# The Relationship of Trust, Demand, and Utility: Be More Trustworthy, Then I Will Buy More

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***Abstract*—In many marketplaces consumers may interact with more than one supplier in order to achieve a particular goal. This paper takes the position that trust mediates agent interactions and that agent demands are likely to increase with increasing trust. Furthermore, trust of one agent in another is updated based upon a trust model. The model proposed in this paper is one in which agent demands can be divided amongst suppliers with the division determined by trust. The model evaluates five prominent trust models in a hypothetical marketplace and demonstrates empirically that FIRE, Regret, Probabilistic Trust Models and a model due to Yu and Singh can be exploited such that a consumer agent will continue to interact with a malicious agent despite periodic contract defaults by the malicious agent. Empirical studies support the hypothesis that adaptive trust models such as AER are resistant to this type of exploitation and discourage periodic or cyclical defaulting on contractual obligations.**

## I. Introduction

Electronically mediated commerce is increasingly important. Such commerce often relies upon individual being trustworthy in their transactions. Trust is a crucial concept driving decision making and relationships among individuals in artificial societies such as are found in e-commerce marketplaces. Generally speaking, trust is an essential aspect of any relationship in which the truster does not have direct control over the actions of a trustee, the decision is important, and the environment is uncertain [1].

In distributed systems, specifically e-commerce marketplaces, individuals are often involved in supply chain relationships and are capable of interacting with multiple suppliers in order to achieve a specific goal. This paper takes the position that trust mediates agent interactions and that supply chain dynamics have natural growth characteristics that vary with time. In this paper, we use a definition for trust provided by Mui et al. [2]: "a subjective expectation an agent has about another's future behavior based on the history of their encounters" and mathematically characterize it using definitions from Marsh [3]. The measure of trust that one agent has in another is updated according to a trust model where updates are dependent upon whether an agent perceives its contract with another agent has been honoured or not. As such, we view agent interactions in a game theoretic manner. This paper considers those marketplaces in which the demand of an agent for a specific product (service) can be satisfied by several providers (sellers) as opposed to classical marketplaces in which the demand of an agent can be satisfied by a single provider.

Many trust models have been proposed [4], [5], [6], [7], [8], [9]; a review of which can be found in [10], [11]. We consider five prominent models in this paper: FIRE [5], Regret [7], Yu and Singh [6], Probabilistic Trust Models [8], [9] and AER [12]. Most recently, researchers have identified the existence of cheaters in artificial societies employing trust and reputation models [13], [12], [14], [15]. Kerr and Cohen [13] examined the security of several e-commerce marketplaces employing a trust and reputation system by proposing several attacks and examined their effects on each marketplace. Kerr and Cohen's marketplace considers only single supplier-consumer interactions for demand satisfaction as opposed to the marketplace in this paper which allows for multiple supplier-to-consumer interactions for a given level of demand. Salehi-Abari and White have shown that FIRE, Regret and Yu and Singh models are susceptible to con-man exploitation [12]; that is, a trust model can be manipulated such that one agent will continue to interact with a malicious agent despite the malicious agent periodically defaulting on its contract obligations. Furthermore, it has been shown [16] that the adaptive AER trust model can bound exploitation behavior; however, the results deal with trust rather than demand-based utility which is considered here.

Several researchers have postulated that seller reputation has significant influence on prices, especially for high-valued products in the eBay market [17], [18]. Similarly, Brainov and Sandholm [19] have studied the impact of trust on contracting in e-commerce marketplaces. This paper is motivated by the hypothesis that trust models improve an agent's performance in a marketplace when the demand of an agent is dependent on its trust in others and utility is dependent on agent demand.

With this hypothesis in mind, this paper makes the following contributions. First, a taxonomy of demand models is proposed. Second, a formal model of trust-dependent demand is proposed. Third, a marketplace is constructed using a trust-dependent demand model which is then empirically evaluated using simulation for 5 prominent trust models. The results support the hypothesis that AER can operate efficiently in such marketplaces.

This paper consists of 5 further sections. In Section II brief descriptions of the 5 trust models evaluated in this paper are

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provided. Section III presents a taxonomy of demand models. Section IV provides details of our simulation model. Section V describes our experimental setup and results. Finally, Section VI concludes and suggests future work.

## II. Background on Trust Models

Direct interaction is the most popular source of information for trust and reputation models [11]. It is used exclusively within this paper. Trust and reputation models usually have a direct interaction trust variable that indicates the level of an agent's trustworthiness. We discuss the direct interaction trust components of Yu and Singh's model, Regret, FIRE, AER, and probabilistic trust models in the following subsections.

### *A. Yu and Singh (YS)*

Yu and Singh's [6] trust variable is defined by $T_{i,j}(t)$ indicating the trust rating assigned by agent $i$ to agent $j$ after $t$ interactions between agent $i$ and agent $j$, with $T_{i,j}(t) \in [-1, +1]$ and $T_{i,j}(0) = 0$.

An agent will update this variable based on the perception of cooperation/defection. Cooperation by the other agents generates positive evidence of $\alpha$, with $1 > \alpha > 0$ and defection generates negative evidence of $\beta$, with $-1 < \beta < 0$.

**If** $T_{i,j}(t) > 0$ **and** $Cooperation$ **then**
$T_{i,j}(t+1) := T_{i,j}(t) + \alpha(1 - T_{i,j}(t))$
**If** $T_{i,j}(t) < 0$ **and** $Cooperation$ **then**
$T_{i,j}(t+1) := (T_{i,j}(t) + \alpha)/(1 - min(|T_{i,j}(t))|, |\alpha|)$
**If** $T_{i,j}(t) > 0$ **and** $Defection$ **then**
$T_{i,j}(t+1) := (T_{i,j}(t) + \beta)/(1 - min(|T_{i,j}(t))|, |\beta|)$
**If** $T_{i,j}(t) < 0$ **and** $Defection$ **then**
$T_{i,j}(t+1) := T_{i,j}(t) + \beta(1 + T_{i,j}(t))$

For our convenience, we refer to this model as YS.

### *B. Regret*

Regret defines an impression as the subjective evaluation made by an agent on a certain aspect of an outcome and bases its trust model upon it. The variable $r_{i,j}(t)$, with $r_{i,j}(t) \in [-1, 1]$, is the rating associated with the impression of agent $i$ about agent $j$ as a consequence of specific outcome at time $t$. $R_{i,j}$ is the set of all $r_{i,j}(t)$ for all possible $t$. A subjective reputation at time $t$ from agent $i$'s point of view regarding agent $j$ is noted as $T_{i,j}(t)$[1]. To calculate $T_{i,j}(t)$, Regret uses a weighted mean of the impressions' rating factors, giving more importance to recent impressions. The formula to calculate $T_{i,j}(t)$ is:

$$T_{i,j}(t) = \sum_{w_k \in R_{i,j}} \rho(t, t_k).w_k \tag{1}$$

where $t_k$ is the time that $w_k$ is recorded, $t$ is the current time, $\rho(t, t_k) = \frac{f(t_k,t)}{\sum_{r_l \in W_{i,j}} f(t_l,t)}$, and $f(t_k, t) = \frac{t_k}{t}$ which is called the rating recency function.

[1]For the purpose of simplification, we have changed the original notations from [7].

### *C. FIRE*

FIRE [5] utilizes the direct trust component of Regret but does not use its rating recency function. FIRE introduced a rating recency function based on the time difference between current time and the rating time. The parameter $\lambda$ is introduced into the rating recency function to scale time values. FIRE's rating recency function is:

$$f(t_k, t) = e^{-\frac{t-t_k}{\lambda}} \tag{2}$$

### *D. Probabilistic Trust Models (PTM)*

Considerable progress has recently been made in the development of probabilistic trust models, the Beta Reputation System (BRS) and TRAVOS being two examples [8], [9]. Probabilistic trust models are built based on observations of past interactions between agents mapping observations to cooperations and defections.

In probabilistic trust models, the probability that agent $j$ satisfies its obligations for agent $i$ is expressed by $B_{i,j}$. The trust value of agent $i$ for agent $j$ at time $t$, denoted by $T_{i,j}(t)$, is the expected value of $B_{i,j}$ given the set of outcomes $O_{i,j}(t)$ at time $t$.

$$T_{i,j}(t) = E[B_{i,j}|O_{i,j}(t)] \tag{3}$$

As the standard equation for the expected value of a beta distribution is $E[B|\alpha, \beta] = \frac{\alpha}{\alpha+\beta}$, the trust value $T_{i,j}(t)$ after $t$ interactions is:

$$T_{i,j}(t) = E[B_{i,j}|\alpha, \beta] = \frac{\alpha}{\alpha + \beta} \tag{4}$$

where $\alpha = n_c(t) + 1$ and $\beta = n_d(t) + 1$. $n_c(t)$ and $n_d(t)$ denote the number of cooperations (successful interactions) and the number of defections (unsuccessful interactions)[2]. For our convenience, we refer to this model as PTM.

### *E. AER*

AER extended the direct trust of [6] by introducing the following update schema for a positive evidence weighting coefficient of $\alpha > 0$ and a negative evidence weighting coefficient $\beta < 0$ when the agent perceives defection:

$$\begin{aligned} \alpha(i) &= \alpha(i-1) \times (1 - |\beta(i-1)|) \\ \beta(i) &= \beta(i-1) - \gamma_d \times (1 + \beta(i-1)) \end{aligned}$$

Where $\gamma_d$ is the discounting factor and is in the range of $[0, 1]$. Note that, $\alpha(i)$ and $\beta(i)$ will be updated when the $i^{th}$ defection occurs.

## III. Taxonomy of Demand

We here present a taxonomy for demand to demonstrate the scope the paper. As illustrated in Figure 1, demand can be distinguished as either *composite* or *simple*. A simple demand is the same in all its parts or particles whereas a composite demand is not the same in all parts and composed of heterogeneous parts. In other words, a composite demand can

[2]It is worth mentioning that the trust value in probabilistic models is in the range of [0, 1] as opposed to Yu and Singh, Regret, AER, and FIRE models in which trust is in the range of [-1, 1].

be decomposed to several simple demands. Consider the need for "skiing equipment". This demand is a composite demand, consisting of simple demands for Gear, Skis, Ski Boots, Ski Helmets, and Ski Clothing. Suppose you need 20 kg flour for baking a cake, this demand is a simple demand.

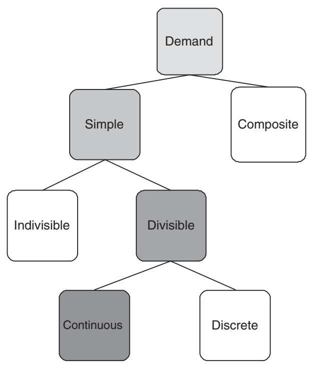



Fig. 1. A Taxonomy of Demand (this paper focused on the darker colors).

Although both demands for Ski Boots and flour are simple demands, there is a subtle difference: we can divide the 20kg flour demand into 15kg and 5kg flour demands or 10kg, 7kg, and 3kg demands but we can not divide the Ski Boots demand to any sub-demands. To capture this difference in the proposed taxonomy, simple demands can fall into two categories: *divisible* and *indivisible*. We formally define them as follows:

- An indivisible demand is not separable to partitions.
- A divisible demand, $D$, can be broken down into $n$ partitions each of which is denoted by $p_i$ where $D = p_1 \cup \cdots \cup p_i \cup \cdots \cup p_n$.

For flour demands, consider two marketplace settings: 1) the flour can be ordered in terms of quantity with any precision (e.g., an order of 12.452 kg flour) and 2) the flour should be ordered by the number of 1kg packages (e.g., an order of 3 one-kilogram packages). In this sense, the divisible demands can be further categorized into *continuous* and *discrete* in our proposed taxonomy. The formal definitions for these two types are as follows.

- A continuous divisible demand, $D$, with $S_D$ size (quantity) can be partitioned into any numbers of $p_i$ partition with $S_{p_i}$ size as long as $\sum_{i=1}^{n} S_{p_i} = S_D$.
- A discrete divisible demand, $D$, with $S_D$ size (quantity) can be broken down into $n$ numbers of $p_i$ partitions while each $p_i$ partition consists of $m_i$ numbers of demand unit $u$. Moreover, $\sum_{i=1}^{n} m_i S_u = S_D$ where $S_u$ denotes the size of unit $u$ and is specified by the nature of each demand type.

This paper focuses on simple demands which are divisible and continuous. This is motivated by the lack of attention to this type of demand in the literature in spite of its diverse possible employment in distributed settings (e.g., file sharing systems, peer-2-peer systems, and e-commerce). From now on, whenever we refer to demand, we mean continuous divisible demands.

## IV. Simulation Model

### A. Interactions

Different fields have their own interpretation and understanding of interaction. In the context of e-commerce, an interaction might be considered as buying or selling a product whereas in peer-to-peer systems (e.g., file sharing systems), an interaction is uploading or downloading files. Providing a service and consuming a service can be regarded as an interaction in the context of web services while asking a question (sending a query) and answering that question (receiving the result of that query) is an interaction from the perspective of information retrieval.

In our model, an agent interacts with the specific set of other agents that are the neighbors of the given agent. Two agents are neighbors if they interact with one another continuously. Interactions are modeled using an extension of the Prisoner's Dilemma called the Iterated Prisoner's Dilemma (IPD) [20]. The Prisoner's Dilemma is a non-zero-sum, non-cooperative, and simultaneous game in which two players may each "cooperate" with or "defect" from the other player. Similar to the other games in game theory, the goal of each individual is maximizing his/her payoff, without any concern for other player's payoff. In the Iterated Prisoner's Dilemma (IPD), the game is played repeatedly. As a result, players have the opportunity to "punish" each other for previous uncooperative play. In our simulation, each agent plays one game with each of its neighbors in each cycle of simulation where it can either cooperate or defect.

Cooperation and defection have different interpretations depending on the context. In the context of e-commerce, defection in an interaction can be interpreted as that the agent does not satisfy the terms of a contract, sells poor quality goods, delivers late or does not pay the requested amount of money to a seller depending on the role of the agent [11]. In the context of information retrieval, defection in an interaction can be interpreted as that the queried agent returns irrelevant documents to the asking agent as the consequence of its query. In contrast, cooperation means that a proper answer is provided according to the query for the questioner.

### B. Agent Model

This paper considers two general types of agents: Service Provider (SP) and Service Consumer (SC) agents. SP and SC are not only restricted to web service applications and can be considered in other contexts. For example, SP and SC in e-commerce represent seller and buyer respectively. To simplify our simulation and analysis but yet be realistic, we consider that all SPs provide (or sell) a specific divisible service (or product) and all SCs seek the same service (or product).

An agent model possesses trust variables, demand variables and interaction strategies. Trust variables assist agents in determining who is trustworthy while demand variables assist agents in determining the demand value for each interaction. Interaction strategies control the behavior of agents by helping them in deciding how to interact with another agent. In other words, the decision to cooperate or defect in an interaction with a specific agent is made by an interaction strategy.

### C. Trust and Demand Variables

Each trust variable is defined by $T_{i,j}(t)$ indicating the trust rating assigned by agent $i$ to agent $j$ after $t$ interactions between agents $i$ and $j$, while $T_{i,j}(t) \in [-1, +1]$ and $T_{i,j}(0) = 0$. One agent in the view of the other agent can be either *Trustworthy*, *Not Yet Known*, or *Untrustworthy*. Following Marsh [3], we define an upper and a lower threshold for each agent to model different levels of trustworthiness. The agent $i$ has its own upper threshold $-1 \leq \omega_i \leq 1$ and lower threshold $-1 \leq \Omega_i \leq 1$. Agent $j$ is *Trustworthy* from the viewpoint of agent $i$ after $t$ interactions if and only if $T_{i,j}(t) \geq \omega_i$. Agent $i$ sees agent $j$ as an *Untrustworthy* agent if $T_{i,j}(t) \leq \Omega_i$ and if $\Omega_i < T_{i,j}(t) < \omega_i$ then the agent $j$ is in the state *Not Yet Known*. Each agent can use one of trust updating schemes that were described in Section II.

We define a demand variable, $D_i(t)$, indicating the demand value assigned by agent $i$ for its $t^{th}$ interactions with other agents, while $D_i(t) \in [0, +1]$. The demand variable is calculated as follows:

$$D_i(t) = \sum_{k \in N(i)} d_{i,k}(t) \tag{5}$$

where $N(i)$ set contains the neighbors of node $i$ and $d_{i,j}(t)$ is a sub-demand variable, indicating the demand value assigned by agent $i$ to its $t^{th}$ interaction with agent $j$, while $d_{i,j}(t) \in [0, +1]$ with the constraint $\sum_{j \in N(i)} d_{i,j}(t) \leq 1$. In our simulation, a sub-demand value of each interaction is always assigned by only SC and consequently SP has to participate in the specified interaction (i.e., there is no exit option for agents). This is motivated by the fact that demand of each SC agent is determined solely by the SC agent and potentially by the marketplace; the SPs simply act to satisfy the demand.

### D. Trust-dependent Demand

It is the position of this paper that the level of trust of an agent (truster) for another agent (trustee) influences the sub-demand value (quantity) of interactions between those agents (e.g., $d_{i,j} \propto T_{i,j}$). This relation of trust and demand can be observed in daily interactions in real life marketplaces. Consider this hypothetical example: Alice is the owner of a bakery and she has the capacity to order daily up to 100kg flour (her maximum possible demand). Bob is the manager of a flour mill and offers to provide high quality flour to Alice. Alice initially accepts daily shipments of 20kg (i.e., $d_{Alice,Bob}(1)$ = 20kg) because she is not assured that Bob can provide high-quality flour as he promised. After 10 satisfactory shipments (cooperations), Alice increases her trust in Bob and consequently doubles her daily order to 40kg (i.e., $d_{Alice,Bob}(11)$ = 40kg). The next day Bob sends low-quality flour at an unchanged price to Alice (a defection). Alice understands the defection and reduces her order to 30kg (i.e., $d_{Alice,Bob}(12)$ = 30kg). We model the direct relationship of trust and demand as follows:

$$d_{i,j}(t+1) = H\left[T_{i,j}(t)\right] \tag{6}$$

Where $H[t]$ is a convertor function which maps the trust value $t$ to demand value in the range of $[0, 1]$. After the calculation of $d_{i,j}$ for a specific $i$ and all possible $j$, we check if the constraint $\sum_{j \in N(i)} d_{i,j}(t) \leq 1$ is satisfied. If not, we normalize $d_{i,j}(t)$ for all $j$ using Equation 7.

$$d_{i,j}(t) := \frac{d_{i,j}(t)}{\sum_{k \in N(i)} d_{i,k}(t)} \qquad if \sum_{k \in N(i)} d_{i,k}(t) > 1 \tag{7}$$

where $N(i)$ set contains the neighbors of node $i$.

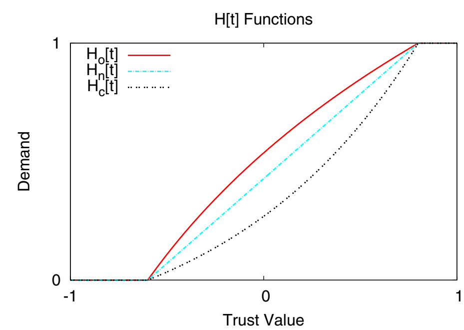



Fig. 2. Conservative, Normal, and Optimistic $H[x]$ functions

We introduce three different $H[t]$ functions: Conservative, Normal, Optimistic, each of which represents a cognitive mapping of trust to demand (see Figure 2). The Conservative function, $H_c(t)$, has the lowest growth rate (for small values of trust) and returns the smallest value of demand for a specific value of trust when compared to the other converter functions. $H_c(t)$ is formulated as follows:

$$H_c[t] = \begin{cases} 0 & -1 \leq t < \Omega \\ \frac{e^{(t-\Omega)}-1}{e^{(\omega-\Omega)}-1} & \Omega \leq t \leq \omega \\ 1 & \omega < t \leq 1 \end{cases} \tag{8}$$

The Normal function, $H_n[t]$, as presented in Equation 9, maps trust value to demand value linearly. Its growth rate is a constant and its returning demand value for a specific trust value is always between the values that conservative and normal functions return.

$$H_n[t] = \begin{cases} 0 & -1 \leq t < \Omega \\ \frac{t-\Omega}{\omega-\Omega} & \Omega \leq t \leq \omega \\ 1 & \omega < t \leq 1 \end{cases} \tag{9}$$

The Optimistic function, $H_o(t)$, increases demand rapidly when the trust value changes slightly. It has the highest growth rate (for low values of trust) and returns the highest value of demand for a specific trust value when compared to the other converter functions. $H_o(t)$ is formulated as follows:

$$H_o[t] = \begin{cases} 0 & -1 \leq t < \Omega \\ \frac{\log(t-\Omega+1)}{\log(\omega-\Omega+1)} & \Omega \leq t \leq \omega \\ 1 & \omega < t \leq 1 \end{cases} \tag{10}$$

### E. Interaction Strategy

The required perception variables (trust and demand variables) have now been introduced; these variables help agents perceive the cooperation/defection of other agents situated in their environment and consequently to determine the trustworthiness of other agents and the demand value for future interactions. This perception is necessary but not sufficient for an agent model since agents need to decide how and when they should interact with other agents. In this sense, each agent requires strategies to help them in making decisions for their interactions with the other agents.

The two kinds of interaction strategy used in our experiments are: Tit-For-Tat (TFT) and Con-Man (CM) [12]. Agents employing TFT will start with cooperation and then imitate the neighbor's last move. In the con-man strategy [12], a con-man is modeled by the parameter $\theta$. The con-man will defect after cooperating $\theta$ times. After each defection, the con-man will again cooperate $\theta$ times possibly repeating this interaction pattern several times. The formal language $L$ over the alphabet $\Sigma = \{C, D\}$ demonstrates the interaction pattern of the con-man:

$$L = \{(C^\theta D)^+ | \theta \geq 1\} \tag{11}$$

where C and D stand for cooperation and defection.

### F. Demand-dependent Utility

In the Iterated Prisoner's Dilemma (IPD), the utility is merely determined by the action of agents indicating whether each player "cooperates" with or "defects" from the other player. This paper extends the classical IPD by letting the demand value of each interaction affect the resulting utility besides the actions of agent. We consider the demand-utility relationship to be linear. More precisely, we calculate $U_{i,j}(t)$, the utility of agent $i$ as a result of interaction with agent $j$ at time step $t$, as follows:

$$U_{i,j}(t) = d_{i,j}(t) \times u(a_i, a_j) \tag{12}$$

where $d_{i,j}(t)$ is the sub-demand value of the interaction between agents $i$ and $j$ at time step $t$. Moreover, $u(a_i, a_j)$ is the maximum possible utility of the interaction where action $a_i$ is taken against action $a_j$. $u(a_i, a_j)$ is calculated based on the following payoff matrix (the well-known payoff matrix of the Iterated Prisoner's Dilemma [20]):

TABLE I
PAYOFF MATRIX OF IPD

| $P_1$/$P_2$ | **Cooperate** | **Defect** |
|---|---|---|
| **Cooperate** | **3,3** | **0,5** |
| **Defect** | **5,0** | **1,1** |

According to Table I, if agent $P_1$ defects and agent $P_2$ cooperates, agent $P_1$ gets the Temptation to Defect payoff of 5 points while agent $P_2$ receives the Suckers payoff of 0. If both cooperate each gets the Reward for Mutual Cooperation payoff of 3 points, while if both defect each gets the Punishment for Mutual Defection payoff of 1 point.

### G. Metrics

In this paper we are interested in examining the internal properties of each agent type, such as utility, trust value, and demand value, cumulative demand, and weighted mean utility.

The utility of agent $i$ as a result of an interaction with agent $j$ at time step $t$, denoted by $U_{i,j}(t)$, is one of the metrics which we used in our experiments. This metric is calculated by Equation 12. The cumulative utility, $CU_i(t)$, represents the total utility of agent $i$ from the beginning until time step $t$.

$$CU_i(t) = \sum_{k=1}^{t} \sum_{j \in N(i)} U_{i,j}(k) \tag{13}$$

The cumulative demand $CD_i(t)$ represents the total demand of agent $i$ from the beginning till time step $t$. We formally define it as follows:

$$CD_i(t) = \sum_{k=1}^{t} D_i(k) \tag{14}$$

where $D_i(k)$ is the demand value of agent $i$ at time step $k$.

$\overline{U_i(t)}$, the weighted mean of utilities for agent $i$ at time step $t$, is calculated by:

$$\overline{U_i(t)} = \frac{CU_i(t)}{CD_i(t)} \tag{15}$$

## V. EXPERIMENTS

Our experiments are categorized into two sets: One-to-one and One-to-multiple. In the former, the interactions are between one service consumer and one service provider. The motivation for the One-to-one experiments is to demonstrate con-man service providers can flourish in a marketplace where agents use non-adaptive schemes, while an adaptive AER trust model limits its exploitation but has unsatisfied (or latent) demand. In contrast, one service consumer interacts with multiple service providers in the latter. The motivation for the One-to-multiple experiments is to demonstrate that agents using AER will learn to shift their demands to trustworthy agents and result is high cumulative utility when compared to agents using non-adaptive trust models.

As mentioned earlier, the agents can utilize various trust updating schemes (i.e., Regret, FIRE, AER, PTM, and YS). When the agent uses Regret, PTM, or FIRE as a trust model, the cooperation and defection is mapped to 1 and $-1$ respectively and the value is used as an input of the trust model. In the case of using YS or AER, cooperation and defection will be used directly for updating the of trust value. We have used the parameters listed in Table II for all experiments.

TABLE II
PARAMETER SETTINGS

| Parameters | Value | Parameters | Value |
|---|---|---|---|
| $\theta$ | 4 | $\gamma$ | 0.1 |
| $\alpha$ | 0.3 | $\beta$ | -0.1 |
| $\omega$ | 0.80 | $\Omega$ | -0.2 |
| $\lambda$ | $\frac{-5}{\ln 5}$ | $time\ steps$ | 30 |

### A. One-to-One

All simulations reported in this section were run with two agents, one Service Consumer agent (SC) and a Service Provider agent (SP). We ran 3 sets of simulations while sets are different in terms of examined converter functions (i.e., $H_c[t]$, $H_n[t]$, $H_o[t]$). Each set consists of 5 simulations in each of which a SC agent utilizes either Regret, FIRE, AER, PTM, or YS as its trust model and uses Tit-for-tat (TFT) as its interaction strategy. In all simulations, the SP agent employs the con-man (CM) strategy. For the simulations of this section, we sometimes refer to TFT and CM instead of SC and SP; however, they are equivalent. Figures 3 and 4 demonstrate the variation of $T_{TFT,CM}(t)$ (the trust value of SC for SP), $U_{TFT,CM}(t)$, $U_{CM,TFT}(t)$, and $D_{TFT}(t)$ over a simulation in which SC (TFT) utilizes the FIRE model as its trust model and $H_n(t)$ as a convertor function.

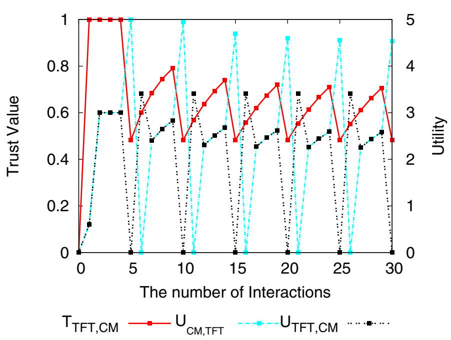



Fig. 3. The variation of trust and utility for SP and SC agents.

It is interesting to note that the interaction pattern of CM causes the fluctuation of trust and consequently a similar fluctuation, with one time step delay, for demand . This delay occurs because the demand value at time step $i$ depends on the trust value at time step $i-1$. Speaking of utility, when both agents cooperate with each other, their utilities are matched ($U_{TFT,CM} = U_{CM,TFT}$). $U_{CM,TFT}$ has its peaks when CM defects from TFT while TFT cooperates with it. $U_{TFT,CM}$ has its local maximum one time step after CM defects. This is because TFT imitates the last move of CM which was defection and CM behave based on its interaction patterns ($\theta = 4$ cooperations after each defection).

According to Figure 3, it is noteworthy that the the peaks of $U_{CM,TFT}$ are significantly higher than the peaks of $U_{TFT,CM}$. This is mainly due to the fact that when CM defects, the demand and corresponding utility is higher than when TFT defects. Although the number of cooperations and defections

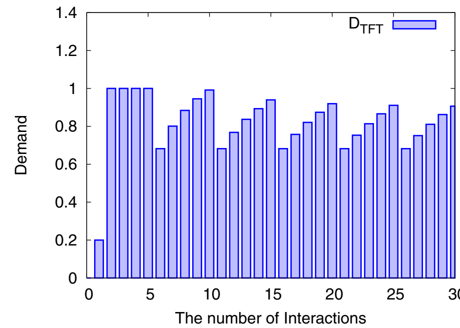



Fig. 4. The variation of Demand.

is equal for both SP and SC over the course of the simulation, this difference of peak values results in higher cumulative utility for SP when compared to SC's cumulative utility (see Figure 5).

In Figure 5, it is interesting that SP which uses CM interaction strategy can gain higher cumulative utility in all trust models and with any converter function settings. For all converter functions, SP has a considerably lower cumulative utility in AER when compared to all other trust models. This is because AER is designed to be con-resistant by not letting the con-man regain its lost trust easily and by punishing more after each defection [12]. As a result the con-man with a constant strategy will have a low value of trust after some cycles of cooperations-defection in AER and consequently its demand decreases. It is clear from this figure that an agent using AER stops interacting with CM after approximately 10 interactions, resulting in latent demand.

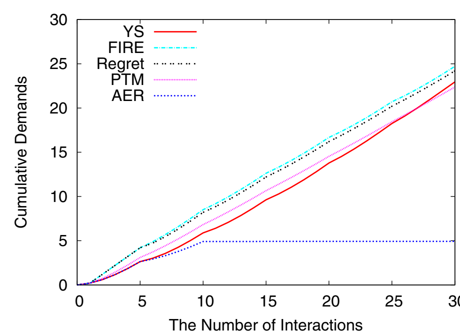
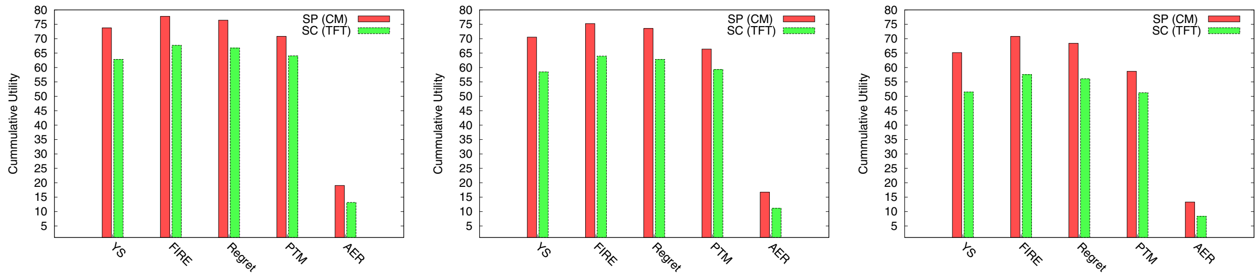



Fig. 6. Cumulative demand over simulations for $H_n(t)$

Figure 6 demonstrates the variation of $CD_{TFT}$ over the simulations with the $H_n(t)$ convertor function setting. For all trust models excluding AER, the cumulative demand monotonically increase over the simulation. In contrast, $CU_{TFT}$ remains steady after almost 10 time steps in AER. This is because the CM in AER is detected as a con-man and is assigned a low value of trust. Moreover, the consequent cooperations of CM are insufficient to increase its trust level and consequently its demand level. Figure 7 illustrate $CU_{TFT}(30)$ for all simulations. It is interesting to observe that all trust models in terms of cumulative demand can be ranked in the same order over three different sets of simulations. By comparing cumulative demand in each of the trust models




(a) $H_o[t]$ converter function (b) $H_n[t]$ converter function (c) $H_c[t]$ convertor function

Fig. 5. Cumulative Utility of SP and SC ($CU_{SP,SC}$ and $CU_{SC,SP}$) for all 3 sets of simulations.

over three different convertor functions, we can observe that the cumulative demand of a specific trust model in $H_o(t)$ is higher than that in $H_n(t)$. Moreover, the cumulative demand of specific trust model in $H_n(t)$ is higher than that of $H_c(t)$.

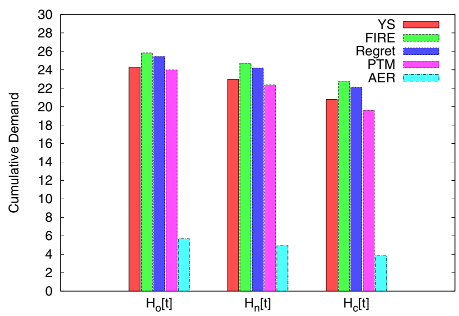



Fig. 7. Cumulative demand after 30 time steps

## B. One-to-multiple

The simulations reported in this section were run with one Service Consumer agent (SC) and two Service Provider agents (SP). As with the One-to-one experiments in Section V-A, we ran 3 sets of simulations while sets are different in terms of the examined convertor functions (i.e., $H_c[t]$, $H_n[t]$, $H_o[t]$). Each set consists of 5 simulations in each of which a SC agent utilizes either Regret, FIRE, AER, PTM, or YS as its trust model and uses Tit-for-tat (TFT) as its interaction strategy. In all simulations, one of the SP agents employs the con-man (CM) strategy and the other one utilizes Tit-For-Tat (TFT).

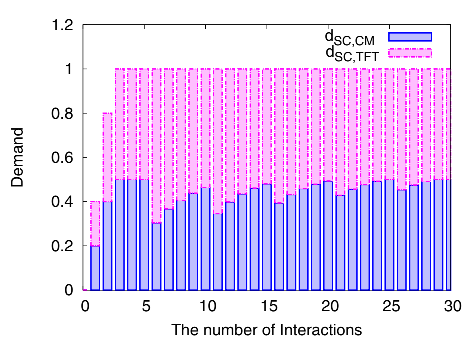



Fig. 8. Distribution of demand over SPs when the SC uses YS.

Figure 8 demonstrates the distribution of SC's demand over two SPs agents (CM and TFT) while SC uses the YS model. As both the TFT service provider and SC use TFT as their interaction strategy, cooperation emerges between them and they stay in equilibrium with each other (continue cooperating with each other). As a result, the trust value of $SC$ on $TFT$ increases monotonically and consequently the corresponding demand ($d_{SC,TFT}$) increases monotonically. On the contrary, $d_{SC,CM}$ fluctuates over the simulation because the corresponding trust (i.e., $T_{SC,CM}$) fluctuates. It is interesting to note that CM agent always covers a considerable part of $D_{SC}$ in YS despite being the con-man. This is because YS, FIRE, Regret, and PTM let the con-man regain trust too easily.

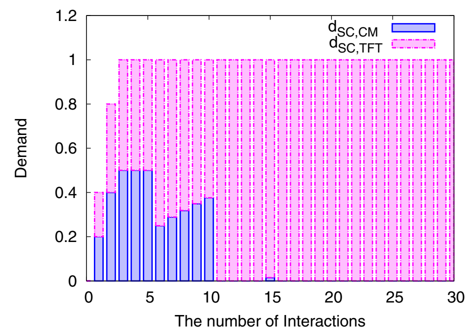



Fig. 9. Distribution of demand over SPs when the SC uses AER.

Figure 9 demonstrates the distribution of SC's demand over two SPs agents (CM and TFT) while SC uses the AER model. As AER is able to detect the CM agent and assigned a low value of trust to it, after 10 interactions, the SC demand will mostly be supplied by the TFT service provider. This adaptability of AER in switching to the trustworthy service provider results in maximizing the utility of the SC agent using AER over the other SC agents, as illustrated in Figure 10. Using AER, the SC agent can gain higher utility than the other SC agents in all simulations over various converter functions. It is interesting that this difference of utility is caused by only the usage of different trust models since all SCs utilize the same interaction strategy (i.e., TFT).

Figure 11 shows $\overline{U_{SC}}$ over the simulation and confirms that the higher utility of an agent using AER is not because it has higher cumulative demand over the simulation. This success is achieved by the adaptability of AER in switching to more trustworthy agents.

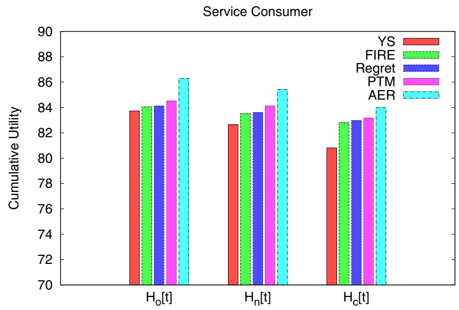



Fig. 10. $CU_{SP}$ for all 3 sets of simulations.

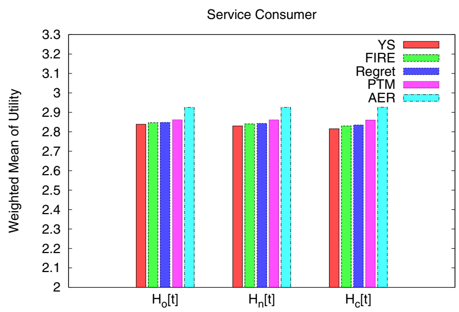



Fig. 11. $\overline{U_{SP}}$ for all 3 sets of simulations.

Figure 12 illustrates $CU_{TFT}$ for all the simulations. When the SC uses AER, the TFT service provider agent has the highest cumulative utility compared to when SC uses other trust models. These results are evidence that using AER is not only benefiting the SP agents but also benefiting the trustworthy SP agents by allocating higher amount of demand to them. Note that these results are independent of the convertor functions used.

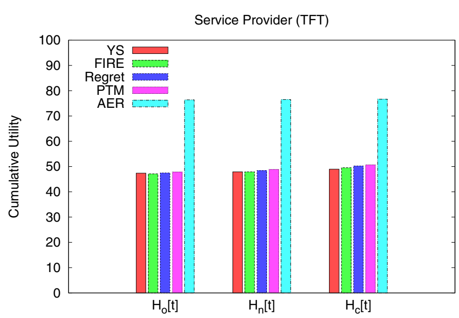



Fig. 12. $CU_{TFT}$ for all 3 sets of simulations.

## VI. Conclusion

In real marketplaces agents will attempt to satisfy their demands by moving demand between service providers based upon their trust in available service providers. This paper has investigated the proposal that demand naturally increases with increasing trust in a service provider. In the 2 classes of experiment described, in a single provider marketplace, service consumers will tend to have unsatisfied demand. In a multi-provider marketplace adaptive trust schemes such as AER will lead to the identification of trustworthy providers and satisfaction of consumer demand by using trustworthy agents. Furthermore, agents using the AER trust model have higher cumulative utility than con-man agents thereby providing an incentive for them to behave in a trustworthy manner. Our results demonstrate that adaptive trust models such as AER discourage periodic or cyclical defaulting on contractual obligations.

Future work will extend the trust-dependent demand model to consider other marketplace factors such as the number of transactions and transaction profile. Moreover, it would be interesting to model discrete divisible demand and analyze the performance of the trust models in such marketplaces.

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