy behavior of immediate neighbors through Nash equilibrium analysis.

#### A. Game model

We model the propagation process as an extensive game  $\mathcal{G}$  because queries are propagated sequentially in the network. All nodes in the network are players. Let  $\mathcal{V}$  denote the player set ( $|\mathcal{V}|$  is the number of players).  $\mathcal{S}$  depicts the collection of strategy sets ( $\mathcal{S} = \mathcal{S}_v$  for  $\forall v \in \mathcal{V}$ ).  $\mathcal{U}_v(\phi)$  is the utility of node  $v$  in the propagation tree. We employ node  $v$ 's incentive function  $\phi_v$  as the strategic variable, which determines the propagation hop  $H$  and the transmission efforts  $k_v$ .

**LEMMA 1.** Denote by  $X$  the number of resource holders retrieved by  $v$ . Then,

$$E(X) = pN_v \quad \text{and} \quad X \sim \text{Poisson}(\mu).$$

*Proof.* Each node in the subtree of  $\mathcal{T}_v$  possesses the resource with probability  $p$ . Let  $P\{X=x\}$  be the probability of  $x$  occurrences in  $N_v$  events and each event occurs with probability  $p_c < 0.01$  [10]. Then,  $E(X) = pN_v$  and

$$P\{X = x\} = \frac{e^{-pN_v} (pN_v)^x}{x!}.$$

$\square$

For one retrieved resource, its probability of eventually receiving the offered rewards  $r_v - \phi(r_v)$  is  $p_r$ . As a result, the average revenues  $v$  obtains from one retrieved resource is  $(r_v - \phi(r_v))p_r$ . Therefore, by LEMMA 1, we establish the utility function of one node  $v$  as

$$\begin{aligned} \mathcal{U}_v(\phi) &= E(X)(r_v - \phi(r_v))p_r - C_v \\ &= pN_v(r_v - \phi(r_v))p_r - C_v, \end{aligned}$$

where  $C_v$  is the cost for query propagation. In the following, we delve into the property of the Nash equilibrium to arrive at the greedy behavior of immediate neighbors.

**THEOREM 1.** The incentive function profile  $\phi^*$  is a *Nash Equilibrium* if

$$\phi^* = \arg \max_{\phi} \mathcal{U}_v(\phi).$$

*Proof.* Since each player  $v$ 's incentive function is chosen independently,  $\mathcal{U}_v(\phi^*) \geq \mathcal{U}_v(\phi_{-v}^*, \phi'_v)$  for any player  $v$  and for any alternative strategy  $\phi'_v \neq \phi_v^*$ , where  $\phi_{-v}^* = [\phi_1^*, \phi_2^*, \dots, \phi_{v-1}^*, \phi_{v+1}^*, \dots, \phi_{|\mathcal{V}|}^*]$  depicts the composition of equilibrium strategies of players other than the player  $v$ . Therefore, the steepest gradient ascent of  $\mathcal{U}_v(\phi)$  is the optimized direction of the evolution of incentive functions. The Nash Equilibrium  $\phi^*$  meets the requirements of no benefits for any player through unilateral deviations [11].  $\square$

### B. Greedy immediate neighbors

In this section, we study the effect of Nash equilibrium on immediate neighbors, namely, neighbors of the root node in the propagation tree. Our goal is to analyze the interactions among immediate neighbors when they strive to maximize their own utility. Intuitively, immediate neighbors will offer minimum incentives to their subtrees and reserve the rest of the rewards. This results in greedy behavior.

**Optimal State Realization.** First consider how to achieve the optimal state as derived in PROPOSITION 2, namely,  $M(r_c^*, p_c) = m$ , in the presence of greedy immediate neighbors. In realistic networks, nodes may only possess local information of the network. Each node strives to optimize its utility function based on this local information. Thus, the greedy behavior analysis is scalable since it only involves interactions among immediate neighbors. In addition, *immediate neighbors analysis epitomizes the nature of interactions among neighbors in any hop of the propagation.*

To achieve the optimal state, statistically each immediate neighbor of the root node needs to cooperate with each other to receive equal number of resource destinations as demanded by the root node. In this way, they increase the probability of receiving offered rewards eventually, and at the same time limit the cost of resource retrieval to a minimum. However, if the root node provides strong enough incentives, then one immediate neighbor tends to undermine other immediate neighbors by retrieving more resource holders to increase its own probability of earning rewards. The interaction among immediate neighbors turns out to be a repeated game whose constituent game is the *Prisoner's Dilemma*.

**Prisoner's Dilemma.** We simplify our analysis to the scenario of two immediate neighbors. Denote by  $\phi_{v^*}$  the root node's incentives. Then, let Player  $i$  retrieve  $m_i$  ( $i = 1, 2$ ) resources at *each round* (i.e., each query session). For each round, provided that the action profile is  $(m_1, m_2)$ , Player 1's and Player 2's payoffs are calculated as follows:

$$\begin{aligned} u_1(m_1, m_2) &= m(\phi_{v^*} - \phi(m_1)) \frac{m_1}{m_1 + m_2} - C(m_1) \\ u_2(m_1, m_2) &= m(\phi_{v^*} - \phi(m_2)) \frac{m_2}{m_1 + m_2} - C(m_2) \end{aligned}$$

where  $\phi_{v^*}$  is the incentives promised by the root node and  $\phi(m_i)$  is the rewards given to Play  $i$ 's descendants. The above

utility function consists of two terms: the first term denotes the Bernoulli rewards of Player  $i$  w.r.t. the other's action. The second term denotes its cost w.r.t. its own action and we only consider the change of the cost function w.r.t.  $m_i$  to lay emphasis on the interactions between the two players according to changing  $m_i$ .

Intuitively, if one player does not change its action, the other can increase its utility by increasing the number of resource holders it retrieves when the root node's incentives are strong enough. The optimal situation is that both nodes retrieve  $\frac{m}{2}$  resource holders. Suppose that Player 1 retrieves  $\frac{m}{2}$  resource holders and the root node's incentives are so strong that Player 2 has incentives to undermine Player 1 by increasing the number of its retrieved resources, i.e.,  $m_2 > \frac{m}{2}$ . Then, we have

$$\begin{aligned} u_1\left(\frac{m}{2}, m_2\right) &= m\left(\phi_{v^*} - \phi\left(\frac{m}{2}\right)\right) \frac{\frac{m}{2}}{\frac{m}{2} + m_2} - C\left(\frac{m}{2}\right) < u_1\left(\frac{m}{2}, \frac{m}{2}\right), \\ u_2\left(\frac{m}{2}, m_2\right) &= m\left(\phi_{v^*} - \phi(m_2)\right) \frac{m_2}{\frac{m}{2} + m_2} - C(m_2) > u_2\left(\frac{m}{2}, \frac{m}{2}\right). \end{aligned}$$

To maximize its utility, Player 2 will increase  $m_2$  until the marginal increase of  $u_2$  w.r.t.  $m_2$  satisfies  $\frac{\partial u_2}{\partial m_2} \Big|_{m_2=m^*} = 0$ .

Hence, we reach the following definition. For Player  $i$ , by "Cooperation" we mean  $m_i = \frac{m}{2}$  (denoted by  $C$ ); by "Defection" we mean  $m_i = m^*$  (denoted by  $D$ ), where  $i \in \{1, 2\}$ . Then, we have

$$\begin{aligned} u_i(C, C) &= u_i\left(m_1 = \frac{m}{2}, m_2 = \frac{m}{2}\right), \\ u_i(D, D) &= u_i\left(m_1 = m^*, m_2 = m^*\right), \\ u_1(C, D) &= u_2(D, C), \\ u_1(D, C) &= u_2(C, D), \end{aligned}$$

where  $u_1(D, C) > u_1(C, C) > u_1(D, D) > u_1(C, D)$ .

**Cooperation Enforcement.** We assume that the neighbor set of one node is relatively stable in query incentive networks [5], so that long-term interactions among neighbors can be formulated. Since each player can deduce the other's action through the change of its own rewards, we assume that each player possesses perfect information about the other player. Using best response functions [11], we trivially obtain the unique Nash Equilibrium (D, D). To enforce mutual cooperation, we model the interactions between the two players as an infinitely repeated *Prisoner's Dilemma* because either player has no access to the explicit game termination time.

Denote by  $a_i^t$  the action of Player  $i$  at round  $t$ , where  $t = 1, 2, \dots$  and  $i \in \{1, 2\}$ . Let  $s_i = (a_i^1, a_i^2, \dots, a_i^t, \dots)$  be Player  $i$ 's strategy and  $\mathcal{S} = (s_1, s_2)$ , the strategy profile. We treat payoffs at different rounds symmetrically, namely, the preference relations are established using the form of *limit of means*:

$$U_i(\mathcal{S}) = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T u_i(\mathcal{S}).$$

According to the *Perfect Folk Theorem for the Limit of Means Criterion* [11], every feasible strictly enforceable payoff profile is a subgame perfect equilibrium payoff profile of the limit of

means infinitely repeated game. Cooperation can be achieved through strategies of *threats of punishment*. That is, if one node defects, the other will punish it via defection for a substantial number of rounds [11]. Detailed mechanism is not discussed here due to limited space.

#### IV. SIMULATION

Through simulation, we look at the effects of greedy behaviors on communication overhead, and investigate whether a root can obtain enough resource holders. We validate the growth pattern derived in Section II, and demonstrate the necessity to contain greedy behaviors in the system.

Incentive function only affects the relationships between the reward and the propagation depth, and does not affect our results. Thus, we assume that each node reserves one unit of reward when propagating the query to the next one. We utilize a random graph of  $10^4$  nodes with average degree being 30. This setting is similar to PPLive [12] overlay structures. Different resource popularities are deployed according to [10], and for each popularity we randomly choose 100 nodes as root. We also assume that a root need  $m = 10$  resource holders to maintain a satisfaction (e.g. streaming or downloading quality in P2P networks). We compare the performance in a system with greedy immediate neighbors and that without greedy behaviors (i.e., cooperation is enforced).

Figure 1 presents the average number of retrieved resource holders and the happiness indices of root nodes. Figure 1(a) validates our analysis that the propagation tree goes through exponential start, polynomial growth, and eventually converges to a constant (PROPOSITION 1). As compared with Figure 1(a), Figure 1(b) shows that the happiness indices are approximately equal despite the decrease of the number of retrieved resource holders when cooperation among immediate neighbors is enforced.

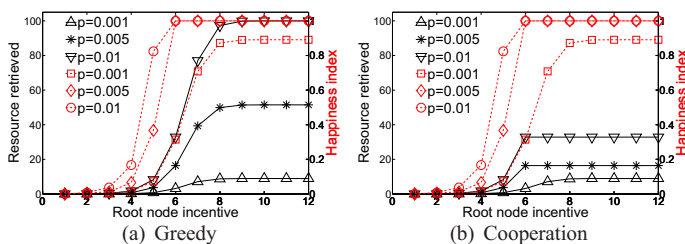


Figure 1. Comparison of Happiness Indices.

Figure 2 present the communication overhead. We can clearly see that, when  $p = 0.001$ , systems with greedy immediate neighbors do not outperform systems without greedy behaviors. This is because the number of retrieved resource holders is less than the root's expectation. However, when  $p > 0.001$ , the communication overhead is obviously lower in systems without greedy behaviors. Therefore, by cooperation enforcement, we succeed in limiting communication overhead while achieving the optimal state.

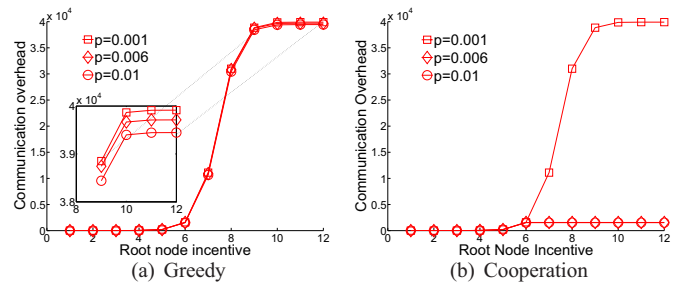


Figure 2. Comparison of Communication Overhead.

#### V. CONCLUSION

In conclusion, we study the problem of discovering multiple resource holders and how to evaluate a node's satisfaction in query incentive networks. We conduct an in-depth analysis of the query propagation pattern. We also model the query propagation as an extensive game, and study the greedy behaviors of immediate neighbors. We demonstrate that cooperation enforcement is required to achieve the optimal state of resource discovery. In the future, we would like to study the relationships between incentives and transmission efforts, the trust management among neighbors [13], and the coalition formulation of this problem.

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