Balancing Trust and Incentive in Peer-to-Peer Collaborative System

Yu Zhang, Li Lin, and Jinpeng Huai
(Corresponding author: Yu Zhang)

Dept. of Computer Science and Technology, Beihang University
Xueyuan Rd., Haidian District, Beijing 10083, P.R. China (Email: zhangyu@act.buaa.edu.cn)

(Received Nov. 6, 2005; revised and accepted Dec. 11, 2005 & Apr. 7, 2006)

Abstract

In order to maximize resource utilization as well as providing trust management in P2P computing environments, we propose a novel framework - **T**rust-**I**ncentive Service **M**anagement (TIM). Having child model, club model, bid model and trust model, TIM is constructed based on role based price strategy. In this mechanism, providers set the price according to demand and supply, and consumers maximize the surplus upon budget and deadline. A weighted voting scheme is also proposed to secure the P2P system by declining the join request from malicious peers. TIM is scalable and efficient in that: (1) it is completely distributed without a central server; (2) it dynamically manages the price and service by integrating valuables of pricing, trust, and incentive. A TIM prototype has been successfully implemented in a real P2P system, CROWN. We evaluate the proposed approach through comprehensive experiments and achieve improved results in service allocation efficiency, system completion time, and aggregated resource utilization.

Keywords: Incentive, P2P, service allocation, trust

1 Introduction

The emerging peer-to-peer model has recently gained significant attention due to its high potential of sharing huge amount of resources among millions of networked users, where each peer acts as both a resource provider and a consumer. A dilemma in P2P computing area is that when every participating peer tries to maximize its own utility, the overall utility of the collaboration might drop. In the worst case scenario, P2P resources are easily depleted due to selfish users take free rides without offering any sharing resource. Unfortunately, such "tragedy of the commons" phenomenon also happens in a number of existing peer-to-peer systems where cooperated scientific research systems emphasize on sharing resource voluntarily. Apparently, certain resource management scheme has to be implemented on P2P systems to ensure them working properly and growing healthily.

To encourage resource sharing, several previous works adopt soft incentive schemes [8, 13, 14, 16], which is essentially a reputation system. Peers get higher degree of trust by sharing more resources, and thus have the permission to access other resources. Soft incentive cannot meet the requirement of P2P systems in that providers not only care about the reputation, but also wish to gain benefit by providing resources. Other works adopt hard incentive scheme [1, 6, 19], in which peers get virtual currency by selling their resources, and then use the currency to bid for other resources. However, the assumption, wealthy peers are more trustful, is not always valid. Simply considering the bid price in resource allocation cannot satisfy the increasing security concerns from different participating organizations.

In this paper, we consider a service market in which each peer sells the service of executing tasks, rather than raw resource. In order to tackle the mentioned above issues, we combine the soft incentive and hard incentive schemes and propose a Trust-Incentive Compatible Dynamic Service Management framework, called **TIM**. TIM framework borrows the principles of market pricing when constructing the trust and incentive model. The primary goals of TIM are securing shared services, promoting users to share valuable services, maintaining the balance of supply and demand in competitive P2P service market, and finally maximizing aggregate resource utilization. Major contributions are summarized as follows.

1) By adopting a continual exchange process and matching user requests with available services, we propose the TIM model which can maximize aggregate resource utilization in an economically and computationally efficient manner. In this model, users can get more only if they are willing to share more and as the same time have higher degree of trust. As a result, it promotes collaborators to share more valuable services and avoid malicious waste.

2) In a P2P system, price fluctuates when service supply and demand changes. We separate the role of

providers and consumers and apply different strategies to each role. Providers simply mark their price based on supply and demand while consumers offer their bids upon deadline and budget constraints. Because the service dynamics are included in our management model, the workload of providers is balanced and the efficiency of P2P system is improved.

3) Peers may join or leave a P2P system randomly. To prevent a system from being attacked by malicious peers, we employ a weighted voting scheme in TIM, such that a secure and balanced environment is constructed.

4) We have successfully implemented TIM in the key project of our lab, CROWN system. Our implementation experiences and experimental results are valuable to research peers.

The rest of this paper is organized as follows. Section 2 introduces related work. Section 3 illustrates the service management architecture and dynamic service management model in CROWN system. We present our TIM framework in Section 4, including price strategy, allocation mechanism, and dynamic peers management scheme. Section 5 presents performance evaluations. We conclude this work in Section 6.

2 Related Work

The objective of resource incentive is to promote users to share more resources. Therefore, "tragedy of the commons" can be avoided. Generally speaking, there are two incentive schemes: Soft Incentive and Hard Incentive.

Soft incentive [8, 13, 14, 16] includes two models, *Peer-Approved and Service-Quality*. Peers in [13, 16] are allowed to access resources only from others with a lower or equal ratings, and the QoS provided to these peers also can be differentiated accordingly.

Feldman [8] proposes a *Reciprocative* decision function, and introduces the notion of generosity. Generosity measures the benefit an entity has provided relative to the benefit it has consumed. Obviously, a peer is willing to cooperate with the collaborators who are more generous than him.

Based on only one type of bandwidth resource and a known user's utility function, Richard et al. [14] present an allocation mechanism and introduce the notion of contribution to maximize aggregate utilization. They design an interactive protocol to help game competitors to reach Nash equilibrium. This approach is not practical for a P2P environment in that a user's utility function of resources is not typically known a priori and determining an allocation policy to maximize utility is difficult.

In essence, soft incentive in above work is a reputation system where the reputation [13, 16] (or generosity [8], contribution [14]) of a peer is consistent with the utility and quantity of resources supplied by the peer, but no price mechanism is involved in above systems. However, in dynamic P2P environment, soft incentive cannot meet the requirement in that resource providers not only care about the reputation, but also wish to gain economic benefit by providing resources.

There have been many researches in resource management approach which are based on economic models. Buyya et al. [5, 17, 19] suggest that the economic models in the human society, such as auction model, commodity market model, contract-net model, and bartering model, can be applied to grid computing. The discussion, however, is at conceptual level and no implementation or performance measurement has been presented.

Resource management based on price scheme can be treated as hard incentive [1, 6], which adopts a *Token-Exchange* approach. Each first-time user might be allotted a fixed number of tokens, but once these run out, the user has to serve resources to earn tokens. Resource price scheme in economics can be broadly categorized into two types: commodities markets [18] and auctions [1, 6, 7]. Chun [1, 6] allocates resources using a centralized combinatorial auction that allows users to express preferences with complementarities. In contrast, we implement a distributed service exchange model that is more scalable. Feldman [9] presents a price-anticipating resource allocation mechanism. In their work, each user can reach the Nash equilibrium by iteratively applying a best response algorithm to adapt his bids. The resource price setting strategy is missing in their work. Additionally, resource allocation approach in above researches mainly considers the bid price of consumers, that is, the higher price the peer bids, the more resources the peer gets. However, wealthy peers are not always with higher degree reputation. Thus only considering the bid price in resource allocation cannot satisfy the increasing security concerns from different participating organizations.

The TIM we proposed combines features from both soft incentive approach and hard incentive approach. The framework is dynamic oriented and completely distributed. Such design allows better scalability when managing practical P2P services. The weighted voting scheme included in our work can decline suspicious peers from joining the P2P system and therefore maintaining a secure and balanced P2P environ

3 System Model

The key project in our lab, CROWN (China R&D Environment Over Wide-area Networks) [10, 11, 12], is aiming at empowering in-depth integration of resources and cooperation of researchers nationwide and worldwide. A number of universities and institutes about 500 peers across several cities in China have joined CROWN. As illustrated in Figure 1, the distributed service management in CROWN adopts a two-tier P2P architecture [2, 4, 20]. The super layer is the backbone consisting of CDSRes (CROWN Distributed Service Register); the

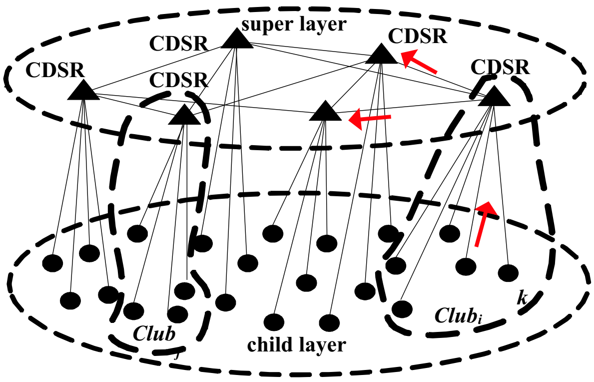

Figure 1: The two-tier architecture of TIM

child layer includes all clients and service providers. Usually, multiple self-organizing peers with the common service aggregate in a club to improve the efficiency of service discovery. To simple the question, we make each club consist of one CDSR and multiple child peers, and provide one type of service, such as Clubj in Figure 1.

CDSR: A CDSR knows not only the service information in its club but also the available services from other clubs through information propagation. Therefore, it can answer queries forwarded from other CDSRes.

Child Peer: According to the area partition, a child peer connects to the nearest and most trustworthy CDSR, and reports its service status periodically to its designated CDSR. A child peer also can send service request to a CDSR and receives responses.

For example, in Figure 1, each CDSR will periodically publish the provision services. A child peer selects the desired service, generates the corresponding bids, and transmits them to the selected CDSR by its own parent CDSR.

Based on the two-tier architecture, we first present our Trust-Incentive Compatible Dynamic Service Management model. The proposed TIM model includes four building blocks, i.e. CHILD model, CLUB model, BIDS model, and TRUST model. Suppose that there are p clubs (that is, p CDSRes), and each club may have one type of service. Let $Club_j$ denote the jth $Club(j = 1, \ldots, p)$, and $Chlid^i_j$ denote the ith child peer in $Club_j$. The dynamic service management model is defined as follows.

Definition 1. (CHILD Model) *$Chlid^i_j$ is defined as ($A_{c^i_j}$, $directtrust^i_j$, $revenue^i_j$): $A_{c^i_j}$ to denote availability quantity of the service provided by $Chlid^i_j$; a direct trust value $directtrust^i_j \in [0, 1]$ in $Club_j$; a peer revenue $revenue^i_j \in \mathbf{R}$.*

Definition 2. (CLUB Model) *$Club_j$ is defined as (num_j, A_j, P_j, $Bids_j$, $RecTrust_j$): a children number $num_j \in N$; A_j, P_j to denote availability quantity and price of the service in $Club_j$, respectively; a bids vector $Bids_j = (bids^1_j, bids^2_j, \ldots, bids^m_j)$ received by $Club_j$, and $bids^q_j$ is the qth bid; a recommendation trust value vector $RecTrust_j = (rectrust_{j1}, rectrust_{j2}, \ldots, rectrust_{jp})$, and $rectrust_j i \in [0, 1]$ $(i = 1, \ldots, p)$ is the recommendation trust value from CDSR in $Club_j$ to CDSR in $Club_i$.*

Definition 3. (BIDS Model) *Bids is defined as (cid, pid, et, Q, directtrust, C, V): $cid \in \{1, \ldots, p\}$, $pid \in N$ to denote the bid coming from $Child^{pid}_{cid}$; a estimated task execution time et; a desired quantity $Q \geq 1$ of services; a direct trust value $directtrust \in [0, 1]$ of the $Child^{pid}_{cid}$; a set of constraints C, such as deadline and budget, etc; and a bidding price V that the consumer is willing to pay.*

Definition 4. (TRUST Model) *We adopt the trust model used in [3, 15]. If T_1 denotes a recommendation trust value from A to B, and T_2 denotes a direct trust value from B to C, then the trust value from A to C is $1 - (1 - T_2)^{T_1}$. Similarly, we suppose that peers in the same club have direct trust relations, peers in different clubs have indirect trust relations, and CDSRes have recommendation trust relations.*

Then we get the following trust inference.

1) Direct trust computing. After peers in $Club_i$ use the services of $Child^k_i$ to execute tasks, the peers will report positive or negative experiences to the CDSR in $Club_i$. A direct trust relationship will set up only if all experiences with that the CDSR in $Club_i$ knows about are positive experiences. Let q be the number of positive experiences, then the direct trust value from the CDSR to $Child^k_i$ is $directtrust^k_i = 1 - \lambda^q$, where λ is the probability of reliability with a single task;

2) Recommendation trust computing. After peers in $Club_j$ have used the services of peers in $Club_i$ to execute tasks, the peers in $Club_j$ will report positive or negative experiences to the CDSR in $Club_j$. Given numbers of positive and negative experiences p and n, the recommendation trust value from the CDSR of $Club_j$ to the CDSR of $Club_i$ is:

$$rectrust_{ji}(p, n) = \begin{cases} 1 - \lambda^{p-n} & if\ p > n \\ 0 & else; \end{cases}$$

3) The trust value from $Club_j$ to $Child^k_i$ is given by:

$$trust^k_i = 1 - (1 - directtrust^k_i)^{rectrust_{ji}}.$$

For example, in Figure 2, the direct trust value from the CDSR of $Club_i$ to $Child^k_i$ is 0.8, and the recommendation trust value from the CDSR of $Club_j$ to the CDSR of $Club_i$ is 0.5, then the trust value from $Club_j$ to $Child^k_i$ is $1 - (1 - 0.8)^{0.5} = 0.55$.

4 Design of TIM

In this section, we present our TIM framework to manage shared services in CROWN.

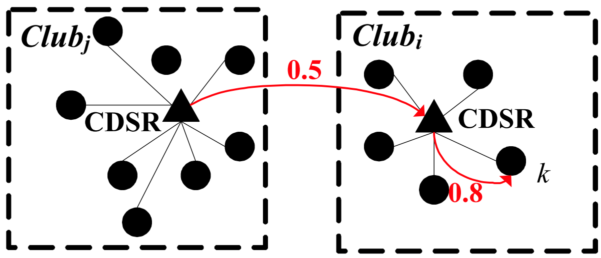

Figure 2: The trust inference in TIM

The prices of services are set by providers who continuously adjust the prices based on supply and demand. When consumers bid for the services, they offer bids that can maximize their surplus and meet the deadline and the budget constraints. Both BID model and TRUST model are making contributions to evaluate peers and are therefore influencing how the service is allocated and managed. And also, TIM is working in a continually exchanged manner, which guarantees the dynamics of the supply and demand are reflected in service allocation and management.

Our work successfully integrates the trust mechanism, incentive mechanism, allocation mechanism, and dynamic management of shared services. First, the peer who supplies valuable services can accumulate more virtual currency and higher degree of trust, thus it can have precedence in bidding for other services. Second, since there is no centralized trust server and peers may join or leave dynamically, collaborative peers need to vote to determine whether to accept the new peers or not. Trust and price are the two major factors that are involved in this decision making process to keep a secured P2P environment. Finally, to ensure the balance of supply and demand in P2P market, prices setting strategy are considered in service allocation.

Because it is possible that multiple peers bid for multiple sets of services simultaneously, we assume that the services in one club has the same sale price. Each CDSR sets the sale price according to supply and demand and periodically publishes its local service information. After getting the sale price, each consumer will then offer a bidding price, which can meet its deadline and budget constraints.

4.1 Price Mechanism

In P2P computing, the evaluation is the key to allocate and manage shared service. It is rather difficult to find a fixed analytic formula to calculate the service price due to geographical distribution, heterogeneity, indeterminably, and large scale in the P2P environment. But with different preconditions and history information, an approximate price model can be constructed. In TIM, we propose the provider price strategy based on supply and demand, and the consumer price strategy upon deadline and budget constraints.

4.1.1 Provider Price Strategy

In TIM, we proposed a distributed service quantity estimation strategy based on weighted average calculations, and then estimate the service price based on service quantity. The weights for computing the estimates are based on the iteration indices until the current iteration.

First, for estimating the available service quantity at a club, each $Club_j$ needs to keep track of the actual service quantity A_j from its previous iterations. Note that for implementation purposes it is sufficient to keep a cumulative value for the weighted service quantity. In any iteration q, each club shall estimate the service quantity that will be available for the next iteration $(q+1)$ as

$$\hat{A}_j^{q+1} = \frac{\sum_{k=1}^{q} k \times A_j^k}{\sum_{k=1}^{q} k}$$

Second, we can estimate the service price for the next iteration $(q+1)$ by the formula $\hat{P}_j^{q+1} = max\{\epsilon, P_j^q + \lambda(A_j^q - \hat{A}_j^{q+1})$, where $\lambda > 0$ is a small step size parameter, $\epsilon > 0$ is a sufficiently small constant preventing price to approach zero.

Finally, the CDSR of each club will periodically publish the available service quantity and price to other clubs.

4.1.2 Consumer Price Strategy

Each P2P user generates the service request for its tasks according to their requirements, and submits the request to a selected CDSR that the user will bid for. The goal of each P2P user is to maximize its own surplus upon deadline and budget constraints. Given the price P_j of service in the $Club_j$ and the completion time constraint T, the utility function of each P2P user can be expressed as follows:

$$U(V) = K(T - \frac{LP_j}{V}) - V$$

in which L is the length of the task, V is the payment value of the user, $\frac{LP_j}{V}$ is the estimated task execution time, and K is a constant coefficient defined by the user. Thus, the utility optimization problem above can be written as:

$$\begin{cases} Max\ U(V) \\ s.t.\ g(V) \geq 0 \end{cases} \quad (g(V) = T - \frac{LP_j}{V}).$$

By using the multiplicator method, we obtain the approximative optimal solution $V^* = \frac{3LP_j}{2T-K}$ as the bidding price, which is also the value V in BIDS model.

4.2 Trust-incentive Compatible Service Allocation Algorithm

After collecting the consumers' bids, the CDSR of each club uses the trust-incentive compatible mechanism to allocate services. The allocation mechanism in TIM has the following property: (1) providing differentiated services according to the bidding price and trust value of peers; (2) promoting peers to accumulate more virtual currency and higher degree of trust by supplying more valuable services. TIM uses the following algorithm:

Step 1: In each period of bidding, we calculate the *per unit* valuation $Bid_j^i = \frac{V_j^i}{Q_j^i \times et_j^i}$ for each bid in $Club_j$, where V_j^i, Q_j^i, et_j^i denote bidding price, service number, and estimated execution time, respectively. Then we scale the Bid_j^i by the formula $bid_j^i = \frac{Bid_j^i - Bid_j^{min}}{Bid_j^{max} - Bid_j^{min}}$.

Step 2: We calculate the evaluation value of each bid by the formula:

$$evlbid_j^i = \alpha \times bid_j^i + (1-\alpha) \times trust_{cid}^{pid},$$

where $trust_{cid}^{pid}$ is the trust value from $Club_j$ to $Child_{cid}^{pid}$, and $\alpha \in [0,1]$ is risk degree of $Club_j$ according to the benefit and secure factors. If $Club_j$ focuses more on benefit than security, set α bigger; otherwise, set α smaller.

Step 3: We sort all bids in descending order according to $evlbid_j^i$.

Step 4: We go through the sorted bid list and schedule each single bid. We will allocate the services to each bid i with $\frac{evlbid_j^i \times total_service_quantity}{\sum_{k=1}^{n} evlbid_j^k}$.

4.3 Dynamic Management for Peers

Peers may join and leave the collaboration dynamically, or transfer from one club to another club. Thus, some CDSRes maybe have the trust records for a child peer. In our TIM approach, the more services a peer provides, the higher degree of trust a peer has. Obviously, every peer is willing to cooperate with a peer with higher trust value.

As illustrated in Figure 1, when the CDSR in $Club_j$ receives the join request, it will propagate the join request to other CDSRes. Since each club may have different trust records and recommendation trust value, it may have different opinions about the requesting peer. In our proposal, this is solved by employing a weighted voting scheme to decide whether to accept the requesting peer or not. After receiving the vote request, the CDSRes make their own decisions as follows:

$$vote_i = \begin{cases} 1 & trust > \tau \\ 0 & no\ trust\ value\ record \\ -1 & trust < \tau \end{cases}$$

where $\tau \in [0,1]$ is the configuration threshold value used by each CDSR. The result will then be returned to the voting sponsor, that is, the CDSR in $Club_j$. According to the majority principle, the CDSR in $Club_j$ uses the constraint in equation $\sum_{i=1}^{p} rectrust_{ji} vote_i \geq 0$ to make the final decision.

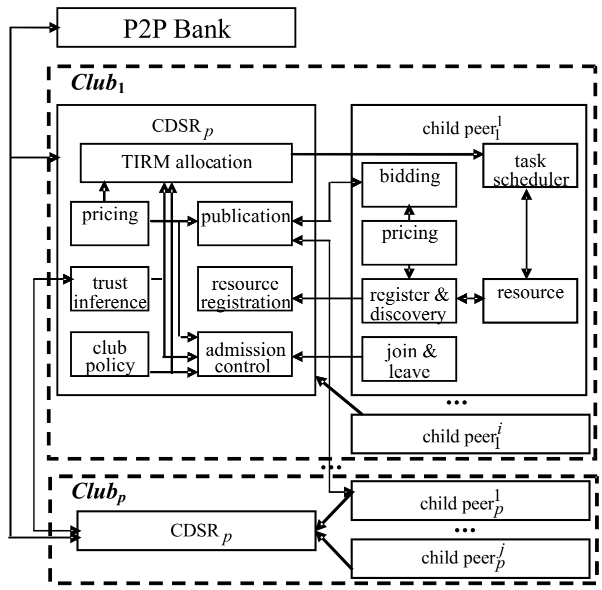

Figure 3: Architectural framework for TIM in CROWN system

If the new peer is a full stranger with no corresponding records, the CDSR who has received the joining request will determine to accept or reject the new peer based on the current services price constraints. Normally, the full stranger will be accepted if it can provide sufficient valuable services to other peers.

5 Implementation

5.1 Implementation Environment

We have implemented the TIM approach in CROWN system with Java. The cooperation facility among peers is provided by CROWN, a fully decentralized P2P middleware infrastructure.

As illustrated in Figure 3, the system has two kinds of peer, CDSR and child peer. Each child peer has a Child Agent. The Child Agent is responsible for various actions defined in TIM, such as service registration and discovery, generating bid values, submitting bids, scheduling the accepted task, and sending the join or leave request to the CDSRes. Similarly, each CDSR has a Server Agent. A Server Agent is responsible for creating the club policy, setting the prices for local services, collecting and publishing local services information, collecting the bids, inferring trust value of peers from other clubs, allocating local services, and accepting or rejecting new peers.

In the setup phase, we created five clubs [11], and each club has a CDSR and 40-50 virtual child peers.

5.2 Efficiency of Allocation Mechanism

We first conduct an experiment with a set of five peers with varying currency and trust value, bidding for some

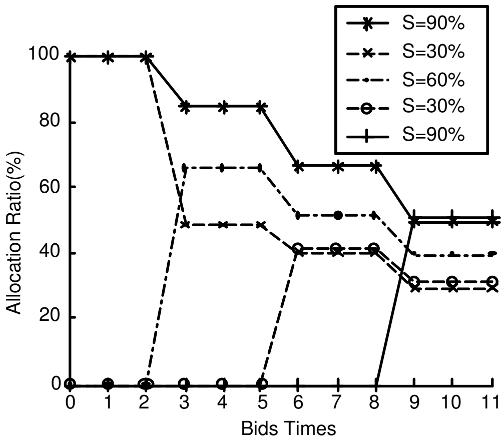

Figure 4: Incentive compatible allocation

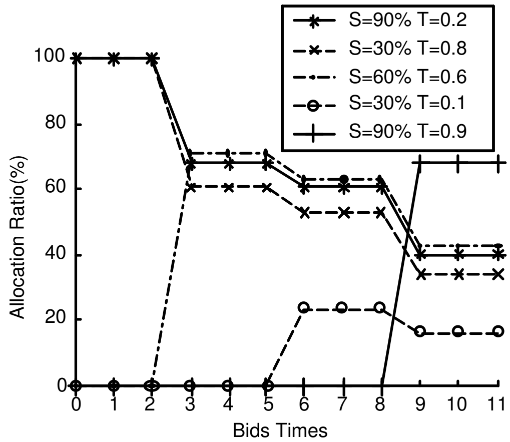

Figure 5: Trust incentive allocation

portion of 200 unit services. To evaluate TIM, we first define a metric named *allocation_ratio* for each bid as follows.

$$allocation\_ratio = \frac{allocation\_quantity}{total\_request\_quantity}.$$

In this experiment, we assume that the total request quantity of each peer is 100 units. There are five curves in Figures 4 and 5, where x-axis represents the bids times, and y-axis represents the allocation ratio. We first set the risk degree $\alpha = 1$ in Figure 4 and consider the security factor and set the risk degree $\alpha = 0.2$ in Figure 5. The symbol S in both figures denotes the ratio of providing services, for example, the first peer provides 90 percent of local services to other peers. The symbol T in Figure 5 denotes the trust value of bidding peers. In the first three periods, only two peers request for 100 units services and the supply meets the demand. Thus the allocation ratios for the two peers are all 100 percent. After the third period, the increasing bids outnumbered the supply.

As shown in Figure 4, without the security consideration, the peers providing the same services nearly obtain the same allocation ratio, and the more services a peer contributes, the higher allocation ratio a peer obtains. However, if considering the trust value in Figure 5, we can see that the provision ratio of peer 3 (60%) is less than that of peer 1 (90%), but peer 3 has a higher trust value ($T = 0.6$) and thus obtains more services than peer 1. Similarly, peer 2 and peer 4 have the same provision ratio: 30%. Peer 2 obtains more services than peer 4 at the sixth bid in Figure 5, because the trust value of peer 2 ($T = 0.8$) is far greater than that of peer 4 ($T = 0.1$).

Thus, by evaluating the allocation scheme in TIM, we can see that peers can obtain more services only having shared more services and accumulated higher degree of trust.

5.3 Impact of TIM Price Strategy

This experiment is to study characteristics of price setting strategy with Round-Robin strategy in terms of task completion time, which is measured from accessing the requested P2P services till task is accomplished. Three clubs are the service providers, with each having 200 unit services. Service requests are generated by the child peers and the bid is generated at an interval of 350 time units. We change the system load from 0.1 to 0.9 with a step of 0.1, where system load is defined as a ratio of aggregate bids load to aggregated capability of providers. The initial value of the service price is 50G$, and each CDSR re-publishes the service price with an interval of 500 time units.

From Figures 6 and 7, we can see that TIM price setting strategy has better efficiency and spends less time to complete tasks compared with the Round-Robin strategy, especially at higher bids. In Figure 6, when system load reaches 0.5, the completion time of Round-Robin strategy increase sharply. The reason is that at higher loads, TIM price direction strategy allows consumers to select the best available service for a task, which will in turn reduce the workload and therefore the execution time.

In Figure 7, we contrast the performance between TIM price direction strategy and Round-Robin strategy with system load at 0.4, 0.6, and 0.8, respectively. At 10,000 time units, the completion ratio for Round-Robin strategy is only around 64%, while our price direction strategy can score 83% of the completion ratios.

5.4 Evaluation of Trust Model

Malicious peers may exist in P2P environments to disturb service exchange or even destroy services of other peers. We consider the security problem from both sides, including malicious consumers and malicious providers. On one hand, when bidding for services, a malicious consumer can either set a higher bit value arbitrarily or does not give the corresponding payment. Such behaviors adversely af-

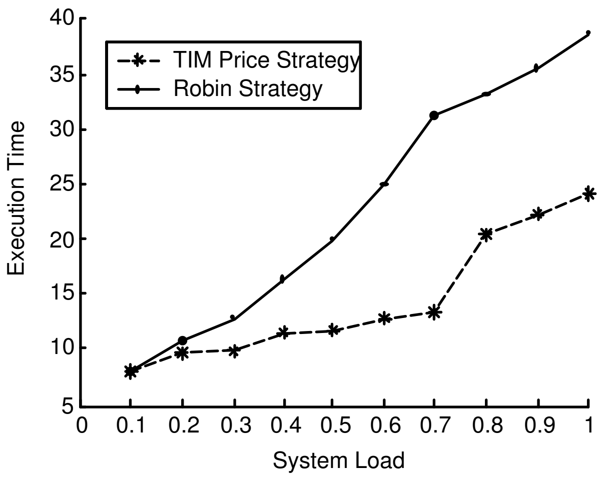

Figure 6: Execution time Vs system load

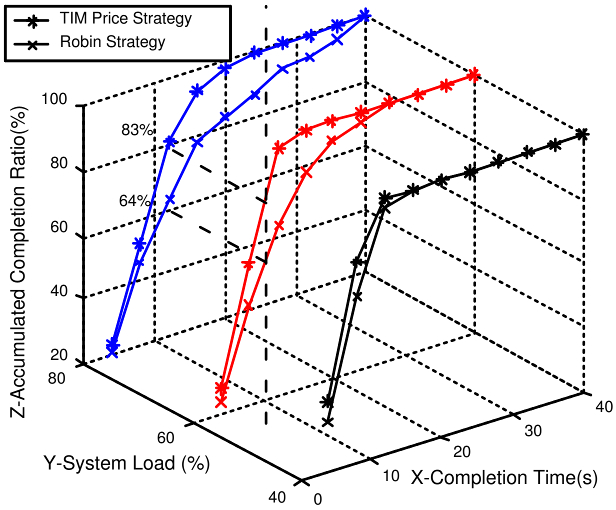

Figure 7: Completion ratio for dynamic system load

fect the interests of service providers. On the other side, a malicious provider can boast of having more services to get more currency. It makes good peers losing the bids and accumulating more currency. Both types of malicious peers will decrease the total revenue of the club and the recommendation trust value of the CDSR.

We first study how malicious consumers affect the P2P system. In this experiment, there are three clubs and 40 peers in each club are service providers. 100 peers from the other two clubs act as consumers and generate bidding requests. We let the three providing clubs receive the 100 bids each time by varying the percentage of malicious consumers from 0 to 0.9 with a step of 0.1. For each scenario, a set of *risk degree* α in TIM are configured: 0, 0.5, and 1. As showed in Figure 8, the club considering both benefit and security factors ($\alpha = 0.5$) obtains more revenue after the percentage of malicious consumers is over 20%. When the percentage of malicious consumers is over 80%, the club considering only the security factors will get more revenue.

We then study how malicious providers affect the P2P system. In the simulations, $Club_1$ implements admission control based on the TIM weighted voting scheme described in Section 4.3, while $Club_2$ dose not. Both clubs have 40 service providers and are handling 40 bids. Consider the case when 40 peers from the other three clubs want to join $Club_1$ and $Club_2$. Still, we set the percentage of malicious join peers from 0 to 0.9 with a step of 0.1. The CDSR in $Club_1$ set the admission policy $\tau = 0.3$, which means that the peer whose trust value is lower than 0.3 will not be accepted. As a result, few malicious peers are able to join $Club_1$, while many of them can join $Club_2$.

As Shown in Figure 9, when the percentage of malicious join increases, the revenue of both clubs decreases. But the revenue of $Club_2$ without TIM is suffering much more

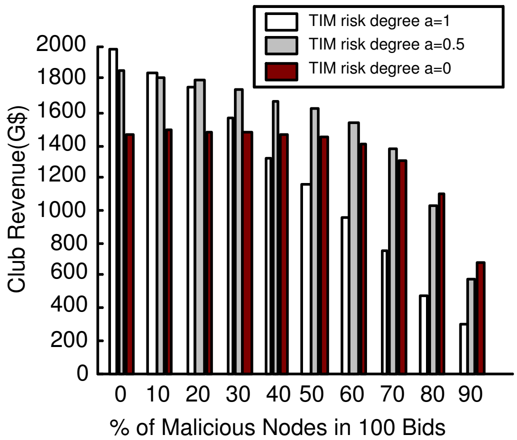

Figure 8: Prevention of malicious consumers

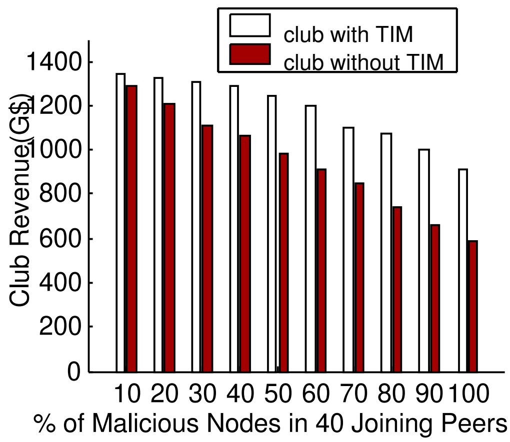

Figure 9: Prevention of malicious providers

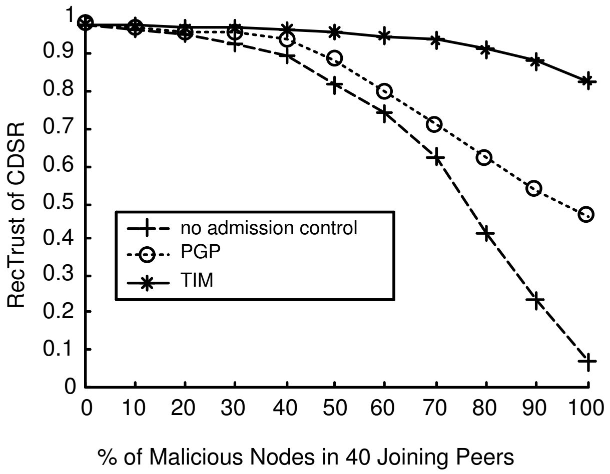

Figure 10: Recommendation trust varying of CDSRes

than $Club_1$ with TIM. At the extreme case when all the new peers are malicious peers, the revenue of $Club_2$ is only 60 percent of the revenue of $Club_1$.

In the last experiment, as more malicious peers request to join a club, we compare the recommendation trust value of the CDSR in the club among three mechanisms. The first mechanism is the CDSR does not implement admission control and each peer can join the club arbitrarily. The second mechanism is Pretty Good Privacy with local certificate repositories in individual nodes. A CDSR verifies the public key of a requester by finding a certificate chain from CDSR to the requester in its local certificate repository. The remaining mechanism is the TIM proposed in this paper. Figure 10 shows that as more malicious peers enter $Club_2$, the recommendation trust value of the CDSR in $Club_2$ without TIM decrease rapidly. In our TIM mechanism, the CDSR will propagate the join request to other CDSRes and employ a weighted voting scheme to decide whether to accept the requesting peer or not. The CDSR can discover and isolate more malicious nodes, so it is able to maintain a high recommendation trust value.

6 Conclusion

Proving trust and incentive in P2P computing environments are of great importance. This paper presents a Trust-Incentive Compatible Dynamic Service Management, TIM, on the basis of economy model and trust model. By introducing the price strategy, trust-incentive compatible service allocation mechanism and the weighted voting scheme, TIM encourages peers to share more services, ensures the balance of supply and demand, enhances the aggregated resource utilization, and maintains the secure environment of a P2P computing system.

TIM scheme has been successfully implemented in our key project, CROWN environment. We evaluate our proposed approach by comprehensive experiments and achieved much improved results in service allocation, system completion time and aggregated resource utilization.

In the future, we will widely deploy our TIM approach in the CROWN to construct a more secured and balanced collaborative P2P environment.

References

[1] A. AuYoung, B. N. Chun, A. C. Snoeren, and A. Vahdat, "Resource allocation in federated distributed computing infrastructures," in *The First Workshop on Operating System and Architectural Support for the on demand IT Infrastructure*, 2004.

[2] S. Banerjee, C. Kommareddy, K. Kar, B. Bhattacharjee, and S. Khuller, "Construction of an efficient overlay multicast infrastructure for real-time applications," in *The 22th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM03)*, pp. 1521-1531, San Franciso, USA, 2003.

[3] T. Beth, B. Malte, and K. Birgit, "Valuation of trust in open networks," in *The Conference on Computer Security*, pp. 3-18, New York, USA, 1994.

[4] L. Bischofs and W. Hasselbring, "A hierarchical super peer network for distributed artifacts," in *The Sixth Thematic Workshop of the EU Network of Excellence DELOS on Digital Library Architectures*, pp. 105-114, Cagliari, Italy, 2004.

[5] R. Buyya, D. Abramson, and S. Venugopal, "The grid economy," *IEEE Special Issue on Grid Computing*, vol. 93, no. 3, pp. 698-714, 2005.

[6] B. N. Chun, J. A. C. Ng, D. C. Parkes, and A. Vahdat, *Computational Resource Exchanges for Distributed Resource Allocation*, Technical Report, http://citeseer.ist.psu.edu/706369.html, 2004.

[7] A. Das and D. Grosu, "Combinatorial auction-based protocols for resource allocation in grids," in *The 19th IEEE International Parallel and Distributed Processing Symposium(IPDPS05)*, pp. 251a–251a, Colorado, USA, 2005.

[8] M. Feldman, K. Lai, I. Stoica, and J. Chuang, "Robust incentive techniques for peer-to-peer networks," in *The ACM E-Commerce Conference (EC2004)*, pp. 102-111, New York, USA, 2004.

[9] M. Feldman, K. Lai, and L. Zhang, "A price-anticipating resource allocation mechanism for distributed shared clusters," in *The ACM E-Commerce Conference*, pp. 127–136, Vancouver, Canada, 2005.

[10] C. Hu, Y. Zhu, J. Huai, Y. Liu, and L. M. Ni, "Efficient information service management using service club in CROWN grid," in *The IEEE International Conference on Services Computing*, pp. 5-12, Florida, USA, 2005.

[11] J. Huai, Y. Zhang, X. Li, and Y. Liu, "Distributed access control in CROWN groups," in *The*

34th International Conference on Parallel Processing (ICPP2005), pp. 435–442, Oslo, Norway, 2005.

[12] Y. L. J. Huai, X. Li, and C. Hu, *Early Experiences with CROWN Grid*, School of Computer Science, Beihang University, Technical Report, TR 2005-2, 2005.

[13] Y. K. Kwok, S. S. Song, and K. Hwang, *Non-Cooperative Grids: Game-Theoretic Modeling and Strategy Optimization*, Technical Report, USC Internet and Grid Computing Lab (TR 2004-19), 2004.

[14] T. B. Ma, S. C. M. Lee, J. C. S. Lui, and D. K. Y. Yau, "A game theoretic approach to provide incentive and service differentiation in P2P networks," in *The ACM SIGMETRICS/PERFORMANCE*, pp. 189-198, New York, USA, 2004.

[15] C. H. Ngai and M. R. Lyu, "Trust-and clustering-based authentication services in mobile ad hoc networks," in *The 24th International Conference on Distributed Computing Systems Workshops (ICDCSW2004)*, pp. 582-587, Tokyo, Japan, 2004.

[16] K. Ranganathan, M. Ripeanu, A. Sarin, and I. Foster, "To share or not to share: An analysis of incentives to contribute in collaborative file sharing environments," in *The Workshop on Economics of Peer to Peer Systems*, pp. 13-18, Berkeley, 2003.

[17] R. Ranjan, A. Harwood, and R. Buyya, *Grid Federation: An Economy Based, Scalable Distributed Resource Management System for Large-Scale Resource Coupling*, Grid Computing and Distributed Systems Laboratory, University of Melbourne, Australia, Technical Report, GRIDS-TR-2004-10, 2004.

[18] R. Wolski, J. Brevik, J. S. Plank, and T. Bryan, "Grid resource allocation and control using computational economies," in *Grid Computing: Making the Global Infrastructure a Reality*, pp. 747-772, 2003.

[19] C. S. Yeo and R. Buyya, "Pricing for utility-driven resource management and allocation in clusters," in *The 12th International Conference on Advanced Computing and Communication(ADCOM04)*, Ahmedabad, India, 2004.

[20] Z. Zhuang, Y. Liu, and L. Xiao, "Dynamic layer management in super-peer architectures," in *The 33th International Conference on Parallel Processing (ICPP2004)*, pp. 29–36, Quebec, Canada, 2004.

Yu Zhang was born on April 15, 1977 in Liaoning, People's Republic of China. She is now a PhD. Candidate in Department of Computer Science and Technology at Beihang University, Beijing, China. Her main research interests include information security, trust establish, and incentive scheme in peer-to-peer systems.

Li Lin was born on March 6, 1979 in Guangxi, People's Republic of China. She is now a PhD. Candidate in Department of Computer Science and Technology at Beihang University, Beijing, China. Her main research interests include information security, grid theory, and algebra application.

Jinpeng Huai was born on 1962 in Harbin, People's Republic of China. After receiving the Master degree in Electrical Engineering and Computer Sciences from Harbin Institute of Technology, he got the PhD degree in Beihang University in 1993. His main research interests include computer software and theory, network middleware and grid computing, network security.