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A TRUSTWORTHY PARTNER SELECTION FOR MMOG USING AN IMPROVED THREE VALUED SUBJECTIVE LOGIC UNCERTAINTY TRUST MODEL

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ABSTRACT

In massively multiplayer online games (MMOG), the player interacts with other players through partners' random selection. Hence, random selection leads to various problems, such as to request contention and cheating in online games. Hence, trust-based partner selection is essential in the virtual world. However, the most existing trust models determine whether the players' absolute trust is either trustworthy or not. Therefore, the proposed work addresses the uncertainty trust assessment in the virtual world. This work proposes to improve the three-value subjective logic uncertainty model (I-3VSL) to assess the trust through a direct and indirect assessment. The Trustwalker (TW) algorithm is designed to assess a selected partner's trust using 3VSL and I-3VSL. As a result, the TW algorithm evaluates trust through other players' recommendations that find the path from trustee to trustee. The recommendations are filtered through the verification of the player's eligibility in the specified depth. To validate the TW algorithm with 3VSL and I-3VSL is assessed using the Travian dataset. The experiment results demonstrate that the I-3VSL with TW algorithm is more efficient than the 3VSL algorithm. I-3VSL provides an optimized error rate using mean absolute error of 5% and root mean square error7.5%. Further, the accuracy at various depth levels is obtained $90-95\%$ and reduces the computation time compared to 3VSL.Keywords: cheating, massively multiplayer online games, recommendations, three-valued subjective logic, trust-partner, Trustwalker, uncertainty, virtual world.

INTRODUCTION

Advances in mobile technology over the internet have resulted in virtual world applications such as Augmented Reality [1], virtual walkthrough [2, 3], virtual online games [4], and many others. Virtual online games, such as massively multiplayer online games (MMOG), interact with other players and share the network's resources [5]. The interactions are established based on the player's interest based on the random selection, which leads to various security problems such as requesting contention, cheating in online games that occur because of misplaced trust, and the players' uncertain behavior [6, 7, and 8]. Hence, the partner selection strategies are essential in MMOG.

The partner selection strategies in a client-server communication, the players' behavior are supervised, and information is stored in a central server; hence, the behaviors are under the server's control. However, in the virtual world, the entire game is loaded into the client machine, which degrades the performance, suffers from the service bottleneck, and many other problems [9]. Therefore, MMOG applications move towards peer-to-peer (P2P) communication. In P2P, the players are behavior uncertain because of the absence of a central server and dynamic nature [10]. However, P2P communication uses 3D streaming, which avoids complete downloading. Therefore, P2P 3D streaming requires trust-based partner selection strategies [11-13].

In the trust assessment in an online environment, the most widely used techniques are reputation-based trust models, which assess the trust based on reliability and service providers [14]. However, the existing reputation models such as topology-based models [15-20], PageRank [21-23], probabilistic models [24-26], and fuzzy models [27] assess the trust based on past transactions and effectively manages the certainty of trust such as trustworthy or not. Nevertheless, the behavior of the players will change over the period.

Thus, the existing techniques are not able to manage the uncertainty behavior. Hence flow-based models are designed [21-26,28].The flow-based models, such as Subjective Logic (SL), evaluate trust using trust propagation and fusion that effectively manage trust uncertainty such as trust, distrust, and neutral [29-30]. However, in SL trust assessment, the uncertainty opinion is maintained constant during trust assessment [9]. Thus, three-valued subjective logic (3VSL) is intended [31-33]. The 3VSL trust assessment manages the trust assessment more accurately compare to SL. However, the 3VSL trust model requires modification in trust propagation rules through that it provides more accuracy.The major challenges in P2P 3D streaming

In MMOG, the player randomly selects the opponent players, leading to the request contention problem.

The trust assessment of selected players based on the trustor perspective is essential.

Assess the trust of the unknown player based on the other players' recommendations from the trustor to a trustee is required.

Based on eligibility criteria, the players' recommendations are accepted in the path from trustor to trustee.

The study's motivation:

With mobile technology enhancement, the mobile devices are categories into thin and thick mobile devices. The thin mobile devices used to display the content based on users' physical environment actions reflect the virtual environment. The virtual environment applications are growing faster, especially in the gaming industry, such as single or multiplayer online games. In multiplayer online games, the player plays the game with 'n' number of players in the network. In this scenario, the opponent player selection is critical because it is maliciously changing the game rules to win the game. Hence, trustworthy partner selection techniques are essential in P2P 3D streaming over thin mobile devices.

The main objective is to design trustworthy partner selection in the context of games and virtual worlds. Virtual world games such as MMOG select the opponent players based on the player perspective and content availability. Further, assess the trust of the player then allow the shared content. Hence, it reduces the malicious activities in the network. The main contribution of the work as follows

The MMOG dataset, such as Travian, represents the trust-relations that establish the Trust network with small regions.

Based 3VSL direct assessment generates the player's interactions trust opinions such as trust, distrust, post, and prior uncertainties.

Propose the modifying the trust propagation or discounting operation and named it an improved 3VSL (I-3VSL).

Evaluate from trustor to trustee using TrustWalker (TW) algorithm with I-3VSL direct and indirect assessment.

Evaluating the time complexity and performance of TW algorithm with I-3VSL

Compare the performance of I-3VSL and 3VSL with TW algorithms in massively multiplayer online games.

This article is structured as, Section II review related to P2P trust models. Section III describes 3VSL uncertainty trust model direct and indirect assessment principles. Section IV Design of TW Algorithm. Section V describes the simulation and performance results. Section VI describes the conclusion.

Related Work

In a P2P environment, the users' trust is evaluated using reputation-based trust models such as topology-based, PageRank, probability-based, and Subjective logic models. The details as follows

Topology-based Trust Model (TTM)

Used in community detection problems.The advantage of this trust model controls the random walk assessment of trust. Hence, TTM identifies trustworthy peers by separating untrustworthy regions from trustworthy regions in the network. Further, a trustor evaluates the trustee's trust based on the reachability probability using the depth-first search algorithms [15-20]. A high probability indicates that the trustee is in the trustworthy region. This model evaluates the trust within the same community and the trust represented as a single quantity such as trust. Hence, this trust model disregards the uncertainty trust.

PageRank-based Trust Model (PRTM)

Evaluates the trustee's trustworthiness based on the trustor's interest. The PRTM uses the PageRank algorithm to rate the users based on an earlier transaction. However, the path finds from the trustor to a trustee using a traditional graph search algorithm. In that path, each edge has the trust value based on that determines the trustee's trust value. The PRTM technique variants are Eigen Trust [21] TrustRank [22].

Eigen Trust (ET):

A global trust reputation is evaluates using the eigenvector matrix, which consists of the local reputation values. The local reputations are measured based on other peers' opinions as satisfied or unsatisfied that they are normalized [1,0] [21]. This technique minimizes un-authentic file downloads spread by malicious peers, robust to gather up the malicious peers from a group of trustworthy peers, i.e., pre-trusted network. In decentralized and node-symmetrical performance with minimal network overhead This reputation system suffering from the various problems that are listed below

The pre-trusted peers focus only on neighboring nodes while evaluating the reputation. Hence, other peers rated low despite being honest, thus affect the system efficiency.

The pre–trusted network member, downloads an un-authentic file from a dishonest peer then other members consider that the file is authentic. Hence, other peers can access and upload the un-authentic file.

In a static pre-trusted community, peers can easily report un-trustworthiness and heterogeneity.

Peer Trust Model (PT):

Community-based reputation system includes the cohesive evolutionary trust model that evaluates and monitors the peer's trust based on the previous interactions in a distributed manner. To determine the peer's trust based on feedback obtained from other peers, the cumulative number of interactions conducted by peers, the quality of the transaction, the reputation of the feedback sources, and community significance [12]. The combination of general trust metrics and all trust factors generates peer trust and reduces the number of attacks such as tampered nodes, propagating suspicious messages, and man-in-the-middle in the P2P context, but it suffers from the following issues.

The trustworthiness of the peer-evaluated based on various factors. Hence, a minimum number of interactions are required to assess the trustworthiness of newly joined peers.

The highest peer trust value always gives reliable feedback, but virtually this is impossible.
The behavior of the peer changes over time. Thus, consider more recent peer reputation value to assess the trustworthiness rather than old reputation.

TrustRank (TR):

the TR model ranks all the peers based on their trust scores and arranges them in descending order [22]. Hence, the top-ranked peers provided for interaction through that minimizes the malicious peers. However, this approach is inaccurate for assessing the trustworthiness of the peers.

Probability-Based Model (PBM):

This model evaluates the trustee's trustworthiness based on previous interactions and context that establishes the probabilities for future behavior [24-26**]**. Hence, the PBM model evaluates trust more accurately using statistical and probability approaches. However, this model is only focused on direct trust but not indirect trust.

Tidal Trust (TT):

This model is an enhanced Breadth-First Search (BFS) and searches the shortest path from source to a target node [19]. The trust ratings are aggregated from origin node to destination node with immediate neighbor nodes of origin to reach the target node in that path. This approach only considers the available ratings, and there is a risk of losing rates from origin to target.

MoleTrust (MT):

This model evaluates the trust of particular users [20]. It starts the walks through the network from the incoming edges trust scores are greater than the threshold value t* are considered. Further, evaluates the trust score by aggregating the path edge weights from source to destination.

Hence, all these trust models assess the trust as a single absolute trust, which is inaccurate. Further, ignored the uncertainty trust

Subjective logic (SL):

Josang proposed an uncertainty trust model known as subjective logic [34-35]. This model computes the trust opinions as probabilities using Beta distribution. The Beta distribution assesses the user's direct trust based on positive, negative, and uncertainty (either positive or negative). Further, indirect trust assessed by using discount and combine operations. This model provides accurate trust, but the uncertainty trust value is constant throughout the trust assessment. However, this model produces an inaccurate assessment of the bridge network.

Three-valued Subjective Logic (3VSL):

This model is an enhanced version of subjective logic, which divides the uncertainty further as prior and posterior. This model evaluates the trust more accurately based on the trustor perspective. In 3VSL, indirect trust assessment uses discounting and combine operations [9, 31-33]. However, in discount operator, the trust evaluation ignores the trustor's distrust of the immediate neighbor; hence, the distrust and uncertainty are not influenced by the results. Therefore, discounting operation is need improvement.

Critical analysis:

In a comparative analysis of reputation trust models, it has been observed that the major challenges in these models are:

Communicational and computational overheads involved in trust management.

Lack of handling uncertainty in trust assessment processes

In-depth statistical analysis of uncertainty models in real-time applications.
Trust parameter variations in trust models to evaluate the most appropriate situation are a highly dynamic trust management environment.

Variation in execution time is unpredictable when the depth search is performed with trust value or user's experience parameters.

Lacks in reliable quantified trust calculation with variations in trustee players

3vsl uncertainty trust model

Table 1: Symbols and notations

Representation	Type
$\boldsymbol{W_B^A}$	The Trust opinion of A on B
$\boldsymbol{b_{AB}}$	Trust opinion
$\boldsymbol{d_{AB}}$	Dis-trust opinion
$\boldsymbol{n_{AB}}$	Posterior uncertainty opinion
$\boldsymbol{e_{AB}}$	Prior uncertainty opinion
$\boldsymbol{r_{AB}}$	Positive interaction between A to B
$\boldsymbol{s_{AB}}$	Negative interaction between A to B
$\boldsymbol{o_{AB}}$	uncertainty (neither trust nor distrust) opinion between A to B

$E(W_B^A)$	Expected belief
a_{AB}	Base rate
$\otimes$	Discount operation
Ω_{ij}	indirect trust opinion
$\cup$	uncertainty opinion
w_{ij}	trust opinion between player "i" to "j."
${V^d}_i$	vector of representation of player "i" 's opinion at depth "d."
Θ	intuition operator

The interactions between the players play a vital role in virtual online games. Hence, to judge the partner whether trustworthy or not is critical. Nevertheless, most of the existing algorithms are judging partners based on certainty trust. However, in real-time applications, in some situations, it is not possible to judge whether a person is trustworthy or not. Therefore, uncertainty trust models are essential in the virtual world.

Josang proposed the uncertainty models composed of probabilistic and graph theory, SL, and 3VSL uncertainty models. These models assess the trust accurately but still need improvement.

The 3VSL trust model is composed of four states such trust, distrust, posterior and prior uncertainties. Hence, the players interacting with other players based that interactions three opinions are illustrated as positive opinion express the trustworthy, negative opinion express distrust, and uncertainty opinion as neither trust nor distrust.

Let us assume a player "Alice" interacting with player "Bob." In their interaction, Bob shares 7 pieces of information with Alice. Alice received 4 pieces of trust, 2 pieces of distrust, and 1 piece of information is neither trust nor distrust. Through this information, the direct trust between Alice and Bob is assessed.

Direct Trust Assessment

$$W_B^A = \begin{cases} b_{AB} = \dfrac{r_{AB}}{r_{AB} + s_{AB} + o_{AB} + 3} \\ d_{AB} = \dfrac{s_{AB}}{r_{AB} + s_{AB} + o_{AB} + 3} \\ n_{AB} = \dfrac{o_{AB}}{r_{AB} + s_{AB} + o_{AB} + 3} \\ e_{AB} = \dfrac{3}{r_{AB} + s_{AB} + o_{AB} + 3} \end{cases} \quad (1)$$

Here W_B^A denotes Alice's trust opinion on Bob. b_{AB}, d_{AB}, n_{AB} *and* e_{AB} are trust, distrust, posterior and prior uncertainty are computed based on the interaction opinions such as $r_{AB}, s_{AB},$ *and* o_{AB} denoted positive, negative, and posterior uncertainty. Hence, trust opinion $W_B^A =< 0.4, 0.2, 0.1, 0.3 >$ and the sum of the opinions are normalized to 1.

$$\boldsymbol{b_{AB} + d_{AB} + n_{AB} + e_{AB} = 1} \qquad (2)$$

This model's benefit is that the uncertainty opinion value changes over the period, whereas uncertain opinion is unchanged in the SL trust model.

Indirect Trust Assessment

In MMOG, Alice, Bob, and Claire are three players in the network. Alice interacts with Bob, and Bob is interacting with Alice and Claire. Now, Alice wants to interact with Claire, but Alice never interacted in the past. However, Alice is having a trusted opinion on Bob through Bob's recommendation. Alice establishes the communication with Claire. Here, Alice's interaction with Bob and Bob with Claire is referred to as direct trust, whereas Alice's interaction with Claire is indirect trust. The indirect can be assessed based on serial and parallel topology.

In serial topology, the path from source to destination is a single path with one or more intermediator nodes. Whereas in parallel topology, multiple paths existing from source to destination with one or more intermediator nodes.Hence, 3VLS discount and combine operations are used to assess the indirect trust.

Discount operation

The discount operation is used to transfer the opinion of one player to another player. Here the direct trust between Alice to Bob and Bob to Claire is denoted as $\boldsymbol{W_B^A} = <\boldsymbol{b_{AB}, d_{AB}, n_{AB}, e_{AB}}>$ and$\boldsymbol{W_C^B} = <\boldsymbol{b_{BC}, d_{BC}, n_{BC}, e_{BC}}>$. Hence, the discount operation evaluates the trust of $\boldsymbol{W_C^A}$ as follows

$$\boldsymbol{W_C^A} = \begin{cases} \boldsymbol{b_{AC} = b_{AB} b_{BC}} \\ \boldsymbol{d_{AC} = b_{AB} d_{BC}} \\ \boldsymbol{n_{AC} = 1 - b_{AC} - d_{AC} - e_{BC}} \\ \boldsymbol{e_{AC} = e_{BC}} \end{cases} \qquad (3)$$

The observation from equation 3, in $\boldsymbol{W_C^A}$ trust evaluation, only $\boldsymbol{b_{AB}, b_{BC}\ and\ d_{BC}}$ parameters are used and $\boldsymbol{d_{AB}}$ is ignored. Thus $\boldsymbol{b_{AB}}$ is fixed value and $\boldsymbol{d_{AB} and\ n_{AB}}$ satisfies the following equation

$$\boldsymbol{d_{AB} + n_{AB} = 1 - b_{AB} - e_{AB}} \qquad (4)$$

Then the changes of $\boldsymbol{d_{AB} and\ n_{AB}}$ do not influence on the trust evaluation of$\boldsymbol{W_C^A}$. However, the trust evaluation $\boldsymbol{W_B^A}$ is determined by the combination of $\boldsymbol{b_{AB}}$, $\boldsymbol{d_{AB}\ and\ n_{AB}}$. Hence the trust obtained from the Josang model is undoubtedly differs from the objective. Therefore, the discount operation has required the improvement.

Improved discount operation

The improved discount operation replaces $\boldsymbol{b_{AB}}$ with the expected belief $\boldsymbol{W_B^A}$. Thus, the efficiency is increased.

$$\boldsymbol{E(W_B^A) = b_{AB} + a_{AB} * n_{AB} + e_{AB} * 0.5} \qquad (5)$$

$$\boldsymbol{W_C^A} = \begin{cases} \boldsymbol{b_{AC} = E(W_B^A) b_{BC}} \\ \boldsymbol{d_{AC} = E(W_B^A) d_{BC}} \\ \boldsymbol{n_{AC} = 1 - (E(W_B^A)(b_{AC} + d_{AC} + e_{BC}))} \\ \boldsymbol{e_{AC} = e_{BC}} \end{cases} \qquad (6)$$

From equation 6, the source node is always treated as a high trustworthy player without knowing the trustworthiness. Hence, opinions based on the few observations and high uncertainty has a high expected value and a high base rate. Thus, in this scenario, player B's recommendation would be high despite the few observations about B's trustworthiness. Therefore, the improved discounting operation is favored with uncertainty.

Combine operation

The combined operation is useful when there are multiple paths existed from trustor to trustee, and then the opinions of each path are aggregated to produce the trust from trustor to a trustee.

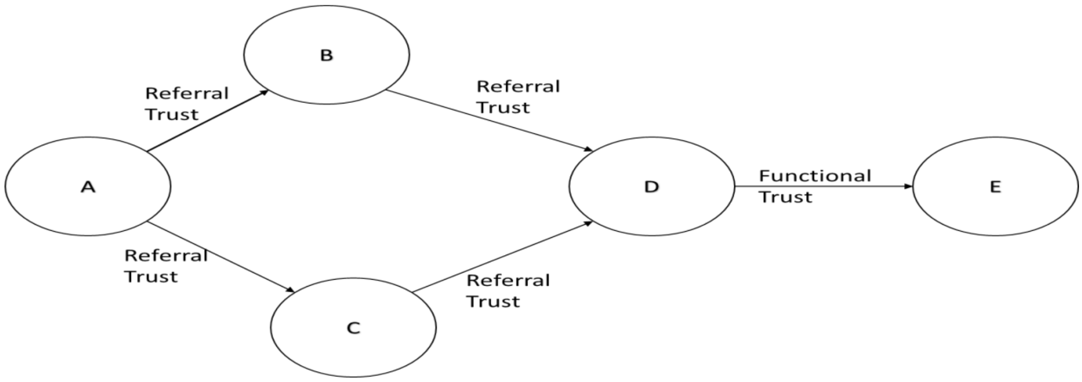


Fig.1: Trust relationships with multiple paths

From Fig.2, the trust opinion is assessed from player A to E combines the different trust opinions from different paths of the source to destination. As a result, generates the single trust opinion in equation 9.

Let us assume from Fig2, the trust opinion from path $\boldsymbol{A \rightarrow B \rightarrow D}$ is $\boldsymbol{W_{D1}^A} =< \boldsymbol{b_{AD1}, d_{AD1}, n_{AD1}, e_{AD1}} >$ and another path $\boldsymbol{A \rightarrow C \rightarrow D}$ is$\boldsymbol{W_{D2}^A} =< \boldsymbol{b_{AD2}, d_{AD2}, n_{AD2}, e_{AD2}} >$. Hence the generated trust opinion $\boldsymbol{W_D^A}$ is

$$N = e_{AD1} + e_{AD2} - e_{AD1}e_{AD2} \qquad (7)$$

$$W_D^A = \begin{cases} b_{AD} = \dfrac{e_{AD2}b_{AD1} + e_{AD1}b_{AD2}}{N} \\ d_{AD} = \dfrac{e_{AD2}d_{AD1} + e_{AD1}d_{AD2}}{N} \\ n_{AD} = \dfrac{e_{AD2}n_{AD1} + e_{AD1}n_{AD2}}{N} \\ e_{AD} = \dfrac{e_{AD1}e_{AD2}}{N} \end{cases} \tag{8}$$

$$W_E^A = W_D^A \otimes W_E^D \tag{9}$$

Hence, the trust opinion of unknown player is computed based on the recommendations of known players that generate the unknown players' trust opinion. However, the uncertain trust opinions converted into certain opinions by computing expected belief, illustrated in equation

Design of TrustWalker Algorithm

In MMOG, the trusted network is constructed as directed acyclic graph topology, which handles the non-series-parallel network topology such as bridge topology. Hence, the constructed graph $\boldsymbol{G}\ (\boldsymbol{V}, \boldsymbol{E})$. In this G, the trustor searches the trustee based on the maximum number of hops. Hence, the number of hops "d" controls the distance between a trustor and trustee. The depth "d" helps optimize the algorithms' running time without compromising the trust assessment model's accuracy. Therefore, TW algorithm designed with the 3VSL improved discount and combine operations.

In G, the direct and indirect relationships are distinguished with $\boldsymbol{\Omega}$ that denotes the indirect opinion. Here G is a large complex network that consists of one direction with trustee remaining indirect connections with the trustor. Therefore, the trust opinion is expressed as $\boldsymbol{G}\ (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{W})$, here $\forall \boldsymbol{i}\ \boldsymbol{and}\ \boldsymbol{j}$ such that $\boldsymbol{i}, \boldsymbol{j}\ \in\ \boldsymbol{V}$, and at least one path exists between "$\boldsymbol{i}$ "$\boldsymbol{to}$" $\boldsymbol{j}$" and compute the" $\boldsymbol{j}$" trust based on "$\boldsymbol{i}$" opinion as W then W calculation depicts the equation

$$\boldsymbol{\Omega_{ij}} = \begin{cases} \boldsymbol{w_{ij}} & \boldsymbol{player\ i's\ direct\ opinion\ on\ j} \\ \cup & \boldsymbol{player\ i\ not\ having\ the\ direct\ connection\ with\ j} \end{cases} \tag{\textbf{10}}$$

Where $\cup$ denotes the uncertainty opinion, such as $< \boldsymbol{0}, \boldsymbol{0}, \boldsymbol{0}, \boldsymbol{U} >$ and from equation 10. The opinion matrix $\boldsymbol{nXn}$ is constructed for 'n' players.

$$OM = \begin{bmatrix} w_{11} & w_{12} & w_{13} & \cdots & w_{1n} \\ w_{21} & w_{22} & w_{23} & \dots & w_{2n} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ w_{n1} & w_{n2} & w_{n3} & \cdots & w_{nn} \end{bmatrix} \tag{11}$$

From the OM, a particular player's trust opinions are stored in an individual opinion vector denoted as V, which consists of the trust opinions from player "i" to all the other players.

$$V^{d}{}_{i} = [\Omega_{i1}, \Omega_{i2} \dots \dots \dots \dots \Omega_{in}] \quad (12)$$

The trustor "i" is interacting with other players in the network, and their opinions are represented as $\Omega^{d}{}_{ij}$. However, the TW Algorithm follows the Breadth-First Search (BFS) in a depth-limited fashion with direct and indirect trust assessment techniques. These techniques are the same as used in 3VSL.In each iteration, the trust opinions are updated based on the number of hops traveled from the trustor to the TW Algorithms' trustee. The updated results are stored in a vector $V^{d}{}_{i}$ as stated.

$$V^{d}{}_{i} = (OM)^{T} \odot V^{(d-1)}{}_{i} \quad (13)$$

Here, 'ʘ' denotes the intuition operator, which performs the matrix multiplication. In normal matrix multiplication, results are evaluated using summation and multiplication operations; instead of these operations, 3VSL combine and discount are used. Hence, the direct trust opinion and TW algorithm is as follows

Algorithm 1: Generating Direct Trust opinions

Input: Directed Trust G, Set of nodes S

Output: direct Trust opinion between user x to y

Goal: Generating trust opinions from player x to y using direct trust relationships from G
Direct_ Trust (G, S)

initialize the opinion matrix OM and individual opinion vector V with uncertain opinions ∪
for x← $1 \; to \; n \; do$
    for y← $1 \; to \; n \; do$
        if $edge(x, y) \in E$ do
            $r_y \leftarrow 0$
            $s_y \leftarrow 0$
            $o_y \leftarrow 0$
        end if
        for z← $1 \; to \; n \; do$
            if $edge(y, z) \in E$ do
                if $z \in S$ and z is trust, then
                    $r_y \leftarrow r_y + 1$
                else
                    if $z \in S$ and z is distrust then
                        $s_y \leftarrow s_y + 1$
                    else
                        $o_y \leftarrow o_y + 1$
                    end if
                end if

20. end if
21. end for loop
22. $b_y \leftarrow \frac{r_y}{r_y+s_y+u_y+3}$
23. $d_y \leftarrow \frac{s_y}{r_y+s_y+u_y+3}$
24. $n_y \leftarrow \frac{o_y}{r_y+s_y+u_y+3}$
25. $e_y \leftarrow \frac{3}{r_y+s_y+u_y+3}$
26. $OM[x][y] \leftarrow (b_y, d_y, n_y, e_y)$
27. $V[y] \leftarrow (b_y, d_y, n_y, e_y)$
28. end for loop
29. end for loop
30. return OM

Algorithm 2 explains all the players' trustworthiness in the trusted network from the player "i" 's perspective. Line 1 initializes OM as the opinion matrix, and individual opinion vector V with uncertain opinions X. Lines 2 to 8 initializes the direct trust opinions with all other players as uncertain opinions. From lines 9 to 21, the direct trust opinions are updated based on trust, distrust, and uncertainty. Lines 22 to 25 uses the 3VSL direct trust assessment technique, and lines 26 to 27 updates the opinion matrix and individual opinion vector.

Algorithm 3: TrustWalker

Input: A directed Graph G, from user, i.e., Trustor, Trustee, Number of hops as a Depth

Output: Finding the trust opinion path from Trustor to Trustee

Goal: To find the path from source to destination based on trust opinions
TrustWalker (G, Trustor, Trustee, Depth)

1. OM=Direct_ Trust (G, S), Initialize $V^{(1)}{}_x$ based on OM
2. Initialize the hop count $d \leftarrow 1$
3. While $d < D\ do$
4. $d \leftarrow d + 1$
5. for all columns $C_y \in OM$ where $y \neq x$ do
6. $\Omega^{(d)}{}_{xy} \leftarrow \cup$
7. for all direct opinion $W_{sy} \in C_y$ where $W_{sy} \neq \cup$
8. $\Omega^{(d-1)}{}_{xs} \leftarrow V^{(d-1)}{}_x\ [s]$
9. if $\Omega^{(d-1)}{}_{xs} \neq \cup$ then
10. if $\Omega^{(d)}{}_{xs} = \cup$ then
11. $\Omega^d{}_{xy} \leftarrow \Delta(\Omega^{(d)}{}_{xs}, w_{sy})$
12. else
13. if $E(w_{xs}) \leq (b_{xs})$ then
14. $\Omega^d{}_{xy} \leftarrow \Theta(\Omega^d{}_{xy}, \Delta(\Omega^{(d-1)}{}_{xs}, w_{sy})$
15. end if

16. end if
17. end if
18. end for loop
19. $V^{d}{}_{x}\,[y] \leftarrow \Omega^{d}{}_{xy}$
20. end for loop
21. end while loop
22. return $V^{d}{}_{x}$

The pseudo-code of the TW Algorithm is shown in Algorthim3. In the algorithm, line 3 is used to limit the searching depth in the network. Lines 5-19 update the indirect trust opinions using discount and combine operations of 3VSL. Line 5 denotes the all the users in the network except the trustor node "i." Lines 6-17 perform the fusion of all the opinions derived from $W_{sy} \neq X$.Line 7 obtains the indirect trust of "i" at d-1 hop friend "s." Line 8 to 10 checks the trust opinion already exists then perform the discount operation $\Delta(\Omega^{(d)}{}_{xs}, w_{sy})$ and update the value $\Omega^{d}{}_{xy}$. Otherwise, Line 12 checks if multiple paths are available, then it filters the recommendations based expected belief. If the node's expected value is smaller, then the node is eligible for recommendation; otherwise, the transfer path is invalid. Line 13 combines the all opinion to $\Omega^{d}{}_{xy}$. Further, assigns that value to individual opinion vector at Line 18. The individual vector contains the player "i" opinion of all other trustworthiness users.

Time complexity Analysis:

In the TW algorithm, two nested loops are running between lines 5-20, and each loop runs 'n' interactions. Hence, the loop complexity is $O(n^2)$. Lines 3-21, while loop is running based on the depth, which is constant. Thus, the complexity becomes $O(dn^2)$. Here "d" is constant; hence, the complexity is $O(n^2)$

SIMULATION AND RESULTS

The trust-based partner selection in the virtual world; the experiment carried out using the Travian dataset and validate the 3VSL improved discount operation with Trustwalker algorithm.

Dataset

The Travian dataset is a browser-based real-time game with more than 5 million players [5, 36]. The game strategy is to build the villages by the residents and defend against other community persons attacks. Hence, the dataset consists the various datasets such as attacks, messages, and trades [36]. In this work, the message dataset establishes the communities based on the players' interactions.

Experiment setup

In virtual world, the players interact with other players through the exchange of messages. These messages are permitted based on the trust opinions, which are evaluated using 3VSL uncertainty trust model.

Table2: Simulation parameters

Number of players	100
Area	1000 X 1000 m^2
Transmission range	5 m
mobility model	random model
Number of interaction	1088
Number of communities	3
interactions within the community	30%
interactions outside the community	2%
community layout	spring

In MMOG, the players' trust is assessed using networkx python programming and simulation parameters listed in Table2. Based on the Table2 parameters, the trusted network is constructed. Hence, the trust relationships are converted into trust ratings using normal probability distribution with mean and standard deviation as 0.9 and 0.1. Through this, the ratings are normalized to[0,1]. Further, the trust ratings are greater than one, and then the ratings are re-assessed with modified mean and standard deviation as 0.3 and 0.0001. Hence, trust ratings are generated, converted into trust opinions using the 3VSL direct trust assessment. The generated trust opinions are depicted in Table3.

Table3: Direct Trust Opinions

S.No.	source	Target	trust	dis-trust	posterior	prior	Time
0	0	2	0.298255047	0.601744953	0	0.1	1615267105
1	0	5	0.314135952	0.585864048	0	0.1	1615267105
2	0	10	0.30001016	0.59998984	0	0.1	1615267106
3	0	14	0.306033138	0.593966862	0	0.1	1615267106
4	0	16	0.285043977	0.614956023	0	0.1	1615267106
5	0	22	0.339292613	0.560707387	0	0.1	1615267106
6	0	25	0.336015174	0.563984826	0	0.1	1615267106
7	0	32	0.2942433	0.6057566	0	0.1	16152671

			47	53			06
8	0	35	0.3245380 61	0.5754619 39	0	0.1	16152671 06
9	0	63	0.3420869 34	0.5579130 66	0	0.1	16152671 07
10	1	4	0.6551398 75	0.2448601 25	0	0.1	16152671 05
11	1	5	0.6508354 61	0.2491645 39	0	0.1	16152671 05
12	1	11	0.6346738 56	0.2653261 44	0	0.1	16152671 06
13	1	12	0.5594726 78	0.3405273 22	0	0.1	16152671 06
14	1	13	0.6170350 57	0.2829649 43	0	0.1	16152671 06
15	1	23	0.7133041 92	0.1866958 08	0	0.1	16152671 06
16	1	26	0.6770546 97	0.2229453 03	0	0.1	16152671 06
17	1	29	0.6832929 16	0.2167070 84	0	0.1	16152671 06
18	1	30	0.6510776 11	0.2489223 89	0	0.1	16152671 06
19	1	36	0.6578972 37	0.2421027 63	0	0.1	16152671 06
20	1	75	0.5798719 17	0.3201280 83	0	0.1	16152671 07

Performance Evaluation

This section explains the I-3VSL uncertainty trust model's performance analysis with TW algorithm and compares it with traditional 3VSL model. In this analysis, restricted depth search (i.e., breadth-first search to a certain level) is applied to selecting the trustor and trustee nodes. Here, a sub-graph of trustors and trustees is generated to keep in account the predecessors and successors. After that, the trustor finds the shortest path to the trustee using

TW with I-3VSL trust model.

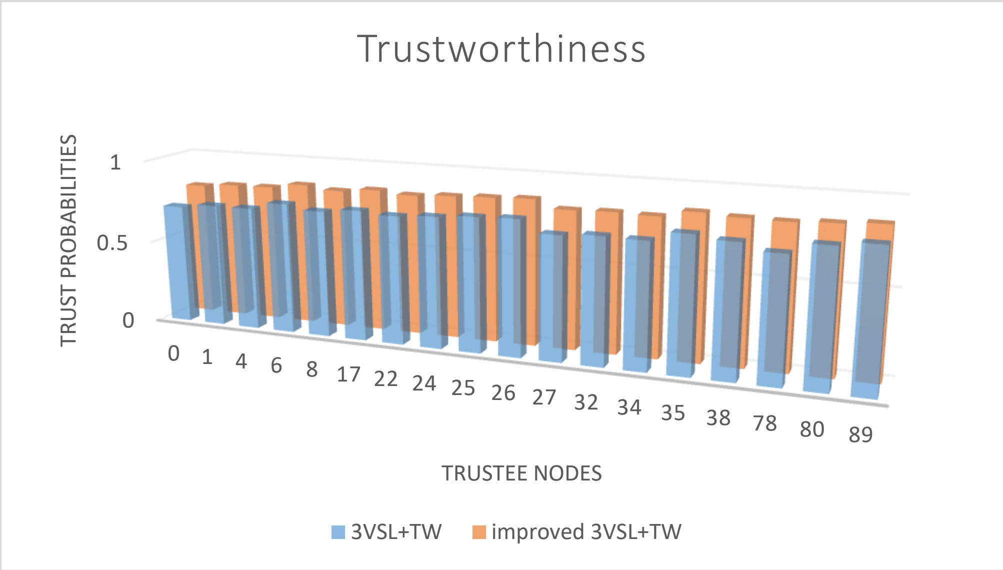


Fig.2 Trustworthiness assessment

Fig.2 shows the trustworthiness variations for different trustee nodes compared to the uncertainty trust models such as 3VSL and I-3VL. The trustor finds the shortest path to trustee using TW algorithm with depth of the search restricted to 2. Further, the trustor is selected random based as 5, then a group of trustees are generated within depth. Hence, each trustee's trust probabilities are generated and select a higher trust probability player for the interactions. The results show the 8% of growth with an I-3VSL trust assessment comparison with a 3VSL assessment.

In this work, various the performance metrics are used, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), to compute the recommendation system's error.

$$MAE = \frac{\sum_{i=1}^{n} |T_{u,v} - E_{u,v}|}{N} \qquad (14)$$

$$RMSE = \sqrt{\frac{\sum_{u.v}(T_{u,v} - E_{u,v})}{N}} \qquad (15)$$

Here $T_{u,v}\ andE_{u,v}$ represent the trustee's actual and expected trustworthiness, and N denotes the number of predictions made by the recommendations system. Further, the RMSE is normalized as a precision.

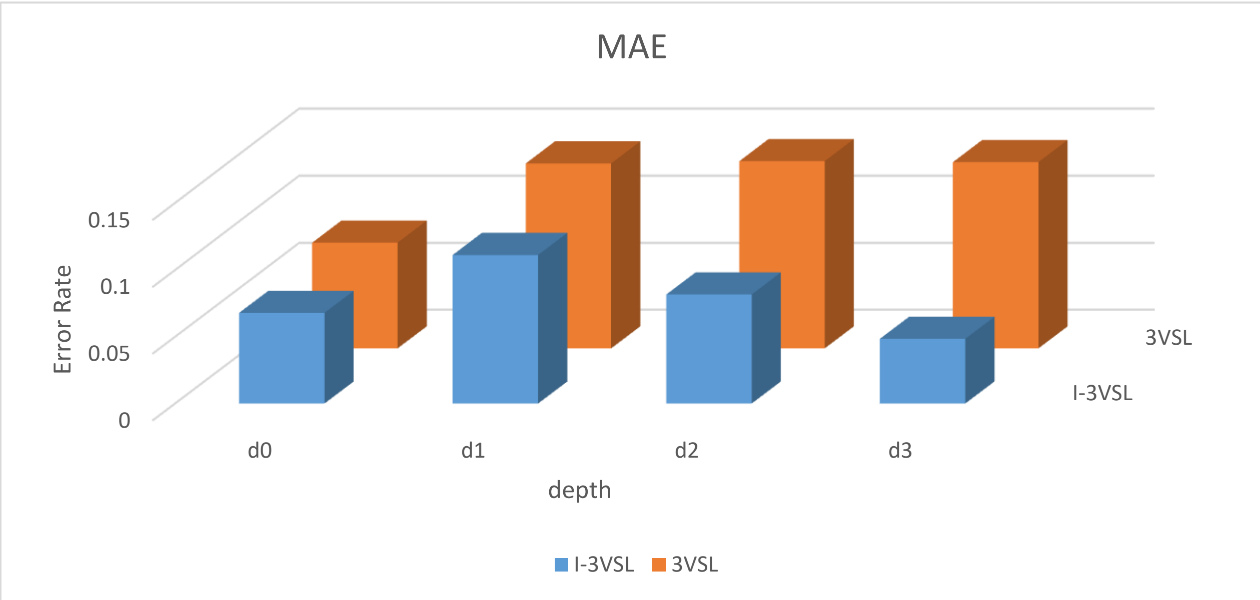
$$precision = 1 - \frac{RMSE}{RMSE_{max}} \qquad (16)$$

Based on the equation 14, 15 and 16 the MAE, RMSE, and precisions are computed with different depths using I-3VSL and 3VSL. The results are depicted in Table3.

Table 4: Comparison of different performance metrics

	I-3VSL	3VSL	I-3VSL	3VSL	I-3VSL	3VSL
Depth level	MAE	MAE	RMSE	RMSE	Accuracy	Accuracy
d0	0.067902671	0.079027	0.260581	0.281118	0.934855	0.929721
d1	0.111218653	0.13805	0.333495	0.371551	0.916626	0.907112
d2	0.081650357	0.139736	0.285745	0.373813	0.928564	0.906547
d3	0.048484363	0.139022	0.220192	0.372857	0.944952	0.906786

From Table 4, the observations are the I-3VSL uncertainty model provides the lower error rate in both MAE and RMSE at depth variations. The accuracy also increased in the levels on average of 8%. Hence, the I-3VSL provides the



better results compare to 3VSL in all the

evaluation metrics.

Fig.3 Mean Absolute Error

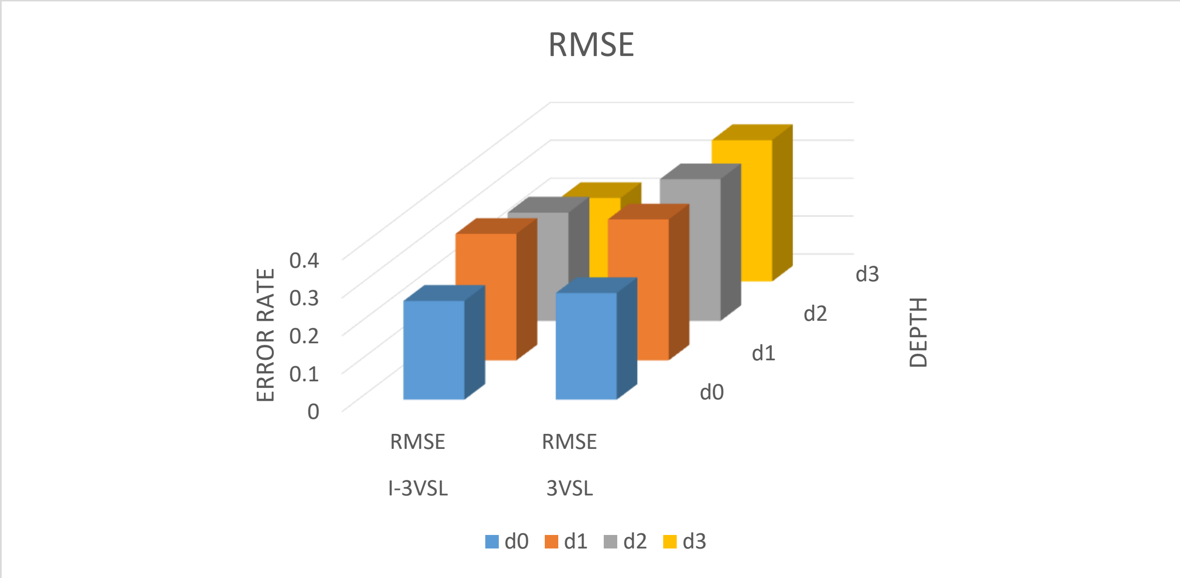


Fig.4: Root Mean Square Error

From Fig.3, the MAE Error rate optimized to 5%, and through Fig.4, the RMSE error reduced to 7.5% with the comparison of the I-3VSL and 3VSL uncertainty trust models. The accuracy evaluated and depicted in Fig.5.

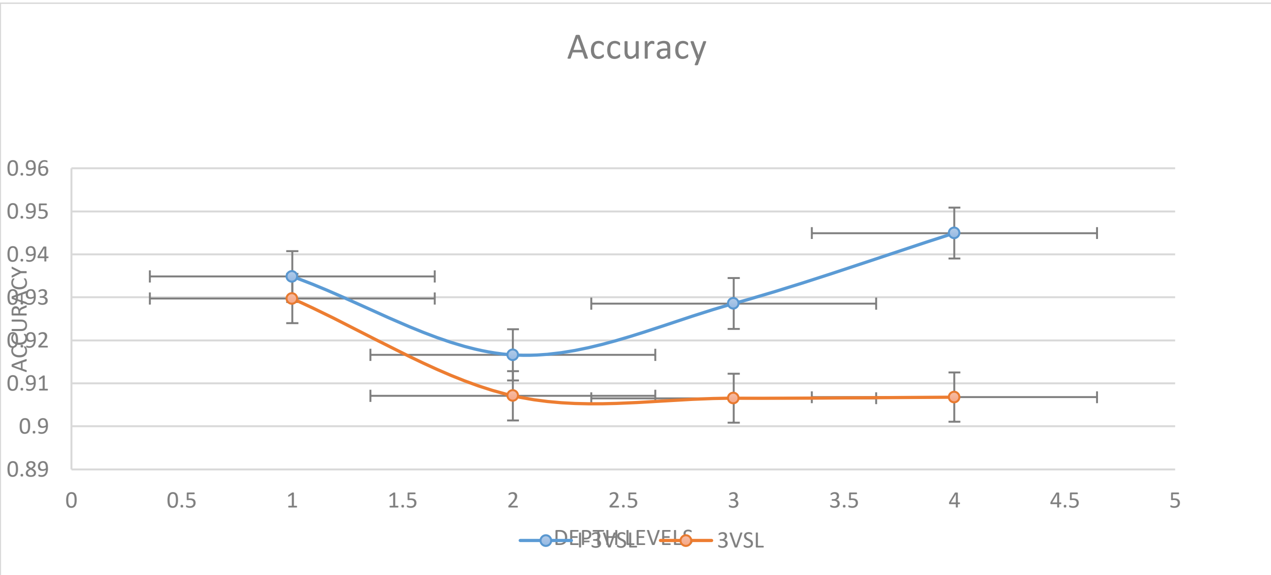


Fig.5: Accuracy at different depths

From Fig.5, at different depth levels, the accuracy plotted using I-3VSL and 3VSL models with TW algorithms. Hence, the I-3VSL provides better accuracy than 3VSL, and an 8% improvement is achieved through the I-3VSL.

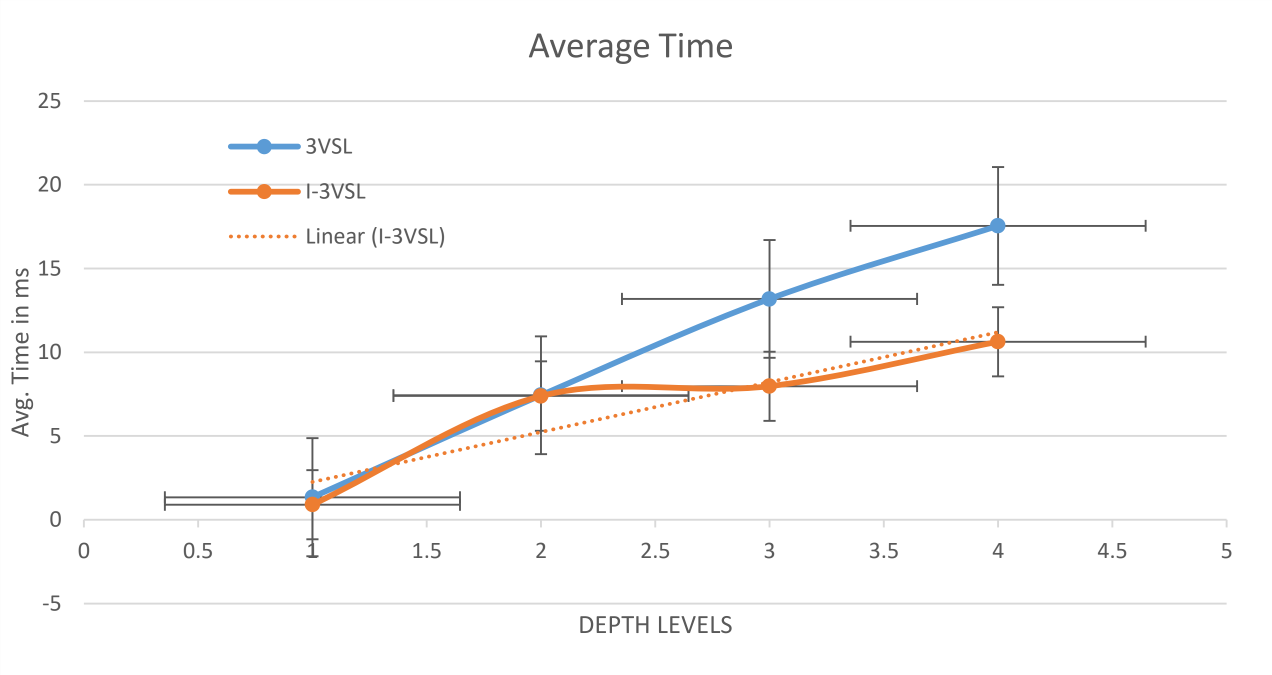


Fig.6: Computational time

From Fig.6, the 3VSL model taking a more amount of time when the depth the increasing whereas in an I- 3VSL taking a lesser amount of time compare to 3VSL, and it is gradually increasing based on the depth. Hence, based on the different evaluation metrics, the I-3VSL provides the better results in all aspects.

Conclusion And Future Work

In virtual online games such as MMOG, the trust partner selection is critical because of the various security aspects such as request contention and cheating in online games. Therefore, to assess the virtual world's trust, the I-3VSL model is proposed to manage the uncertainty and express the quantified trust. Further, the dynamic trust assessment is essential because of the players' dynamic nature; hence, the network topology changes quite often. In this work, the trustor selects the trustee randomly using TW algorithm. The TW algorithm finds the trustor's path to the trustee based on the depth restricted breadth-first search manner using 3VSL and I-3VSL trust models. Hence, the experiments are conducted using Travian dataset and validate the performance using various evaluation metrics. Thus, the results show that I-3VSL provides high performance by 8%, the error rate is optimized with MAE as 5% and RMSE as 7.5% compare to the 3VSL uncertainty model. In the future, we intended to use the metaheuristic approaches to optimize the searching complexity.

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