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## An Incentive Compatible Reputation Model for P2P Networks

Jianli Hu<sup>a</sup>, Bin Zhou<sup>b</sup>

<sup>a</sup>*Department of Information, Guangzhou General Hospital of Guangzhou Military Command, Guangzhou 510010, China*

<sup>b</sup>*School of Computer, National University of Defense Technology, Changsha 410073, China*

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### Abstract

An important challenge regarding peer's trust assessment in peer-to-peer (P2P) networks is how to cope with such issues as the fraudulent behaviors and the dishonest feedback behaviors from malicious peers, and the issue of inactive recommendations to others. However, these issues cannot be effectively addressed by the existing solutions. Thus, an incentive compatible reputation management model for P2P networks, named ICRM, is proposed to solve them. In ICRM, the metric of time zone is used to describe the time property of the transaction experience and the recommendation. Three other metrics such as the direct trust value, the recommendation trust value and the recommendation credibility, based on the metric of time zone are applied to express accurately the final trust level of a peer. Furthermore, the participating level is introduced as the metric to identify a peer's activeness degree. Theoretical analysis and simulation experiments demonstrate that, ICRM can effectively suppress the malicious behaviors such as providing unreliable services, or giving dishonest feedbacks to others in the P2P networks. What's more, it also can incent peers to offer recommendations to others more actively.

**Index Terms:** P2P; reputation model; incentive compatible mechanism; recommendation credibility

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### 1. Introduction

In recent years, P2P computing has achieved its popularity in many distributed applications, including file-sharing, digital content delivery, and so on [1]. Yet, due to the open and dynamic feature of P2P system, it is easily attacked by selfish and malicious peers. Previous work [1-4] indicates that reputation-based trust models can be built up to suppress effectively these malicious behaviors. However, most of the current reputation-based trust models cannot effectively identify malicious peers and isolates them from the network. Moreover, another issue is that they don't enable effectively each peer to provide others with trusted recommendations actively.

With these research problems in mind, we propose an incentive compatible reputation management model for P2P networks (ICRM), ICRM takes into account the time factor fully in computing the peer trust value (PTV), applying the index of the time zone (TZ) to flag the time property of experiences and recommendations

\* Corresponding author.

E-mail address: lxman82@gmail.com, bin.zhou.cn@gmail.com

from other peers. In ICRM, the concepts of the direct trust value (DTV), the recommendation trust value (RTV) and the recommendation credibility (RC) are introduced to illustrate accurately the trust of each peer, and give precise definitions for these metrics. Besides, the index of participating level (PL), proposed as the metric to check if a peer is active or not, can be applied to incent peers to offer actively honest feedbacks, making P2P system run in a normal state. The remaining parts of the paper are organized as follow: Section 2 reviews the related work. Section 3 formally gives our trust model ICRM. Section 4 illustrates the RC-based incentive mechanism. Section 5 simulates and discusses ICRM. Finally, we conclude the paper and make suggestions for further research work.

## 2. Literature review

Many researchers have paid much attention to the field of how to describe accurately the peer's trust in P2P networks, and present many trust management models, in which the methodology of reputation based trust modeling is an important research direction to pursue. Li Xiong discusses the factors forming the reputation in P2P networks in detail, in which several metrics, including the feedback credibility, the peer's interaction number, the transaction feature and the transaction community, etc., are introduced to construct the model PeerTrust [2, 4]. Yao purposes a Bayesian network based reputation model [5]. Kamvar exploits the approach of centrality measurement in social networks, putting forward a recommendation based global reputation model EigenTrust [1]. However, these models are proposed to combat some special malicious behaviors of peers, and pay less attention to the issue of how to incent peers to give actively more recommendations to others.

Introducing incentive mechanism in reputation system is to achieve the aim of making this system incentive-compatible [3]. This is to say, how to offer honest recommendations actively is the optimal choose for the rational peer, ensuring the maximum effectiveness for it. The current incentive mechanism compelling peers to give honest recommendations actively includes two types: the micropayment based incentive mechanism [6] and the reputation based incentive mechanism. As for the former, after receiving some services, the peer must pay some virtual money to the service provider. However, this mechanism needs corresponding expense-counting facility to trace each small transaction. Thus it is not feasible in engineering [7].

The reputation based incentive mechanism is featured by the characteristics that applying some strategies to direct peers to enter the system as expected in terms of the condition whether peers give trusted recommendations or not. However, in current related researches, most of them tend to regard a peer's reputation as the criterion of service choice by others, but not as the criterion whether the feedbacks need providing to others. Thus, to address this issue, an incentive compatible reputation model for P2P networks is proposed in this paper, in which RC and PL are introduced as the gauge judging if peers actively provide others with trusted recommendations, incenting peers to give more honest feedbacks to others.

## 3. Trust rating algorithm

**Definition 1** PTV. PTV is integrated with two parts: DTV and RTV. DTV represents the trust assessments on the trustee (the service provider) the trustor (the service assumer) provides based on the actual interactions with it, while RTV represents the trust assessments on the trustee the recommender provides. Let  $i$ ,  $j$  and  $k$  denote trustor, trustee and the recommender respectively,  $T_{ij}$  denote the PTV peer  $i$  assigns peer  $j$ , whose computing formula is as follows:

$$T_{ij} = \begin{cases} \alpha * D_{ij} + (1 - \alpha) * R_{ij}, & K \neq \phi, \alpha \in [0, 1] \\ 0.5, & K = \phi, D_{ij} = 0 \end{cases} \quad (1)$$

in which,  $\alpha (0 < \alpha < 1)$  is the trust regulatory factor, which is directly proportional to the importance the trustor pays to DTV or to RTV.  $D_{ij}$  and  $R_{ij}$  denote DTV and RTV, respectively, and  $K$  represents the set of recommenders. In particular, we can set the PTV of the newly-entered peer as 0.5 in ICRM; rather. Literature [8] points out that the probability of malicious peers in P2P networks is often small. As usual, in case of the net

work for peers to enter or leave dynamically and frequently, it is more rational for us to believe these peers are trustworthy before validating these peers untrusted, since doubting these peers would decrease the whole performance of the reputation system.

**Definition 2** Time fading function. In the actual experience, in contrast with the transaction in the current time zone (the  $n$ th time zone), the past transaction in the  $k$ th time zone ( $k < n$ ) would be somewhat devaluated. Thus, we defined the time fading function as:

$$g(k) = g_k = \rho_{fade}^{n-k} \quad \rho_{fade} \in (0, 1), k \in [n] \quad (2)$$

in which  $\rho_{fade}$  denotes the time fading rate.

**Definition 3** DTV. After transacting with each other, one peer  $i$  would submit its satisfactory ratings to the other peer  $j$ , which can be defined as the following map function  $f(i, j)$ :

$$f(i, j) = \begin{cases} 1, & \text{totally satisfactory} \\ 0, & \text{totally unsatisfactory} \\ e \in (0, 1), & \text{else} \end{cases} \quad (3)$$

where, we use the method of probability to distinguish the QoS provided by different peers: The number 1 denotes peer  $i$  feels totally satisfactory to the service provided by peer  $j$ , while zero means nothing.

In the time zone  $t$ , assuming  $m$  denotes the number for which peer  $i$  has interacted with peer  $j$ , so the DTV peer  $i$  offers to peer  $j$  can be defined:

$$D_{ij}^t = \begin{cases} \frac{\sum_{k=1}^m f(i, j)}{m}, & m \neq 0 \\ 0, & m = 0 \end{cases} \quad (4)$$

DTV has the time correlation characteristics. In another word, with the time elapsing, DTV would become smaller and smaller. Thus, the DTV model must consider the factor of RZ, which can be finally defined as follows:

$$D_{ij} = \frac{\sum_{k=1}^n g_k * D_{ij}^k}{\sum_{k=1}^n g_k} \quad (5)$$

in which  $g(k) = \rho_{fade}^{n-k}$  is the fading factor within the time zone  $t_k$ , and  $0 < f_k < f_{k+1} < 1$ ,  $1 \leq k < n$ .

**Definition 4** RTV. The trustor aggregates the ratings (DTVs) from different recommenders and the credibility of recommenders themselves into the unique index  $R_{ij}$ , which can be formulated as follows:

$$R_{ij} = \frac{\sum_{k \in K} D_{ij} * Cr_{ik} * g_k}{\sum_{k \in K} Cr_{ik} * g_k} \quad (6)$$

in which,  $K$  represents the set of recommenders. Moreover, RTV is also time dependent. Hence, the RZ factor is embodied in (6) as above.

**Definition 5** RC. The recommendation credibility is used to describe the veracity of the recommendation information. Assuming  $Cr_{ij}^k$  represents the credibility peer  $i$  offers peer  $j$  after the  $k$ th recommendation activity is finished. Hence, we can make use of the following formula to compute the recommendation credibility peer  $i$  places in peer  $j$ :

$$Cr_{ij}^{k+1} = \begin{cases} Cr_{ij}^k + \delta(1 - Cr_{ij}^k)(1 - \varepsilon) & 0 \leq \varepsilon \leq 1, k > 0 \\ Cr_{ij}^k - \gamma Cr_{ij}^k(1 - 1/\varepsilon) & \varepsilon > 1, k > 0 \\ 1/2 & k = 0 \end{cases} \quad (7)$$

in which,  $0 < \delta < \gamma < 1$ ,  $k$  denotes recommendation number, and  $\varepsilon = |R_n(i, j) - D_n(m, j)| / s_{ij}$ , where  $s_{ij}$  denotes the standard deviation of the DTVs that all the recommenders offer to peer  $j$ .

#### 4. Rc-based incentive mechanism

In the above section, we provide a reputation model, by which some malicious peers would be isolated. However, this model has little incentive effect on peers in P2P networks. In this Section, we propose a RC based incentive mechanism based on ICRM. The service differentiating mechanism - including two service differentiating parameters: PL and RC (see Definition 5) - is introduced into this incentive mechanism. These two parameters can be used to judge the behavioral characteristics of recommenders. The definition of PL is offered in the following section.

##### A. Participating Level

Assuming the PL peer  $i$  places in peer  $j$  at time zone  $t$  is  $I_{ij}^t$ , which is computed by the following steps:

At first, we suppose that  $I_{ij}^t$  denotes the total number for which peer  $i$  has provided recommendations to peer  $j$  at time zone  $t$ , and the threshold for the number of recommendations is  $I_{max}$ . Thus, the PL is defined as (8):

$$I_{ij}^t = \begin{cases} \frac{I_{ij}^t}{I_{max}}, & \text{if } I_{ij}^t \leq I_{max} \\ 0, & \text{else} \end{cases} \quad (8)$$

From the above formula, we can know that with the increase of the number of recommendations peer  $i$  place in peer  $j$ , the PL would becomes larger and larger. Until the number of recommendations reaches the specified critical value such as  $I_{max}$ , the PL would finally reach the maximum 1. While  $I_{ij}^t$  equals to zero, this means peer  $i$  has no recommendations for peer  $j$  at all. In next section, we would implement service differentiating mechanism by constructing a simple reputation information exchange algorithm.

##### B. Reputation Information Exchange Algorithm

We suppose if the PL peer  $i$  places in peer  $j$  meets this condition  $I_{ij}^t > \delta_i$ , peer  $j$  would be regarded as the active peer by peer  $i$ , in which,  $\delta_i$  is the threshold for judging recommendation activeness ( $0 < \delta_i < 1$ ). Similarly, if the RC peer  $i$  places in peer  $j$  meets such condition as  $C_{r_{ij}}^t > \delta_c$ , peer  $j$  would be regarded as the honest peer by peer  $i$ , in which,  $\delta_c$  is the threshold for judging peer's honesty ( $0 < \delta_c < 1$ ).

While receiving peer  $j$ 's query requirement, peer  $i$  looks through its own local database see if there exist assessments of the peer peer  $j$  is interacting with. If there are not, peer  $i$  would neglect this query; otherwise it would proceed as follows based on the PL and RC of peer  $j$ .

(1) If conditions meet:  $I_{ij}^t > \delta_i$  and  $C_{r_{ij}}^t > \delta_c$ , peer  $i$  would regard peer  $j$  as honest and active peer, and respond to its query.

(2) If conditions meet:  $I_{ij}^t > \delta_i$  and  $C_{r_{ij}}^t < \delta_c$ , peer  $i$  would regard peer  $j$  as dishonest and inactive peer, and throw away its query.

(3) Otherwise, peer  $i$  would provide recommendations to others with probability  $p = (1 - \eta) * I_{ij}^t + \eta * C_{r_{ij}}^t$ , where,  $0 \leq \eta \leq 1$  (usually, to counter the accidental fraudulent behaviors, we can set  $\eta > 0.5$ ).

Based on the above reputation information challenge-response policy, if peer  $j$  applies the non-participating policy, all the other peers would respond to peer  $j$  with a small probability when receiving peer  $j$ 's query requirements. In this case, peer  $j$  cannot gain any query response from others. Thus, if peer  $j$  wishes obtain more useful reputation information from others, it need change its inactive state, and take part in the reputation system actively.

**Procedure** ReplyRepInfo( $i, \delta_i, \delta_c, \eta, I_{ij}^t, C_{r_{ij}}^t$ )

//Upon receiving peer  $j$ 's query requirements  $rw(j, s, ttl, t)$  about peer  $s$ , peer  $i$  would proceed as follows:

upon(receipt of a  $rw(j, s, ttl, t)$  message at peer  $i$ ) do

//There are transaction information with peer  $s$  in peer  $i$ 's local database.

if ( $i$  has ever interacted with  $s$  in the last several time units)

```

//Computing the probability issuing a recommendation  $p$ 
  if (  $I_{ij}^t > \delta_i$  )
    if (  $Cr_{ij}^t > \delta_c$  )
       $p = 1$ ;
    else
       $p = 0$ ;
    else
       $p = (1 - \eta) * I_{ij}^t + \eta * Cr_{ij}^t$ ;
//Peer  $i$  responds to peer  $j$ 's query requirements with probability  $p$ , issuing recommendations.
  with (probability  $p$ ) do
     $rec_{is}^t \leftarrow \langle D_{ij}^t, \rho_{ij}^t \rangle$ ;
    send  $rec_{is}^t$  to  $j$ ;
  end do
else
  ignore message;
end if
//peer  $i$  provides recommendations to peer  $j$  in case of  $ttl$  not equal 0.
  if ( $ttl \neq 0$ )
     $A \leftarrow \text{getRandomNeighbor}(b)$ ;
    For each peer  $k$  in  $A$  do
//Issuing recommendations to peer  $j$ 
      send a witness( $s, k, t$ ) to  $j$ ;
    end do
  end if
end do

```

## 5. System performance analysis

We apply the file sharing application as the simulation case. The simulation setting setup is shown in Table I. In simulation, we assume that all the files can be located successfully, that each file is possessed by at least one normal peer, and that the newly joined peer has a probability of 10% to be chosen as the service provider. Here, we simulate 100 query cycles, and each peer can execute transactions for 100 times.

To compare, we simulate EigenTrust trust mode at the same time. The evaluation standard is the successful transaction rate (STR), which is described as the percentage of the number of successful transactions to the total transaction number. This index intuitionistically reflects the applying effect of the trust model. The hardware platform of simulation consists of CPU for Intel(R) Pentium(R) Dual E2200 @2.2GHz, and the memory of 2GMB, and the simulation software is developed in Java.

Table I. SIMULATION PARAMETER SETTINGS

Notations	Parameter descriptions	Initial values
$N$	total number of peers	1000
$\rho_{fade}$	time fading rate	0.8
$\delta$	credibility regulatory factor	0.4
$\gamma$	credibility regulatory factor	0.8
$\alpha$	trust regulatory factor	0.5
$\delta_i$	threshold for judging recommendation activeness	0.6
$\delta_c$	threshold for judging peer's honesty	0.8
$\eta$	recommendation credibility weight for the challenge-response possibility	0.6
$I_{max}$	threshold for the number of recommendations	20

The malicious peers in P2P networks can be sorted into two types including the malicious service peer and the dishonest recommendation peers. Here, for the former, we study a basic malicious peer- the malicious service peer (MSP), who only provides malicious uploading service to others; On the other hand, the dishonest recommendation peer only provides dishonest feedbacks to others: if considering the factor whether the peer is active or not when offering recommendations to others, we can get four types of peers: the inactive honest peer (IHP), the inactive dishonest peer (IDP), the active honest peer (AHP), and the active dishonest peer (ADP).

A. MSP Simulation and Discussion

This experiment mainly aims at assessing the effectiveness of ICRM and EigenTrust, where only exist MSP peers. We can see from Fig. 1, with the increase of the number of MSP peers, the curve labeled by EigenTrust drops quickly - when the percentage of MSP peers reach 50%, the STR for EigenTrust drops to only about 48%, while for ICRM the corresponding value keeps over 71%. The results show that ICRM is more effective to combat the malicious behaviors from MSP peers than EigenTrust.

B. Simulation and Discussion for the Number of Receiving Honest Recommendations

Fig. 2 illustrates the changing tendency of the number of receiving honest recommendations for the above four kinds of peers with the time. In Fig. 2, during the initial period, these peers all receive less honest recommendations. However, with the increase of transaction experiences, the RCs of trusted peers can accumulate to a higher level by keeping on presenting recommendations to others. Through a long time's transaction, the number of receiving honest recommendations for these four kinds of peers forms the relationship: AHP > IHP > IDP > ADP. To be specific, AHPs would receive the most honest recommendations, IHPs and IDPs rank second and third, respectively, and ADPs receive the least honest recommendations. The results would incent peers change their feedback policies, and switch to only provide actively honest recommendations to others, in order to receive more honest recommendations from others.

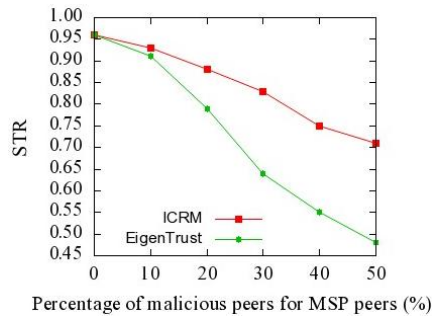


Figure 1. The varying tendency of STR with the percentage of MSPs

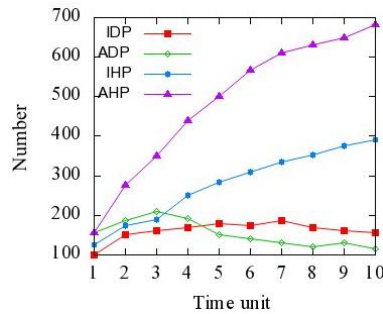


Figure 2. The number for gaining the honest recommendation

C. Simulation and Discussion for the Number of Wrong Decisions

Fig. 3 shows the changing tendency of the number of wrong trust decisions for these four kinds of peers with

the time. Peers receiving less honest recommendations tend to make wrong decisions. For example, some peers would mistake others: overrate or underrate others. As shown in Fig. 3, with the transactions proceeding, the number of every one of these four kinds of peers has decreased. With the effect of honest recommendation behavior, the number of wrong decisions for AHP is the smallest, while for ADP the index reaches the largest. The final results display as such a relationship as  $AHP < IHP < IDP < ADP$ .

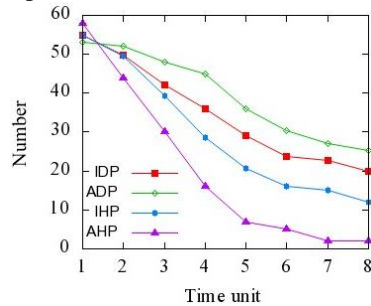


Figure 3. The number of wrong decisions

From the above two simulation experiments, we can conclude that the RC based incentive mechanism can effectively incent peers to actively provide honest recommendations to others, since they will gain more benefits by doing this.

## 6. Conclusions and further work

In this paper, we propose an incentive compatible reputation model for P2P networks, and make simulation experiments to assess the performance of our scheme as compared to EigenTrust. Analysis and simulation experiments show, the proposed model ICRM can overcome partly some limitations of current models, combat effectively the attacks from different malicious peers, and incent peers to provide actively honest recommendations to others.

Besides the above research points, many vital issues, such as the distributed storage mechanism of the reputation information and how to resist collusive and strategic malicious peers, etc., will be paid more attention to in the future researches.

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## References

- [1] Kamwar S. D., Schlosser M. T., Hector Garcia-Molina. The eigentrust algorithm for reputation management in P2P networks [C]. Proceedings of the 12th International Conference on World Wide Web. Budapest, Hungary, 2003: 640-651
- [2] Xiong L, Liu L. PeerTrust: Supporting reputation-based trust in peer-to-peer communities [J]. IEEE Transactions on Data and Knowledge Engineering, Special Issue on Peer-to-Peer Based Data Manage

- ment , 2004, 16(7): 843-857
- [3] C Dellarocas. Immunizing online reputation reporting systems against unfair ratings and discriminatory behavior [C]. Proceedings of the 2nd ACM Conference on Electronic Commerce. Minneapolis, MN, USA, 2000: 150-157
  - [4] Xiong L., Liu L. A reputation-based trust model for peer-to-peer ecommerce communities [C]. Proceedings of the 4th ACM conference on Electronic commerce (CEC'03), San Diego, CA, US, ACM Press 2003: 228-229
  - [5] Wang Y., Vassileva J. Bayesian Network-Based Trust Model in P2P Networks [C]. Proceedings of Agents and Peer-to-Peer Computing, Second International Workshop (AP2PC 2003), Melbourne, Australia, IEEE Computer Society. 2003: 372-378
  - [6] Golle P, Leyton-Brown K, Mironov I. Incentives for sharing in peer-to-peer networks. In: Wellman MP, Shoham Y, eds. Proceedings of the 3rd ACM Conf. on Electronic Commerce. New York: ACM Press, 2001: 264-267
  - [7] Buragohain C, Agrawal D, Suri S. A game theoretic framework for incentives in P2P systems. In: Shahmehri N, Graham RL, Carroni G, eds. Proceedings of the 3rd Int'l Conf. on Peer-to-Peer Computing (P2P 2003). Los Alamitos: IEEE Press, 2003: 48-56
  - [8] Friedman E and Resnick P. The social cost of cheap pseudonyms [J]. Journal of Economics and Management Strategy, 2001, 10(2): 173-199