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Abstract

Purpose – The purpose of this paper is to enhance trust in multi-agent systems by presenting a new computational model, named reputation-distribute-conflict (R-D-C), to select the most trustworthy provider agent based on computing reputation, disrepute, and conflict of each provider agent.

Design/methodology/approach – R-D-C propose based on three vital components for evaluating trustworthiness of providers as reputation, disrepute, and conflict, where disrepute is a component almost all trust models ignored. The R-D-C model presents a computational method for evaluating to select the most trustworthy provider agent. In order to evaluate the R-D-C model, the experimentation was carried out in two stages, by designing a simulated multi-agent environment. First, the accuracy of the R-D-C model in computing R-D-C was investigated. Second, the performance of the model was compared with other existing trust models. Moreover, comparison of the performance of the R-D-C model with other models demonstrates that the R-D-C model performs significantly better than the other models. Therefore, the R-D-C model is capable of evaluating the trustworthiness of agents more accurately and it can select the most trustworthy provider better than the other models.

Findings – The results show that the R-D-C model works well in different multi-agent environments, even when the number of untrustworthy providers is higher than that of the trustworthy ones.

Originality/value – The R-D-C model is useful for researchers to enhance the safety of online transactions in multi-agent environments, especially if the researchers explore more components; in fact the R-D-C model is capable of adding these new components and selects the most trustworthy provider agent.

Keywords Reputation, Conflict, Multi-agent systems, Disrepute, Trust models

Paper type Research paper

1. Introduction

Intelligent software agents apply information to organize and filter data to meet the users' needs (Khan *et al.*, 2012). The multi-agent systems in an e-commerce environment organize and constrain the actions that the agents can perform at a given time (Tampitsikas *et al.*, 2012). It should be considered that many of the methodologies proposed by the concept of multi-agent systems are mainly based on business applications. It means that the main motivation for these methodologies is to design and develop the business application that is used in the real environment (Mirzaie and Fesharaki, 2012). However, e-commerce has increased the likelihood or negative consequences of some risks that already exist in the offline environment and created some risks that are completely new (Zendehdel and Paim, 2012). As such, the generation of economic activities via electronic transactions which is based on multi-agent systems requires the presence of a system of trust and distrust in order to ensure

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the fulfilment of a contract (Walter *et al.*, 2008; Zhou, 2009), but in the absence of personal experience, trust often has to be based on referrals from others (Bradai, 2014; Jøsang *et al.*, 2007). Hence, reputation can be considered as a collective measure of trustworthiness based on the referrals or ratings from members in a community (Jøsang *et al.*, 2007; Tong, 2015). For instance, the beta reputation system (Commerce *et al.*, 2002; Yu *et al.*, 2014) represents a witness information model that agents employ not only their own experience in evaluating a provider, but also reports made by other agents in multi-agent environments (Kerr and Cohen, 2009).

On the other hand, if a provider cheats, it may damage its reputation, and hinder its ability to engage in future sales. Since the behaviour of each provider agent can change in an uncertain multi-agent environment (Bale *et al.*, 2015), to evaluate the trustworthiness of each agent, both reputation and disrepute value of that agent should be considered according to its previous behaviours. Moreover, the multi-agent environment involves autonomous provider agents, agents that may show unstable behaviours. As a result, it is necessary to measure the conflict in previous behaviour of agents.

Thereby, this paper aims to propose a trust model based on three components: reputation, disrepute, and conflict (R-D-C), which should be considered for designing a trust model, and selecting the most trustworthy provider agent. This proposed model can enrich the trust in multi-agent systems by considering previous positive and also negative behaviours of providers in a heterogeneous multi-agent environment, in which each agent is autonomous and self-interested.

The rest of the paper is organized as follows: Section 2 describes the most representative related models. The proposed model, named R-D-C is presented in Section 3 which explains the procedure of R-D-C, and a computational example is given in Section 4. This is then followed by evaluating the R-D-C with two stages of experimentations in Section 4. The results are discussed in Section 5. Finally, Section 6 contains the conclusions and recommendations for future work.

2. Background

In this section, the concepts of reputation, disrepute, and conflict are described by presenting several related models according to these components.

2.1 Reputation

Reputation is a collective evaluation of an agent carried out by many agents. In fact, it is a total measure of trust by other agents in a network of a service provider (Nusrat and Vassileva, 2012). When an agent has to select the most promising interlocutors, it should be capable of allocating a proper weight to the reputation (Rosaci, 2012). Therefore, reputation is the public's opinion about the character or standing (e.g. honesty and capability) of an entity, which could be a person, an agent, a product, or a service.

SPORAS presented by Sabater and Sierra (2005) is a reputation mechanism for a loosely connected environment, in which agents share the same interest. In this model, the reputation value is calculated by aggregating users' opinions. In fact, two most recent agents are considered for gathering the rating values. Moreover, this model suggests a new recursive reputation rating method at a specific time; the more recent ratings carry more weight based on previous reputation ratings. However, this model has two main limitations. First, SPORAS aggregates only the most recent ratings between two users. Second, after each update, users with very high reputation values achieve much lower rating changes than users with low reputation values (Lee, 2014; Sabater and Sierra, 2005).

On the other hand, an integrated reliability-reputation model for the agent societies (TRR) presented by Rosaci *et al.* (2011) measures the reputation of agents by considering the trustworthiness of an agent that rates other agents. In fact, in this model, the reputation of each agent is computed based on the ratings given by other agents that have had previous interactions with them and the trustworthiness of the rater agents. In this case, the ratings reported by highly trustworthy agents have higher values than the ratings reported by agents with lower trust. Hence, the rater agents with less trustworthiness have less effect on the evaluation of reputation.

In another model, REGRET, the reputation is considered to consist of multi-facet concepts, instead of single or abstract concepts (Sabater and Sierra, 2001b). The REGRET model has an ontological structure, in which the ontological interactions come from a combination of multiple aspects. Hence, the reputation value of each aspect should be evaluated separately using the individual or social dimensions, and the values of these reputations are then combined to constitute the ontological reputation. The advantage of the REGRET model is that it computes reputation based on the number of agents, and the interaction frequency of the rater agents (Sabater and Sierra, 2001a).

Literature review shows that reputation is a component that has been considered more than other components. Each model has used different variables to evaluate the reputation of each agent. For example, the TRR model revealed that the reliability of rater agents should be considered in determining the reputation. If the rater agent is reliable, the rate presented by that agent is considered as an accurate rate. However, TRR considers the same weight for all the interactions. This may not proof to be accurate, as recent interactions that show the recent behaviour of agents should have higher values. On the other hand, SPORAS reflected the time in evaluating reputation of agents by placing more values on interactions that are closer to current time. However, both TRR and SPORAS ignored the effect of the number of agents that rate a specific agent and the interaction frequency of the rater agents, as shown by the REGRET model. Therefore, it is clear that each model has focused on different aspects in calculating the reputation of agents. In order to improve the reputation calculation, the R-D-C model will consider the reliability of rater agent, time of interaction, the interaction frequency of the rater agents and the number of rater agents.

2.2 Disrepute

In multi-agent systems, agents are autonomous and behave self-interested, so it is possible that the agents, which had benevolent roles in their previous interactions, change their behaviours to malicious. Thus, in this unpredictable environment for selecting the trustworthy agent among other agents, it is necessary to consider the previous dissatisfying interactions (negative outcomes) of agents in addition to the previous satisfying interactions (positive outcomes). However, the agents seem ignorant of the effect of negative behaviours on recognizing the most trustworthy agent by existing trust models. In this paper, a new concept which considers a darker side of reputation is proposed based on previous dissatisfying interactions, which is named disrepute. In general, the concept of disrepute is the public's opinion about the character or standing (e.g. dishonesty and incapability) of an entity; this could be a person, an agent, a product, or a service (Bijani and Robertson, 2014; Brusilovsky *et al.*, 2003).

Disrepute is computed based on the negative opinions of other agents about a specific agent, while the reputation of each agent is based on the positive opinions of other agents about a specific agent. In fact, requester agents can avoid the risk of purchasing and maximize their expected value of goods by dynamically maintaining and considering both sets of reputation and disrepute of a provider agent (Brusilovsky *et al.*, 2003; Gu *et al.*, 2010).

Accordingly, an agent, who has to select the most promising agent, should consider the value of disrepute of that agent in a multi-agent environment, along with its reputation value.

Very few studies considered disrepute in evaluating the trustworthiness of agents. Regan *et al.* (2005) presents sharing models of sellers for evaluating the trustworthiness of agents by considering both reputation and disrepute. According to this study, after each interaction, a requester rates the provider and then compares the given rate with the threshold value which it has defined for that interaction. If the recorded rate is higher than the threshold value, the provider is considered reputable; otherwise disreputable.

In Kerr (2007), a threshold value was applied to distinguish between reputable and disreputable agent. For this purpose, each requester stores the ratings of each provider (i.e. reputation range between −1 and 1). Moreover, each requester also keeps an expected value function for each provider agent, that is, the expected value that the requester will derive from accomplishing a transaction. Therefore, a requester keeps sets of known reputable providers (i.e. those with ratings above a reputable threshold Θ) and known disreputable providers (i.e. those with ratings below a disreputable threshold θ). Providers who fall into neither category are considered to be non-disreputable (Kerr, 2007). Three categories of providers were used, namely, reputable, disreputable, and non-disreputable. However, although these models distinguished between reputable and disreputable providers, they did not consider the size of the multi-agent environment, which usually consists of different number of untrustworthy and trustworthy agents. In addition, a notable gap in these studies is that it is impossible to determine the reputation of a provider when the provider's behaviour is not consistent, that is, roles of interaction can vary from trustworthy to untrustworthy. Therefore, it is inaccurate to select a trustworthy provider based only on its positive ratings. In other words, agents should consider both previous positive and negative interactions of each provider, and evaluate the reputation value along with its disrepute.

2.3 Conflict

The agents can exhibit different behaviours in different times of interactions, while some of them have the habit of practicing inconsistent behaviours. Therefore, in order to calculate the trust value of each agent more accurately, it is essential to consider the conflict behaviours agents had in their previous interactions.

Formal trust model (FTM) presented by Wang and Singh (2007), based on the probability theory, divides the outcomes of past interactions into positive (satisfying) and negative (dissatisfying). This model combines the trust values defined from multiple sources (Hang *et al.*, 2008; Wang and Singh, 2010). The model calculates the trust of each agent according to the posterior probability of previous satisfying and dissatisfying interactions.

FTM (Wang and Singh, 2007) offers the expected value of the probability of a positive outcome, $\alpha = (s+1)/(t+1)$; it shows the conflict in the evidences, where, s is the number of previous satisfying interactions and t is the total number of previous interactions. While $\alpha \in [0, 1]$, if α approaches 0 or 1, it means unanimity; otherwise, if $\alpha = 0.5$, it means the number of satisfying interactions is equal to the number of dissatisfying interactions, which indicates the maximum conflict in the evidences. Ultimately, FTM (Wang and Singh, 2007) calculates the conflict in evidences as min (α, $1-\alpha$).

Evidence-based trust model (Wang and Singh, 2010) defines the same method as FTM for evaluating conflict based on computing the minimum of the proportion of previous satisfying interactions to the total number of previous interactions, and the proportion of previous dissatisfying interactions to the total number of previous interactions.

Similarly, Noorian *et al.* (2014) proposed a trust-oriented mechanism to calculate conflict. According to this model, when an evidence is received from each interaction, the requester agent computes the expected value of the probability of a previous satisfying interaction for that provider agent using a β distribution (Commerce *et al.*, 2002) as; $P(R) = r+1/r+s+2$ where r indicates the number of previous satisfying interactions and s denotes the number of previous dissatisfying interactions.

If the calculated value approaches 0 or 1, it indicates unanimity in previous behaviours of the agent, which shows that the agent has more stable behaviours. Otherwise, it illustrates a maximal conflict in the gathered evidence (Noorian *et al.*, 2014).

Based on the reviews, all the existing models determined the conflicting value for an agent based on the same approach that is, by using the posterior probability of previous satisfying and dissatisfying interactions.

Overall, it is noted the existing models mostly presented methods to evaluate the trustworthiness of agents based on different components, such as reputation, conflict, etc. Apart from the fact that these components were analysed separately, the models also failed to suggest a specific method to select the most trustworthy provider based on all the recommended providers. It is important to investigate if trust components such as reputation, conflict and disrepute can be integrated together so as to increase the trust in the online environment. Therefore, the current study was undertaken with the aim of developing an integrated computational model based on R-D-C to enhance trust in a multi-agent environment by selecting the most trustworthy provider. The next section presents the proposed R-D-C model in detail.

3. R-D-C model

In this section, a computational method for calculating R-D-C of each provider agent is presented based on the related models which were described in Section 2, and then an approach is proposed for selecting the most trustworthy provider agent based on the calculated R-D-C values of the providers. In this case, first, the requester agent sends a query to their neighbourhood agents, as an advisor agent, and asks them if they are familiar with the identified providers, to define the number and also rating of previous satisfying and dissatisfying interactions that they had with those providers. This query contains the following:

(1) the ID of the requester agent that has issued the query (Re*q*);

(2) the kind of services which the requester needs (*S*);

(3) the ID of providers that claim they can provide the services (Pr*o*);

(4) request for the ID of the providers which claim that they can provide the demanded services (if any);

(5) request for the number and the overall rating of previous satisfying interactions with the providers (if any); and

(6) request for the number and the overall rating of previous dissatisfying interactions with the providers (if any).

After collecting the responses, the requester agent calculates the R-D-C of each provider to select the most trustworthy one.

In the following sections, the method of computing reputation is described, disrepute, and conflict. Ultimately, the method of selecting the most trustworthy provider is presented based on these three components.

As shown in Figure 1, the first requester agent sends a query to advisor agents and asks them to suggest a trustworthy provider; then the requester collects the responses of the advisors. After collecting the information from the responder advisors, including their suggested provider, the requester calculates the reputation, disrepute, and also conflict of each suggested provider. Finally the requester selects the most trustworthy provider according to the computed components by using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method.

3.1 Computing reputation

Based on the analysis of previous models for computing the reputation of each agent, the rate of satisfaction, and the number of satisfying interactions reported by advisors should be considered. Moreover, to reduce the effect of malicious advisor agents which

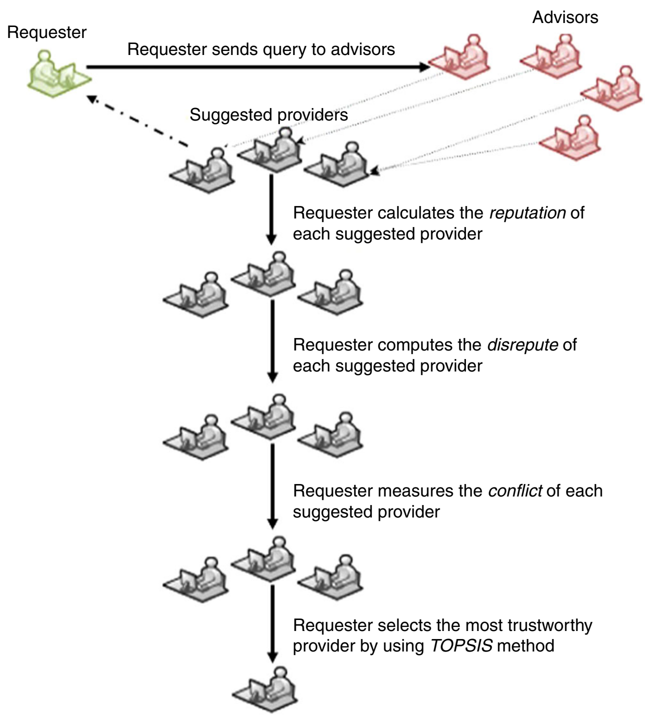

Figure 1.
R-D-C model

give a wrong rate to a provider, the requester should weigh the reliability of each advisor agent, who rates the providers.

According to this explanation, a formula for computing the reputation value of each provider agent is as follows:

$$r_{A\to\mathrm{Pr}o} = \frac{\sum_{a_i\in A}\left(\omega_{\mathrm{Re}q\to a_i}\times t_{a_i\to\mathrm{Pr}o}\times\lambda_{a_i\to\mathrm{Pr}o}\right)}{\sum_{a_i\in A}\omega_{\mathrm{Re}q\to a_i}} \tag{1}$$

where $A=\{a_1, a_2, ..., a_n\}$ shows the advisors the rate of the providers $\omega_{\mathrm{Re}q\to a_i}\in[0,1]$ is the reliability value that the requester, Req, gives to the advisor agent, a_i, according to their previous interactions; $t_{ai}\to_{\mathrm{Pr}o}$ is the total satisfaction rate which the rater advisor agent, a_i, gives to provider agent, Pro, according to their previous interactions; $\lambda_{a_i\to\mathrm{Pr}o}=\sum_{l\in s}l_{a_i\to\mathrm{Pr}o}/\sum_{i\in\text{interactions}}I_{a_i\to\mathrm{Pr}o}$ denotes the proportion of the number of satisfying interactions to the total number of previous satisfying and dissatisfying interactions between the rater advisor, a_i and the provider agent, Pro. In fact, the growth in the proportion of satisfying interactions to the total previous satisfying and dissatisfying interactions increases the confidence degree of the rated provider.

The satisfaction rate of each provider according to the previous interactions is a numerical between 0 and 1.

Moreover, the number of advisors which send the ratings for a provider affects the accuracy of the reputation value of that provider. It means, by growing the number of advisors that rate a specific provider agent, the reputation value of that provider increases. Hence, the final formula for computing the reputation of each provider is as follows:

$$R_{\mathrm{Re}q\to\mathrm{Pr}o} = \frac{\sum_{n\in N}n}{N}\times r_{A\to\mathrm{Pr}o} \tag{2}$$

where $\sum_{n\in N}n$ is the total number of advisors that rate the provider agent, Pro; N represents the total number of advisors that responded to the query; $r_{\mathrm{A}\to\mathrm{Pr}o}$ denotes the reputation value of the specific provider agent, Pro, obtained by Equation (1).

3.2 Calculating disrepute

Disrepute shows the opinion of other advisors that a specific provider cannot be trusted. In this case, the requester measures the disrepute of each provider agent according to the collected ratings of previous dissatisfying interactions, which is achieved through the responder advisors, as shown in the following:

$$\neg r_{A\to\mathrm{Pr}o} = \frac{\sum_{a_i\in A}\left(w_{\mathrm{Re}q\to a_i}\times\left|dt_{a_i\to\mathrm{Pr}o}\right|\times\mu_{a_i\to\mathrm{Pr}o}\right)}{\sum_{a_i\in A}w_{\mathrm{Re}q\to a_i}} \tag{3}$$

where $w_{\mathrm{Re}q\to ai}\in[0, 1]$ is the weight of reliability the requester considers for the rater advisor agent, a_i, according to their previous interactions; $\left|dt_{a_i\to\mathrm{Pr}o}\right|$ is the rating of previous dissatisfying interactions which the advisor agent, a_i, gives to the provider agent, Pro, according to their previous interactions; $\mu_{a_i\to\mathrm{Pr}o}=\sum_{J\in ds}J_{a_i\to\mathrm{Pr}o}/\sum_{i\in\text{interactions}}i_{a_i\to\mathrm{Pr}o}$ represents the proportion of number of previous dissatisfying interactions to the total number of interactions between rater advisor agent, a_i, and provider agent, Pro.

The dissatisfaction rate of each provider is considered as a numerical value between −1 and 0.

In addition, the number of agents that send their ratings of dissatisfaction affects the accuracy of disrepute value of the provider. As a result, the final formula for calculating disrepute of each provider is as follows:

$$\neg R_{\mathrm{Re}q \to \mathrm{Pr}o} = \frac{\sum_{m \in M} m}{N} \times \neg r_{\mathrm{Re}\ q \to \mathrm{Pr}o} \tag{4}$$

where $\sum_{m \in M} m$ is the total number of advisors that rate the provider agent, Pro; N denotes the total number of advisors that have responded to the query; $r_{A \to \mathrm{Pr}o}$ shows the disrepute value of the provider agent, Pro, obtained by Equation (3).

3.3 Evaluating conflict

Conflict in the evidences shows that some of them are positive (satisfying interactions) and some others are negative (dissatisfying interactions). Referring to the presented formula by FTM (Wang and Singh, 2007), the value of conflict in the previous behaviour of each provider is evaluated according to the number of previous satisfying and dissatisfying interactions that the advisor experienced with providers, as follows:

$$\psi_{A \to Pr\ o} = \min(\alpha, 1-\alpha) \tag{5}$$

where $\psi_{A \to \mathrm{Pr}o}$ represents the conflict in previous interactions of the provider, Pro, which are reported by the advisors, A; $\alpha = s/t$ is the proportion of the number of previous satisfying interactions, s, to the total previous satisfying and dissatisfying interactions, t, which are reported by the advisors, A, about the provider, Pro; $1-\alpha = ds/t$ shows the proportion of the number of previous dissatisfying interactions, ds, to the total previous interactions, t, which are reported by the advisors, A, about the provider, Pro.

3.4 Selecting the most trustworthy provider agent

After measuring the R-D-C of each provider agent, the requester selects the most trustworthy agents among all providers by using the TOPSIS. TOPSIS is a decision-making method, which can be applied when several factors need to be considered. The method selects only one best solution based on the shortest geometric distance from the positive ideal solution (PIS), and the longest geometric distance from the negative ideal solution (NIS) (Chen, 2000). In this study, the PIS is produced when a provider agent has the highest values for R-D-C, whilst the opposite is true for a NIS. Therefore, TOPSIS method was deemed to be appropriate to be used in the current study to select the most trustworthy provider agent based on the three different components.

Using the TOPSIS method, the decision matrix is derived by calculating the values of R-D-C of each provider, as follows:

$$D = \begin{array}{c} \\ \mathrm{Pr}\,o_1 \\ \mathrm{Pr}\,o_2 \\ \vdots \\ \mathrm{Pr}\,o_n \end{array} \begin{array}{c} \begin{array}{ccc} R & \neg R & \psi \end{array} \\ \begin{bmatrix} \mathrm{Pr}\,o_{11} & \mathrm{Pr}\,o_{12} & \mathrm{Pr}\,o_{13} \\ \mathrm{Pr}\,o_{21} & \mathrm{Pr}\,o_{22} & \mathrm{Pr}\,o_{23} \\ \vdots & \vdots & \vdots \\ \mathrm{Pr}\,o_{n1} & \mathrm{Pr}\,o_{n2} & \mathrm{Pr}\,o_{n3} \end{bmatrix} \end{array} \tag{6}$$

According to the constructed decision matrix (D), obtained by Equation (6), the following steps should be carried out to select the most trustworthy provider.

Step 1: normalize the decision matrix through inclusion of the computed R-D-C values of each provider.

Step 2: make a weighted matrix using entropy method.

Step 3: construct the weighted normalized decision matrix, as follows:

$$v_{ij} = r_{ij} w_{ij}, \quad j = 1, \ ..., \ J; \quad i = 1, \ ..., \ I \tag{7}$$

where v_{ij} shows the normalized weighted matrix, w_i is the weight of the ith attribute or criterion, and r_{ij} represents the normalized decision matrix.

Step 4: determine the PIS and NIS:

$$A^* = \{v_1^*, \ ..., \ v_n^*\} = \left\{ \left(\max_j v_{ij} | i \in I' \right), \left(\min_j v_{ij} | i \in I'' \right) \right\} \tag{8}$$

$$A^- = \{v_1^-, \ ..., \ v_n^-\} = \left\{ \left(\max_j v_{ij} | i \in I' \right), \left(\min_j v_{ij} | i \in I'' \right) \right\} \tag{9}$$

where A^* shows the PIS, I' is associated with benefit criteria, A^- denotes the NIS, and I'' is associated with cost criteria.

Step 5: calculate the separation measures, using the N-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as follows:

$$D_J^* = \sqrt{\sum\nolimits_{i=1}^{n} \left(v_{ij} - v_i^* \right)^2}, \quad i = 1, \ ..., \ I \tag{10}$$

$$D_J^- = \sqrt{\sum\nolimits_{i=1}^{n} \left(v_{ij} - v_i^- \right)^2}, \quad i = 1, \ ..., \ I \tag{11}$$

where D_J^* is the distance of each normalized weighted decision matrix from PIS and D_J^- shows the distance of each the normalized weighted decision matrix from NIS.

Stage 6: calculate the closeness coefficient of each alternative, as follows:

$$C_j^* = \frac{D_j^-}{D_j^- + D_j^*}, \quad j = 1, \ ..., \ J \tag{12}$$

where C_j^* is the relative closeness to the ideal solution, D_J^* represents N-dimensional Euclidean distance from PIS, and D_J^- shows N-dimensional Euclidean distance from NIS.

Stage 7: the ranking order of all the alternatives is determined in the final stage according to the closeness coefficient. Then the most trustworthy advice can be chosen accordingly.

4. Simulation set up

In this section, a simulation of the multi-agent environment was constructed as a controlled experiment by using MATLAB (R2012a). Then the accuracy of R-D-C was examined in two stages; in the first stage, the average accuracy of calculating R-D-C values for the trustworthy and untrustworthy providers was examined. In this case, the R-D-C values of the providers in average times of iteration were calculated.

The expectation was that the reputation values of the trustworthy providers should be higher than their disrepute while the reputation values of the untrustworthy providers should be less than their disrepute.

In the second stage of simulation, the accuracy of R-D-C in selecting the trustworthy provider was compared with those of FTM, SPORAS, and TRR which have more similarity to the R-D-C, as described in Section 2, by considering both the previous satisfying and dissatisfying interactions.

The accuracy of the models was evaluated based on the average times of choosing trustworthy providers in different interactions with various numbers of trustworthy and untrustworthy providers, and different numbers of advisors. The expectation was that the performance of the R-D-C in selecting the trustworthy providers should be better than those of the FTM, SPORAS, and TRR.

In this case, the multi-agent environment was simulated according to the following settings.

4.1 Composition

The analysis was performed for three distributions with different percentages of trustworthy and untrustworthy providers, as shown in Table I. In addition, to test the scalability of our approach, further experiments were done with different numbers of agents in three groups, as shown in Table I.

According to Table I, the distributions refer to the segregation of the number of trustworthy and untrustworthy providers. For instance, looking at Group 1 and Distribution 1, the number of trustworthy providers for this scenario is 1 whilst the number of untrustworthy providers is 3. The total number of agents simulated is based on the three groups. The number of requesters was kept constant, whilst the numbers of providers and advisors were gradually increased. Each simulation execution was repeated ten times to maintain consistency and to ensure the models produced similar results. Their accuracies were then averaged into a single value. The maximum number of interactions in each time of running was set at 500 in this study.

4.2 Structure

The experiments were designed using simulations based on Zhang and Cohen (2008) and Gorner *et al.* (2013). The requester, advisors and providers were selected randomly and the advisor agents rated the providers arbitrarily as satisfying and dissatisfying. The R-D-C model defines the satisfaction rate to be between 0 and 1, like Huynha *et al.* (2004), whereas the dissatisfaction rate is between −1 to 0 like Huynha *et al.* (2004). In other words, the dissatisfying rate is represented by a negative rate.

To compare the performance of the R-D-C against other existing trust models, additional simulations were carried out. To be precise, simulations were done for the

No. of	Distribution 1	Distribution 2	Distribution 3
Trustworthy providers	25%	50%	75%
Untrustworthy providers	75%	50%	25%
No. of	Group 1	Group 2	Group 3
Requester	1	1	1
Advisor	5	6	3
Provider	4	8	16
Total	10	15	20

Table I. Parameters of experimental set up famous trust models described in this study, namely FTM, SPORAS, and TRR. All the models were tested using the same scenario as shown in Table I.

Accuracy in selecting the most trustworthy provider was determined by counting the number of times the models selected the most trustworthy provider (Kaljahi *et al.*, 2013; Li and Kao, 2009) in 500 times of interactions. As mentioned previously, the interactions were repeated ten times for each scenario and the accuracies of the models were averaged to produce the final mean accuracy.

Finally, in order to determine if there are any significant differences between the R-D-C model and the existing models, Analysis of Variance (ANOVA) was carried out, followed by a *post-hoc* analysis. Differences are deemed to be significant at $p < 0.05$.

5. Results and discussion

The results of evaluation R-D-C model in the simulated multi-agent environment are presented in the following subsections. First the results of the average accuracy for R-D-C are determined, and then the results of comparison R-D-C with the existing models are described.

5.1 Average accuracy of R-D-C

This section presents the results for the average accuracy for R-D-C calculated based on different number of agents, that is, 10, 15, and 20. The first experimental configuration involves ten agents with Distribution 1, in which 75 per cent of the providers were randomly selected as trustworthy and 25 per cent were untrustworthy as shown in Table I. The average accuracy of R-D-C in all the interactions is shown in Figure 2.

As shown in Figure 2, the reputation values of trustworthy providers are higher than their disrepute values, while the reputation values of untrustworthy providers are less than their disrepute values.

Then, the size of network was extended to 15 and then further to 20 agents. The summary of the experimental results across all groups and distributions is illustrated in Table II.

Table II contains nine stages of simulation with three distributions of trustworthy and untrustworthy provider agents along with three groups of agents.

As shown in Table II, in all stages of simulation, the reputation values of trustworthy provider agents are higher than their disrepute values, while the average reputation values of untrustworthy provider agents are less than their disrepute values. This result confirms our expectations about the accuracy of the

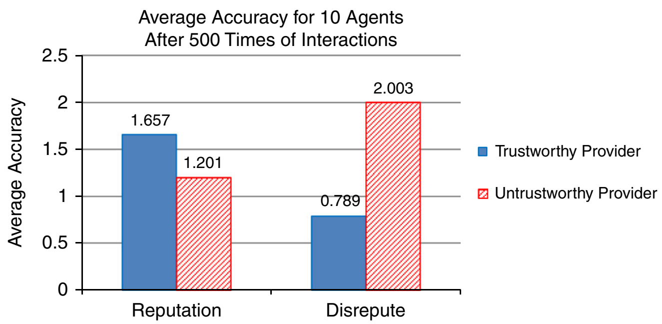

Figure 2. Comparison of the average accuracy of the reputation, disrepute, for trustworthy and untrustworthy providers in Distribution 1, Group 1

Type of Provider	Reputation	Disrepute	Conflict	Group
Distribution 1 (25% trustworthy, 75% untrustworthy)				
Trustworthy provider	1.657	0.789	0.631	G1
Untrustworthy provider	1.201	2.103	0.545	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
Trustworthy provider	2.657	1.456	0.571	G1
Untrustworthy provider	1.056	1.79	0.438	
Distribution 3 (75% trustworthy, 25% untrustworthy)				
Trustworthy provider	1.690	0.850	0.342	G1
Untrustworthy provider	0.631	1.459	0.261	
Distribution 1 (25% trustworthy, 75% untrustworthy)				
Trustworthy provider	1.751	0.648	0.731	G2
Untrustworthy provider	1.021	2.131	0.468	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
Trustworthy provider	2.031	1.567	0.421	G2
Untrustworthy provider	0.987	1.982	0.637	
Distribution 3 (75% trustworthy, 25% untrustworthy)				
Trustworthy provider	2.141	1.381	0.128	G2
Untrustworthy provider	0.963	1.812	0.482	
Distribution 1 (25% trustworthy, 75% untrustworthy)				
Trustworthy provider	1.786	0.849	0.329	G3
Untrustworthy provider	1.054	2.004	0.381	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
Trustworthy provider	2.124	1.098	0.573	G3
Untrustworthy provider	1.103	1.967	0.495	
Distribution 3 (75% trustworthy, 25% untrustworthy)				
Trustworthy provider	2.310	1.031	0.219	G3
Untrustworthy provider	0.981	2.017	0.365	

Table II. Summary of the results for all experimental settings

R-D-C model. Moreover, conflict in behaviours of agents was not predictable, as it may be possible that a trustworthy agent has higher conflict behaviours than the untrustworthy ones.

5.2 Comparison of R-D-C with existing models

This section presents the results of the second stage of experimentation, which involves comparing the performance of R-D-C with FTM, SPORAS, and TRR models. The summary of the experimental results for 15 and 20 agents is summarized in Table III.

Overall, as shown in Table III, the comparison of the R-D-C model with other models indicates that the performance of R-D-C is better because it introduces a new component, disrepute, and evaluates both disrepute and reputation of each provider agent by using previous satisfying and dissatisfying interactions. Moreover, R-D-C selects the trustworthy provider based on a powerful multi-criteria decision-making process, TOPSIS method, which can provide accurate support in selecting the trustworthy provider. Further ANOVA results revealed R-D-C to outperform FTM, SPORAS and TRR significantly.

Model	250 iteration	500 iteration	Average iteration	Group
Distribution 1 (25% trustworthy, 75% untrustworthy)				
R-D-C	0.710	0.713	0.694	G1
FTM	0.658	0.648	0.635	
SPORAS	0.612	0.586	0.571	
TRR	0.685	0.640	0.672	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
R-D-C	0.698	0.705	0.698	G1
FTM	0.631	0.674	0.657	
SPORAS	0.598	0.591	0.586	
TRR	0.653	0.698	0.632	
Distribution 3 (75% trustworthy, 25% untrustworthy)				
R-D-C	0.701	0.682	0.695	G1
FTM	0.674	0.624	0.673	
SPORAS	0.620	0.599	0.612	
TRR	0.681	0.640	0.634	
Distribution 1 (25% trustworthy, 75% untrustworthy)				
R-D-C	0.687	0.674	0.669	G2
FTM	0.614	0.610	0.617	
SPORAS	0.571	0.588	0.569	
TRR	0.610	0.599	0.632	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
R-D-C	0.708	0.696	0.696	G2
FTM	0.589	0.601	0.593	
SPORAS	0.685	0.651	0.668	
TRR	0.643	0.648	0.6551	
Distribution 3 (75% trustworthy, 25% untrustworthy)				
R-D-C	0.725	0.718	0.722	G2
FTM	0.701	0.697	0.703	
SPORAS	0.647	0.651	0.638	
TRR	0.678	0.648	0.689	
Distribution 1 (25% trustworthy, 75% untrustworthy)				
R-D-C	0.698	0.709	0.694	G3
FTM	0.631	0.629	0.622	
SPORAS	0.547	0.589	0.594	
TRR	0.628	0.617	0.613	
Distribution 2 (50% trustworthy, 50% untrustworthy)				
R-D-C	0.703	0.696	0.697	G3
FTM	0.682	0.659	0.666	
SPORAS	0.589	0.557	0.587	
TRR	0.694	0.639	0.658	
Distribution 3 (75% benevolent, 25% untrustworthy)				
R-D-C	0.710	0.718	0.710	G3
FTM	0.698	0.677	0.701	
SPORAS	0.603	0.640	0.635	
TRR	0.672	0.674	0.657	

Table III.
Summary of the results for comparison of R-D-C and FTM, SPORAS, and TRR model

In fact, R-D-C considers the disrepute value of each provider based on previous negative interactions that FTM, SPORAS, and TRR did not do. Disrepute of a provider is a component ignored by most of the previous trust models. R-D-C applies this component in trust evaluation of providers.

However, FTM evaluates conflict in behaviours of providers by considering the number of previous satisfying and dissatisfying interactions. This model did not compute reputation and disrepute values of a provider, and it did not present a proper selection method of the most trustworthy provider. Therefore, R-D-C performs better than FTM, because R-D-C evaluates the reputation and disrepute of each provider. Moreover, R-D-C is capable of selecting the most trustworthy provider if these three components are added: R-D-C. On the other hand, unlike SPORAS and TRR models, which only consider reputation based on the previous satisfying interactions and ignore the effect of negative interactions, R-D-C incorporates negative interactions in the evaluation of disrepute and conflict of each provider; hence R-D-C performs significantly better than the SPORAS and TRR models.

Finally, the strong point of R-D-C model is integration of these components and selection of the most trustworthy provider by using TOPSIS method.

Therefore, the results prove that R-D-C can significantly enhance the trust models by selecting the most trustworthy provider in a different multi-agent environment. This can lead to more successful transactions between a requester and provider agents.

The experimental results clearly show that R-D-C has produced significantly better performance across all groups with different distributions of the trustworthy and untrustworthy providers.

Moreover, Figure 3 represents a comparison of the average accuracy of experimental results, which were obtained from the second stage of experimentation in different groups of agents.

As shown in Figure 3, R-D-C has yielded significantly better performance in all distributions and groups, even in Distribution 1 with a majority number of untrustworthy providers (75 per cent); these results show that R-D-C can support multi-agent interactions in different multi-agent environments, even in an unsafe multi-agent environment which has a larger number of untrustworthy agents than the trustworthy.

The overall results demonstrate that R-D-C can accurately calculate the R-D-C values of agents in different distributions and with various numbers of agents. Moreover, the performance of R-D-C in selecting the trustworthy providers is significantly better than other trust models, across all groups. Finally, the experimental

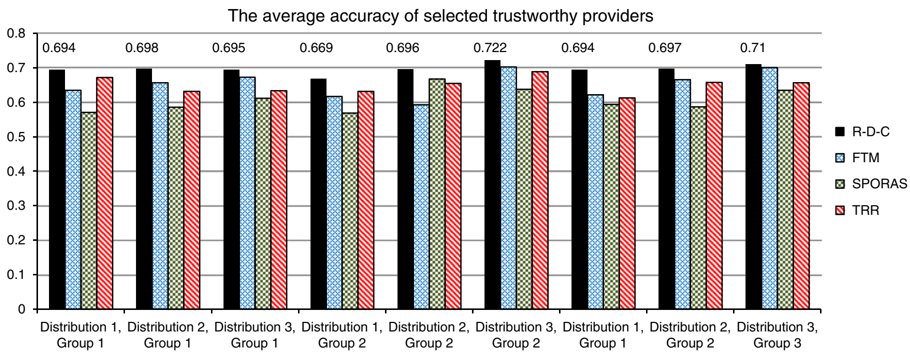

Figure 3.
Comparison of the average accuracy of selected trustworthy provider agents

results suggest that R-D-C can significantly enrich the trust models in multi-agent environments by selecting the most trustworthy provider, and this in turn leads to more successful transactions between a requester and provider agents.

6. Conclusion

This paper proposed an integrated approach, namely R-D-C to select the most trustworthy provider by computing the R-D-C values of behaviours of each provider. There is a lack of trust models addressing a method for evaluating disrepute of providers based on previous negative outcomes. In fact, most of the existing trust models only consider previous satisfying interactions, without giving attention to the effects of dissatisfying interactions in selecting the most trustworthy provider agent. In contrast, R-D-C considers both previous satisfying and dissatisfying interactions of each provider to find the most trustworthy one. Moreover, there is a need to find a proper selection method in identifying the most trustworthy provider; hence R-D-C proposes to use TOPSIS which is a multi-criteria decision-making method. The experimental results show that R-D-C can compute the R-D-C values of each provider accurately. In addition, the comparison results illustrate that the performance of R-D-C in selecting the most trustworthy provider is significantly better than the other existing trust models, regardless of the number of providers. Therefore, applying R-D-C in multi-agent systems can enhance the safety of electronic transactions by finding the most trustworthy provider agent in multi-agent environments.

For future work, the intent is to find other components that are effective in evaluating the trustworthiness of agents, and also implement the R-D-C model in the real-world environment.

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