

# AN AUTOMATED TRUST MODEL FOR CLIENT-SERVER AND PEER-TO-PEER SYSTEM

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**Abstract**—To maintain trust in peer-to-peer system is to difficult as there is no central server in between peers. To create trust in between peers can avoid attacks from malicious peers. This paper presents an automated trust model which takes into consideration peers past interaction and recommendations to choose trustworthy peer. While evaluating trustworthiness parameters like importance, recentness and peer satisfaction is taken into consideration. Recommenders trustworthiness and confidence about a recommendation are also considered while evaluating recommendations. We have implemented access control technology in the P2P file sharing system and for that we have used symmetric encryption with shared secret key. Proposed automated trust model can mitigate attacks on different malicious behaviour models. Our experiments help to detect malicious peers and form a group of good peers.

**Keywords**—An Automated Trust Model, Reputation, Security and Protection, Peer-to-peer system.

## I. INTRODUCTION

ON e-commerce website like Olx, Quikr and Flipkart before deciding to buy any product visitors usually look for customer reviews. In the above example centralized mechanism is used for storing and manipulating reputation data. In our paper we have explored possibilities for trust management in completely decentralized environment, where no central database is used i.e. peer-to-peer system.

Reputation must be associated with self-maintained trust model rather than global trust model hence an automated trust model is used at each peer. To form trust relationship in peers proximity can provide more security and also provide reduced risk and uncertainty in future P2P interactions. In computational model metrics are used to represent trust. Peers are classified as trustworthy or untrustworthy and also ranked according to their trustworthiness. Trust among peers can be measured using interactions and feedbacks of peers. Interaction gives certain information about the peer but feedback might information,. Reputation must be associated Reputation must be associated with self-maintained trust model rather than .

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We propose an automated trust model that aims to improve security in P2P system by establishing trust relations among peers in their proximity. Each peer develops its own view of trust about the peers with

whom he interacted in the past. In this way good peers form dynamic trust groups and can isolate malicious peers. At the beginning, peers are assumed to be strangers to each other and becomes an acquaintance of another after providing a service, e.g. download a file. If peer has no interaction in the past, it chooses to trust strangers.

Using a service of a peer is an interaction, which is evaluated based on weight (importance), recentness of the interaction and satisfaction of the requester. An acquaintances feedback about a peer, recommendation is evaluated based on recommenders trustworthiness. It contains the recommenders own experience about the peer, information collected from the recommenders acquaintances, and the recommenders level of confidence in the recommendation. If the level of confidence is low, the recommendation has a low value in evaluation and affects less the trustworthiness of the recommender. An automated trust model defines two primary metrics to calculate trustworthiness among peers: service trust metric and recommendation trust metric. Service trust metric is used for selecting service provider and recommendation trust metric is used for requesting recommendations from other peers. Reputation metric is a secondary metric calculated using recommendation trust metric. In experiment we have studied 4 types of malicious peer behaviors, which perform both service and recommendation-based attacks. An automated trust model mitigates service-based and recommendation-based attacks.

Our experiment shows that good peers defend themselves against malicious peers and assess trustworthiness of other peers based on the information available with it.

## II. LITERATURE SURVEY

Guha et al. show that expressing trust or distrust per peer allows hito predict between any two people in

the network with high accuracy. Result of their experiment shows that distrust is helpful to measure trustworthiness accurately. J. Douceur explained 'the sybil attack' to reputation system are vulnerable to sybil attack, where malicious peers gives bogus feedbacks by creating multiple fake entities. To overcome Sybil attack, Yu et al. as well as Tran et al. propose system which is based on the observation that fake entities and have many trust relationships among each other but they rarely have relationships with real users.

Decentralized network have more challenges comparing to centralized platform. Due to lack of central authority malicious peers have more attack opportunities in P2P system. Attacks like self promoting, white-washing, slandering, orchestrated and denial of service attacks in P2P trust model are discussed by Hoffman et al.

In network peer is assumed as trustworthy unless there are complaints against it. In Aberer and Despotovic's trust model, peer reports their complaints using P-Grid. Eigentrust uses transitivity of trust to calculate global trust values stored on content addressable network i.e. CAN. L. Xiong and L. Liu's peer trust defines transaction and community context parameters to make trust calculations adaptive on PGrid.

Both Eigentrust and Peertrust evaluate a recommendation based on trustworthiness of the recommender.

Can and Bhargava defines a self-Organizing trust model for P2P system. Instead of considering a particular trust holders feedback as authentic, public opinion from all acquaintances is considered as a more credible information. Instead of considering global trust information, local trust information is used to take decisions as peers develop their own trust networks. For efficient aggregation of trust values gossip trust defines a randomized gossiping protocol. This experiment shows that gossiping reduces reputation query traffic. We send reputation queries only to those peers with whom we have interacted in the past, which reduces network traffic.

### III. IMPLEMENTATION DETAILS

#### A. Mathematical Model

Model developed in this paper is built on such an environment where reciprocity norms are expected. In our experiment suppose peer  $p_j$  is evaluating  $p_i$ 's reputation for being cooperative. We define embedded social network of  $p_j$  as the set of all the peers that  $p_j$  asks for this evaluation. So by the way, the reputation of a peer  $p_i$  is relative to the particular embedded social network in which  $p_i$  is being evaluated. For the simplicity, we are not adding any new peer to the system. We reinforcing relationships among the three concepts they are reciprocity, trust

and reputation. For an peer  $p_j$  with an embedded social network A: increase  $p_j$ 's reputation in A should also increase the trust from other peers for  $p_j$  and the increase in  $p_i$ 's trust of  $p_j$  should also increase the likelihood that  $p_i$  will reciprocate positively to  $p_j$ 's action; since  $p_j$ 's reciprocation action to others in A increased, its reputation in

A should also be increased.

Reciprocity is defined as mutual exchange of deeds. Two types of reciprocity are considered in this model: direct reciprocity refers to interchange between two concerned peers while indirect reciprocity refers to interchange between two concerned peers interceded by mediating peers in between. The model defines reputation as perception that an peer creates through past actions about its intentions and norms. Mathematically, let  $\theta_{ji}(c)$  represent  $p_i$ 's reputation in an embedded social network of concern to  $p_j$  for a context  $c$ . This value is subjective to every other peer since the embedded

social network difference when  $p_i$  connects to different  $p_j$ . In this way  $\theta_{ji}(c)$  measures the likelihood that  $p_i$  reciprocates  $p_j$ 's actions.

In this model, trust is defined as a subjective expectation a peer has about another's future behavior based on the history of their encounters. Thus to evaluate the trustworthiness of  $p_i$ , let  $D_{ji}(c)$  represents history of encounters that  $p_j$  has with  $p_i$  within the context  $c$ . Moreover, we should take note that trust is a subjective quantity calculated based on the two peers concerned in a dyadic encounter. So we can model trust using  $T(c) = E[\theta_{ji}(c)|D_{ji}(c)]$ . The higher the trust level for peer  $p_i$ , the higher the expectation that  $p_i$  will reciprocate peer  $p_j$ 's action.

We describe the computational model in detail with the following scenario:

We assume the notations used for this scenario are:

$\theta_{ab}$ :  $b$ 's reputation in the eyes of  $a$

$X_{ab}(i)$ : The  $i$ th encounter between  $a$  and  $b$

$$X_{ab}(i) = \begin{cases} 1 & \text{if } b \text{'s action is complete} \\ 0 & \text{otherwise} \end{cases}$$

$D_{ab}$ : history; The set of  $n$  previous encounters between  $a$  and  $b$ .

$$D_{n,k} = \{X_{ab}(1), X_{ab}(2), \dots, X_{ab}(n)\}$$

Let  $p$  be the cooperative actions by agent  $b$  towards  $a$  in the  $n$  previous encounters,  $b$ 's reputation  $\theta_{ab}$  could be modeled by a simple proportion function of  $p$  cooperative actions over  $n$  encounters. In statistics, a proportion random variable can be modeled as a Beta distribution:  $p(\hat{\theta}) = \text{Beta}(c_1, c_2)$  where  $\hat{\theta}$  represents an estimator for  $\theta$ .

If peers  $a$  and  $b$  are complete strangers, when they first meet, their estimate for each other's reputation is assumed to be uniformly distributed across the reputation's domain:

$$p_{\theta}(i) = \begin{cases} 1 & 0 \leq \hat{\theta} \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

In this model, the beta distribution will be uniform when  $c_1 = c_2 = 1$ .

Now we have a simple estimator for  $\theta_{ab}$  which is the proportion of cooperation in  $n$  finite encounters:  $\theta_{ab} = p/n$ . Assuming that each encounter's cooperation probability is independent of other encounters between  $a$  and  $b$ , the likelihood of  $p$  cooperations and  $(n-p)$  defections can be modeled as  $L(D_{ab}|\hat{\theta}) = \theta^p(1-\theta)^{n-p}$ . Combining the prior and the likelihood, the posterior estimate for  $\hat{\theta}$  becomes:  $p(\hat{\theta}|D) = \text{Beta}(c_1 + p, c_2 + n - p)$ . As we mentioned previously, trust toward  $b$  from  $a$  is the conditional expectation of reputation  $\hat{\theta}$  so it can be computed by

$$T_{ab} = p(X_{ab}(n+1) = 1|D) = E[\hat{\theta}|D] = \frac{c_1 + p}{c_1 + c_2 + p}$$

## B. Proposed system

The proposed P2P file sharing system is a windows based program that allows you to host secure P2P file sharing. Users just need to install client software on each peer side. Key features of our model are listed below:

Represent trust in computational model  
Studies service and recommendation-based attacks  
Rank peers according to their trustworthiness  
Create trust network by only using local information  
Shared secrete key for symmetric encryption

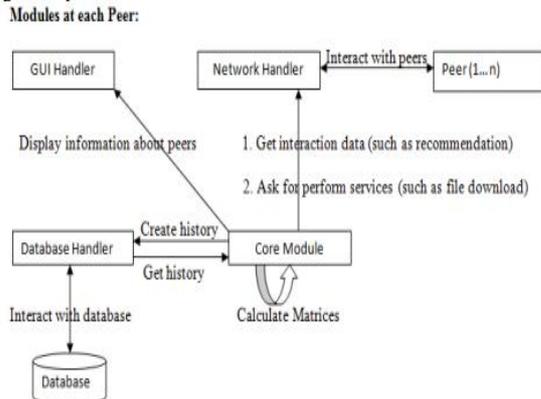
Access control facility to every peer

### 1) System Architecture:

In P2P network system architecture consist of four components

Description:

Fig. 1. System Architecture



### 1) Network Handler

Search for peers.

Interact with peers (getting or providing services to peer).

Get recommendations from peers.

### 2) Core Module

Calculate matrices:

a) Service Trust Metric

b) Reputation Metric

c) Recommendation Trust Metric

Create interaction History.

### 3) Database Handler

interact with database:

Store interaction history.

Fetch interaction history.

Update interaction history.

### 4) GUI Handler

Display information about peers (such as IP address, trustworthiness etc).

Display information about recommenders.

Display information about past interaction with respective peers.

## C. Computational Model:

In our experiment we have assumed that all the peers are of same computational power and responsibility.

We dont have any centralized or trusted peer to manage trust relationship.

Notations :

Notations on the trust metrics are shown below:

Notation	Description
$p_i$	$i^{th}$ peer
$A_i$	$p_i$ 's set of acquaintances
$SH_{ij}$	$p_i$ 's service history with $p_j$
$sh_{ij}$	Current size of history
$sh_{max}$	upper bound for service history size
$s_{ij}^k$	$p_i$ 's satisfaction about $k^{th}$ interaction with $p_j$
$w_{ij}^k$	weight of $p_i$ 's $k^{th}$ interaction with $p_j$
$f_{ij}^k$	fading effect of $p_i$ 's $k^{th}$ interaction with $p_j$
$r_{ij}$	$p_i$ 's reputation value about $p_j$
$st_{ij}$	$p_i$ 's service trust value about $p_j$
$rt_{ij}$	$p_i$ 's recommendation trust about $p_k$

Table 1: Notations used

To improve importance of new interactions fading effect parameter is calculated which forces peers to stay consistent in future interactions. It is calculated as follows:

$$f_{ij}^k = \frac{k}{sh_{ij}}, 1 \leq k \leq sh_{ij}$$

Before starting downloading or uploading peers in a network make bandwidth agreement. The ratio of average bandwidth(AveBw) and agreed bandwidth (AgrBw) is measure of reliability of a peer in terms of bandwidth. Ratio of online and offline period of peer represent availability of an peer. The satisfaction parameter is calculated based on above variables:

$$s_{ij}^k = \begin{cases} \left( \frac{AveBw}{AgrBw} + \frac{OnP}{OnP+OffP} \right) / 2 & \text{if AveBw} < \text{AgrBw} \\ \left( 1 + \frac{OnP}{OnP+OffP} \right) / 2 & \text{otherwise} \end{cases}$$

Lets assume that  $U_{uploader_{max}}$  be the number of uploaders of the most popular file.  $size$  and  $\#Uploaders$  denote the file size and the number of uploaders, respectively.  $p_i$  calculates the weight parameter of  $k^{th}$  interaction with  $p_j$  as follows:

$$w_{ij}^k = \begin{cases} \left( \frac{size}{100MB} + \frac{\#Uploaders}{U_{uploader_{max}}} \right) / 2 & \text{if size} < 100 \text{ MB} \\ \left( 1 + \frac{\#Uploaders}{U_{uploader_{max}}} \right) / 2 & \text{otherwise} \end{cases}$$

### 1) Service Trust Metric ( $st_{ij}$ ):

Competence belief ( $cb_{ij}$ ) and integrity belief ( $ib_{ij}$ ) parameters are used to calculate Service trust metric. Competence belief represent how well an acquaintance satisfied the needs of past interaction.  $p_i$  calculates  $cb_{ij}$  as follows:

$$cb_{ij} = \frac{1}{\beta_{cb}} \sum_{k=1}^{sh_{ij}} (s_{ij}^k \cdot w_{ij}^k \cdot f_{ij}^k)$$

$\beta_{cb}$  is a normalization effect and it is given by  $\beta_{cb} = \sum_{k=1}^{sh_{ij}} (w_{ij}^k \cdot f_{ij}^k)$ . Competence belief ( $cb_{ij}$ ) always take value between 0 and 1.

Consistency is as important as competence. Level of confidence in predictability of future interactions is called integrity belief.

$$ib_{ij} = \sqrt{\frac{1}{sh_{ij}} \sum_{k=1}^{sh_{ij}} (s_{ij}^k \cdot w_{ij}^k \cdot f_{ij}^k - cb_{ij})^2}$$

$w_{ij}^k$  and  $f_{ij}^k$  are the mean of  $w_{ij}^k$  and  $f_{ij}^k$  values in  $SH_{ij}$ , respectively. We can approximate  $f_{ij}^k$  as follows:

$$f_{ij}^k = \frac{1}{sh_{ij}} \sum_{k=1}^{sh_{ij}} f_{ij}^k = \frac{sh_{ij}+1}{2sh_{ij}} \approx \frac{1}{2}$$

$p_i$  may calculate  $st_{ij}$  as follows:

$$st_{ij} = cb_{ij} - ib_{ij}/2$$

We have not considered  $p_j$ 's reputation in above equation so the equation is not complete. In the early phases of trust relationship reputation is very important. When there is no any interaction with acquaintance, a peer needs to depend on reputation metric only. There for  $p_i$  calculates  $st_{ij}$  as follows:

$$st_{ij} = \frac{sh_{ij}}{sh_{max}} (cb_{ij} - ib_{ij}/2) + (1 - \frac{sh_{ij}}{sh_{max}}) r_{ij}$$

When  $p_j$  is stranger to  $p_i$  value taken for  $sh_{ij} = 0$  and  $st_{ij} = r_{ij}$

### 2) Reputation Metric ( $r_{ij}$ ):

Reputation metric is used to calculate stranger's trustworthiness based on recommendations. In our experiment we have assumed that  $p_j$  is stranger to  $p_i$  and  $p_k$  is acquaintance of  $p_i$ . To calculate  $r_{ij}$ ,  $p_i$  sends reputation query to its acquaintances. Below algorithm shows how peer  $p_i$  chooses trustworthy acquaintances and request their recommendations.  $\eta_{max}$  represent the maximum number of recommendation collected through reputation query and  $|S|$  denotes the size of set  $S$ .  $p_i$  sets high threshold value for recommendation trust values and request recommendation from highly trusted acquaintances first. It repeats the same operation until  $\eta_{max}$  reach or threshold drops under ( $\mu_{rt} - \sigma_{rt}$ )

#### Algorithm 1. getRecommendation( $p_j$ )

```

 $\mu_{rt} \leftarrow \frac{1}{A_i} \sum_{p_k \in A_i} rt_{ik}$ 
 $\sigma_{rt} \leftarrow \frac{1}{A_i} \sqrt{\sum_{p_k \in A_i} (rt_{ik} - \mu_{rt})^2}$ 
 $th_{high} \leftarrow 1$ 
 $th_{low} \leftarrow \mu_{rt} + \sigma_{rt}$ 
 $rset \leftarrow \emptyset$ 
while  $\mu_{rt} - \sigma_{rt} \leq th_{low}$  and  $|rset| < \eta_{max}$  do
for all  $p_k \in A_i$  do
if  $th_{low} \leq rt_{ik} \leq th_{high}$  then
 $rec \leftarrow RequestRecommendation(p_k, p_j)$ 
 $rset \leftarrow rset \cup \{rec\}$ 
end if
end for
 $th_{high} \leftarrow th_{low}$ 
 $th_{low} \leftarrow th_{low} - \sigma_{rt}/2$ 
end while
return  $rset$ 

```

Let  $er_{ij}$  denote  $p_i$ 's estimation about reputation of  $p_j$ . In this calculation,  $r_{kj}$  values are considered with respect to  $\eta_{kj}$  as shown:

$$er_{ij} = \frac{1}{\beta_{er}} \sum_{p_k \in T_i} (rt_{ik} \cdot \eta_{kj} \cdot r_{kj})$$

$\beta_{er} = \sum_{p_k \in T_i} (rt_{ik} \cdot \eta_{kj})$  is the normalization coefficient.

Then  $p_i$  calculates estimation about competence and integrity belief of  $p_j$  denoted by  $ecb_{ij}$  and  $eib_{ij}$ , respectively.

$$ecb_{ij} = \frac{1}{\beta_{ecb}} \sum_{p_k \in T_i} (rt_{ik} \cdot sh_{kj} \cdot cb_{kj})$$

$$eib_{ij} = \frac{1}{\beta_{eib}} \sum_{p_k \in T_i} (rt_{ik} \cdot sh_{kj} \cdot ib_{kj})$$

Both these equations represent own experience of  $p_i$ 's acquaintances with  $p_j$ , where  $\beta_{ecb} = \sum_{p_k \in T_i} (rt_{ik} \cdot sh_{kj})$  is the normalization coefficient.

$p_i$  calculates the average of history sizes in all recommendations,  $\mu_{sh} = \sum_{p_k \in T_i} (sh_{kj})/t_i$  value. With these observations,  $r_{ij}$  is calculated as follows:

$$r_{ij} = \frac{[\mu_{sh}]}{sh_{max}} (ecb_{ij} - eib_{ij}/2) + (1 - \frac{[\mu_{sh}]}{sh_{max}}) er_{ij}$$

3) Recommendation Trust Metric ( $rt_{ik}$ ): According to  $p_k$ 's recommendation  $p_i$  updates recommendation trust metrics ( $rt_{ik}$ ) value.

Three parameters are calculated the satisfaction ( $rs_{ik}^z$ ), weight ( $rw_{ik}^z$ ), and fading effect ( $rf_{ik}^z$ ) of  $p_i$ 's  $z^{th}$  recommendation from  $p_k$ , respectively. Then the calculation of  $rs_{ik}^z$  is as follows:

$$rs_{ik}^z = ((1 - \frac{|r_{kj} - er_{ij}|}{er_{ij}}) + (1 - \frac{|cb_{kj} - ecb_{ij}|}{ecb_{ij}}) + (1 - \frac{|ib_{kj} - eib_{ij}|}{eib_{ij}})) / 3$$

The weight of the recommendation should be calculated with respect to  $sh_{kj}$ ,  $\eta_{kj}$ ,  $[\mu_{sh}]$  values.  $p_i$  calculates  $rw_{ik}^z$  as follows:

$$rw_{ik}^z = \frac{[\mu_{sh}]}{sh_{max}} \frac{sh_{kj}}{sh_{max}} + (1 - frac[\mu_{sh}]sh_{max}) \frac{\eta_{kj}}{\eta_{max}}$$

$p_i$  calculates  $rt_{ik}$  in similar way to  $st_{ik}$

$$rcb_{ik} = \frac{1}{\beta_{rcb}} \sum_{z=1}^{r_{h_{ik}}} (rs_{ik}^z \cdot rw_{ik}^z \cdot f_{ik}^z)$$

$$rib_{ik} = \sqrt{\frac{1}{r_{h_{ik}}} \sum_{z=1}^{r_{h_{ik}}} (rs_{ik}^z \cdot rw_{ik}^z \cdot f_{ik}^z - rcb_{ik})^2}$$

$$rt_{ik} = \frac{r_{h_{ik}}}{r_{h_{max}}} (rcb_{ik} - rib_{ik}/2) + \frac{r_{h_{max}} - r_{h_{ik}}}{r_{h_{max}}} r_{ik}$$

### D. Experimental Setup:

In our experiment we have used 7 P2P client setup and 5 upload peers with 3 download peers. Hardware configuration for all the peers is same to maintain consistency. Hardware configuration for each peer is described in below table:

Hardware Configuration	
Processor	Pentium IV
Speed	1.1 Ghz
RAM	256 MB(min.)
Hard Disk	20 GB

Table 2: Hardware Configuration

We have implemented module on java platform; software configuration is shown in below table:

Software Configuration	
Operating System	Windows XP
Programming Language	Java
DATABASE	SQL Server 2005
Development Tool	Eclipse

Table 3: Software Configuration

### 1) Screen Shots:

Server:

In P2P file sharing Application a server is dedicated to provide services to the requesting peers.

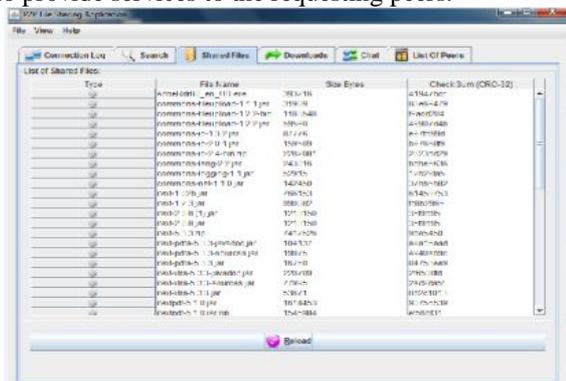
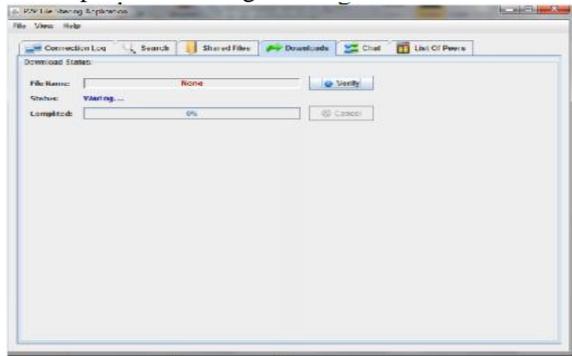


Fig 2: Server Side setup

**Client**

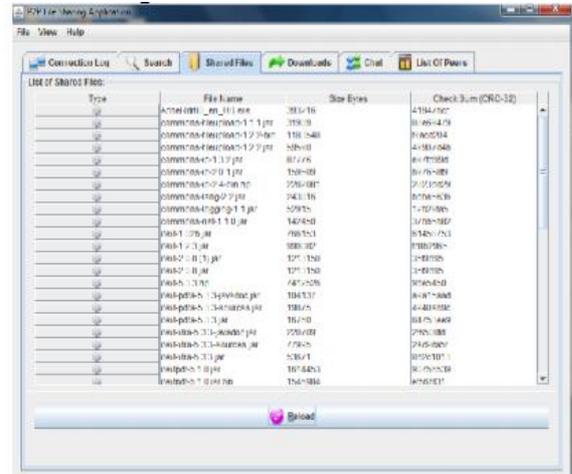
In P2P file sharing application client is one who select uploader with highest service trust value.



**Fig 3:Client Side setup**

**File Sharing**

File sharing refers to the uploading and downloading of file over a P2P network.



**Fig 4:File sharing Application windows**

**IV. RESULT**

In our experiment we have studied both service and recommendation-based attacks. A peer is called good one who uploads authentic file and also gives fair recommendation; at the other side a malicious peer perform service as well as recommendation-based attacks.

for the malicious peer we have studied 4 different attack behaviors, they are as follows:

- 1) Naive: In this case malicious peer uploads inauthentic file and also gives unfairly low recommendation about other peers.
- 2) Discriminatory: Here malicious peer targets group of peers and always upload inauthentic files to them.It also gives unfairly low recommendations about the victims but with other peers it behaves as a good peer.
- 3) Hypocritical: Here with x percent probability malicious peer uploads inauthentic file and gives unfairly low recommendations, but at other time it behaves as a good peer.

4) Oscillatory: By being good for long time period peer gets high reputation. Then it behaves as a naive attacker for a short period of time and again after some time period it becomes good peer.

We have studied all these attack behaviors one by one against our automated trust model and found that it mitigates all the attacks. We have also used shared secrete key for communication which helped us to maintain authorization in P2P network.

**A. Analysis of attacks**

We have studied service and recommendation-based attacks individually.

1) Service-based attacks: When any malicious peer uploads inauthentic file, then it is recorded as servic-based attack.

Percentage of attacks prevented				
	Attack type	SORT	FloodRQ	trust model
Malicious peers	Naive	65.3	64.7	68.3
	Discriminatory	72.2	72.7	75.3
	Hypocritical	43.0	47.5	46.6
	Oscillatory	37.0	44.0	44.2

**Table 4:Service-based attacks**

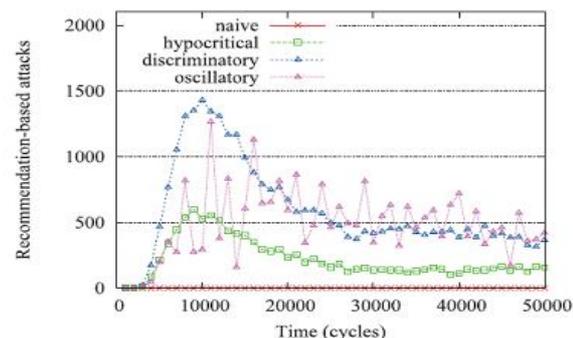
Our experiments expected results are compared with SORT model [1]. Above table shows the percentage of service-based attacks preventad by each trust model. While calculating per-centage of success we have considered base case to understand how many attacks can happen without using any trust model.

All the detected attacks for each trust model is compared with the base case to determine the percentage of attacks prevented.

In the above table we have shown result for Self-Organizing trust model (SORT) and an automated trust model.

Result shows that both the method are able to find more than sixty percent of malicious peer. Naive case shows high percentage of success because in naive case good peer identi- fies a naive attacker after having the first interaction. In all the other attacks good peer is not able to find an attacker in the first interaction.Trust model interacts less with the strangers as its set of acquaintances grows and it helps to decrease service-based attacks with time.

2) Recommendation-based attacks: When any peer gives misleading recommendation then it is treated as a recommendation-based attack.



**Fig 5:Recommendation-based attacks**

Above figure shows percentage of recommendation-based attacks in malicious network. With our implemented trust model peers form their own trust network and do not re-quest any recommendation from any untrustworthy peers. An automated trust model collects recommendations from limited trustworthy peers and avoid overloading. It also check peers authenticity by using shared secrete key. Our experi- ment on recommendation-based attacks shows that collecting recommendations from acquaintances provide more accurate information.

## CONCLUSION

An automated trust model implemented for P2P system, in which a peer can develop its own trust network in its proximity. A peer can distinguish between trustworthy and untrustworthy peers. Peer develop trust relationship with good peers. Each peer develop its own local view of trust about the peer with whom he interacted in the past using two metrics, service trust and recommendation trust. Parameters like satisfaction, weight and fading effect are used while evaluating interactions and recommendations. While calculating recommendation, recom- mender's own experience, information from its acquaintances and level of confidence in the recommendation are considered. Interaction gives certain information about peer which is used to calculate service trust.

## FUTURE SCOPE

It is difficult for a peer to determine a recommendation- based attack as a recommender might be cheated by attackers, so their is no any proof to prove that the recommendation is intentionally given. A selection algorithm can be used for load balancing to utilize all resources of peers. Thus this issue nees more investigation in future work. Trust information is not enough to solve all security related problem in P2P system but it can improve security and effectiveness of this system. Our experiment deals with both srvice and recommendation based attacks; more work is necessary to deal with the recommendation base problems.

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