# A Trust-based Mechanism for Avoiding Liars in Referring of Reputation in Multiagent System

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***Abstract*—Trust is considered as the crucial factor for agents in decision making to choose the most trustworthy partner during their interaction in open distributed multiagent systems. Most current trust models are the combination of experience trust and reference trust, in which the reference trust is estimated from the judgements of agents in the community about a given partner. These models are based on the assumption that all agents are reliable when they share their judgements about a given partner to the others. However, these models are no more longer appropriate to applications of multiagent systems, where several concurrent agents may not be ready to share their private judgement about others or may share the wrong data by lying to their partners.**

**In this paper, we introduce a combination model of experience trust and experience trust with a mechanism to enable agents take into account the trustworthiness of referees when they refer their judgement about a given partner. We conduct experiments to evaluate the proposed model in the context of the e-commerce environment. Our research results suggest that it is better to take into account the trustworthiness of referees when they share their judgement about partners. The experimental results also indicate that although there are liars in the multiagent systems, combination trust computation is better than the trust computation based only on the experience trust of agents.**

***Keywords*—*Multiagent system, Trust, Reputation, Liar.***

## I. Introduction

Many software applications are open distributed systems whose components are decentralized, constantly changed, and spread throughout network. For example, peer-to-peer networks, semantic web, social network, recommender systems in e-business, autonomic and pervasive computing are among such systems. These systems may be modeled as open distributed multiagents in which autonomous agents often interact with each other according to some communication mechanisms and protocols. The problem of how agents decide with whom and when to interact has become the active research topic in the recent years. It means that they need to deal with degrees of uncertainty in making decisions during their interaction. Trust among agents is considered as one of the most important foundations based on which agents decide to interact with each other. Thus, the problem of how do agents decide to interact may reduce to the one of how do agents estimate their trust on their partners. The more trust an agent commits on a partner, the more possibility with such partner he decides to interact.

Trust has been defined in many different ways by researchers from various points of view [7], [15]. It has been being an active research topic in various areas of computer science, such as security and access control in computer networks, reliability in distributed systems, game theory and multiagent systems, and policies for decision making under uncertainty. From the computational point of view, trust is defined as a quantified belief by a truster with respect to the competence, honesty, security and dependability of a trustee within a specified context [8].

These current models utilize the combination of experience trust (confidence) and reference trust (reputation) in some way. However, most of them are based on the assumption that all agents are reliable when they share their private trust about a given partner to others. This constraint limits the application scale of these models in multiagent systems including concurrent agents, in which many agents may not be ready to share with each other about their private trust about partners or even share the wrong data by lying to their opponents.

Considering a scenario of the following e-commerce application. There are two concurrent sellers $S_1$ and $S_2$ who sell the same product $x$. An independent third party site $w$ is to collect the consumer's opinions. All clients could submit their opinions about sellers. In this case, the site $w$ could be considered as a reputation channel for clients. It means that a client could refer the given opinions on the site $w$ to select the best seller. However, since the site $w$ is a public reputation and all clients could submit their opinions. Imagining that $S_1$ is really trustworthy, but $S_2$ is not fair, some of its employments intentionally submit some negative opinions about the seller $S_1$ in order to attract more clients to them. In this case, how a client could trust on the reputation given by the site $w$? These proposed models of trust may not be applicable to such a situation.

In order to get over this limitation, our work proposes a novel computational model of trust that is a weighted combination of experience trust and reference trust. This model offers a mechanism to enable agents take into account the trustworthiness of referees when they refer the the judgement about a given partner from these referees. The model is evaluated experimentally on two issues in the context of the e-commerce environment: (i) It is whether necessary to take into account the trust of referees (in sharing their private trust about partners) or not; (ii) Combination of experience trust and reputation is more useful than the trust based only on the experience trust of agents in multiagent systems with liars.

The rest of paper is organized as follows. Section II presents some related works in literature. Section III describes the model of weighted combination trust of experience trust, reference trust with and without lying referees. Section IV describes the experimental evaluation of the model. Section V is offered to some discussion. Section VI is the conclusion and the future works.

## II. Related Works

By basing on the contribution factors of each model, we try to divide the proposed models into three groups. Firstly, The models are based on *personal experiences* that a truster has on some trustee after their transactions performed in the past. For instance, Manchala [19] and Nefti et al. [20] proposed models for the trust measure in e-commerce based on fuzzy computation with parameters such as cost of a transaction, transaction history, customer loyalty, indemnity and spending patterns. The probability theory-based model of Schillo et al. [28] is intended for scenarios where the result of an interaction between two agents is a boolean impression such as good or bad but without degrees of satisfaction. Shibata et al. [30] used a mechanism for determining the confidence level based on agent's experience with Sugarscape model, which is artificially intelligent agent-based social simulation. Alam et al. [1] calculated trust based on the relationship of stake holders with objects in security management. Li and Gui [18] proposed a reputation model based on human cognitive psychology and the concept of direct trust tree (DTT).

Secondly, the models combine both personal experience and reference trusts. In the trust model proposed by Esfandiari and Chandrasekharan [4], two one-on-one trust acquisition mechanisms are proposed. In Sen and Sajja's [29] reputation model, both types of direct experiences are considered: direct interaction and observed interaction. The main idea behind the reputation model presented by Carter et al. [3] is that "the reputation of an agent is based on the degree of fulfillment of roles ascribed to it by the society". Sabater and Sierra [26], [27] introduced ReGreT, a modular trust and reputation system oriented to complex small/mid-size e-commerce environments where social relations among individuals play an important role. In the model proposed by Singh and colleagues [36], [37] the information stored by an agent about direct interactions is a set of values that reflect the quality of these interactions. Ramchurn et al. [24] developed a trust model, based on confidence and reputation, and show how it can be concretely applied, using fuzzy sets, to guide agents in evaluating past interactions and in establishing new contracts with one another. Jennings et collegues [12], [13], [25] presented FIRE, a trust and reputation model that integrates a number of information sources to produce a comprehensive assessment of an agent's likely performance in open systems. Nguyen and Tran [22], [23] introduced a computational model of trust, which is also combination of experience and reference trust by using fuzzy computational techniques and weighted aggregation operators. Victor et al. [33] advocate the use of a trust model in which trust scores are (trust, distrust)-couples, drawn from a bilattice that preserves valuable trust provenance information including gradual trust, distrust, ignorance, and inconsistency. Katz and Golbeck [16] introduces a definition of trust suitable for use in Web-based social networks with a discussion of the properties that will influence its use in computation. Hang et al. [10] describes a new algebraic approach, shows some theoretical properties of it, and empirically evaluates it on two social network datasets. Guha et al. [9] develop a framework of trust propagation schemes, each of which may be appropriate in certain circumstances, and evaluate the schemes on a large trust network. Vogiatzis et al. [34] propose a probabilistic framework that models agent interactions as a Hidden Markov Model. Burnett et al. [2] describes a new approach, inspired by theories of human organisational behaviour, whereby agents generalise their experiences with known partners as stereotypes and apply these when evaluating new and unknown partners. Hermoso et al. [11] present a coordination artifact which can be used by agents in an open multi-agent system to take more informed decisions regarding partner selection, and thus to improve their individual utilities.

Thirdly, the models also compute trust by means of combination of the experience and reputation, but consider unfair agents in sharing their trust in the system as well. For instances, Whitby et al. [35] described a statistical filtering technique for excluding unfair ratings based on the idea that unfair ratings have some statistical pattern being different from fair ratings. Teacy et al. [31], [32] developed TRAVOS (Trust and Reputation model for Agent-based Virtual OrganisationS) which models an agent's trust in an interaction partner, using probability theory taking account of past interactions between agents, and the reputation information gathered from third parties. And HABIT, a Hierarchical And Bayesian Inferred Trust model for assessing how much an agent should trust its peers based on direct and third party information. Zhang, Robin and collegues [39], [14], [5], [6] proposed an approach for handling unfair ratings in an enhanced centralized reputation system.

The models in the third group are closed to our model. However, most of them used Bayes network and statistical method to detect the unfairs in the system. This approach may result in difficulty when the number of unfair agents become major.

This paper is a continuation of our previous work [21] in order to update our approach and perform experimental evaluation of this model.

## III. Computational Model of Trust

Let $A = \{1, 2, ...n\}$ be a set of agents in the system. Assume that agent $i$ is considering the trust about agent $j$. We call $j$ is a *partner* of agent $i$. This consideration includes: (i) the direct trust betwwen agent $i$ and agent $j$, called *experiment trust* $E_{ij}$; and (ii) the trust about $j$ refered from community called *reference trust (or reputation)* $R_{ij}$. Each agent $l$ in the community that agent $i$ refers for the trust of partner $j$ is called a *referee*. This model enables agent $i$ to take into account the trustworthiness of referee $l$ when agent $l$ shares its private trust (judgement) about agent $j$. The trustworthiness of agent $l$ on the point of view of agent $i$, in sharing its private trust about partners, is called a *referee trust* $S_{il}$. We also denote $T_{ij}$ to be the overall trust that agent $i$ obtains on agent $j$. The following sections will describe a computational model to estimate the values of $E_{ij}$, $S_{il}$, $R_{ij}$ and $T_{ij}$.

TABLE I: Summary of recent proposed models regarding the fact of avoiding liar in calulation of reputation

| Models | Experience Trust | Reputation | Liar Judger |
|---|---|---|---|
| Alam et al. [1] | ✓ | | |
| Burnett et al. [2] | ✓ | ✓ | |
| Esfandiari and Chandrasekharan [4] | ✓ | ✓ | |
| Guha et al. [9] | ✓ | ✓ | |
| Hang et al. [10] | ✓ | ✓ | |
| Hermoso et al. [11] | ✓ | ✓ | |
| Jennings et al. [12], [13] | ✓ | ✓ | |
| Katz and Golbeck [16] | ✓ | ✓ | |
| Lashkari et al.[17] | ✓ | ✓ | |
| Li and Gui [18] | | ✓ | |
| Manchala [19] | ✓ | | |
| Nefti et al. [20] | ✓ | | |
| Nguyen and Tran [22], [23] | ✓ | ✓ | |
| Ramchurn et al. [24] | ✓ | ✓ | |
| Sabater and Sierra [26], [27] | ✓ | ✓ | |
| Schillo et al. [28] | ✓ | | |
| Sen and Sajja's [29] | ✓ | ✓ | |
| Shibata et al. [30] | ✓ | | |
| Singh and colleagues [36], [37] | ✓ | ✓ | |
| Teacy et al. [31], [32] | ✓ | ✓ | ✓ |
| Victor et al. [33] | ✓ | ✓ | |
| Vogiatzis et al. [34] | ✓ | ✓ | |
| Whitby et al. [35] | ✓ | ✓ | ✓ |
| Zhang, Robin and collegues [39], [14], [5], [6] | ✓ | ✓ | ✓ |
| Our model | ✓ | ✓ | ✓ |

### A. Experience trust

Intuitively, experience trust of agent $i$ in agent $j$ is the trustworthiness of $j$ that agent $i$ collects from all transactions between $i$ and $j$ in the past.

Experience trust of agent $i$ in agent $j$ is defined by the formula:

$$E_{ij} = \sum_{k=1}^{n} t_{ij}^{k} * w_k \tag{1}$$

where:

- $t_{ij}^{k}$ is the transaction trust of agent $i$ in its partner $j$ at the $k^{th}$ latest transaction.
- $w_k$ is the weight of the $k^{th}$ latest transaction such that
$$\begin{cases} w_{k_1} \geqslant w_{k_2} \text{ if } k_1 < k_2 \\ \sum_{k=1}^{n} w_k = 1 \end{cases}$$
- $n$ is the number of transactions taken between agent $i$ and agent $j$ in the past.

The weight vector $\overrightarrow{w} = \{w_1, w_2, ..w_n\}$ is decreasing from head to tail because the aggregation focuses more on the later transactions and less on the older transactions. It means that the later the transaction is, the more its trust is important to estimate the experience trust of the correspondent partner. This vector may be computed by means of Regular Decreasing Monotone (RDM) linguistic quantifier $Q$ (Zadeh [38]).

### B. Trust of referees

Suppose that an agent can refer all agents he knows (referee agents) in the system about their experience trust (private judgement) on a given partner. This is called *reference trust* (this will be defined in the next section). However, some referee agents may be liar. In order to avoid the case of lying referee, this model proposes a mechanism which enables an agent to evaluate its referees on sharing their private trust about partners.

Let $X_{il} \subseteq A$ be a set of partners that agent $i$ refers their trust via referee $l$, and that agent $i$ has already at least one transaction with each of them. Since the model supposes that agent always trusts in itself, the trust of referee $l$ from the point of view of agent $i$ is determined based on the difference between experience trust $E_{ij}$ and the trust $r_{ij}^{l}$ of agent $i$ about partner $j$ referred via referee $l$ (for all $j \in X_{il}$).

Trust of referee (sharing trust) $S_{il}$ of agent $i$ on the referee $l$ is defined by the formula:

$$S_{il} = \frac{1}{\mid X_{il} \mid} * \sum_{j \in X_{il}} h(E_{ij}, r_{ij}^{l}) \tag{2}$$

where:

- $h$ is a *referee-trust-function* $h : [0, 1] \times [0, 1] \rightarrow [0, 1]$, which satisfies the following conditions:
$$h(e_1, r_1) \leqslant h(e_2, r_2) \text{ if } \mid e_1 - r_1 \mid \geqslant \mid e_2 - r_2 \mid .$$
These constraints are based on the following intuitions:
  - The more the difference between $E_{ij}$ and $r_{ij}^{l}$ is large, the less agent $i$ trust on the referee $l$, and conversely;
  - The more the difference between $E_{ij}$ and $r_{ij}^{l}$ is small, the more agent $i$ trusts on the referee $l$.
- $E_{ij}$ is the experience trust of $i$ on $j$
- $r_{ij}^{l}$ is the reference trust of agent $i$ on partner $j$ that is referred via referee $l$:

$$r_{ij}^{l} = E_{lj} \tag{3}$$

### C. Reference trust

Reference trust (also called reputation trust) of agent $i$ on partner $j$ is the trustworthiness of agent $j$ given by other referees in the system. In order to take into account the trust of referee, the reference trust $R_{ij}$ is a combination between the single reference trust $r_{ij}^l$ and the trust of referee $S_{il}$ of referee $l$.

Reference trust $R_{ij}$ of agent $i$ on agent $j$ is a non-weighted average:

$$R_{ij} = \begin{cases} \dfrac{\sum\limits_{l \in X_{ij}} g(S_{il}, r_{ij}^l)}{\mid X_{ij} \mid} & \text{if } X_{ij} \neq \varnothing \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

where:

- $g$ is a *reference-function* $g : [0,1] \times [0,1] \rightarrow [0,1]$, which satisfies the following conditions:

$$\begin{array}{ll} (i) & g(x_1, y) \leqslant g(x_2, y) \text{ if } x_1 \leqslant x_2 \\ (ii) & g(x, y_1) \leqslant g(x, y_2) \text{ if } y_1 \leqslant y_2 \end{array}$$

  These constraints are based on the intuitions:
  - The more the trust of referee $l$ is high in the point of view of agent $i$, the more the reference trust $R_{ij}$ is high;
  - The more the single reference trust $r_{ij}^l$ is high, the more the final reference trust $R_{ij}$ is high
- $S_{il}$ is the trust of $i$ on the referee $l$
- $r_{ij}^l$ is the single reference trust of agent $i$ about partner $j$ referred via referee $l$

### D. Overall trust

Overall trust $T_{ij}$ of agent $i$ in agent $j$ is defined by the formula:

$$T_{ij} = t(E_{ij}, R_{ij}) \qquad (5)$$

where:

- $t$ is a *overall-trust-function*, $t : [0,1] \times [0,1] \rightarrow [0,1]$, which satisfies the following conditions:

$$\begin{array}{ll} (i) & min(e, r) \leqslant t(e, r) \leqslant max(e, r); \\ (ii) & t(e_1, r) \leqslant t(e_2, r) \text{ if } e_1 \leqslant e_2; \\ (iii) & t(e, r_1) \leqslant t(e, r_2) \text{ if } r_1 \leqslant r_2. \end{array}$$

  This combination satisfies these intuitions:
  - It must neither lower than the minimal and nor higher the maximal of experience trust and reference trust;
  - The more the experience trust is high, the more the *overall trust* is high;
  - The more the reference trust is high, the more the *overall trust* is high.
- $E_{ij}$ is the experience trust of agent $i$ about partner $j$.
- $R_{ij}$ is the reference trust of agent $i$ about partner $j$.

### E. Updating trust

Agent $i$'s trust in agent $j$ can be changed in the whole its life-time whenever there is at least one of these conditions occurs (as showed in Algorithm 1, line 2):

- There is a new transaction between $i$ and $j$ occurring (line 3), so the experience trust of $i$ on $j$ changed.
- There is a referee $l$ who shares to $i$ his new experience trust about partner $j$ (line 10). Thus the reference trust of $i$ on $j$ is updated.

1: **for all** agent $i$ in the system **do**
2:   **if** (there is a new transaction $k-$th with agent $j$) or (there is a new reference trust $E_{lj}$ from agent $l$ about agent $j$) **then**
3:     **if** there is a new transaction $k$ with agent $j$ **then**
4:       $t_{ij}^k \leftarrow$ a value in interval [0,1]
5:       $t_{ij} \leftarrow t_{ij} \cup t_{ij}^k$
6:       $t_{ij} \leftarrow Sort(t_{ij})$
7:       $w \leftarrow GenerateW(k)$
8:       $E_{ij} \leftarrow \sum_{h=1}^{k} t_{ij}^h * w_h$
9:     **end if**
10:     **if** there is a new reference trust $E_{lj}$ from agent $l$ about agent $j$ **then**
11:       $r_{ij}^l \leftarrow E_{lj}$
12:       $X_{il} \leftarrow X_{il} \cup \{j\}$
13:       $S_{il} \leftarrow \frac{1}{\mid X_{il} \mid} * \sum_{j \in X_{il}} h(E_{ij}, r_{ij}^l)$
14:       $R_{ij} \leftarrow \frac{\sum_{l \in X_{ij}} g(S_{il}, r_{ij}^l)}{\mid X_{ij} \mid}$
15:     **end if**
16:     $T_{ij} \leftarrow t(E_{ij}, R_{ij})$
17:   **end if**
18: **end for**

**Algorithm 1:** Trust Updating Algorithm

$E_{ij}$ is updated after the occur of each new transaction between $i$ and $j$ as follows (lines 3 - 9):

- The new transaction's trust value $t_{ij}^k$ is placed at the first position of vector $t_{ij}$ (lines 4 - 6). Function $Sort(t_{ij})$ sorts the vector $t_{ij}$ in ordered in time.
- Vector $w$ is also generated again (line 7) in function $GenerateW(k)$.
- $E_{ij}$ is updated by applying formulas 1 with the new vector $t_{ij}$ and $w$ (line 8).

Once $E_{ij}$ is updated, agent $i$ sends $E_{ij}$ to its friend agents. Therefore, all $i$'s friends will update their reference trust when they receive $E_{ij}$ from $i$. We suppose that all friend relations in system are bilateral, this means that if agent $i$ is a friend of agent $j$ then $j$ is also a friend of $i$. After having received $E_{lj}$ from agent $l$, agent $i$ then updates her/his reference trust $R_{ij}$ on $j$ as follows (lines 10 - 15):

- In order to update the individual reference trust $r_{ij}^l$, the value of $E_{lj}$ is placed at the position of the old one (line 11).

- Agent $j$ will be also added into $X_{il}$ to recalculate the referee trust $S_{il}$ and recalculate the reference trust $R_{ij}$ (lines 12 - 14).

Finally, $T_{ij}$ is updated by applying the formulas 5 from new $E_{ij}$ and $R_{ij}$ (line 16).

## IV. Experimental Evaluation

This section presents the evaluation of the proposed model by taking emperimental data. Section IV-A presents the setting up our experiment application. Section IV-B evaluates the need of avoiding liars in refering of reputation. Section IV-C evaluates the need of combination of experience trust and reputation even if there are liars in refering reputation.

### A. Experiment Setup

*1) An E-market:* *An e-market system is composed of a set of seller agents, a set of buyer agents, and a set of transactions. Each transaction is performed by a buyer agent and a seller agent. A seller agent plays the role of a seller who owns a set of products and it could sell many products to many buyer agents. A buyer agent plays the role of a buyer who could buy many products from many seller agents.*

- Each seller agent has a set of products to sell. Each product has a quality value in the interval $[0, 1]$. The quality of product will be assigned as the transaction trust of the transaction in which the product is sold.
- Each buyer agent has a transaction history for each of its sellers to calculate the experience trust for the corresponding seller. It has also a set of reference trusts referred from its friends. The buyer agent will update its trust on its sellers once it finishes a transaction or receives a reference trust from one of its friends. The buyer chooses the seller with the highest final trust when it want to buy a new product. The calculation to estimate the highest final trust of sellers is based on the proposed model in this paper.

*2) Objectives:* The purpose of these experiments is to answer two following questions:

- First, is it better if buyer agent judges the sharing trust of its referees than does not judge it? In order to answer to this question, the proposed model will be compared with the model of Jennings et al.'s model [12], [13] (Section IV-B).
- Second, what is better if buyer agent uses only its experience trust in stead of combination of experience and reference trust? In order to answer this question,the proposed model will be compared with the model of Manchala's model [19] (Section IV-C).

*3) Initial Parameters:* In order to make the results comparable, and in order to avoid the effect of random aspect in value initiation of simulation parameters, the same values for input parameters of all simulation scenarios will be used: number of sellers; number of products; number of simulations. These values are presented in the Table.II.

TABLE II: Value of parameters in simulations

| Parameters | Values |
|---|---|
| Number of runs for each scenario | 100 (times) |
| Number of sellers | 100 |
| Number of buyers | 500 |
| Number of products | 500000 |
| Average number of bought products/buyer | 100 |
| Average number of friends/buyer | 300 (60% of buyers) |

*4) Analysis and evaluation criteria:* Each simulation scenario will be ran at least 100 times. At the output, the following parameter will be calculated:

- The average quality (in %) of brought products for all buyers. A model (strategy) is considered better if it brings the higher average quality of brought products for all buyers in the system.

### B. The need of avoiding liar in reputation

*1) Scenarios:* The question need to be answerd is: is it better if buyer agent uses reputation with trust of referees (agent judges the sharing trust of its referees) or uses reputation without trust of referees (agent does not judge the sharing trust of its referees)? In order to answer this question, there are two strategies will be simulated:

- *Strategy A - using proposed model*: Buyer agent refers the reference trust (about sellers) from other buyers *with* taking into account the trust of referee.
- *Strategy B - using model of Jennings et al. [12], [13]*: Buyer agent refers the reference trust (about sellers) from other buyers *without* taking into account the trust of referee.

The simulations are launched in various values of the percentage of lying buyers in the system (0%, 30%, 50%, 80%, and 100%).

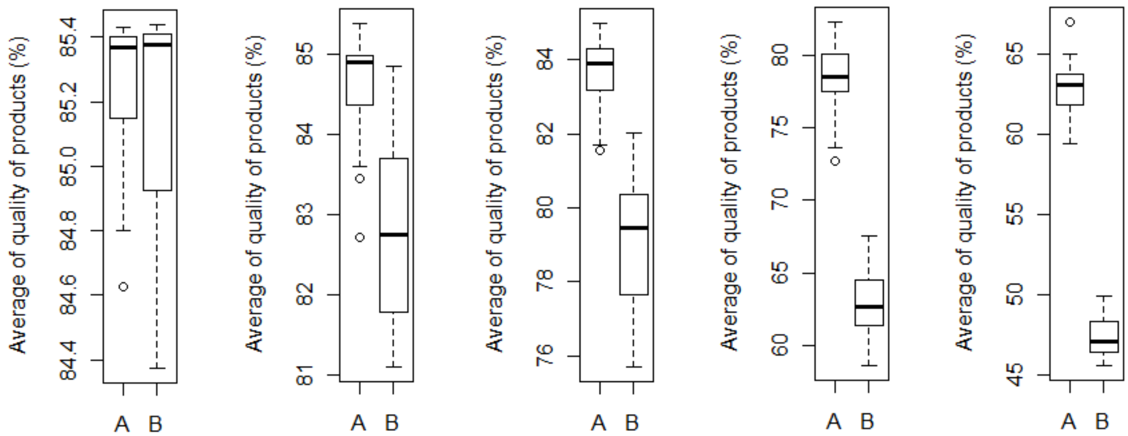
*2) Results:* The results indicate that the average quality of bought products of all buyers in the case of using reputation with considering of trust of referees is always significantly higher than those in the case using reputation without considering of trust of referees.

When there is no lying buyer (Fig.1.a). The average quality of bought products for all buyers in the case using strategy A is not significantly different from that in the case using strategy B ($M(A) = 85.24\%$, $M(B) = 85.20\%$, significant difference with $p\text{-}value > 0.7$)[1].

When there is 30% of buyers is liar (Fig.1.b). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy B ($M(A) = 84.64\%$, $M(B) = 82.76\%$, significant difference with $p\text{-}value < 0.001$).

When there is 50% of buyers is liar (Fig.1.c). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy

[1] We use the *t-test* to test the difference between two sets of average quality of bought products of two scenarios, therefore if the probability value $p\text{-}value < 0.05$ we could conclude that the two sets are *significantly different*.




(a) 0% liars (b) 30% liars (c) 50% liars (d) 80% liars (e) 100% liars

Fig. 1: Significant difference of average quality of bought products of all buyers from the case using proposed model (strategy A) and the case using Jennings et al.'s model (strategy B)

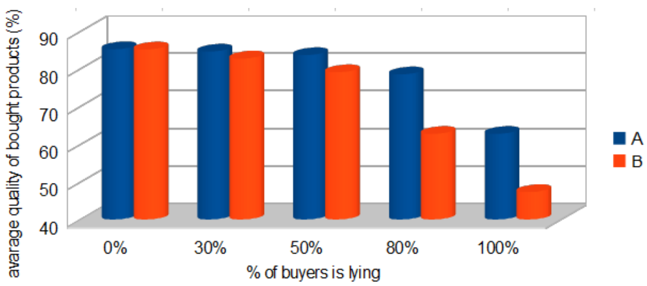



Fig. 2: Summary of difference of average quality of bought products of all buyers between the case using our model (A) and the case using Jennings et al.'s model (B)

B ($M(A) = 83.68\%$, $M(B) = 79.11\%$, significant difference with $p\text{-}value < 0.001$).

When there is 80% of buyers is liar (Fig.1.d). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy B ($M(A) = 78.55\%$, $M(B) = 62.76\%$, significant difference with $p\text{-}value < 0.001$).

When all buyers are liar (Fig.1.e). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy B ($M(A) = 62.78\%$, $M(B) = 47.31\%$, significant difference with $p\text{-}value < 0.001$).

In summary, as being depicted in the Fig.2, the more the percentage of liar in buyers is high, the more the average quality of bought products of all buyers in the case using our model (strategy A) is significantly higher than those in the case using Jennings et al.'s model [12], [13] (strategy B).

### *C. The need of combination of experience with reputation*

*1) Scenarios:* The results of the first evaluation suggest that using reputation with considering of trust of referees is better than using reputation without considering of trust of referees, especially in the case there are some liars in sharing their private trust about partners to others. And in turn, another question arises: in the case there are some liars in sharing data to their friends, is it better if buyer agent use reputation with considering of trust of referees or use only experience trust to avoid liar reputation? In order to answer this question, there are two strategies also simulated:

- *Strategy A - using proposed model*: Buyer agent refers the reference trust (reputation) from other buyers by taking into account their considering of trust of referees.
- *Strategy C - using Manchala's model [19]*: Buyer agent does not refer any reference trust from other buyers. It bases only on its experience trust.

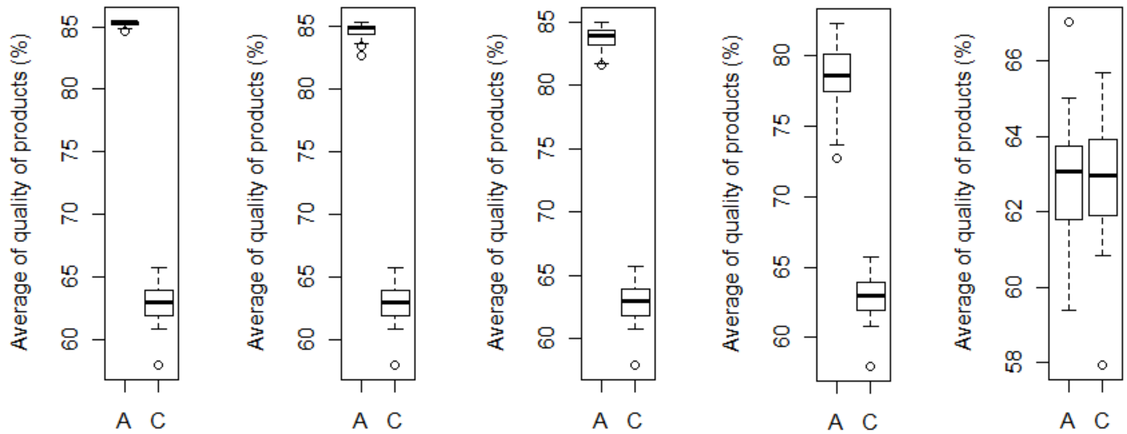
The simulations are also launched in various values of the percentage of lying buyers in the system (0%, 30%, 50%, 80%, and 100%).

*2) Results:* The results indicate that the average quality of bought products of all buyers in the case with considering of trust of referees is almost significantly higher than those in the case using only the experience trust.

When there is no lying buyer (Fig.3.a). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy C ($M(A) = 85.24\%$, $M(C) = 62.75\%$, significant difference with $p\text{-}value < 0.001$).

When there is 30% of buyers is liar (Fig.3.b). The average quality of bought products for all buyers in the case using strategy A is significantly higher than the in case using strategy C ($M(A) = 84.64\%$, $M(C) = 62.74\%$, significant difference with $p\text{-}value < 0.001$).

When there is 50% of buyers is liar (Fig.3.c). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using C ($M(A) = 83.68\%$, $M(C) = 62.76\%$, significant difference with $p\text{-}value < 0.001$).




(a) 0% liars (b) 30% liars (c) 50% liars (d) 80% liars (e) 100% liars

Fig. 3: Significant difference of average quality of bought products of all buyers between the case using proposed model (strategy A) and the case using Manchala's model (strategy C)

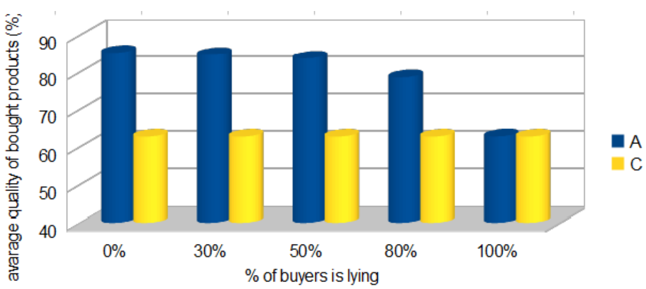



Fig. 4: Summary of difference of average quality of bought products of all buyers between the case using our model (A), and the case using Manchala's model (C)

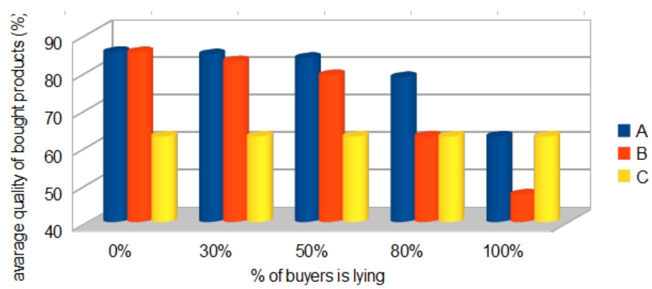



Fig. 5: Summary of difference of average quality of bought products of all buyers among the case using our model (A), the case using Jennings et al.'s model (B), and the case using Manchala's model (C)

When there is $80\%$ of buyers is liar (Fig.3.d). The average quality of bought products for all buyers in the case using strategy A is significantly higher than in the case using strategy C ($M(A) = 78.55\%$, $M(C) = 62.78\%$, significant difference with $p\text{-}value < 0.001$).

When all buyers are liar (Fig.3.e). There is no significant difference between the case using strategy A and the case using strategy C ($M(A) = 62.78\%, M(C) = 62.75\%$, significant difference with $p\text{-}value > 0.6$). It is intuitive because in our model (strategy A), when almost referees are not trustworthy, the trustor tends to trust in himself instead of other. In other word, the trustor has the tendency to base on its won experience rather than others.

The overall result is depicted in the Fig.4. In almost cases, the average quality of bought products of all buyers in the case of using our model is always significantly higher than those in the case of using Manchala's model [19]. In the case that all buyers are liar, there is no significant difference of the average quality of bought products from all buyers between two strategies.

In summary, Fig.5 illustrates the value of average quality of bought products of all buyers in three scenarios. In the case there is no lying buyer, this value is the highest in the case using our model and Jennings et al.'s model [12], [13] (there is no significant difference between two mosels in this situation). Using Manchala's model [19] is the worst case in this situation. In the case there are $30\%$, $50\%$ and $80\%$ buyers to be lying, the value is always highest in the case of using our model. In the case that all buyers are liar, there is no significant difference between agents using our model and agents using Manchala's model [19]. Both of these two strategies win a much more higher value compared with the case using Jennings et al.'s model [12], [13].

## V. Discussion

Let us consider a scenario of an e-commerce application. There are two concurrent sellers $S_1$ and $S_2$ who sell the same product $x$, there is an independent third party site $w$ which collects the consumer's opinions. All clients could submit its opinions about sellers. In this case, the site $w$ could be considered as a reputation channel for client: a client could refer the given opinions on the site $w$ to choose the best seller. However, because the site $w$ is a public reputation: all clients could submit their opinions. Imagining that $S_1$ is really trustworthy, but $S_2$ is not fair, some of its employments intentionally submit some negative opinions about the seller $S_1$ in order to attract more clients from $S_1$ to $S_2$.

Let consider this application in two cases. Firstly, the case without mechanism to avoid liars in the applied trust model. If an user $i$ is considering to buy a product $x$ that both $S_1$ and $S_2$ are selling. User $i$ refers the reputation of $S_1$ and $S_2$ on the site $w$. Since there is not any mechanism to avoid liars in the trust model, the more negative opinions from $S_2$'s employments are given about $S_1$, the lower the reputation of $S_1$ is. Therefore, the lower the possibility that user $i$ chooses buying the product $x$ from $S_1$.

Secondly, the case of our proposed model with lying against mechanism. User $i$ will refer the reputation of $S_1$ and $S_2$ on the site $w$ with considering the sharing trust of the owner of each opinion. Therefore, the ones from $S_2$ who gave negative opinions about $S_1$ will be detected as liars. Their opinion weights thus will be decreased (considered as unimportant ones) when calculating the reputation of $S_1$. Consequently, the reputation of $S_1$ will stay high no matter how many people from $S_2$ intentionally lie about $S_2$. In other word, our model helps agent to avoid some liars in calculating the reputation of a given partner in multiagent systems.

## VI. Conclusion

This paper presented a model of trust which enables agents to calculate, estimate and update trust's degree on their partners based not only on their own experiences, but also based on the reputation of partners. The partner reputation is estimated from the judgements from referees in the community. In which, the model taken into account the trustworthiness of the referee in judging a partner.

The experimental evaluation of the model has been set up for multiagent system in the e-commerce environment. The research results indicate, firstly, that it is better to take into account the trust of referees to estimate the reputation of partners. Seconly, it is better to combine the experience trust and the reputation than using only the experience trust in estimating the trust of a partner in the multiagent system.

Constructing and selecting a strategy, which is appropriate to the context of some application of a multiagent system, need to be investigated furthermore. These research issues will be presented in our future work.

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