EVALUATION OF REPUTATION METRIC FOR THE B2C e-COMMERCE REPUTATION SYSTEM

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Abstract: This paper evaluates recently developed novel and comprehensive reputation metric designed for the distributed multi-agent reputation system for the Business-to-Consumer (B2C) E-commerce applications. To do that an agent-based simulation framework was implemented which models different types of behaviours in the marketplace. The trustworthiness of different types of providers is investigated to establish whether the simulation models behaviour of B2C E-commerce systems as they are expected to behave in real life.

1 INTRODUCTION

The process of globalization creates new challenges and opportunities for companies by offering an access to new markets that were previously closed due to cost, regulations etc. The adoption of the Internet, in particular Internet-enabled B2C E-business solutions, allows many Small and Medium Enterprises (SMEs) to respond to these challenges and opportunities by extending the geographic reach of their operations. Very often however, Websites created for sales purposes are simple in design and functionality and therefore, do not arouse trust at first glance. Furthermore, in contrast to "big brands" which have already established their reputation in the online marketplaces, SMEs are unknown to many E-commerce customers.

In the E-commerce environment, which does not require the physical presence of the participants, there is a high level of "uncertainty" regarding the reliability of the services, products, or providers. Although many technologies exist to make the transaction more secure, there is still the risk that the unknown provider will not comply with the protocol used. Thus, the decision of who to trust and with whom to engage in a transaction becomes more difficult and falls on the shoulders of the individuals. In such an environment, reputation systems come in place to assist consumers in decision making. The basic idea is to let parties rate each other to derive a trust or reputation rating. This can assist in deciding whether or not to engage in a transaction with this party. Reputation systems are particularly useful in cases where the trustee is unknown to the individual involved but well known to others.

There are a number of existing consumer-to-consumer (C2C) on-line reputation systems such as eBay (2008) or Amazon (2008). However, unlike C2C E-commerce marketplaces, most B2B sites do not provide users with feedback information. There are some centralized services/websites though, which offer store ratings and reviews to their users, such as BizRate (2008) or Resellerratings (2008). All of them however, rely only on simple algorithms calculating the average rating based on the given feedback.

Nevertheless, much academic work on reputation systems has been devoted to the C2C part of E-commerce (Peer-to-Peer networks) which can be found reviewed in (Sabater and Sierra, 2005; Josang et al., 2007; Gutowska and Bechkoum, 2007a; Marti and Garcia-Molina, 2006). Unlike the existing centralized approaches (e.g. eBay, Amazon) which are single-factor based, many authors proposed distributed reputation systems which still tend to be "one issue-centric" (Lin et al., 2005; Bamasak and Zhang, 2005; Huynh et al., 2006; Fan et al., 2005) (addressing only one of many problems existing in the reputation systems (Josang et al., 2007; Gutowska and Bechkoum, 2007a; Marti and Garcia-

Molina, 2006)). Even in studies attempting to provide more complex reputation methods, for example work on Histos/Sporas (Zacharia et al., 2000), some issues are still not taken into consideration, such as the transaction value, age of rating, or credibility of referees.

Many of the problems addressed in C2C reputation models also apply to the B2C E-commerce environment. Not many authors however, concentrate on the latter model of the marketplace. The only work known to the authors addressing it is (Cho et al.) and (Ekstrom and Bjornsson, 2002). Nevertheless, to the best of the authors' knowledge, there are no studies whose main focus is to derive reputation ratings in B2C E-commerce environment taking into account the characteristics of the providers.

This paper aims to evaluate a novel reputation metric for computing reputation in a multi-agent distributed B2C E-commerce system. To do that, the agent-based simulation framework was implemented. The strength of the metric is measured by how well it reflects the agents (providers) behaviour including resistance against different hostile agents. Other important aspects of reputation systems such as privacy of transaction data, protection against collaboration attacks, and unfair ratings are out of the scope of this work.

The proposed reputation metric evaluated in this paper offers a comprehensive approach by including age of rating, transaction value, credibility of referees, and number of malicious incidents. Furthermore, in addition to the information about past behaviour it also incorporates other aspects affecting online trust which are based on providers' characteristics. Past behaviour, is not the only information source affecting trust/reputation rating of an online vendor. According to previous research (Gutowska, 2007; Gutowska and Bechkoum, 2007b), there are many issues influencing online trust-based decisions such as existence of trustmark seals, payment intermediaries, privacy statements, security/privacy strategies, purchase protection/insurance, alternative dispute resolutions as well as existence of first party information. The extended approach evaluated in this paper yields a promising improved distributed B2C reputation mechanism. The problem of complexity of the reputation metric is further described in (Gutowska and Buckley, 2008a; Gutowska et al., to appear).

2 REPUTATION SYSTEM FRAMEWORK

The simulated reputation metric in this study is designed for the B2C E-commerce reputation system in which two main roles are considered: buyer agent i.e. agent representing a user and provider (web service). A *user agent* collects for its user the distributed reputation ratings about a *web service (provider)*. In return, a user provides the agent with ratings about a transaction in order to build the reputation database of the services. Agents create a network where they exchange transaction ratings about web services their users have dealt with, this is called a *buyers' coalition* in the paper. In this way they are involved in a joint *recommendation process*.

User agents and providers are engaged in a *transaction process* e.g. buying-selling, where money and products/services are involved.

To assess the reputation of a provider, first, a user agent will use the information from the direct interactions it has had with that party and second, the ratings provided by other agents (indirect ratings) from the buyers' coalition which have dealt with the provider.

The proposed reputation system is distributed where each user agent will store their opinion about transactions with other parties.

The assumption is that it is in users' interest to leave feedback after each transaction as that is the only way the reputation system will work. The participants are aware that if they want to calculate the reputation rating about a particular provider the only source of information will be their feedback from the past and feedback received from other users. Also, when entering the system as a new member they are duty-bound to both. The users rate transactions they were involved in and share this information with others when requested.

3 REPUTATION METRIC

The reputation metric (Gutowska and Buckley, 2008a) evaluated in this paper is based on the weighted average. The reputation value of provider p is calculated as the arithmetic mean of the compulsory reputation (Section 3.1) and the optional reputation (Section 3.2). In addition the weight $wm(p)$ based on the number of malicious incidents is applied.

If optional reputation metric is not calculated then the reputation metric takes the value of compulsory reputation metric multiplied by *wm(p)*. Further, the full rating scale of trust is [0; 1].

3.1 Compulsory Reputation

Compulsory reputation is based on the set of the compulsory parameters and is defined as the arithmetic mean of *aggregated direct and indirect ratings* (see below). The rating scale for compulsory reputation metric is [0; 1].

3.1.1 Compulsory Parameters

Transaction Ratings. In the proposed system the quality factors constitute the explicit ratings left by the user after the transaction and consist of three components (as vector values): transaction outcome i.e. if the product/service was received, fulfilling provider's signals (Rein, 2005) e.g. if the delivery time, the product were as promised, as well as customer service/support.

Raters' Credibility (Implicit User Reputation). Whilst choosing the group of users to require the data from to calculate indirect reputation, it is important to take their credibility as referees into account. The reason for that is three-fold. Firstly, it is often too costly or impossible to collect ratings results from all interactions with the provider in question (Josang et al., 2007). Secondly, to avoid the inclusion of dishonest feedback into reputation calculations from users demonstrating colluding behaviour or leaving unfair ratings. Thirdly, to choose the right subset of users with "similar opinions". Namely, different people have different standards and they tend to trust the opinions of people who have the same standards with themselves (Zacharia et al., 2000). The solution applied here is to extract users' reputation automatically and implicitly from their past transaction rating data and use it to choose *"n best/most suitable raters"*. The method presented here is inspired by (Cho et al.) and uses raters' ratings to estimate their underlying credibility. It is based on the source credibility theory (Best et al., 2003) which employs several schemes of collaborative filtering methods (using similarities between a target rater and the rest of the users). The theory was shown to support rating mechanisms both in the B2B (Ekstrom and Bjornsson, 2002) and B2C (Cho et al.) E-commerce.

Source of Feedback. The reputation metric in this study applies the weight *ws(p)* based on the rating tendency concept proposed in (Cho et al.). It decreases the rating from the rater who has a tendency to rate higher than others, and vice versa.

$$ws(u) = 1 - (\overline{g}_u - \overline{g}_{A(u)}) \tag{1}$$

Where:

g_u is the average transaction ratings from a rater u

$g_{A(u)}$ is the average ratings of the other users from the subset of the "best/most suitable users" (for the providers that the rater u rated).

Reputation Lifetime. In order to model the dynamic nature of reputation, the weight associated with the reputation lifetime *wt* is applied which constitutes an exponential function of time. In this way the more recent ratings are considered more important and are valued higher comparing to the older ones. Furthermore, as in (Zacharia et al., 2000), the memory of the reputation system is considered which disregards very old ratings.

$$wt_x = \beta^{-\Delta t(x)} \tag{2}$$

Where, $\Delta t(x)$ is the time difference between the current time (i.e. time of request) and the time when the transaction x took place. β is used to scale $\Delta t(x)$ and $\beta > 1$. The time weight is applied to the reputation metric in a recursive algorithm (Section 3.1.2).

Transaction Value. In counting reputation ratings the value of the transactions is also taken into account counteracting users who try to build a high reputation by cooperating in many small transactions and then cheat in a very large transaction. Also, the transaction value range depends on the context to which the reputation system will be applied i.e. the maximum price of sold goods/services in the marketplace. The weight associated with the **transaction value** wv_x is calculated using the formula below:

$$wv_x = 1 - \gamma^{-v(x)} \text{ and } \gamma = \sqrt[x]{1/vMax} \quad where \quad x \to 0 \tag{3}$$

Where, $v(x)$ is the value of transaction x and *vMax* is the transaction range i.e. the maximum value of the goods/services in the marketplace (based on the context to which the reputation system is applied). γ is used to scale $v(x)$ and $\gamma > 1$.

Number of Malicious Incidents. As in (Bamasak and Zhang, 2005), in the proposed metric the reputation value is reduced to the minimum when a party reaches a certain threshold of malicious incidents. Up to that threshold the appropriate weight $wm(p)$ is applied based on the exponential function:

$$\begin{cases} if \quad 0 \le m < M \quad then \quad wm(p) = \alpha^{-m} \\ if \quad m \ge M \quad\quad then \quad wm(p) = 0 \end{cases} \quad (4)$$

where

$$\alpha = \sqrt[x]{1/M} \quad where \quad x \to 0 \quad\quad (5)$$

Where, m is a number of malicious incidents of provider p that occurred within the transactions taken into calculation. M is the set threshold of the number of malicious incidents above which the reputation value is reduced to minimum. In the equation above α is used to scale $wm(p)$ and $\alpha > 1$.

3.1.2 Computing Aggregated Ratings

The aggregated ratings are calculated with the application of the recursive algorithm used on the list of the transaction data records sorted according to the time value.

The *aggregated direct rating* value is calculated based on the data stored in the requesting agent a database i.e. regarding its direct interactions:

$$AGRD_{a,x}(p) = UR_{a,x}(p) \cdot \left[wt_x / (wt_x + wt_{x-1}) \right] + \\ + AGRD_{a,(x-1)} \cdot \left[wt_{x-1} / (wt_x + wt_{x-1}) \right] \quad (6)$$

For the case where $x=0$ the aggregated direct rating is equal to the updated rating for that transaction. Where $UR_{a,j}(p)$ is the updated rating value of transaction j with provider p calculated by agent a and x is the index of the last transaction on the list (n-1).

The *aggregated indirect rating* values are calculated in the same manner as above but are based on the list of the transaction data from the subset of the "n best/most suitable users". In addition, the weight ws is applied for each user providing information.

3.1.3 Computing Updated Ratings

Updated reputation rating $UR_{a,x}(p)$ is calculated by agent a for transaction x in which a was involved with provider p. In general, each provider is reputed by an agent after each transaction by providing a transaction rating g. This is the average of two components: fulfilling provider's signals and

customer service, where both can take values [0; 1]. In addition, appropriate weight wv based on the transaction value is applied.

3.2 Optional Reputation

In addition to the parameters presented above, a user may choose to include some or all of the *optional parameters* into calculations, which will influence the rating value of a provider. They are: existence of trustmark seals, existence of payment intermediaries, existence of first party information, existence of privacy statements, existence of security/privacy strategies, existence of purchase protection/insurance, and existence of alternative dispute resolution and are further described in (Gutowska and Bechkoum, 2007a; Gutowska, 2007).

The *optional reputation* is based on the set of optional parameters (providers' characteristics) which take values [0; 1] and is presented by the average of the above parameters which have been chosen to be included into calculation. The rating scale for optional reputation metric is [0; 1].

Optional reputation constitutes the initial reputation for newcomers as at that point there is no information of the past behaviour available.

4 SIMULATING B2C e-COMMERCE REPUTATION SYSTEM

The reputation system simulator used in this study was developed in Java and it is based on a slightly modified version of the RePast agent-based simulation toolkit (Schlosser, 2004).

In the presented simulation the market is populated by a number of agents that are divided into buyers and providers. The simulation is based on discrete time ticks. At each tick buyer agents are supposed to initiate a transaction with a provider and rate him afterwards. After the agents finished their actions the data is collected and represented graphically.

In the simulation the agents may enter or leave the community with equal probability (see Simulation parameters in Section 4.5.).

4.1 Modeling the Buyers

The buyers in the simulation framework differ in types. The buyer agent type is a combination of its trust disposition and its expectations.

Disposition to trust and the same risk attitude refer to the fact that people have a baseline attitude when they approach any trust situation. Some of them have a higher baseline level of trust than others thus, some individuals may find it easier/more difficult to trust. The disposition to trust affects the decision of either the buyer agent wants to engage in a transaction with the provider or not (see the acceptance function in Section 4.4.1.). Based on the above there are different types of the buyer agents in the simulation:

Risk Taking. This type of buyers is willing to take risk easily which means they accept the high value transactions even with the provider with low reputation.

Very Cautious. This type of buyers is risk averse and they are very careful with their decisions. They accept the transactions only if the provider has high reputation.

Conservative. Buyers representing this type come between the two above extremes.

In the presented framework the buyer agents have also different expectations towards the outcome of the transaction which affects the way they rate the transaction (see the rating function in Section 4.4.2.). As in (Michalakopoulos and Fasli, 2005), there are three types of the buyers agents in this study: optimists, realists, and pessimists.

Combining the two attributes discussed above the following types of buyers agents were implemented in the simulation framework: Risk Taking Optimists, Risk Taking Realists, Risk Taking Pessimists, Vary Cautious Optimists, Very Cautious Realists, Very Cautious Pessimists, Conservative Optimists, Conservative Realists, and Conservative Pessimists.

4.2 Modeling the Providers

The effectiveness of a reputation system and its metric depends on its resistance against malicious behaviours. The success of non-honest agents is its measurement for the quality of the metric (Schlosser et al., 2005). Therefore there are different types of providers implemented in the framework which are called Trustworthy, Shady, Player, and Fly-By-Night. They differ in their behaviour while transacting (this is also correlated with their characteristics). The characteristics of the interest are the cheating probability (*ChP*) and the range of the transaction outcomes they produce in terms of

customer service and fulfilling providers' signals (in other words the quality of services they provide). The remaining attributes constitute the optional parameters in the reputation metric and include: existence of trustmark seals, payment intermediaries, privacy statements, security/privacy strategies, purchase protection/insurance, alternative dispute resolutions as well as existence of first party information. They have been chosen based on the previously conducted survey discussed in (Gutowska and Bechkoum, 2007a). The above characteristics/optional parameters can take values between 0 and 1 where 0 means no existence of the attribute. In this way each type of the provider has the optional reputation (OP) value based on the above which constitutes the initial reputation value for any new provider in the system. In the reputation system there would be a devoted agent that would gather the optional parameters information from the providers' Websites. The properties of different providers are as follows:

Trustworthy. This type of the providers does not cheat in the transactions (ChP=0) and provides high service quality. All the parameters mentioned above have high values (OP=0.92).

Shady. This agent does not have a particular pattern in its behaviour (ChP=50). It provides false statements on its Website which results in high values of the optional parameters apart from Trustmark Seals and Payment Intermediaries (OP=0.63). The quality of the services it provides is low.

Player. This type of a provider tries to build high reputation by not cheating (ChP=0). When it achieves its goal however, it starts behaving in a malicious way (ChP:=100). When its reputation falls down below the threshold then it starts being honest again (ChP:=0). Player agent has got high values for First Party Information, Privacy Statements and Security Strategies (OP=0.43). When it does not cheat the services provided are of a high quality.

Fly-By-Night. This agent's goal is to cheat (ChP=100). It provides false information about the services it offers. The way of payment is direct to the bank account (OP=0.51). The quality of the services it provides is low.

4.3 The Simulation Cycle

The simulation framework is highly automated where the handling of the agents, initiation of the

transactions and storing the ratings are part of the framework. The simulator repeatedly iterates a cycle of events that would occur in the marketplace. The steps of a transaction are as follows:

1. The simulation engine selects a buyer agent who initiates a transaction with another provider agent.
2. The buyer agent tests if the transaction is acceptable i.e. he calculates the reputation of the provider in question based on his previous direct interactions as well as information from the buyers community (the acceptance function is described in Section 4.4.1.)
3. If the transaction takes place, the provider agent determines the outcome of it and the buyer agent rates it and stores the ratings. The ratings depend on the buyer agent type and his expectations and may not match exactly the real outcome (the rating function is described in Section 4.4.2.)

4.4 Modeling the Transaction and Rating Processes

4.4.1 Transaction Acceptance Function

In the presented simulation the buyer agents have a trust disposition which allows them to make different decisions when it comes to engaging in a transaction with a provider.

In this work the assumption is that no buyer agent will transact voluntarily with a non-trustworthy provider i.e. the provider with low reputation. The other factor taken into consideration while making the decision is the value of the transaction. The acceptance function therefore, is a correlation between the provider's reputation and the value of the transaction. The higher the value of the transaction the higher the reputation should be for the buyer to engage in this transaction. As different people have different disposition to trust, in the presented framework different types of buyer agents have different acceptance functions. In this way different types of agents accept the transaction of a specific value at the different reputation level

Users' willingness to trust however, can be changed by experience (Shneiderman, 2000). In the proposed framework all buyer agents representing a specific type start with the same acceptance function which is affected/changed later on by the outcome of the transaction (experience) and in particular by the providers' malicious incidents. The calculation of the acceptance threshold for a specific transaction

value with a specific provider is based on the Lagrange Interpolation (Cheney and Kincaid, 1998).

4.4.2 The Rating Function

In the proposed framework each buyer agent rates each transaction he has been involved in and collects these ratings (see Transaction ratings Section 3.1.1) in his database.

In a real marketplace, different people will rate a transaction differently based on their experience and their expectations towards the transaction outcome. In the discussed simulation framework, three cases are considered (as in (Michalakopoulos and Fasli, 2005)): optimists, realists, and pessimists. When it comes to the transaction, optimists will be expecting a very positive outcome, pessimists on the other hand a rather bad outcome, and realists will come somewhere between the two extremes. The simulation framework addresses the above scenario in a way that the optimist agent will hope for the best outcome (in terms of customer service and provider's signals) he has had so far with the provider in question, the pessimist agent will anticipate the worst one, and the realist agent will expect the average result based on his experience. If the expected outcome ($expOut$) is higher than the actual one ($realOut$), the buyer agent applies the punishment value (p) to the transaction rating ($rating$) which is a difference between the expected and the real outcome value. If the expected outcome value is equal or lower than the actual one, the ratings reflect the outcome. The above rules are presented below:

```
p:= expOut - realOut
if p>0 then
     if p<= realOut then
          rating:=realOut-Random(0, p)
     else
          rating:=realOut–Random(0,
realOut)
```

Apart from the transaction rating, the final reputation value includes also the other component which is Optional Reputation discussed in Section 3.2.

4.5 Simulation Parameters

There are several parameters which values can be changed in the simulation framework depending on the simulation needs. These are as follows: number of starting agents (buyers and providers), number of agents to add and remove in each step, add/remove probability, the probability of initiating transaction

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at each tick by a buyer agent, the amount of agents of each type in the community, and number of parallel simulations.

There are also some parameters which affect the reputation metric itself. These are the maximum number of malicious incidents, the transaction value range, weight for the source of feedback and weight for time factor. The maximum number of malicious incidents is a threshold above which the provider's reputation is decreased to zero. The transaction value range depends on the context to which the reputation system will be applied i.e. the maximum price of sold goods/services in the marketplace. The above values determine the weights for the time factor and malicious incidents of the reputation metric which are based on the exponential function. The weight for the source of feedback scales the importance of the ratings coming from the indirect interactions (buyers' community) and the weight for the time factor determines the impact of old ratings vs. the more recent ones. This weight is also based on the exponential function and is applied to the reputation metric in the form of a recursive algorithm (more details on the proposed reputation metric in (Gutowska and Buckley, 2008b; Gutowska and Buckley, 2008a)).

5 EVALUATION CRITERIA

The strength of the metric is measured by how truly it reflects the agents (providers) behaviour and in particular by its resistance against different hostile agents. In the simulation the average requested reputation, the market honesty, the acceptance rate, the average number of transactions and the average number of malicious incidents are calculated separately for each type of the provider agents.

Average requested reputation is the mean value of all reputation ratings of providers from a specific type as if calculated/received by a buyer when requesting reputation rating. This is based on the rating information stored in the buyers' databases.

Market honesty is the mean value of the actual outcomes from the transactions produced by the provider agents (not ratings). These are stored in providers' databases.

Acceptance rate is the proportion of accepted/completed transactions with all initiated transactions with providers of a specific type.

Average number of transactions is the average number of transaction that a provider of a specific type was involved in (accepted transactions).

Average number of malicious incidents is the average number of malicious incidents for a specific type of a provider.

The horizontal axis in the Figures below represents the time. In Figures 1, 2 and 6 the vertical axis corresponds to the computed reputation, in Figures 3, 4 and 7 it represents the number of transactions and in Figure 5 the acceptance rate.

6 SIMULATION RESULTS

As there is no work known to the authors that introduces the reputation metric for the B2C E-commerce reputation system, this paper presents pioneering results and it does not compare the efficiency of the evaluated reputation metric with any other.

Table 1 presents the parameters and their values used in the simulation.

Table 1: Parameters used in simulation.

Simulation Parameter	Value
Num. of starting Buyer agents	100
Num. of starting Provider agents	50
Num. of agents to add/remove in each step	1
Agents add/remove probability	1
Probability of initiaiting transaction	20
Percentage of the Providers of a specific type:	
Trustworthy	40
Shady	20
Player	20
Fly-By-Night	20
Percentage of the Buyers of each type	11
Max. num. of malicious incidents	3
Transaction value range	150
Weight for the source of feedback	0.9
Weight for the time factor	1.03

The simulation results are depicted in Figures 1-5. Market Honesty (Figure 1) and Average Requested Reputation (Figure 2) show that the reputation metric correctly reflects the behaviour of different types of providers i.e. Trustworthy agents keep their high reputation scores throughout the experiment and the different types of malicious agents have low reputation due to their transaction history. It is noticeable that initially the reputation of the malicious agents is a bit higher and it decreases with time. This is caused by the fact that the initial

reputation for new providers with no transaction records is their optional reputation which in many cases is based on the false information provided by them on their Websites. When the transaction information comes into the equation however, the reputation algorithm appropriately deals with the scenario and decreases the reputation value.
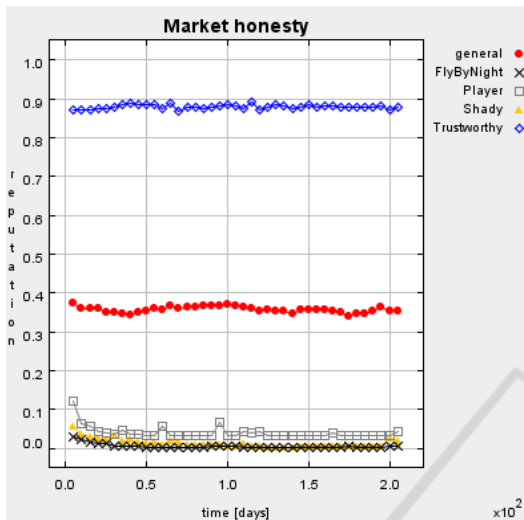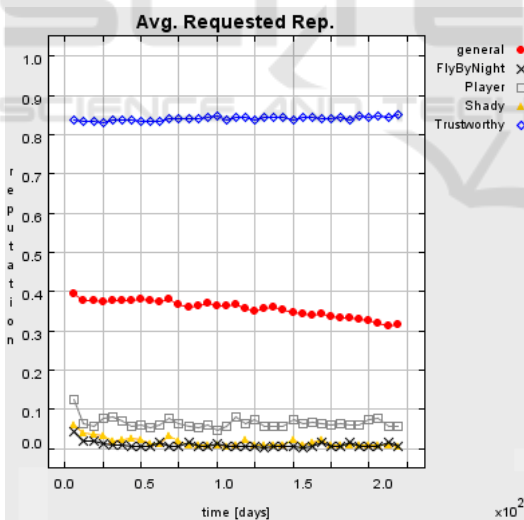

Figure 1: Market honesty.

Figure 2: Average Requested Reputation.

The slight difference in values between Market Honesty and Average Requested Reputation reflects the fact that different types of buyer agents rate the transactions differently which does not always match the real outcomes. The dissimilarity however, is not significant which strongly suggests that the reputation metric closely mirrors the behaviours in the marketplace.

The results shown in Figures 3-5 indicate that malicious agents are not involved in many transactions (Figure 3) due to their low reputation. The Acceptance Rate (Figure 5) decreases as the buyer agents do not accept transactions with the providers with low reputation. The Average Number of Malicious Incidents (Figure 4) is kept stable which is controlled by the Maximum Number of Malicious Incidents simulation parameter. If the parameter is set as M=1 then the reputation metric will decrease the reputation of this provider to 0 which means he will not be accepted as a transaction partner anymore and it will not get a chance to gain profit by cheating. This scenario is illustrated in Figure 6, ceteris paribus (i.e. while other parameters stay unchanged).
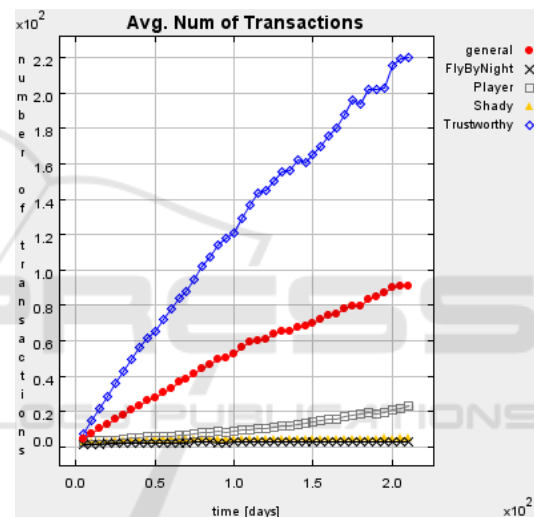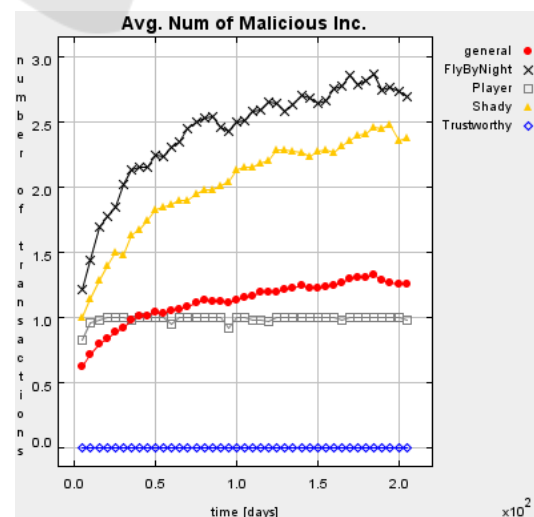

Figure 3: Average Number of Transactions.

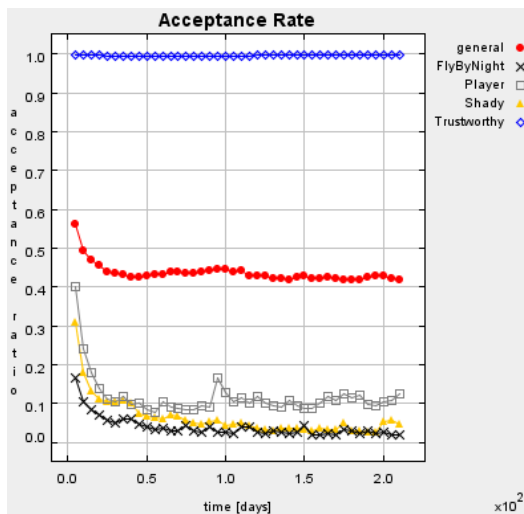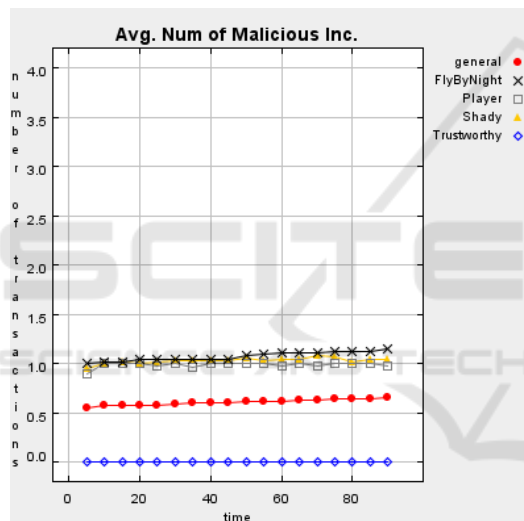Figure 4: Average Number of malicious Incidents.

Figure 5: Acceptance Rate.

Figure 6: Average Number of Malicious Incidents, M=1, ceteris paribus.

7 CONCLUSIONS

This paper presents and evaluates the novel, comprehensive reputation metric designed for the multi-agent distributed B2C E-commerce reputation system. An agent-based simulation framework was implemented that models the B2C E-commerce marketplace. The results show that the proposed reputation metric closely reflects different types of behaviours in the marketplace. The method is particularly resistant to malicious behaviour.

One of the assumptions of the proposed system i.e., that there are no external parties included in the framework can be easily amended in the future by including the information coming from other systems or reputation authorities. The other area which could be looked at more closely is the distribution of different buyer behaviours/types in the real marketplace. The work on inclusion of those in the proposed framework is underway.

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