A Strategy-proof Trust Mechanism for Pervasive Computing Environments

Zhiqiang Wei,Wei Zhou,Mijun Kang
College of Information Science and Engineering
Ocean University of China
Qingdao, Shandong, China
Email: weizhiqiang@ouc.edu.cn,{weizhou.ouc,kangmijun}@gmail.com

Michael Collins,Paddy Nixon
Department of Computer Science
University College Dublin
UCD Belfield, Dublin 4, Ireland
Email: {michael.collins,paddy.nixon}@ucd.ie

***Abstract*—As pervasive applications become prevalent in our day-to-day lives, the interactions of service provision and consumption between unknown and strange users are commonplace. Trust and reputation systems play a vital role in such application scenarios. One of the problems is that selfish users are reluctant to render the truthful recommendation without incentive. Even if there are incentives, self-interested users may maximise their profit by falsely declaring their opinions strategically. In this paper, we propose a strategy-proof trust mechanism which is a VCG (Vickrey-Clarke-Groves) mechanism for honest recommendation elicitation. The characteristics of the mechanism, such as the characteristics of social choice function and the properties of the payments, are also discussed. Simulation results show that our mechanism is effective in preventing strategic manipulation and guarantee that selfish users will give honest recommendations.**

I. Introduction

Due to the proliferation of mobile devices, the vision of pervasive computing is becoming a reality. In the pervasive computing environment, users gather around in an ad hoc way not and have not any prior knowledge of each other. Trust and reputation system hence plays a foundational role in establishing the relationship between users [1]. Based on trust and reputation, any interaction can be limited to users who already gained a good reputation. When one user wishes to avail of a service from an unknown user, it is quite natural for the requestor to ask for some recommendations on the service provider from its neighbours. If the reputation of the service provider is lower than its secure access level, the requestor can then make the decision not to interact with or walk away from the suspected service provider.

However, in an open environment such as pervasive computing, most entities are selfish and self-interested and their unique goals are to maximise their own profit. The existence of such selfish users presents two difficulties in recommendation elicitation, which pose a significant threat to the proper functionality of the trust and reputation system. Firstly, selfish users are reluctant to render the recommendation since this will consume some of the limited resources that are a common characteristic in a pervasive computing environment. Meanwhile, any recommendation received may also be false or was subject to manipulation. The user may give a higher rating to its colluder and a lower rating to its potential competitor. Therefore, incentives are needed for the selfish users to render the recommendation and truthful recommendation. Following our previous work [2] where we addressed the first problem, this paper will focus on the second one, i.e., how to make a selfish user give honest recommendation.

Although some solutions are proposed to address the truthful recommendation elicitation issue, many of these solutions do not address the issue of strategic attack. For example, a user may offer honest recommendations for a period of time to obtain enough recommendation influence and then suddenly begin to render false feedback to gain more benefits. Some users [3] implement a strategy-proof mechanism. However, their mechanism can only be incorporated into a binary trust system and is not suitable to many other graded trust systems.

In this paper, we model the trust based interaction decision process as a public decision process. Each recommender give its opinion, which reflects its own trust value on the service provider, on the decision about whether the requestor should interact with the service provider and receive some credits from the requestor as incentive. A VCG (Vickrey-Clarke-Groves) based strategy-proof trust mechanism is proposed to address the problems descirbed above. In this mechanism, the user will maximise its profit only when it offers a truthful recommendation. Our trust mechanism can utilize the graded trust value as well as a binary trust value system and is effective with all kinds of strategic manipulation. Moreover, the proposed mechanism is efficient because the recommender will receive payments before the actual outcome of the interaction with the service provider can be observed. This property is essential for the incentive mechanism in the mobile environment, since sometimes the desired observation may take such a long time that the mobile user cannot wait to get the payments.

The paper is structured in the following way: Section 2 describes related work. Section 3 introduces a basic knowledge of mechanism design and VCG mechanism. Section 4 describes a strategy-proof trust mechanism. Section 5 studies the characteristics of the trust mechanism. Section 6 presents our simulation results and finally Section 7 concludes the paper and discusses future work.

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II. Related Work

There has been rapid progress in recent years in understanding how to elicit truthful recommendations from different recommenders.

Jurca and Faltings [3] describe an incentive compatible reputation mechanism. A special broker called R-nodes will sell a recommendation about a service provider to a client and buy the feedback from the client after the interaction. The client will only get the payment when the feedback matches the next report from another client. However, one problem is that the client may suffer from an alternative behavior of the service provider. Wang et al., [4] propose a VCG-like truthful rating feedback mechanism. The mechanism utilizes a transitive trust network based on both referral trust and functional trust to elicit the honest feedback. In different to their work, our mechanism has no such requirement and can be applied to both transitive and non-transitive trust systems. Gerding et al., [5] propose a strictly proper scoring rules based mechanism to elicit and fuse costly estimates from multiple suppliers. This two-stage mechanism is also incentive compatible and individually rational. Nevertheless, a central server is needed and the payment given in the mechanism must be made after the actual outcome can be observed. Abrams et al., [6] propose a mechanism that is used to keep peers honest in the Eigentrust system. However, this mechanism is only non-manipulatable rather than incentive compatible, i.e., the peers have no incentive to lie but also have no incentive to tell the truth. Besides, a notional strategy-proof trust model based on VCG mechanism is given in [7]. However, in this paper, there are only concepts and no details on how to adapt the VCG mechanism to the trust and reputation system are given. Neither proof of strategyproof nor description of implementation of such mechanism are presented.

Liu and Issarny [8] present a beta distribution based reputation system. Since the honest recommenders will treat recommendation requests from different types of requestors such as truth-tellers, liars, inactive truth-tellers or liars differently, the nodes are actively motivated to provide truthful feedback. Although this mechanism is effective, it is not strictly incentive compatible which means it is optimal for nodes to share recommendations truthfully each time.

III. Mechanism Design and the VCG mechanism

In this section, we briefly introduce mechanism design and the VCG mechanism. A more detailed description can be found in [9] [10].

Mechanism Design studies how to design mechanisms to implement a desired social choice that is aggregated from the preferences of rational and self-interested individuals in a game theoretical sense. For example, in a political election, the selection of a certain candidate, which is the social choice, is determined by each voter's preference. The outcome of the social choice will in turn influence the profit of each individual.

From the social and global view, the social goal such as maximizing the total profit of all individuals should be implemented. While from the individual view, its only purpose is to maximise its own profit. The individual may lie about its preference, which is private information and unknown to others, in order to manipulate the social choice and achieve greater profit. Some payments p_i are used in the mechanism to incentivize the individual to reveal its preference truthfully.

Definition 1. *A* mechanism *is a social choice function $f : V_1 \times \ldots \times V_n \to \mathbb{R}$ and a vector of payment functions $p_1, \ldots, p_n$, where $p_i : V_1 \times \ldots \times V_n \to \mathbb{R}$ is the amount that individual i pays.*

Definition 2. *The preference of individual i is expressed by a* valuation function *$v_i : A \to \mathbb{R}$, where $v_i(a) \in \mathbb{R}$ denotes the "value" that i will gain when the social choice* outcome *$a \in A$ is chosen.* Utility *is used to abstract the profit which the player desires to obtain and to maximise. The utility is denoted as $u_i = v_i(a) - p_i(v_i, v_{-i})$. $p_i(v_i, v_{-i})$, which is determined by the preference of individual v_i and the preferences of the other individuals v_{-i}, denotes the* payment *paid from the individual i to the mechanism executer. This notation is the equivalent to $p_i(v_1, \ldots, v_n)$ and p_i.*

Definition 3. *A mechanism $(f, p_1, \ldots, p_n)$ is* incentive compatible *if for every individual i, every $v_i \in V_1, \ldots, v_n \in V_n$, if we denote $a = f(v_i, v_{-i})$ for i's truthful preference v_i and $a' = f(v_i', v_{-i})$ for its lie v_i', then $v_i(a) - p_i(v_i, v_{-i}) \geq v_i(a') - p_i(v_i', v_{-i})$. A mechanism is called* individual rational *if the utilities of all individuals are always non negative, i.e., $u_i \geq 0$. A mechanism is called* strategy-proof *when it is incentive compatible and individual rational.*

An well known incentive compatible mechanism is the Vickrey-Clarke-Groves (VCG) mechanism whose social goal is to maximise the social welfare $\sum_i v_i(a)$, the total valuations of all participants.

Definition 4. *Vickrey-Clarke-Groves (VCG for short) mechanism is the mechanism which meets:*

(i) The social choice function maximises the social welfare, i.e., $a = f(v_1, \ldots, v_n) \in argmax_{a \in A} \sum_i v_i(a)$.

(ii) For all $v_i \in V_1, \ldots, v_n \in V_n, p_i(v_1, \ldots, v_n) = h_i(v_{-i}) - \sum_{j \neq i} v_j(a)$ where $h_i : V_{-i} \to \mathbb{R}$ is the function that does not depend on v_i.

By defining the form of the payment function which is independent of its own declaration, the VCG mechanism aligns the social welfare with the utility of each individual. That is, the individual will archive its maximum utility by exactly telling the truth of its private information (i.e., preference) and maximise the social welfare at the same time.

Definition 5. *The* Clarke pivot rule *defines that $h_i(v_{-i}) = max_{b \in A} \sum_{j \neq i} v_i(b)$. Under this rule the payment of individual i is $p_i(v_1, \ldots, v_n) = max_{b \in A} \sum_{j \neq i} v_j(b) - \sum_{j \neq i} v_j(a)$.*

According to the Clarke pivot rule, each individual will pay the difference between the social welfare of the others with and without its participation. The payment can be interpreted as the total harm to the other individuals caused by it. The Clarke pivot rule guarantees that the VCG mechanism is individual rationality and has positive payment, i.e., $u_i \geq 0$ and $p_i \geq 0$.

IV. STRATEGY-PROOF TRUST MECHANISM

In this section we study the strategy-proof trust mechanism which is a kind of VCG mechanism. In a music sharing scenario in pervasive environment, mobile users exchange songs between themselves. Since some users may share songs which contains malicious programs such as virus or Trojan house, a trust model running on each user's mobile device is employed to manage the trust values derived from interactions. The trust value, denoted as $t_i \in [0, 1]$, takes any value over the interval as a graded measurement. Since the trust value is regarded as private information, no trust propagation happens between users without explicit request. When a requestor asks the recommender for its trust value to a music sharing service provider, the recommender gives its recommendation which contains its own preference (i.e., the trust value) and receives some credits from the requestor. Trust based decision making is taken based on the recommendations from its neighbours. When interacting with the service provider, the requestor shares all the recommendations related to it so that the provider may improve its quality of service according to feedback.

Note that, different from [5] where the recommendations contains both positive and negative observations of the service provider, the estimates from multiple recommenders are regarded as interdependent and the VCG mechanism is therefore not appropriate. In our work, although all the recommendations are related to the same service provider, the trust values are considered as subjective opinions and therefore independent to each other.

During the decision making process, the requestor aggregates recommendations and its own trust value, denoted as t_r, to a single overall trust value and then can make a interacting decision if the overall trust value is greater than some trust level. The trust level is denoted as λ and the overall trust value T is calculated as:

$$T = p(\sum_{i=1}^{n} \omega_i t_i) + q t_r \tag{1}$$

in which ω_i, p, q are the weights for each recommendation, total recommendations and its own trust value respectively and $\sum_i^n \omega_i = 1, \omega_i > 0, p + q = 1, p > 0, q \geq 0$.

For the recommender who renders the feedback, making a recommendation, particularly when the rating is low, will make it face the cost as a result of the outcome of the service interaction. The recommender may suffer from the revenge of the service provider (e.g., no music sharing or deliberately low recommendation to the recommender) due to its poor feedback. This cost is modeled by the cost function (2) in which μ_i, η_i are used to describe how serious the recommender thinks of the risk of the recommendation in an linear function manner.

$$c_i = f_i^c(t_i) = \mu_i t_i + \eta_i,\ \mu_i < 0, c_i \geq 0 \tag{2}$$

The cost function implies that the lower the recommendation is, the higher cost will be. This assumption is based on the following observation introduced in [4]: (1) Since a good rating will not annoy the service provider, the recommender tends to provide a higher rating. (2) A truthful low rating is based on long-term interaction and it will take more effort to obtain this rating. (3) There is a high probability of suffering revenge when giving a lower rating. We assume that every user has the same cost function and the function is common knowledge to everyone, i.e., $\mu_i = \mu, \eta_i = \eta$.

Given the cost of recommendation, each user has a value v_i, expressing its willingness to recommend, defined as:

$$v_i = -c_i = -\mu_i t_i - \eta_i,\ \mu_i < 0, v_i \leq 0. \tag{3}$$

The recommendation received by the requestor actually contains the declared value v_i called *opinion* rather than its trust value. Then the valuation of the recommender, $v_i(a)$, is equals to the v_i when a decision to interact with the service provider is made and equals 0 when the requestor makes the opposite decision. Since making recommendation incurs a cost to the recommender, it deserves credits from the requestor. The payment expressing the money the recommender pays to the mechanism executor should be negative. Hence the utility of the recommender is expressed as

$$u_i = v_i(a) - p_i(v_1, \ldots, v_n),\ p_i(v_1, \ldots, v_n) \leq 0. \tag{4}$$

The valuation of the requestor is a fixed value $-C, C < 0$ when it decides to interact or is 0 when not to. How to decide the value of C will be defined later. Now, the social welfare of all participants including recommenders and the requestor, $\sum_i v_i(a) - C$, equals $\sum_i v_i - C$ or 0 in the two situations.

The process of making a trust based decision can be regarded as a social choice process in which all individuals express their opinions v_i and lead to a social choice a, whether to access the service provided by the service provider or not. The social choice function defined in (5) maps individual opinions to the social outcome.

$$a = f(v_1, \ldots, v_n) = \begin{cases} I & T \geq \lambda \\ NI & T < \lambda \end{cases} \tag{5}$$

where I represents the social choice to interact with the service provider and NI means not to consume the service provision.

To make this problem simpler, we assume the requestor assign equal weight for every recommendation, i.e., $\omega_i = \omega = 1/n$. Note that, even without this restriction, the mechanism is still a VCG mechanism. We then proof that the social choice function f maximises the social welfare.

Theorem 1. *The social choice function $f(v_1, \ldots, v_n)$ maximises the social welfare.*

Proof: We substitute (1) into the condition of the social choice function f:

$$p(\sum_{i=1}^{n} \omega t_i) + q t_r \geq \lambda$$

$$\sum_{i=1}^{n} t_i \geq \frac{\lambda - q t_r}{\omega p}.$$

TABLE I
SUMMARY OF PAYMENT SITUATIONS

Situation Type	Role of i	Conditions	social choice	Payment $p_i(v_1,\ldots,v_n)$	Valuation $v_i(a)$	Utility u_i
I	not pivotal	$\sum_{j\neq i} v_j - C < 0$, $\sum_i v_i - C < 0$	NI	C	0	$-C$
II	not pivotal	$\sum_{j\neq i} v_j - C \geq 0$, $\sum_i v_i - C \geq 0$	I	C	v_i	$v_i - C$
III	pivotal	$\sum_{j\neq i} v_j - C \geq 0$, $\sum_i v_i - C < 0$	NI	$\sum_{j\neq i} v_j, j = 1\ldots, n.$	0	$-\sum_{j\neq i} v_j$

According to (3), we transform the condition as below:

$$(\sum_{i=1}^{n} -\mu t_i - \eta) \geq \frac{\mu q t_r - \lambda\mu}{\omega p} - n\eta.$$

Let

$$C = \frac{\mu q t_r - \lambda\mu - np\omega\eta}{\omega p},$$

then we have

$$\sum_{i=1}^{n} v_i - C \geq 0. \tag{6}$$

Recall that the social welfare equals $\sum_i v_i - C$ if the requestor decides to interact and 0 when it decides not to. When condition (6) holds the outcome of the social choice function f chooses the outcome (i.e., interacting) where the larger social welfare, $\sum_i v_i - C$, will be achieved. When $\sum_i v_i - C < 0$, the larger social welfare 0 will be achieved according to the outcome of f(i.e., no access). Therefore, the social choice function in (5) exactly maximises the social welfare. ■

After receiving recommendations and making a decision, the requestor pays some credits as incentives back to all the recommenders before interacting with the service provider. This prompt action can make the elicitation mechanism more efficient and is compatible with the high mobility of users in pervasive computing. The value of credits equal to the absolute value of the payments. The credits received by the recommender will be stored and used to elicit recommendations from other users when the recommender make its own trust based decision making.

The Clarke pivot rule cannot be applied directly in our mechanism since the valuations and payments are both negative. According to the spirit of the Clarke pivot rule, the payment is defined as:

$$\begin{aligned} p_i(v_1,\ldots,v_n) \;&=\; max_b \textstyle\sum_{j\neq i} v_j(b) - \sum_{j\neq i} v_j(a) \\ &\quad +K, j = 1,\ldots,n+1. \end{aligned} \tag{7}$$

where $K = C$ makes sure that the payment is negative and the $n+1$ player is the requestor.

Based on different declared opinions $(v_1,\ldots,v_n)$ and that $v_i < 0$, there are three kinds of payment situations which are summarized in Table I. Each situation is identified by the condition indicating the relationships between the declared opinions from different individuals. Only in situation III, the recommender i becomes a pivotal. In that situation, $max_b \sum v_i(b) = \sum_{j\neq i} v_j - C$ since the decision to interact will be made and $\sum_{j\neq i} v_i(a) = 0$ since the requestor will choose not to interact when i gives its opinion. At this point, the recommender will pay the payment: $p_i(v_1,\ldots,v_n) = \sum_{j\neq i} v_j$. When the recommender i is not a pivotal, its payment only equals C. Since $\sum_i v_i - C < 0$ and $\sum_i v_i < 0$, the requestor will never become a pivotal and will not pay itself.

Theorem 2. *The trust mechanism $(f, p_1,\ldots,p_n)$ is strategy-proof.*

Proof: (Incentive compatible) For a particular participant i with direct trust t_i and corresponding opinion v_i, its utility when giving a truthful opinion v_i is no less than that when giving a false opinion v'_i. Denote $a = f(v_i, v_{-i})$ and $a' = f(v'_i, v_{-i})$. When rendering truthful recommendation, $u_i = v_i(a) - p_i(v_i, v_{-i}) = v_i(a) - max_b \sum_{j\neq i} v_j(b) + \sum_{j\neq i} v_j(a) - C = \sum_i v_i(a) - C - max_b \sum_{j\neq i} v_j(b)$. When a false recommendation is given, $u'_i = v_i(a') - p_i(v'_i, v_{-i}) = \sum_i v_i(a') - C - max_b \sum_{j\neq i} v_j(b)$. Then $u_i > u'_i$ since $a = f(v_i, v_{-i})$ maximises the social welfare $\sum_i v_i(a) - C$ over all participants and $max_b \sum_{j\neq i} v_j(b)$ is independent on v_i.

(Individual rationality) Consider the three payment situations. Note that $C < 0$ and $v_i \leq 0$. The utility in situation I and situation III are non negative. In situation II, $\sum_i v_i - C \geq 0$, then $\sum_i v_i - C - \sum_{j\neq i} v_j \geq -\sum_{j\neq i} v_j$ and note that $v_j \leq 0$, therefore $v_i - C \geq 0$. In summary, the mechanism is individual rationality. ■

V. CHARACTERISTICS OF THE TRUST MECHANISM

In this section, we will study the properties of the proposed mechanism in more detail.

A. *Characteristics of the Social Choice Function*

In many trust management systems, users rate on a binary scale (trusted or not trusted). For more accurate and confidential decisions, a graded trust value which can be measured on interval scales is necessary.

Whether a social choice function can be truthfully implemented by a mechanism $(f, p_1,\ldots,p_n)$, i.e., whether a mechanism $(f, p_1,\ldots,p_n)$ is incentive compatible, has a very strong relationship with the properties of the social choice function and the possible domain of valuation V_i. In our strategy-proof trust mechanism, the valuation of the user is only single dimensional, our mechanism as well as most trust mechanisms fall into the one-parameter domain.

Besides, in [10] a direct characterization of the incentive compatible mechanism is given that a mechanism $(f, p_1,\ldots,p_n)$ is incentive compatible if and only if for every i and every v_{-i} it satisfies that: (1) The payment p_i does not depend on v_i but only on the alternative chosen $f(v_i, v_{-i})$

and (2) The mechanism maximizes the utility of each player. Obviously, the VCG mechanism meets these requirements, so is the VCG based strategy-proof trust mechanism.

Such characterization leaves much space for other kinds of social choice function whose form are not maximizing the social welfare. More complex social choice functions such as maximizing the euclidean norm $argmax_a \sum_i v_i(a)^2$ may been implemented.

B. Characteristics of the Payment

From the requestor's point of view, its valuation is $-C$ and it will pay $-\sum_i p_i$ as credits to the recommenders. We will discuss the relationship between these two values.

Theorem 3. *The credits the requestor paid will never be less than its valuation.*

Proof: Consider in the situation III,

$$\begin{aligned} -\sum_i p_i - (-C) &= -\sum_i(\sum_{j\neq i} v_j) + C \\ &= -\sum_i(\sum_j v_j - v_i) + C \\ &= -\sum_i(\sum_j v_j) + \sum_i v_i + C \\ &= (1-n)(\sum_i v_i - C) + (2-n)C \end{aligned}$$

Note that $\sum_i v_i - C < 0$ in this situation. This value is bigger than 0 when there are no less than two recommenders.

In situations I and II, $-\sum_i p_i - (-C) = (1-n)C > 0$ when there are no less than two recommenders. Hence the valuation will always be no more than the paid credits. ∎

The difference between the valuation and the paid credits can be considered as the cost of the recommendation elicitation process. This difference is actually caused by the form of payment function. Indeed, there does not exist certain kind of payment functions that can eliminate such differences because the payment function is essentially uniquely determined by the social choice function. This property is called *uniqueness of prices*. In [10], it is proved that if the social choice function maximises the social welfare, the payments making the mechanism strategy-proof must be identical to those obtained using the Clarke pivot rule.

VI. SIMULATION

In this section, we evaluate the performance of the strategy-proof trust mechanism. We use JIST/SWANS [11] to simulate the MANETs which are considered as the underlying networking paradigm for pervasive computing environments. The field is an area of 400m $\times$ 400m and contains 40 nodes. The random waypoint model with a minimum speed of 2m/s and maximum of 10m/s is used for mobility. All the nodes are indexed. Nodes no.21 to no.30 are service providers. Node no.19 is the requestor. Nodes no.1 to no.10 are the recommenders and only node no.1 will strategically give false opinions. The deviation types of the false opinions are summarized in Table II. For example, deviation type II means node no.1 will lie on its trust value by increasing 0.1. The deviation types in which the node increasing the original trust value are called *positive deviations*. The *negative deviations* denote the types in which the node will decrease the opinion value. In our simulation, the parameters are set as $\mu = -1$, $\eta = 1$, $\lambda = 0.6$ and $n = 10$.

TABLE II
DEVIATION TYPES OF THE FALSE OPINIONS

Type	I	II	IV	VI	VIII	X
Deviation	0	+0.1	+0.3	+0.5	+0.7	+0.9
Type		III	V	VII	IX	XI
Deviation		-0.1	-0.3	-0.5	-0.7	-0.9

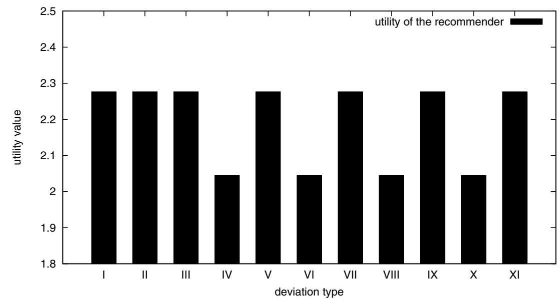

Fig. 1. Example of the lying node suffering from positive deviations

Firstly, we evaluate how the mechanism works with different kinds of deviation. In one experiment, the requestor asks all the recommenders about the trust values about one service provider. The lying node chooses one kind of deviation type and lies on its trust value to this service provider in each of the total 11 experiments. The trust values of the recommenders are randomly generated in the first experiment and stay the same in all the experiments. Figure 1 shows that the lying node will suffer the reduction in its utility when it adopts the positive deviation policy. In this group of experiments, when the node gives the truthful recommendation, the payment situation type is III in which $\sum_i v_i - C < 0$. Some positive deviations change this condition to $\sum_i v_i - C \geq 0$ so that the situation becomes type II. Figure 2 shows another group of experiments whereby the lying node suffers when it chooses the negative deviation policy and some negative deviations change the payment situation from II to III. These two groups of experiments show that whether the lying node takes the positive deviation policies or negative deviation policies, its utility may decline due to the false recommendation. Since

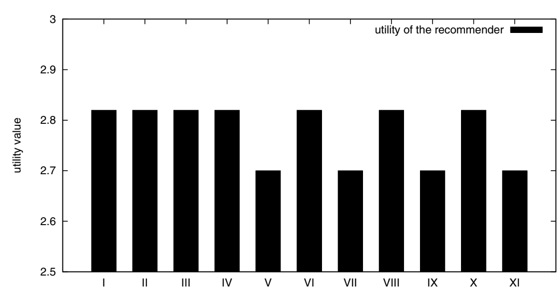

Fig. 2. Example of the lying node suffering from negative deviations

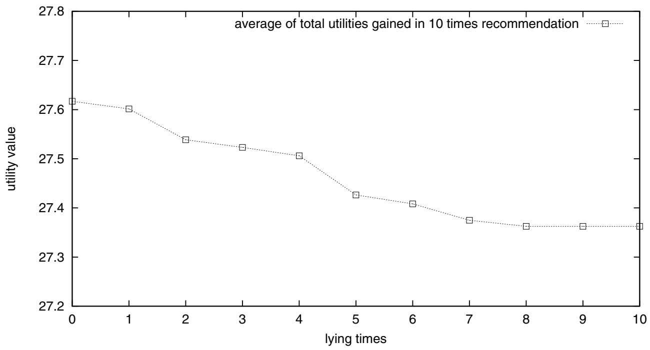

Fig. 3. Average of total utilities gained in 10 times recommendations

the identification of the payment situation also depends on the opinions of other recommenders, the best strategy for the node is to render the truthful recommendations.

The evaluation above indicates that it is impossible for the lying node to gain more utilities by adopting some deviation type and manipulating its opinion in one time recommendation. Since each time the lying node cannot benefit by lying, it will also fail in having more utilities by strategic manipulations in many times recommendations. We next evaluate the gained utilities when the lying node adopts more combined strategies and lies many times. The lying node will choose the same deviation type on the same service provider. In one experiment, the lying node will render 10 recommendations and lie on its trust value on k service providers in the k^{th} experiment. For one group of 11 experiments, the randomly generated trust values are unchanged. There are 10 groups of experiments in total. Figure 3 shows the average of the total utilities gained in the 10 recommendation renderings when lying k times. The results shown in the Figure 3 indicate that the more times the node is lying, the less average total utilities it will get.

VII. Conclusion

In this paper, we introduced a strategy-proof trust mechanism which is a kind of VCG mechanism. This mechanism can be incorporated into variant graded and binary trust and reputation systems. In our mechanism, the decision making process of trust based interaction can be regarded as a social choice and the largest utility of each self-interested user can only be achieved when it provides truthful feedback. We discussed the type of the social choice function and the characteristics of the payment function. The simulation results show that the mechanism is effective regarding both positive and negative deviations as well as strategic manipulations.

There are still a number of interesting directions for our future work. First, we are going to evaluate the actual effect of our mechanism on an open source pervasive computing platform [12] [13] in an empirical way. Moreover, we will further explore more possible types of social choice function in other trust systems so that a more complex trust aggregating function can be expressed. Furthermore, we will further study the relationship between the strategy-proof trust based composite service interaction, which appears in service oriented architecture, and the combinatorial auction which is the paradigmatic problem on the interface of economics and computer science. Finally, the VCG mechanism is not group strategy-proof, i.e., some users may collude as a coalition and gain more utilities together. The group strategy-proof trust mechanism is another interesting issue.

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