A TRUST MODEL FOR ADVISOR NETWORKS IN MULTI-AGENT ENVIRONMENTS

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ABSTRACT

Multi-agent systems can break interactions in distributed and heterogeneous environments. One of the fundamental challenges in such settings is that agents can enter and leave the system at will; hence malicious agents may take advantage of others by behaving in an untrustworthy way. In this case, if an agent wants to interact with unknown provider agents, they need to request other agents to advise a trustworthy provider. The crucial issues are then how to rely on the information provided by advisor agents. A trust mechanism was proposed that measures and analyzes the trust value of advisors. In fact, the proposed mechanism measures the belief and disbelief value of each advisor in multi-agent environments utilizing reliability/ unreliability, reputation/ disrepute of each interaction. In this mechanism, the aim was to select the trustworthy provider agent through an advice of benevolent advisors in which the actions of advisors are accurately under analysis. The theoretical analysis was done in two parts; first the validation of model was investigated by analyzing the average accuracy of model in calculating the trust and trust transitivity value among advisors and by comparison with other alternative models. Second, the average accuracy of our model in decision-making process was investigated by trust network game. The results denote that our approach outperforms current models in providing accurate credibility measurements and computing an accurate trust mechanism for advisor agents in an advisor network, also presenting an accurate decision making process to choose the trustworthy provider. The experimental results also show the superior performance of our proposed model in comparison with other trust models. Applying this trust model can ensure critical transactions are performed more securely, such as those related to banking or e-commerce.

ABSTRAK

Sistem multi-ejen boleh memecahkan interaksi dalam persekitaran teragih dan heterogen. Salah satu cabaran asas dalam tetapan ini ialah seperti ejen boleh menasuki dan meninggalkan sistem itu bila-bila sahaja; oleh itu agen yang berniat jahat akan mengambil kesempatan melakukannya dengan cara yang tidak boleh dipercayai. Dalam kes ini, jika agen mahu untuk berinteraksi dengan ejen-ejen pembekal yang tidak diketahui, mereka perlu meminta nasihat daripada ejen yang lain utuk mendapatkan pembekal yang boleh dipercayai. Isu-isu penting kemudiannya adalah bagaimana untuk bergantung kepada maklumat yang diberikan oleh agen penasihat.Kami mencadangkan satu mekanisme amanah yang dapat mengukur dan menganalisis nilai kepercayaan dan kesangsian penasihat berdasarkan komponen utama yang dikumpulkan daripada model-model semasa.Malah, mekanisme yang dicadangkan mengukur nilai kepercayaan dan kesangsian oleh sikap percaya setiap penasihat dalam persekitaran multi-ejen dengan menggunakan kebolehpercayaan/ tidak boleh percaya, reputasi/tidak popular bagi setiap interaksi. Dalam mekanisme ini, ia bertujuan memilih ejen pembekal yang boleh dipercayai melalui nasihat daripada penasihat baik hati di mana tindakan penasihat di bawah analisis adalah tepat. Analisis teori dilakukan dalam dua bahagian; pertama pengesahan model telah disiasat dengan menganalisis ketepatan purata model dalam menghitung kepercayaan dan nilai transitivity kepercayaan di kalangan penasihat dan dengan perbandingan dengan model alternatif, model asas, model berasaskan bukti amanah, dan model TREPPS. Kedua, purata ketepatan model kami yang dalam proses membuat keputusan telah dianalisis dengan menggunakan amanah permainan rangkaian. Keputusan eksperimen juga menunjukkan prestasi unggul daripada model yang dicadangkan kami dalam perbandingan dengan model amanah lain. Menggunakan model amanah ini boleh memastikan transaksi kritikal dilakukan lebih selamat, seperti yang berkaitan dengan perbankan atau e-dagang.

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I would like to thank my committee members for their insights and suggestions. Additionally, I would like to thank the University of Malaya and the Department of Information Systems for the support, resources and teaching opportunities they afforded me over the duration of my studies.

DEDICATION

This dissertation is dedicated to:

My loving parents, **Dr. Ahmad Majd** and **Dr. Sedigeh Mehrabian**, who instilled in me a love of learning and to **my brothers** for their encouragement and support.

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LIST OF SYMBOLS AND ABBREVATIONS

FNIS	FuzzyNegative Ideal Solution
FPIS	FuzzyPositive Ideal Solution
FTOPSIS	Fuzzy Technique for Order of Preference by Similarity to Ideal Solution
NIS	Negative Ideal Solution
PIS	Positive Ideal Solution
TMAN	Trust Model for Advisor Networks
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TREPPS	Trust-based Recommender System for the Peer Production Services
TRR	Integrated Reliability-Reputation

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CHAPTER 1: INTRODUCTION

1.1 Introduction

This dissertation addresses the topic of presenting a trust model for advisor agents which make up an advisor network in a multi-agent system to recommend a trustworthy provider to a requester agent.

The agent environment coordinates and constrains the actions that the agents can perform at a given time. At the same time, the agent environment provides the agents with the interfaces that are necessary in order to perceive the environment and the other agents situated in it (Tampitsikas et al., 2012). In multi-agent environments, the same behavior exhibited in real life among persons happens when agents work in a cooperative way to get a recommendation. They ask other agents for the information necessary to make a decision when they do not have that information in their knowledge bases. Thus, recommended trust enables agents to evaluate the credibility of a stranger agent through the recommended information provided by other users (Ding et al., 2012).

In a complex multi-agent environment, the agents cannot define the capabilities and behavior of other agents. In this environment, the behavior of each agent forms the global operation and evolution of the system (Griol et al., 2013). Hence, malicious agents may take advantage of others by behaving in an untrustworthy manner. Agents in an e-commerce environment can break contracts due to their own benefits (Jing & Ying, 2010). Therefore, the establishment of trust among stranger agents enables the extension of a successful transaction to a much broader range of participants in an e-commerce multi-agent environment (Majd & Balakrishnan, 2014; Noorian & Ulieru, 2010). In fact, a major problem arises when a requester agent has no previous experience with providers, but it needs a critical product offered by these providers. In this case, the requester should select one of the providers according to the advice of other requesters, called advisors, which have had previous interactions with those providers(Gorner et al., 2011). Since providers and requester agents interact to achieve their goals and maximize their profit in an agent-based e-commerce environment(Sanchez & Molina, 2010), requester agents try to buy appropriate products based on their preferences(Battiston et al., 2006) such as low product price, high product quality, and good customer service. In the case that the requester agent is not familiar with providers, it needs to consult with other requesters; they serve as advisors that suggest trustworthy providers and report the ratings of their suggested providers according to their past interactions(Gorner et al., 2011). The requester can then estimate the trustworthiness of providers through these ratings(Gorner et al., 2011). However, the advisor agents can also behave maliciously by providing wrong advice for their personal gain or exaggerate the trustworthiness of providers in their reports(Wang et al., 2011). To ensure good interaction among agents, the requester agents should evaluate the trustworthiness of advisors and consult with the benevolent ones that present the correct reports about the providers (Khosravifar, 2012).

There may be a breach of trust if the requester agents select a provider according to advice of advisors, but it does not provide proper service and fails to perform the action as required; hence, there is a need for mechanisms which can minimize the risks of wrong or exaggerated advice. One way of reducing risks is to build a good trust level related to agent interactions (Botêlho et al., 2011; Herzig et al., 2010; Nedev & Nedeva, 2008).

In this chapter, a brief review of the topic is presented in Section 1.2. This is followed by the motivation of doing this research in Section 1.3. Then the statement of problem is defined in Section 1.4. Next, the aim of doing this research is described in Section 1.5. The summary of the research objectives and scope of research are presented in Sections 1.6 and 1.7, respectively. The chapter ends with the significance of research in Section 1.8 and the outline of the dissertation in Section 1.9.

1.2 Overview

Agents are "sophisticated computer programs that act autonomously on behalf of their users, across open distributed environments to solve a growing number of complex problems"(Suriyakala et al., 2013; Yosra et al., 2013). A multi-agent system is composed of several agents which are collectively capable of reaching goals that are difficult to achieve by an individual agent of a monolithic system (Spinelli & Basharat, 2011).

Multi-agent systems can be developed to retrieve, apply and sort information relevant to other agents. These systems have been used in different areas such as legal (Drumond et al., 2007), marketplace (Wei et al., 2008), tourism (Lorenzi et al., 2010), and e-commerce (Zhang et al., 2008). In fact, multi-agents in artificial intelligence are closely related to agents in e-commerce, which is inherently dynamic (i.e. price of an item changes over time), uncertain (i.e. global or ground truth is often unavailable to an individual agent due to unreliable communication channels, faulty sensors, or the complex and nonlinear nature of a domain), and insecure (i.e. presence of malicious agents or new, unknown agents) (Lehtinen, 2012). As a result, electronic transactions of e-commerce based on multi-agent systems require the presence of a mechanism of trust and distrust in order to ensure the fulfillment of a contract (Walter et al., 2008a; Zhou, 2009), and minimize the uncertainty associated with interactions in open distributed systems.

The problem is that, multi-agent systems can be pressured by events outside a defined system boundary. Moreover, in these systems it is difficult to control the agents and their interactions. Naturally, agents can enter and leave a system at their own will. Hence, at any given time an individual agent within the system may not be familiar with all the other agents that exist (Teacy et al., 2006). In this situation, critical information can be leaked and lost easily without an appropriate solution to support the security of a system. As a result, trust established among agents promises to create more successful transactions. In fact, trust in a multi-agent environment is "a particular level of beliefs which an agent has about another agent or group of agents to perform a particular action" (Bøegh, 2014; Khanna & Babu, 2012; Moyano et al., 2013; Phulre et al., 2013)

The evaluation of trust is indirectly obtained from a target agent (provider) based on the advice of another intermediate agent, which is known as indirect trust. In this case, the requester agent asks other agents which have similar preferences (Vassileva, 2012) to discover agents that have had interaction with provider agents to create trust advisor paths, which comprise a network of advisor agents. A sample of an advisor network is shown in Figure 1.1.

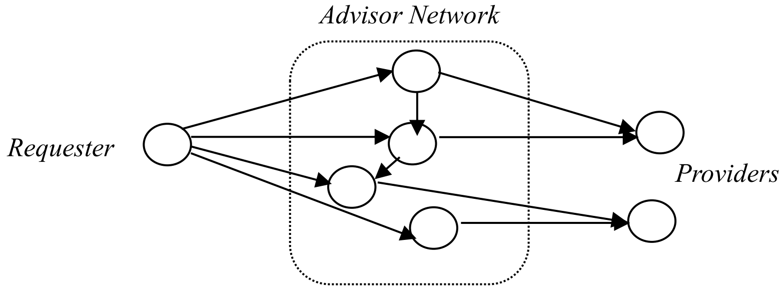


Figure 1.1: A sample of an advisor network

Trust models in multi-agent systems are designed to enable agents to find optimal partners that can produce high-quality services, and even create a good collaborative environment (Lijian et al., 2008). Current trust models apply some approaches, such as statistics (Pinyol & Sabater-Mir, 2013; Yuan et al., 2010), probability theory (Teacy et al., 2006), and fuzzy logic (Li & Kao, 2009) to compute the trustworthiness of a target agent (provider) (He et al., 2011). However, these models focus on measuring the trust value of target agents. It is important to note that the intention of this study is not to replicate this body of existing work. Rather, this study focuses on recognizing a trustworthy provider through the advice of benevolent advisors. In fact, this study proposes a trust model that measures the trustworthiness of advisor agents among all existing advisors and selects a trustworthy provider according to advice of these benevolent advisors.

1.3 Motivation

Agents are incapable of determining the capabilities and behaviors of others. Hence, malicious agents may take advantage of others by behaving in an untrustworthy way. However, even with this uncertainty in an environment, agents must be able to make wise decisions and successfully interact with other agents. Therefore, agents should be completely aware of their opponents, the environment, and the existing issues when making decisions. Such information should enable agents to predict probabilities of particular events happening and help them to act in a way that enhances their expected effectiveness (Helbing, 2013; Yu et al., 2010). In order to minimize the uncertainty associated with interactions in this case, agents have to trustother agents as advisors and make a decision according to their advices.

Although current researches present useful solutions to compute the trustworthiness of agents in multi-agent systems, challenges still remain. These emerging and related challenges highlight the need for research on the way of evaluating trust based on advice of advisor agents; in line with this, the purpose of carrying out this research is to recognize a trustworthy provider agent through the advice of benevolent advisors. The relevant issues are discussed in the following subsections.

1.3.1 Dissimilarity preferences

If agents have disadvantages in only some specific aspects in the marketplace such as customer service but were to be labelled as dishonest agents, this may pose some challenges. The dishonest reputation of these agents will discourage future requester agents from interacting with them, though these agents can provide advantages in other aspects such as product quality. As a result, those agents cannot go through a more detailed selection process although those agents and requester may actually have similar preferences (Zhang & Cohen, 2013).

1.3.2 Inaccurate trust value

In heterogeneous multi-agent environments where agents behave autonomously, predicting the behavior of agents cannot be completely accurate. Therefore, evaluating the trustworthiness of agents and predicting their behavior according to this evaluation might be inaccurate; due to this limitation, the trust mechanism should be able to consider the effect of inaccurate reports to maintain the trustworthiness of agents and to reduce the effect of inaccurate trust values (Jung et al., 2012).

1.3.3 Unpredictable behaviors

The agents can change their behavior in a multi-agent environment; the agent which has a benevolent behavior in one interaction can exhibit a malicious behavior in the next interaction. It is noted that some of the agents show more unstable behaviors than others, and they have a habit of changing their behaviors in different interactions. The unstable behavior of an agent shows that the agent cannot be trusted and engaged in an interaction. This may pose another challenge, to explore a method which allows less unpredictable agents to be chosen as a benevolent agent (Zhang & Cohen, 2013).

1.3.4 Trust transitivity

The importance of trust composition is obvious when considering the organization of agent groups. In a group, agents generally interact with one another to achieve their common goals. In this case, trust will be transitive among a network of agents. In fact, the trustworthiness of agents which have indirect interaction with the requester should be evaluated by transitivity of trust from the agents which have direct interaction with requester. In such circumstances, the trust composition can play a critical role in determining the trust values for unknown agents (Jung et al., 2012).

1.4 Problem Statement

Malicious advisor agents may make requester agents deviate from achieving their goals. For instance, a malicious advisor agent may recommend a provider that claims to provide services it cannot actually provide. This action can result in loss of critical information and payment of a high price. The situation will be more critical when requester agents have had no previous interactions with providers and select one of the providers according to the wrong advice.The advisors act maliciously will cause an unsuccessful interaction, especially in e-commerce areas, where the safety of interaction is vital.The existing studies ignored the effect of malicious advisors and did not compute the trust level of advisors.On the other hand, a mechanism of trust which does not consider the similarity between the preferences of advisor and requester leads to selecting a provider that cannot really provide services according to preferences of requester (Zhang & Cohen, 2013). The agents of a multi-agent environment are autonomous; thus, prediction of the behaviors of agents according to previous interactions might be inaccurate and uncertain (Jung et al., 2012). Moreover, some agents exhibit very inconsistent behavior (Zhang & Cohen, 2013). Another point to highlight is that, the provider suggested by advisors leads to transitivity of trust between advisors and their suggested providers, since the trustworthiness of these providers is not the same as that of the advisors which suggested them (Jung et al., 2012). In fact, the consequences of selecting a malicious advisor are especially apparent in critical transactions, such as those related to e-commerce.

Furthermore, the major challenge faced in this research is malicious advisors that impact the decision of requester agents and cause them to interact with untrustworthy provider agents.

1.5 Research Aim

In light of the impact of malicious advisors on the decision of requester agents, the aim of this research is to present a computational trust model for evaluating the trustworthiness of each advisor and its suggested provider agent.This value can be used to help requester agents recognize the trustworthiness of provider agents. Then, according to the trustworthiness of each advisor and the trust transitivity between advisors and their suggested providers, the requester makes a decision concerning which providers are trustworthy, based on the advice provided by these benevolent advisors. Figure1.2 illustrates the aim of this research in more detail.

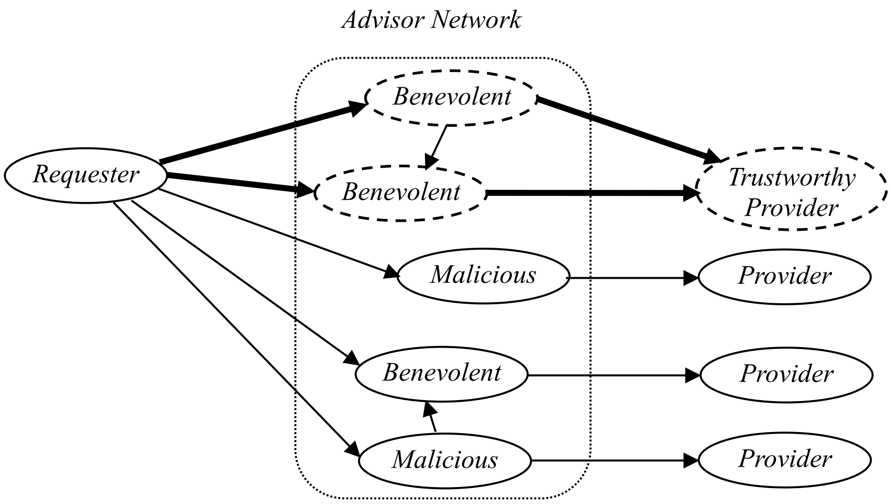


Figure 1.2: A sample of multi-agent environment

In fact, this study is based on the requester that needs to buy a service, but it has no information about providers which can provide its needed service. In this case, to select the most trustworthy provider, the requester asks other agents that may be familiar with any provider which can provide its needed service. As shown in Figure 1.2, the agents which are selected as advisors can be malicious or benevolent ones. Moreover, these advisors as shown in Figure 1.2 may have had previous interactions with each other and form an advisor network. According to this explanation, this research intends to evaluate the trustworthiness of advisors and their suggested providersto select the most trustworthy provider according to advice of benevolent advisors.

1.6 Research Objectives

The objectivesof this research can be broken down as follows:

i. To identify the main components that can be used to present a trust model for advisor network in multi-agent environment.

ii. Todesign and implement thetrust model based on the identified components.

iii. To evaluate the performance of the proposedmodelin a multi-agent environment.

1.7 Research Questions

This study is based on the following questions:

i. What are the main components that can be considered to build a trust model in a multi-agent environment?

ii. How can the components be integrated into a single trust model?

iii. How to determine the trustworthiness between the various agents, in order to select the most trustworthy provider?

iv. How the proposed model can be evaluated?

v. How the model can be compared with other existing models to assess its effectiveness?

1.8 Scope of Research

The scope of this research is multi-agent systems that focus on the e-commerce area, especially business-to-business e-commerce where the agents can play the roles of requesters, providers and advisors. Business-to-business (B2B) commerce is a type of commerce transaction that exists between businesses, such as those involving a manufacturer and wholesaler, or a wholesaler and retailer (Xu, 2012). In fact, business-to-business e-commerce refers to substitution of computer data and processing for labor services in the production of economic transactions (Grewal et al., 2010).

On the other hand, he software used for the purpose of simulating the multi-agent environment and evaluating the performance of TMAN is MATLAB. In fact, MATLAB provides a technical computing environment for numeric computation and visualization (Etter & Kuncicky, 2011). It integrates numerical analysis, matrix computation, signal processing, and graphics in the same environment. The system is equipped with a mouse-driven graphical interface made up of a number of displays (Etter & Kuncicky, 2011). Numerical calculation in MATLAB applies to well-written scientific/mathematical subroutines. Overall, MATLAB is a useful programming language for simulating computational projects because it has a useful tool for mathematical equations and matrix manipulations. Since TMAN was proposed by matrix and mathematical equations, TMAN was evaluated by using MATLAB.

1.9 Significance of Research

A system of trust is required in order to ensure the fulfillment of a contract in an e-commerce multi-agent system, and minimize the risk associated with interactions in electronic transactions. Trust-based advisor agents allow requester agents to be aware that the advice is given by benevolent agents. Moreover, it can improve the accuracy of advice and decrease the occurrence of errors in common interactions. Thus, the interaction between requesters and provider agents can be more successful because agents receive advice from benevolent advisor agents and select a trustworthy provider.

Based on the above, TMAN can significantly enrich the trust models by selecting the most trustworthy provider by evaluating the trustworthiness of advisors and their suggested providers; this can lead to more successful transactions between requester and provider agents. Moreover, the advisors encourage benevolent behaviors by using a punishment and reward mechanism. In fact, applying TMAN can ensure critical transactions related to e-commerce are performed more securely, especially in business-to-business e-commerce.

1.10 Dissertation Structure

This dissertation is organized in five chapters as follows:

Chapter 1: This chapter presents a description that addresses the problem statement. It indicates the issue to be studied, contextualizes the study, contains the motivation of doing the study, provides an introduction to the basic components, including an overview of the focus of the study, and identifies the significance of study to address the benefits that may be derived from doing this study. The chapter also covers the scope of the study and sets out a clear and valid representation of what will be found in the remaining parts of the dissertation.

Chapter 2: This chapter involves research in the context of previous models and research pertaining to the topic, reviews primary sources that are mostly recent empirical studies from scholarly journals and publications, presents a critical comparison of the main components of previous models, and justifies how the identified components are relevant to present a trust model for multi-agent environments. This chapter consists of two parts. The first part describes the concept of the keywords of the study and states the areas of the literature that will be covered. It also classifies the existing models. The second part presents the main components which are essential for designing the suggested trust model and investigates different methods of computing each component. This part is concluded with the initial schema of the proposed model based on the relationship between the identified components.

Chapter 3: This chapter describes the research methodology of this study in three parts. The first part cites appropriate methodological literature, identifies the selected methods of computing identified components from literature and previous models, and determines the reasons for selecting each method. The second part proposes a mechanism of suggested model for selecting the most trustworthy provider according to advice of the benevolent advisor agents. This part presents the final schema of the proposed model based on the identified components which are derived from literature. Finally, the third part describes and justifies selection of the research setting for evaluation of the proposed model. This part explains clearly the samples and the simulation environment for testing the proposed model.

Chapter 4: This chapter reports the study's main findings. In fact, this chapter presents the findings collected from a simulated environment and presents a comparison of the proposed model with previous existing models. This chapter contains two parts; the first part contains the findings of testing each component of the proposed model. In this part, the average accuracy of computing each component of the proposed model is examined and presents the findings of comparing the proposed model with other existing models. Then, the second partcontains the findings of testing performance of TMAN in evaluating the trustworthiness and selecting the most trustworthy provider based on different types of agent's behaviors. In addition, this chapter synthesizes and discusses the findings in light of the study's research objectives and proposed model by providing an in-depth interpretation, analysis, and synthesis of the findings.

Chapter 5: This chapter presents a set of concluding statements and recommendations. In this chapter, the conclusion provides a summary of the major research findings, highlighting the key achievements and drawing final conclusions. A number of areas for further research are also outlined in this final chapter. Conclusions are built on an integration of the study findings and analysis of the proposed model. The conclusion part investigates each research objective according to the proposed model and findings, identifies the proposed solutions for the problem statement, and determines the contributions of this study. The chapter includes suggested implications for practice based on the findings and recommendations for future research.

CHAPTER 2:LITERATURE REVIEW

2.1 Introduction

This chapter reviews related literature and previous models pertaining to the topic, and investigates related literature comprising empirical studies from scholarly journals and publications. First, the concept of multi-agent systems, advisor networks, trust in multi-agent systems, and also trust models in multi-agent systems are described according to the information gathered from the primary sources, namely scholarly journals and publications. This description presents an overall view of the focus area for this study. Then the chapter is followed by analyzing the previous trust models. Based on this analysis, several components which should be considered when proposing TMAN are identified; these components can help to support the research objectives and solve the issues raised in the problem statement.

However, it must be noted that this part does not aim to cover all the existing trust models. Instead, it focuses on the most representative models which help to introduce the main components and also present different existing methods of computing these components. The comparison of different existing methods for computing the main components can reveal which method is more suitable for designing TMAN. This chapter ends with a presentation of the basic schema of TMAN and introduces its main structure, which is described in more detail in Chapter 3.

2.2 Agents and multi-agent systems

"An agent is an autonomous decision-making entity that receives sensor information from an environment and acts based on that information." The agents are communicative, cooperative, goal-oriented, autonomous, adaptive, and reactive (Hakansson & Hartung, 2012).

The environment that agents interact within is cooperative, accessible, episodic, deterministic, dynamic and discrete. This environment can be divided into atomic episodes, where each episode has an agent that performs a single task. Dynamic multi-agent environment refers to an environment that does not remain static. While discrete environment can have a finite number of states, it also can have a discrete set of perceptions and actions (Gaur et al., 2013; Moradian & Håkansson, 2010).

"Agents interact, collaborate, coordinate and negotiate in a system that was designed and implemented as a multi-agent system. In fact, a multi-agent architecture is based on cooperative agents and has been developed for the integration of design, manufacturing and shop-floor control activities" (Andreadis, Bouzakis, et al., 2014; Andreadis, Klazoglou, et al., 2014).

2.3 Advisor agent and advisor network in multi-agent systems

In the multi-agent environment, the requester agent which does not have enough information about providers, needs to consult with other agents that serve as advisors reporting the ratings for each provider according to their past interactions. Based on this information, the requester can make a decision whether to interact with providers through the advice of these advisor agents (Gorner et al., 2013). Thus, advisor agents are those agents that share preferences and viewpoints that are similar to preferences of requester agent most of the time (Biswas et al., 2010).

The advisor agents may have interactions with each other, which form an advisor network (Gorner et al., 2013). A sample of an advisor network is shown in Figure 2.1.

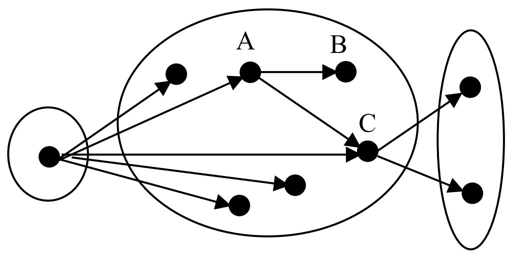


Figure 2.1: A sample of an advisor network

As shown in Figure 2.1, advisor agent A had interaction with advisor agents B and C. Therefore, the advisor network consists of several advisors which have interactions with requester, provider and other advisor agents.

In multi agent environment, benevolent agents always try to support other agents because they consider system benefit is the priority (Talib & Elshaiekh) and they does not expect an immediate reward for its actions (Hollander & Wu, 2011) while the malicious agents prior its own benefits. According to this explanation, in this research a benevolent advisor is defined as the agents which consider system benefit and they provide honesty advice according to their previous evidences. Otherwise, a malicious advisor exaggerates is their presented information or they provide a wrong advice to support of their own benefits. On the other hand, a benevolent provider is a trustworthy agent which provide services according to the requester order, while a malicious provider cannot provide the services that they claimed or according to the order of requester

2.4 Trust in multi-agent systems

"Trust (or symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action" (Döbelt et al., 2012; Kaljahi et al., 2013; Prajapati et al., 2013; Thirunarayan et al., 2014). In fact, trust plays a crucial role not only in supporting the security of interact between agents, but also because agents rely on the expertise of other trusted agents in their decision-making (Walter et al., 2008b). Trust as a dynamic item can increase or decrease with further experiences (i.e. interactions or observations), and they also decay over time (Sherchan et al., 2013). New experiences are more important than old ones since old experiences may become obsolete or irrelevant with the passing of time.

Agents can misbehave in a number of ways, such as providing fake recommendations on servers or showing a misleading, deceptive and malicious behavior to create problems for its competitors especially in an e-commerce competitive environment. The challenge of building a trust mechanism is how to effectively cope with such malicious behavior (Kaljahi et al., 2013).

In a multi-agent environment, each interaction can be divided into direct and indirect trust. Direct trust evaluates agents according to the historical experience of digital content, which consists of records from previous interactions between itself and the evaluated agent (Sherchan et al., 2013). Meanwhile, indirect trust occurs when the trust evaluation is indirectly obtained from the target agent (provider) based on the recommendation or advice of another intermediate agent. In this case, an agent asks recommender or advisor agents which have similar preferences and viewpoints concerning the evaluated agents, to suggest a trustworthy provider (Sherchan et al., 2013). In an indirect trust, agents can play any one of the following roles: requester, advisor, or provider,as shown in Figure 2.2.

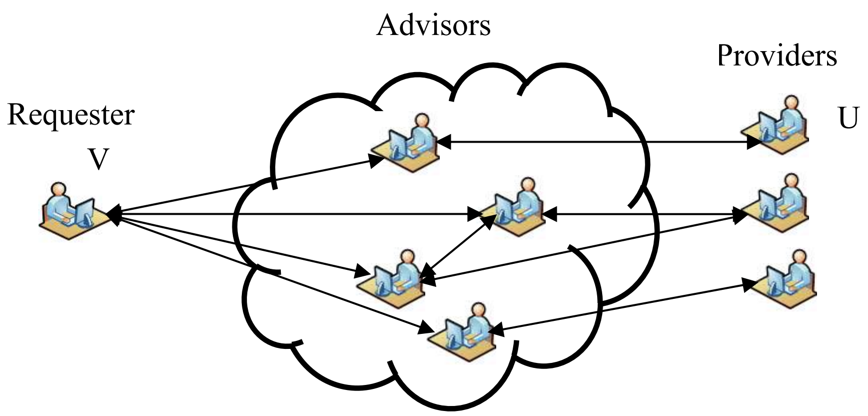


Figure 2.2: A sample of indirect trust in multi-agent environment

For example, as shown in Figure 2.2 to evaluate the advisor trust between agent U and V, V needs to ask adjacent advisor agents that have had previous interactions with U to establish trust advisor paths, which generate a network of advisor agents. Figure 2.2 is a schematic diagram of an advisor network. As shown in this figure, there is no direct trust relation between providers and the requester, but there are many trust advisor paths.

Several trust models have been introduced in multi-agent systems, which enable agents to find benevolent partners that can bring high utility, and they help in creating a good cooperation environment. However, there are not enough research topics which focus on advisor agents to find benevolent advisors for recommending a trustworthy provider among all provider agents.

2.5 Trust models in multi-agent systems

"Trust models are designed into the multi-agent systems to enable agents to find optimal partners that can produce high quality services, and even create a good collaborative environment" (Lijian et al., 2008). These models,like TREPPS model (Li & Kao, 2009), manage and aggregate the information which is essential for agents to select partners in uncertain situations, and they also present information based on the properties of multi-agent systems. These models are based on different components which denote several roles and formulas for computing trust evaluation of each agent and ultimately making a decision according to the evaluation of the overall trustworthiness of an agent in different aspects(Walter et al., 2008a).

There are two main approaches to record trust values of agents and archive the activities of all the agents in a multi-agent environment, which entail the emergence of two types of architecture; centralized and distributed.

Centralized architecture is based on a central agent; however, this is not an appropriate approach in a dynamic environment as the network node that houses the central data is not accessible all the time (Balakrishnan & Majd, 2013). Under such circumstances, if an agent requests ratings from a database, it will not be able to find any source of data for those ratings. Consequently, the agent will be unable to compute the accurate level of reputation value (Logenthiran et al., 2012). Furthermore, the centralized solutions ignore possible personal affinities, biases, and standards that may vary across various users (Logenthiran et al., 2012).

In contrast to the centralized architecture, the agents in a distributed architecture keep track of all the agents' activities. Hence, the user models are maintained locally by the agents. It is not necessary to reveal personal information to a central server, and agents also communicate with one another to collect information or find resources and experts in order to pursue their users' goals(Nusrat & Vassileva, 2012).

2.6Main components of trust models

The current trust models are presented based on several main components. In this section, these components are introduced then existing trust models related to these components are described. In fact, determining these components can help to support the first objective of this research. The collected components from the most representative trust models are similarity, satisfaction/dissatisfaction, reliability, reputation, belief/disbelief, uncertainty, conflict, trust transitivity, and decision-making process. Each of these components is explained in the following sections.

2.6.1 Similarity

In a heterogeneous multi-agent environment, each agent has particular preferences because they have different experiences (Conitzer, 2010). For instance, requester agent A, which wants to buy a product from agent B, has particular preferences for each aspect of the interaction, as shown in Figure 2.3.

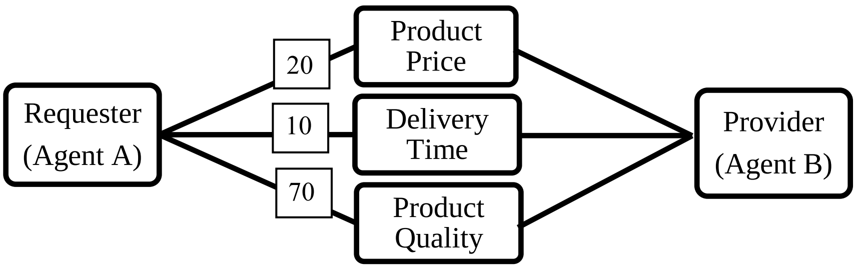


Figure 2.3: The ontological structure of an interaction (Sabater & Sierra, 2001c)

According to this example, agent A as a requester emphasizes on three aspects, the product quality, product delivery time, and product price. In other words, when agent A wants to purchase a product from provider agent B, it emphasizes 70% on product quality, 20% on product price and 10% on delivery time. Thereby, the requester agent A tries to select the provider that can provide the product with high quality, then it will check the price of the product, and, finally, consider the delivery time suggested by the providers.

Requester agents need advice when they want to buy items from several unknown provider agents. In this case, they should consult their familiar agents to find out which one of these providers can provide the items according to their highest value of preference. Therefore, the trust of requester agent A towards advisor agent B should contain a similarity between the preferences experienced by the advisor agents (Battiston et al., 2006).

2.6.2 Satisfaction/Dissatisfaction

Agents are autonomous and any two agents may have diverse preferences for the same item, thus they meet different productivity or degrees of satisfaction or dissatisfaction from the consumption of the same item (Battiston et al., 2006). Hence, when the agents complete an interaction, the service requestor needs to rate the provider's performance through the feedback interface in order to convey its satisfaction or dissatisfaction of the current interaction (Li & Kao, 2009). Thus, the satisfaction/ dissatisfaction rating represents the confidence of the services and resources that the provider agents provide (Woo et al., 2010).

Rating the satisfaction/dissatisfaction for a service provision is more complex than rating according to the success or failure of the interaction. This is because the criteria of the qualified services depend on what the requestor cares about the most, while the requester can have dissimilar sensitivities concerning the different perspectives of the provider's performance.

Simply gauging the satisfaction/dissatisfaction of service performance in a single dimension with binary rating (i.e. yes or no) may lead to a wrong prediction (Li & Kao, 2009). This means that by dividing the behavior of each agent into exactly positive and negative like the Multi-agent Recommendation Agents (Walter et al., 2008b) and Dynamic Trust Model (Das et al., 2011), the evaluation of the satisfaction or dissatisfaction of agents cannot be accurate. Generally, linguistic termleads to more accurate judgment (Zarandi et al., 2012).

If the trust model wants to provide different formula for evaluating the trustworthiness and untrustworthiness of agents, the range of service satisfaction should be different from the range of service dissatisfaction. Hence, presenting formulas based on linguistic terms, which present the value of service satisfaction of the agents as well as the service dissatisfaction of those agents in separate ranges, is more suitable like FIRE model (Huynh et al., 2006; Huynha et al., 2004) and REGRET model (Sabater & Sierra, 2001a), in which the previous satisfying interactions range is between 1 and 0, and the previous dissatisfying interactions range is between 0 and -1, and 0 represents the neutral behavior of agents.

2.6.3 Reliability

Cooperation among agents can solve large-scale complex problems, which cannot be solved by a single agent (Iantovics, 2012). However, when agents cooperate, the possibility arises that an agent may deceive its partner for its own benefit; therefore, selecting a reliable partner can guarantee successful cooperation to a great extent as well as reduce unnecessary risk and expenses. In order to ensure the selection of a reliable partner, it is necessary to investigate the reliability among agents.

The reliability of a system has generally been defined as the probability that a system will perform as its specification for a specified duration of time (Steghöfer et al., 2010; Sundresh, 2006). In fact, when an agent has to choose a prospective partner, it computes the reliability value of that partner based on its past interactions with other agents (Garruzzo & Rosaci, 2010). The lack of information about the background in computing the reliability of the agents causes a lot of suspicion and mistrust among agents (Wei, 2007).

TREPPS (Li & Kao, 2009) and FIRE (Huynha et al., 2004) models propose the reliability formula based on two factors, closeness and stability factors. These two factors can appropriately determine the concept of reliability of a specific agent. Indeed, to define how well an agent is reliable; it is necessary to investigate the frequency of previous interactions between two agents. In addition, the stability of agents should be evaluated to determine whether or not the result of the interaction between two agents is stable. The stability in previous interactions can also increase the degree of confidence of the agents.

Moreover, FIRE model measures the reliability of each agent based on the ratings that the agent gives to the provider according to previous interactions. In fact, FIRE model presents a slightly different formula for calculating the closeness and stability factor by considering range of -1 and 1 for the evaluation of satisfaction and dissatisfaction. According to FIRE model as the number of previous interactions (n) grows, the degree of the closeness factor increases until it reaches a defined threshold (m). However FIRE model did not clearly explain how to evaluate the defined threshold.

FIRE model (Huynh et al., 2006; Huynha et al., 2004) evaluates the rating of stability factor called deviation reliability by using the rating that agent a gives to agent b for each criterion (e.g. price, delivery time, quality), the range of this weight is between -1 and 1, and also the freshness weight of timethat gives more weight to more recent interaction. FIRE model like TREPPS calculates the reliability of each agent by integrating closeness and stability factor.

However, TREPPS and FIRE models ignored the effect of negative behaviours of agents; it means that these models considered the increasing of the reliability by the growth in the total number of previous interactions. The previous interactions involved satisfying and dissatisfying interactions. It seems that considering the number of previous dissatisfying interactions between two agents separate from the number of satisfying interactions leads to a better estimate of the level of trustworthiness of the agent. Therefore, an agent that has to select the most promising agent should calculate the unreliability of that agent in a multi-agent environment, along with its reliability value. It is clear that the computation of unreliability is based on the previous dissatisfying interactions, while the reliability of each agent is calculated based on the previous satisfying interactions. In fact, the unreliability of a system has generally been described as the probability that a system will not perform according to its specification for a specified duration of time.

2.6.4 Reputation

Reputation is a collective evaluation of an agent carried out by many other agents. It is the total measure of trust by other agents in a network of a service provider (Nusrat & Vassileva, 2012). Reputation is the positive 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. When a requester agent has to select the most promising agent, it should be capable of allocating a proper weight to the reputation in order to determine the reliability(Rosaci et al., 2011). Reputation values are based on two aspects; endogenous and exogenous. The endogenous reputation value relates to the concept of reciprocity, meaning an agent trusts its friends more than strangers. This is a simple solution to deal with unreliable opinions. The endogenous method essentially reduces the risk of receiving bad evidence by selecting reputation information from good sources (i.e. friends) (Marsh, 1994). For example, an increase in agent X's trust in Y should also increase the likelihood that X will reciprocate positively to Y's actions at some point in the future. This form of reciprocity is evident in online transactions, such as eBay, where a high correlation between the requester and the provider feedback exists (Resnick & Zeckhauser, 2002). In contrast, the exogenous reputation value accepts the positiveratings presented by stranger agents. Instead of calculating the reputation based on the neighbourhood agents opinion, in this case the probability that a specific agent provides accurate report, given its past opinion, is used to calculate the reputation value (Medić, 2012).

However, the existing models did not consider the effect of the negative opinions of other agents about a specific agent. Most existing models evaluate the reputation of each agent 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 considering both sets of reputable and disreputable providers (Brusilovsky et al., 2003).

Therefore, an agent that 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. In general, the concept of disrepute is the negative 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.

It seems that few previous studies consider the disrepute in evaluating the trustworthiness of agents, whereas the proposed learning algorithm presents a scenario for evaluating the trustworthiness of the agent 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 considered for that interaction with the provider. If the recorded rate is more than the threshold, the provider is considered reputable, otherwise it is disreputable.

2.6.5 Belief/Disbelief

A fundamental aspect of the human condition is that nobody can ever determine with absolute certainty whether a proposition about the world is true or false. In addition, whenever the truth of a proposition is expressed, it is always done by an individual, and it can never be considered to represent a general or objective belief (Jøsang, 2011). Trust relates to the beliefs that the trusting agent holds, which include the belief that the second trusted agent is capable of bringing about the goal, and that it will carry out the action to bring about the goal (Tang et al., 2011).

These philosophical ideas are directly reflected in the mathematical formalism and belief representation of subjective logic (Jøsang, 2011). The trust models, which are based on the subjective logic, follow the belief and disbelief components. In fact, subjective logic requires trust relationships to be expressed as belief and disbelief. The belief theory, which is based on subjective logic, is a framework related to the probability theory, but where the probabilities over the set of possible outcomes do not necessarily add up to 1, and the remaining probability is assigned to the union of possible outcomes (Jøsang et al., 2006).

Dempster-Shafer evidence theory is based on subjective logic (Oren et al., 2007), which applies a belief matrix called the opinion to express belief. An opinion, as represented by $W_x^A = (b, d, u, \alpha)$, expresses the belief of the relying agent a in the trustworthiness of service provider b(Jøsang et al., 2006). Where b denotes the belief of how well the agent can be trusted, d represents the disbelief in how well the agent cannot be trusted, and u shows the uncertainty about the prediction of the agent's behavior, respectively. The b, d and u are between 0 and 1, and $b + d + u = 1$. The parameter α is called the base rate, and is used for calculating an opinion's probability expectation of value (Jøsang et al., 2006).

2.6.6 Uncertainty

The accurate prediction of advisors' behaviors is not possible while the advisors are autonomous agents that can work independently. A provider that satisfies the requester in one interaction may not satisfy the requester in the next interaction. Thus, prediction of the agent's behavior cannot be completely certain and a trust model should consider the uncertainty existing in calculating the trustworthiness of advisors based on their previous interactions.

While the values of belief and disbelief of each agent are calculated by the requester according to the rating of previous satisfying and dissatisfying interactions (Alani et al., 2003). With referring toJøsang et al. (2006), the interaction outcome can be satisfying, dissatisfying and neutral. In subjective logic, the uncertainty relates to the probability estimates of binary events.

2.6.7 Conflict

The agents can present different behaviours at different times of interactions, in that some of them have the habit of practicing inconsistently. In order to calculate the trustworthiness of each advisor more accurately, it is essential to consider the conflict that advisors have in their behaviour according to the previous interactions.

The new theory, named Dezert-Smarandache theory, which is based on the subjective logic, is able to handle both uncertainty and paradoxical information. The Dezert-Smarandache theory is an extension of the subjective logic by overcoming this strong constraint to consider the conflict in previous evidences(Jin & Huai-Jiang, 2010).

According to the analysis of the most representative trust models, there is one method which presented for evaluating conflict in the agents outcomes presented by Evidence-based Trust model (Wang & Singh, 2010). This method is based on computing the minimum of the proportion of previous satisfying interactions to the total number of previous satisfying and dissatisfying interactions and the proportion of previous dissatisfying interactions to the total number of previous satisfying and dissatisfying interactions.

2.6.8 Trust transitivity

Trust transitivity is considered as the possibility of using trust information from other entities in order to infer a trust evaluation of a given entity (Alcalde & Mauw, 2010). Thus, trust transitivity is a key concept of the recommendation systems and has attracted growing interest from researchers in recent years (Dong et al., 2007).

In this scenario, if there are two agents, *A* and *B;* inwhich *A* trusts *B*, and *B* believes that proposition *x* is true. Then, by transitivity,agent *A* will also believe that proposition *x* is true. Thismeans that *B* recommends *x* to *A*. Thetransitive linking of these two opinions consists ofdiscounting *B*'s opinion about *x* by *A*'s opinion about *B*,in order to derive *A*'s opinion about *x* (Bhuiyan et al., 2009). It is also noted that trust is affected by the length of a chain of recommendations, falling as the chain gets longer, thereby shorter paths indicate stronger links (O'Hara et al., 2004).

2.6.9 Decision-Making Process

After evaluating the trustworthiness of each agent, a decision-making mechanism is vital to determine how theagent should be selected as the most trustworthy agent among all agentsin a standard way. Unfortunately, the most representative presented methods for evaluating trustworthiness of agents ignores providing a mechanism for selecting the most trustworthy agent. However, there are a few trust models that propose a decision-making process after calculating the trustworthiness of agents.

2.7 Related trust models

According to the identified components in section 2.7, each component collected from existing trust models. In this section, the most representative trust models which applied these components and proposed methods for computing them are described as follows.

2.7.1 Dynamic Trust Model

Battiston et al. (2006)presented a dynamic trust model, which provides a simple formula to evaluate the similarity between the preferences of two agents, with each agent's predetermined preference on each item, in the range of -1 to 1. According to this model, the similarity between the preferences of two agents is computed as follows:

$$\omega_{i,j} = \sum_{a} (1 - | f_{a_i} - f_{aj} |) \qquad (2.1)$$

Where:

$\omega_{i,j}$ represents the similarity between agents i and j

f_{a_i} shows the preference value of agent i for each item a

f_{a_j} denotes the preference value of agent j in each item a

2.7.2 PBTrust Model

the Priority-Based Trust model (PBTrust model) presented by Su et al. (2013) computes the trustworthiness of potential providers based on the similarities between the description of the requested service and the reference reports in terms of different priorities for criteria. The model applies a matrix to denote a service, since the criteria for both the requested service and the referenced service are of the same order. A description matrix is a vector that represents priority values for corresponding criteria. The angle between the directions of two vectors' is named θ, the dot product of the two vectors indicates the cosine value of angle θ in mathematics. Since all the priorities of the criteria are positive numbers and the sum of them is 1, the range of angle θ is 0◦ to 90◦, and the range of cos θ is 0 to 1. If θ = 0 and cos θ = 1 then there is no difference between the direction of the two vectors and the criteria priorities of the requested service and the referenced service are the same; hence, the reference can completely reflect the provider's performance for the requested service. On the other hand, if θ = 90◦ and cos θ = 0 then there is the largest possible difference between the direction of the two vectors and the criteria priorities of the requested service and the referenced service are totally different; hence, the reference cannot reflect the provider's performance for the requested service.

However, both of the models PBTrust model (Su et al., 2013) and Dynamic Trust Model (Battiston et al., 2006)present an applicable method to compute the similarity between two agents. The PBTrust model (Su et al., 2013) presents a more complicated method, especially for transferring to programming language codes, while the Dynamic Trust Model (Battiston et al., 2006) provides a simple method for measuring the similarity between two agents by evaluating the differences in their preference values for each criterion.

2.7.3 TREPPS

Trust-based Recommender System for the Peer Production Services model (TREPPS) (Li & Kao, 2009). In the TREPPS model, the requester rates each provider service in terms of each criterion for a particular interaction. The satisfaction and dissatisfaction values in this model are computed by linguistic numbers based on triangle fuzzy numbers (Bustos et al., 2009), as shown in Table 2.1.

Table 2.1: Service satisfaction values presented by TREPPS (Li & Kao, 2009)

Linguistic terms **Service satisfaction**	**Fuzzy numbers**
Bad (B)	(0,0,0.3)
Slightly Bad (SB)	(0,0.3,0.5)
Neutral (N)	(0.2,0.5,0.8)
Slightly Good (SG)	(0.5,0.8,1)
Good (G)	(0.7,1,1)

According to the TREPPS (Li & Kao, 2009) model, the closeness factor is applied to examine the frequency of the previous interactions between the agents. As the number of interactions grows, the value of the closeness factor increases; this relationship indicates that the confidence degree of an advisor is higher (Li & Kao, 2009). TREPPS model (Li & Kao, 2009) evaluates the closeness factor based on the number of interactions between the requester and the provider and the scale of the underlying social network.

The stability factor is used to define whether or not the result of the interaction between the requester and provider is stable. According to the TREPPS model, a lower stability in previous interactions represents a lower confidence value for that specific advisor. TREPPS model calculates the stability factor based on the ratings that the requester agent gives to the provider and the freshness weight of time which gives a higher value to the interaction which is closer to the current time. Finally, the TREPPS model integrates these two factors and presents the final formula for evaluating the reliability.

According to the TREPPS model, the transitivity of trust along the chain of connected trust networks can be formulated as:

$$T_{\alpha,\beta} = \frac{\sum_{k \in neigbors(\alpha)} T_{\alpha,k} \times T_{K,\beta}}{\sum_{k \in neigbors(\alpha)} T_{\alpha,k}} \qquad (2.1)$$

Where

α and β are two distinct agents in trust network

k is denoted as the neighbour agent of α from which a one-way trust relationship exists.

Overall, TREPPS presents a simple approach for evaluating the trust transitivity; in fact, this model considers the aggregation of trustworthiness, without considering the combination of trustworthiness between agents. Moreover, its proposed approach is not based on the belief theory, which involves the value of uncertainty and conflict in the previous evidence.

TREPPS model (Li & Kao, 2009) proposes a decision-making process based on the FTOPSIS-fuzzy multi-criteria decision making method presented by Chen (Chen, 2000). According to this method, the TREPPS model makes a decision matrix from the trust values of agents for each criterion and also constructs a weighted matrix according to the importance of each criterion. Then it selects the most trustworthy agent in six steps, as follows:

Step 1: Normalize the fuzzy decision matrix through the linear scale transformation in order to transform the various criteria scales into a comparable scale.

Step 2: Construct the weighted normalized fuzzy decision matrix according to the weight of each criterion.

Step 3: Determine the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS)

Step 4: Compute the distance of each alternative from FPIS and FNIS, respectively.

Step 5: Compute the closeness coefficient of each alternative.

Step 6: The ranking order of all alternatives is determined at the final step according to the closeness coefficient and the best service provider can be selected accordingly.

It seems that TREPPS model (Li & Kao, 2009) proposed an appropriate decision-making process by using one of the multi-criteria decision-making methods, such as FTOPSIS. According to this method, the trustworthiness of each agent is weighted, and then the agent with the maximum ranking can be selected. This method seems more applicable to find the most trustworthy agent among all the evaluated agents.

2.7.4 FIRE

FIRE model (Huynh et al., 2006; Huynha et al., 2004) considers the range of -1 to +1 for rating each provider agent after each interaction, where -1 means absolutely negative, +1 means absolutely positive, and 0 means neutral.

FIRE model (Huynh et al., 2006; Huynha et al., 2004) presents two kinds of reputation mechanism: witness reputation and certified reputation. The witness reputation of the provider agent is built on observations about its behaviour by other agents. In order to evaluate the witness reputation of provider, b, an agent, a, needs to find the witnesses that have interacted with provider b. Then FIRE calculates the witness reputation as the set of witness ratings that witness agent a gives to agent b.

The certified reputation is the ratings presented by the rated agent b about itself, that have been obtained from its partners in past interactions (Keung & Griffiths, 2010). These ratings are based on the certifications presented by agent b about its past performances. The value of certified reputation is measured with the same method of witness reputation, while the input is the set of ratings provided by the provider agent b itself.

The FIRE model evaluates the overall reputation for each provider agent identified by the others, without considering the ontological structure; however, this model weights each rating by allocating more weight to more recent ratings.

2.7.5 SPORAS

Zacharia (1999)presented the SPORAS model to improve online reputation models, such as those used in eBay and Amazon auctions. SPORAS (Zacharia, 1999; Zacharia & Maes, 2000) 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 the opinions of users. The reputation level of an individual is evaluated after each transaction by collecting feedback ratings from another user involved in the transaction. This model considered two most recent agents for gathering the rating values. In addition the ratings applied to measure reputation are discounted over time, so that recent ratings have more weight

The SPORAS has several limitations. It does not have a mechanism which an agent can evaluate reputation from the agents that it has more trustworthy (Patel, 2006). The presented formula by this model can only consider the most recent rating between two agents without considering the rating from many other agents (Patel, 2006). More specifically, in this model agents do not have an individual database of their own ratings, since ratings are deposited centrally. This is not an appropriate method especially in a dynamic multi-agent environment, in such cases if an agent requires ratings from the database, it will not have an alternative source of data for those ratings and the agent will be unable to calculate an effective level of reputation (Patel, 2006).

2.7.6 HISTOS

HISTOS (Zacharia & Maes, 2000) model, which was presented by the same authors, provides a more personalized or endogenous reputation than SPORAS, which provides a global reputation. The HISTOS (Zacharia & Maes, 2000) model is more appropriate for highly connected communities by proposing a more personalized reputation, in which it is based on the principle that an agent trusts its friends more than strangers. HISTOS (Zacharia & Maes, 2000) applies a directed graph, which is used as the pair-wise rating, as shown in Figure 2.4, in which the nodes represent the agents, the weighted edges refer to the latest reputation values, and the direction of the edge shows the rated agent (Medić, 2012).

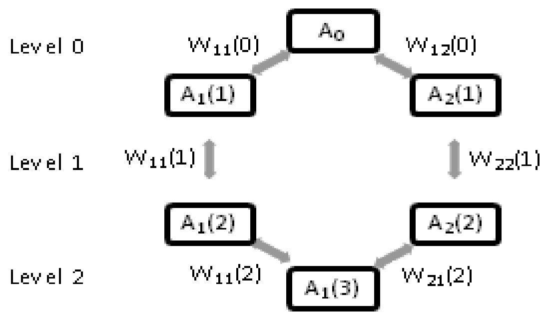


Figure 2.4: HISTOS directed graph (Zacharia & Maes, 2000)

According to this model, the agent A_0 computes reputation level of $A_1(3)$, if a path exists from A_0 to $A_1(3)$ and if the search to discover a path connections in the algorithm fails, the SPORAS mechanism will be applied to evaluate the reputation level.

Applying HISTOS is not possible in a large-scale open system because it is difficult to draw a global graph between agents. While many agents will have a local view of the entire system and they may be able to construct a social graph by using this local information, in this context, HISTOS algorithm will fail to deliver the desired results (Patel, 2006).

2.7.7 TRR

An integrated reliability-reputation model for the agent societies (TRR) model (Rosaci et al., 2011), combines the trustworthiness of the rater agent and reputation in a synthetic trust model. This model considers one issue, which exists in measuring the reputation of agents by evaluating the trustworthiness of an agent that rates the other agents. In this model, the reputation of each agent is computed based on the ratings given by other agents that have had previous interactions with it 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. Thereby, the rater agents with less trustworthiness have less effect on the evaluation of reputation.

However, TRR considers the trustworthiness of the rater agent in its presented formula for evaluating the reputation of the provider agent. It seems that this model considers the satisfaction rate of each provider agent from the perspective of other agents, without considering dissatisfaction rates. Moreover, this model did not consider the ontological structure with different weights for different aspects of interaction.

2.7.8 REGRET

The REGRET model (Sabater & Sierra, 2001b) calculates the reputation in three specialized types depending on the information source that is applied to compute reputation, as:

– Witness reputation, which is calculated from the information coming from the witness agents

– Neighbourhood reputation, which is measured using the information extracted from the social relations between partners

– System reputation, which is based on the roles and general properties

Moreover, the REGRET model incorporates a credibility value that allows the agent to measure the reliability of the witnesses.

The REGRET model has an ontological structure. In fact, this model considers that reputation has no single and abstract concepts but rather multi-facet concepts. The ontological interactions come from a combination of multiple aspects. REGRET computes the ontological dimension through graph structures similar to the one shown in Figure 2.5.

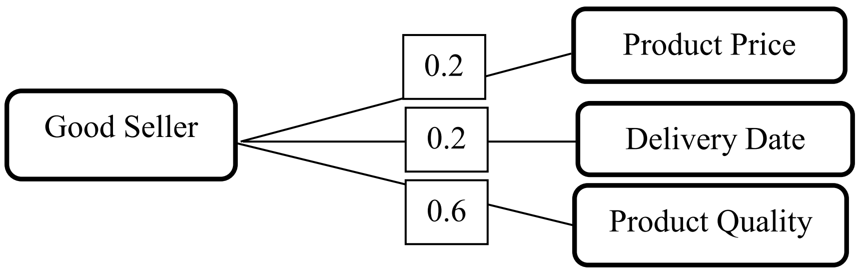


Figure 2.5: The ontological structure (Sabater & Sierra, 2001c)

The diagram illustrates that a good seller reputation value is related to the reputation of a product quality, product delivery date and customer service, where agent A gives distinct reputation values to each aspect of agent B as a seller. For instance, Figure 2.5 shows that good (seller) has been given a high reputation value for product quality, whereas low values are given for delivery date and product price.

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 examines the reliability of the computed reputation regarding the number of agents used to calculate the reputation of provider agent and the interaction frequency of the rater agents. Finally, the REGRET model presents a stronger reputation system by considering the ontological structure. In this model, the reputation value has an associated reliability measure.

2.7.9 TNA-SL

The Trust Network Analysis with Subjective Logic (TNA-SL) model presented by Jøsang et al. (2006) divides the outcomes of each interaction into a binary event, satisfying and dissatisfying interactions. The TNA-SL measures the belief of each agent as:

$$b = \frac{r}{r+s+2} \tag{2.1}$$

Where:

b shows the belief value of a specific agent

r denotes the number of previous satisfying interactions

s represents the number of previous dissatisfying interactions

Moreover, the TNA-SL model calculates the disbelief of each agent as:

$$d = \frac{s}{r+s+2} \tag{2.2}$$

Where:

d indicates the disbelief value of a specific agent

r shows the number of previous satisfying interactions

s represents the number of previous dissatisfying interactions

2.7.10 Probability Certainty Distribution Model

Probability Certainty Distribution Model (Wang & Singh, 2006a) places the value of certainty on its proposed method, while the basis of its evaluation is the subjective logic based on the numbers of satisfying and dissatisfying interactions, as follows:

$$b = c\frac{r+1}{r+s+2} \tag{2.3}$$

Where:

b indicates the belief value of a specific agent

c denotes the certainty value of an agent's interaction outcomes

r denotes the number of previous satisfying interactions

s represents the number of previous dissatisfying interactions

In addition, this model computes the disbelief of each agent as:

$$d = c\frac{s+1}{r+s+2} \tag{2.4}$$

Where:

d shows the disbelief value of a specific agent

$c$denotes the certainty of an agent's interaction outcomes

r denotes the number of previous satisfying interactions

$s$represents the number of previous dissatisfying interactions

The transitivity of trust among a network of agents is taken into consideration in the Probability Certainty Distribution Model (Wang & Singh, 2006b; Wang & Singh, 2010). According to this model trust transitivity is measured using the Dempster-Shafer belief theory, through two operators, concatenation "⊗" and aggregation "⊕". In fact, two transitivity operators exist in subjective logic to evaluate trust transitivity; the concatenation operator for the corresponding combination as "⊗" and the aggregation operator for the corresponding fusion as "⊕" (Jøsang et al., 2008). The concatenation operator can be used to derive trust from a trust path consisting of a chain of trust edges, and the aggregation operator can be used to integrate trust from parallel trust paths (Bhuiyan et al., 2008). As depicted in Figure 2.6, there is a path in a trust network between agent A and C: $A \rightarrow B \rightarrow C$. The trust of agent A in B is:

$$M_1 = (b_1, d_1, u_1) \tag{2.1}$$

Where:

b_1 indicates the number of previous satisfying interactions

d_1 shows the number of previous dissatisfying interactions

u_1 represents the amount of uncertainty

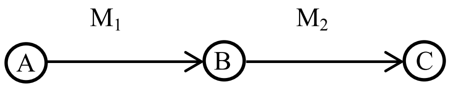


Figure 2.6: A multi-agent path between agent A and C

Similarly, the trust of B in C is M_2 where $M_2 = (b_2, d_2, u_2)$. Then the transitivity of trust in this chain of agents is computed by the concatenation operator, as follows:

$$M_1 \otimes M_2 = (b, d, u) = \begin{cases} b = b_1 b_2 \\ d = d_1 d_2 \\ u = 1 - b_1 b_2 - b_1 d_2 \end{cases} \tag{2.2}$$

Where:

b is the number of previous satisfying interactions

d is the number of previous dissatisfying interactions

u is the amount of uncertainty of agent's interaction outcomes

On the other hand, Figure 2.7 illustrates the situation where agent A has more than one neighbour.

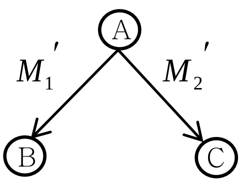


Figure 2.7: Two multi-agent paths from agent A

In this case, the propagation of trust is calculated by the aggregation operator, "⊕", as follows:

$$M_1' \oplus M_2' = (b,d,u) = \begin{cases} b = B(r_1 + r_2, s_1 + s_2) \\ d = D(r_1 + r_2, s_1 + s_2) \\ u = U(r_1 + r_2, s_1 + s_2) \end{cases} \quad (2.3)$$

Where:

$M_1' = (b_1, d_1, u_1)$ shows the trust rating of agent B in A

$M_2' = (b_2, d_2, u_2)$ represents the trust rating of agent C in A

Ultimately, the overall trust transitivity formula presented by the Probability Certainty Distribution Model (Wang & Singh, 2006b; Wang & Singh, 2010) is obtained by merging the concatenation and aggregation operators. For instance, the trust transitivity value of the multi-agent network in Figure 2.8 is $M_1' \oplus (M_2' \otimes M_3') = (b,d,u)$.

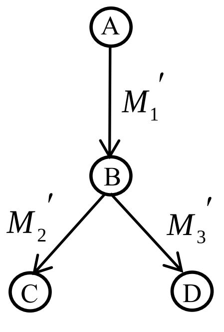


Figure 2.8: A multi-agent network

The Probability Certainty Distribution Model (Wang & Singh, 2006b; Wang & Singh, 2010)applied the Dempster-Shafer theory. However, the Dempster-Shafer theory, which it uses, does not consider the conflict in the previous behavior of the agents. Therefore, the extension method of the Dempster-Shafer theory, called the Dezert-Smarandache Theory, is presented to measure the conflict in the previous behaviour of the agents. In fact, the Dezert-Smarandache Theory was developed for dealing with imprecise, uncertain and also paradoxical sources of information (Smarandache & Dezert, 2006).

2.7.11 Evidence-based Trust Model

Evidence-based trust model (Wang & Singh, 2010) measures the probability of uncertainty based on two elements, positive and negative outcomes (Hang et al., 2008; Wang & Singh, 2010). In this model, the outcomes of the interactions are divided into positive and negative, as $E = \{(r,s) \mid r > 0, s > 0\}$ where the pair (r,s) shows the amount of positive (satisfying) and negative (dissatisfying) outcomes of past interactions, respectively.

This model presents the following formula for evaluating uncertainty based on the probability theory as:

$$u = 1 - c \tag{2.1}$$

Where:

u indicates the uncertainty of the agent's interaction outcomes

$c = \frac{1}{2}\int_0^1 \left| \frac{x^r(1-x)^s}{\int_0^1 x^r(1-x)^s} - 1 \right| dx$ denotes the certainty of the agent's interaction outcomes

r represents the number of previous satisfying interactions

s shows the number of previous dissatisfying interactions

This model presents an applicable method for evaluating uncertainty based on the posterior probability of a binary event, and positive and negative outcomes.

The Evidence-Based Trust Model (Wang & Singh, 2010) calculates the conflict in previous behaviour of agents as follows:

$$\alpha = \frac{s+1}{t+2} \tag{2.1}$$

Where:

s represents the number of previous satisfying interactions

t is the total number of previous satisfying and dissatisfying interactions

While, $\alpha \in (0,1)$, if α approaches to 0 or 1 means unanimity, otherwise, if $\alpha = 0.5$ it means the number of satisfying interactions is equal to the number of unsatisfying interactions, which indicates the maximum conflict in evidence.

2.7.12 New Evidential Trust Model

New Evidential Trust Model(Wang & Sun, 2009) used the Dezert-Smarandache Theory for evaluating trust transitivity based on four variables – belief, disbelief, uncertainty and conflict.This model is based on the set, Θ, considering $\Theta = \{T, \neg T\}$ which is the general frame of discernment based on two hypotheses: T (agent, a, trusts agent, b) and $\neg T$ (agent, a, distrusts agent, b). The set D^{θ} is defined as $\{\phi, T, \neg T, T \cap \neg T, \Theta\}$.

Moreover, a general basic belief assignment (gbba) is a function as follows:

$$m = D^{\theta} \rightarrow [0,1] \tag{2.4}$$

Where:

$$\begin{cases} m(\varphi) = 0 \\ \sum_{A \subseteq D^{\theta}} m(A) = 1 \end{cases}$$

Thus, $m(\{T\}) + m(\neg T\}) + m(\{\Theta\}) + m(\{T \cap \neg T\}) = 1$

Then, the New evidential trust model (Wang & Sun, 2009) describes the trust evaluation of agent, *A*, to agent, *B*, by the gbba m(.) as:

$m(\{T\})$ describes value of trust.

$m(\neg T\})$ represents the value of distrust.

$m(\{\Theta\})$ denotes the value of uncertainty, where the uncertainty here means a lack of evidence. If A has no evidence at all, then $m(\{\Theta\}) = 1$, and if agent *A* gets more evidence, $m(\{\Theta\}) \prec 1$.

$m(\{T \cap \neg T\})$ is the value of conflict caused by paradoxical behaviour.

Suppose advisor, *a*, evaluates the trustworthiness of agent, *b*, as:

$$(T)_{a \rightarrow b} = (m_{a \rightarrow b}(\{T\}), m_{a \rightarrow b}(\{\neg T\}), m_{a \rightarrow b}(\{T \cap \neg T\}), m_{a \rightarrow b}(\{\Theta\})) \tag{2.5}$$

This situation is shown in Figure 2.9.

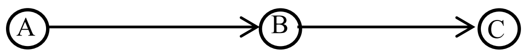


Figure 2.9: Trust combination

and$b$'s trust evaluation of agent, c, is as follows:

$$(T)_{b\to c} = (m_{b\to c}(\{T\}), m_{b\to c}(\{\neg T\}), m_{b\to c}(\{T \cap \neg T\}), m_{b\to c}(\{\Theta\})) \qquad (2.6)$$

Then the New evidential trust model (Wang & Sun, 2009) calculates the trust combination through this referral chain as follows:

$$T_{a\to c} = T_{a\to b} \otimes T_{b\to c} \qquad (2.7)$$

Where:

$$m_{a\to c}(\{T\}) = (m_{a\to b}(\{T\}) + m_{a\to b}(\{T \cap \neg T\})) \times m_{b\to c}(\{T\})$$

$$m_{a\to c}(\{\neg T\}) = (m_{a\to b}(\{T\}) + m_{a\to b}(\{T \cap \neg T\})) \times m_{b\to c}(\{\neg T\})$$

$$m_{a\to c}(\{T \cap \neg T\}) = (m_{a\to b}(\{T\}) + m_{a\to b}(\{T \cap \neg T\})) \times m_{b\to c}(\{T \cap \neg T\})$$

$$m_{a\to c}(\{\Theta\}) = 1 - (m_{a\to c}(\{T\}) + m_{a\to c}(\{\neg T\}) - m_{a\to c}(\{T \cap \neg T\})$$

On the other hand, suppose m_1 and m_2 are two independent gbba over the same general discernment frame Θ, as shown in Figure 2.10.

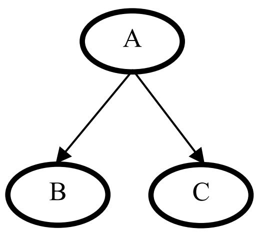


Figure 2.10: Trust aggregation

Then, New evidential trust model (Wang & Sun, 2009) computes the trust aggregation as follows:

$$m(c) = m_1(A) \oplus m_2(B) = \sum_{\substack{A,B \subseteq D^{\Theta} \\ A \cap B = C}} m_1(A) m_2(B) \tag{2.8}$$

Where:

$$m(A) = (m_{c \to a}(\{T\}), m_{c \to a}(\{\neg T\}), m_{c \to a}(\{T \cap \neg T\}), m_{c \to a}(\{\Theta\}))$$

$$m(B) = (m_{c \to b}(\{T\}), m_{c \to b}(\{\neg T\}), m_{c \to b}(\{T \cap \neg T\}), m_{c \to b}(\{\Theta\}))$$

Evidence-based trust model (Wang & Singh, 2010) considers three situations for selecting the most trustworthy agent, as follows:

i. The agent is trustworthy if belief is high, disbelief is low and uncertainty is low.

ii. The agent is untrustworthy if belief is low, disbelief is high and uncertainty is low.

iii. Moreover, a lack of trust is placed on an agent where belief is low, disbelief is low and uncertainty is high.

It seems that this method can fail in a situation where the model uses other components like conflict for evaluating the trustworthiness of agents. For instance, these three conditions are not applicable in models, such as the New Evidential Trust Model, which evaluate the trustworthiness of agents based on belief, disbelief, uncertainty and the conflict of agents. If more than one agent has the belief value higher than disbelief then selecting one of them as the most trustworthy one is not cleared. Unless the system order the gents based on their belief values and selects the agent with the highest belief value as the most trustworthy provider.

The comparative analysis of the existing trust models which were studied in this research is described in Table. 2.2.

Table 2.2: Comparative analysis of related trust models

Models	Author	Similarity	Satisfaction	Reliability	Reputation	Belief & Disbelief	Uncertainty	Conflict	Trust Transitivity	Decision -making	Advantage	Disadvantage
Dynamic Trust Model	Battiston et al. (2006)	Different preferences between two agents	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Present a simple formula for evaluating similarity	N/A
PBTrust Model	Su et al. (2013)	Different priorities between two agents	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Present a complicate formula for evaluating similarity
TREPPS	Li and Kao (2009)	N/A	Using Linguistic numbers	Closeness and Stability factor based on previous satisfying interactions	N/A	N/A	N/A	N/A	Combination trustworthiness between agents	FTOPSIS method	- Closeness and stability factor - Using multi criteria decision-making process	Combination trustworthiness between agents
FIRE	Huynh et al. (2006)	N/A	Rage of -1 to +1	Closeness and Stability factor based on previous	Witness Reputation that other agents rate, Certified Reputation	N/A	N/A	N/A	N/A	N/A	- Closeness and Stability factor - Calculating	N/A

Models	Author	Similarity	Satisfaction	Reliability	Reputation	Belief & Disbelief	Uncertainty	Conflict	Trust Transitivity	Decision -making	Advantage	Disadvantage
				satisfying interactions	that each agent presents its own rate (Recent rating have more weight)						reputation considering to the more weight recent ratings	
SPORAS	Zacharia (1999)	N/A	N/A	N/A	Aggregating the opinion of other agents (Recent rating have more weight)	N/A	N/A	N/A	N/A	N/A	- Calculating reputation considering to the more weight recent ratings	N/A
HISTOS	Zacharia and Maes (2000)	N/A	N/A	N/A	Using a directed graph for gathering the opinion of other agents	N/A	N/A	N/A	N/A	N/A	N/A	Using a directed graph for gathering the opinion of other agents
TRR	Rosaci et al. (2011)	N/A	N/A	N/A	Aggregating the opinion of other agents (Reliability of rater agents are considered)	N/A	N/A	N/A	N/A	N/A	- Reliability of rater agents are considered for evaluating the reputation	N/A

Models	Author	Similarity	Satisfaction	Reliability	Reputation	Belief & Disbelief	Uncertainty	Conflict	Trust Transitivity	Decision -making	Advantage	Disadvantage
REGRET	Sabater and Sierra (2001b)	N/A	N/A	N/A	Aggregating the opinion of other agents Considering ontological dimension (Reliability of rater agent is considered)	N/A	N/A	N/A	N/A	N/A	- Considering ontological dimension in evaluating the reputation - Reliability of rater agents are considered for evaluating the reputation	N/A
TNA-SL	Jøsang et al. (2006)	N/A	N/A	N/A	N/A	Divide each interaction into binary events (Satisfying interactions as belief and dissatisfying interactio	N/A	N/A	N/A	N/A	N/A	Combination and aggregation between agents by considering 3 variables as; Belief, Disbelief and Uncertainty

Models	Author	Similarity	Satisfaction	Reliability	Reputation	Belief & Disbelief	Uncertainty	Conflict	Trust Transitivity	Decision -making	Advantage	Disadvantage
						ns as disbelief)						
Probability Certainty Distribution	Wang and Singh (2006a)	N/A	N/A	N/A	N/A	Divide each interaction into binary events (Satisfying interactions as belief and dissatisfying interactions as disbelief)	N/A	N/A	Combination and aggregation between agents by using Belief, Disbelief and Uncertainty	N/A	N/A	Combination and aggregation between agents by considering 3 variables as; Belief, Disbelief and Uncertainty
Evidence-based Trust Model	Wang and Singh (2010)	N/A	N/A	N/A	N/A	Divide each interaction into binary events (Satisfying interactions as belief and	Base on certainty value which computes by the posterior probability of previous satisfying and dis satisfying interactions	Minimum of the proportion of previous satisfying interactions to the total number of previous	N/A	N/A	- Calculating uncertainty by the posterior probability of previous satisfying and dis satisfying interactions -	N/A

Models	Author	Similarity	Satisfaction	Reliability	Reputation	Belief & Disbelief	Uncertainty	Conflict	Trust Transitivity	Decision -making	Advantage	Disadvantage
						dissatisfying interactions as disbelief)		satisfying and dis satisfying interactions			Computing conflict considering the numbers of previous satisfying and dis satisfying interaction	
New Evidential Trust Model	Wang and Sun (2009)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Combination and aggregation between agents by using Belief, Disbelief and Uncertainty and Conflict	N/A	Combination and aggregation between agents by considering 4 variables; Belief, Disbelief, Uncertainty and Conflict	N/A

2.8 Initial structure of TMAN

According to the analysis of the related trust models in the second part, this analysis of the literature led to the forming of the initial structure of TMAN, as shown in Figure 2.11

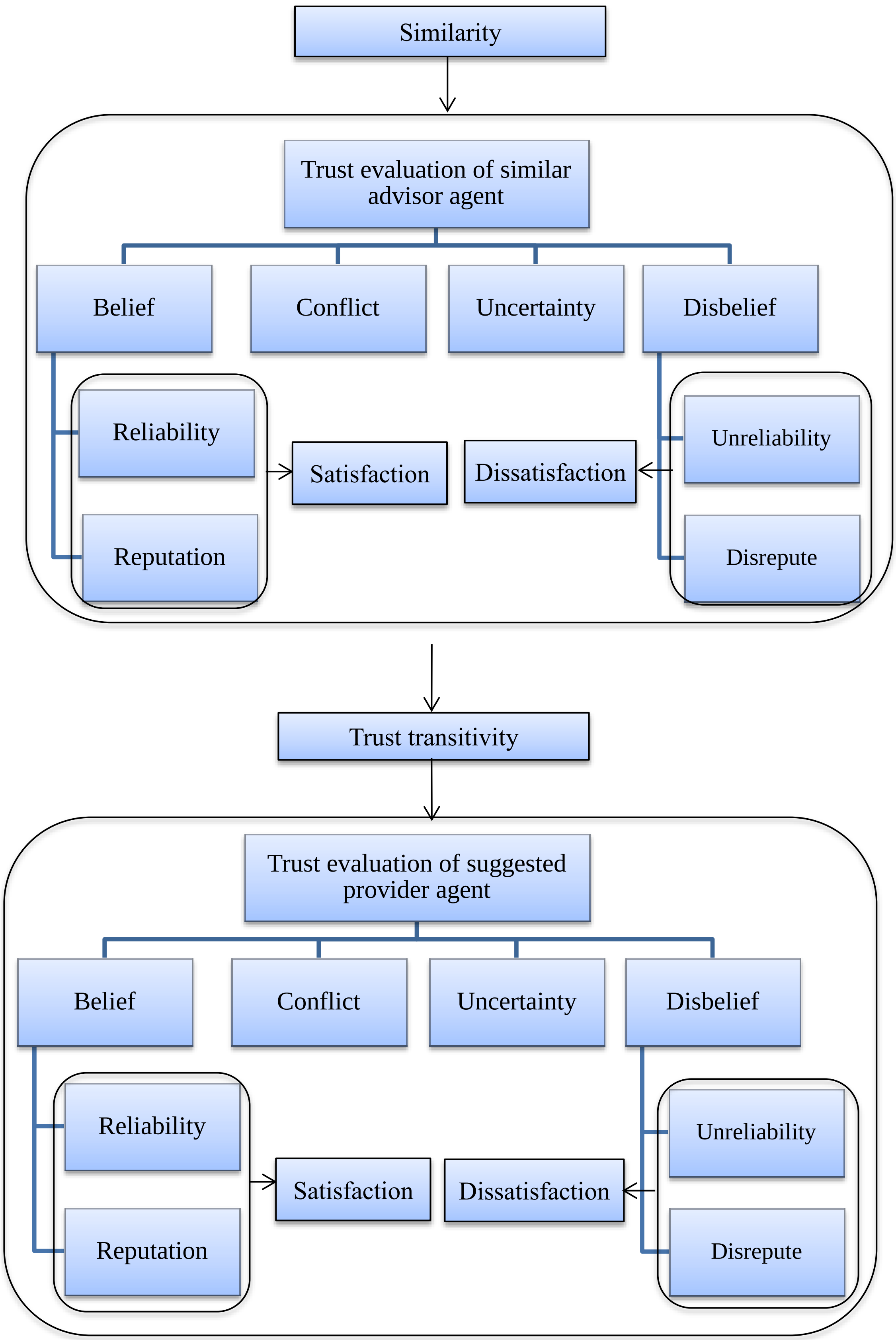


Figure 2.11 Required components for TMAN

As shown in Figure 2.11, first the requester should check the similarity between the agents and itself(Battiston et al., 2006; Su et al., 2013). Then, to evaluate the trustworthiness of each similar agent and its suggested provider according to Dezert-Smarandache Theory(Wang & Sun, 2009), four components should be considered – belief, disbelief, uncertainty and conflict. To measure the belief value of each advisor and provider(Jøsang et al., 2006; Wang & Singh, 2006a, 2010), the reliability (Huynh et al., 2006; Li & Kao, 2009)and reputation of agents (Huynha et al., 2004; Rosaci et al., 2011; Sabater & Sierra, 2001b; Zacharia & Maes, 2000)are calculated based on the previous satisfying interactions, and, to compute the disbelief of agents, the unreliability and disrepute of agents are calculated based on the previous dissatisfying interactions. Then the uncertainty and conflict of each agent are evaluated based on both the satisfying and dissatisfying interactions. This leads to obtaining the trustworthiness of each advisor and its suggested provider based on belief, disbelief, uncertainty, and conflict. Finally, the transitivity of trust from the advisor agents to its suggested provider agent is evaluated based on the obtained trustworthiness of the advisor and the suggested provider.

2.9 Summary

In this chapter, the literature was reviewed from the domains of trust models. First, the concepts of multi-agent system, advisor agents and trust models in multi-agent systems were described. Then, the main components presented by the most representative trust models were introduced, along with a summary of several examples, to address some of the requirements for designing a trust model.

According to the analysis of the most representative trust models, similarity, satisfaction/dissatisfaction, reliability, reputation, belief/disbelief, uncertainty, conflict, trust transitivity, and, finally, decision-making process were identified as essential components for designing a trust model. However, two more components – unreliability and disrepute – were introduced, which can be considered based on dissatisfying interactions to evaluate the disbelief of how much an agent cannot be trusted. These components cover the first objective of this research, which was identifying the main components that can be used to present a trust model for advisor networks in a multi-agent environment.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter starts by describing the research methodology employed in this project, followed by the research methodology strategy used to present a mechanism to detect the trustworthy provider according to advice of benevolent advisors in an advisor network.

The methodology of this research consists of three main phases, where each phase has its own activities as explained in the following sections. In the first part, the methodology used to collect and select the necessary components for presenting TMAN is described; this phase was used to determine the components of TMAN and how these components can be measured. This phase also addresses the first objective of this research by identifying the main components that can be used to present a trust model for advisor networks in a multi-agent environment. In the second phase of this research methodology, the performance of TMAN is explained based on components identified in the first phase. In fact, this phase leads to the proposed TMAN and deals with the second objective of this research by building a trust model based on the components identified to recognize trustworthy provider according to advice of benevolent advisors. The final phase involves evaluation of the performance of TMAN to investigate whether TMAN can accurately select the most trustworthy provider according to advice of benevolent advisors, in different multi-agent environments and with various numbers of benevolent and malicious agents. This phase proved the accuracy of TMAN and revealed that TMAN can be applied to an e-commerce multi-agent environment to create a safe environment for transactions; this phase addresses the final objective of this research by evaluating the accuracy of the proposed trust model for advisor networks. Figure 3.1 shows the different phases of the research methodology in a flow chart.

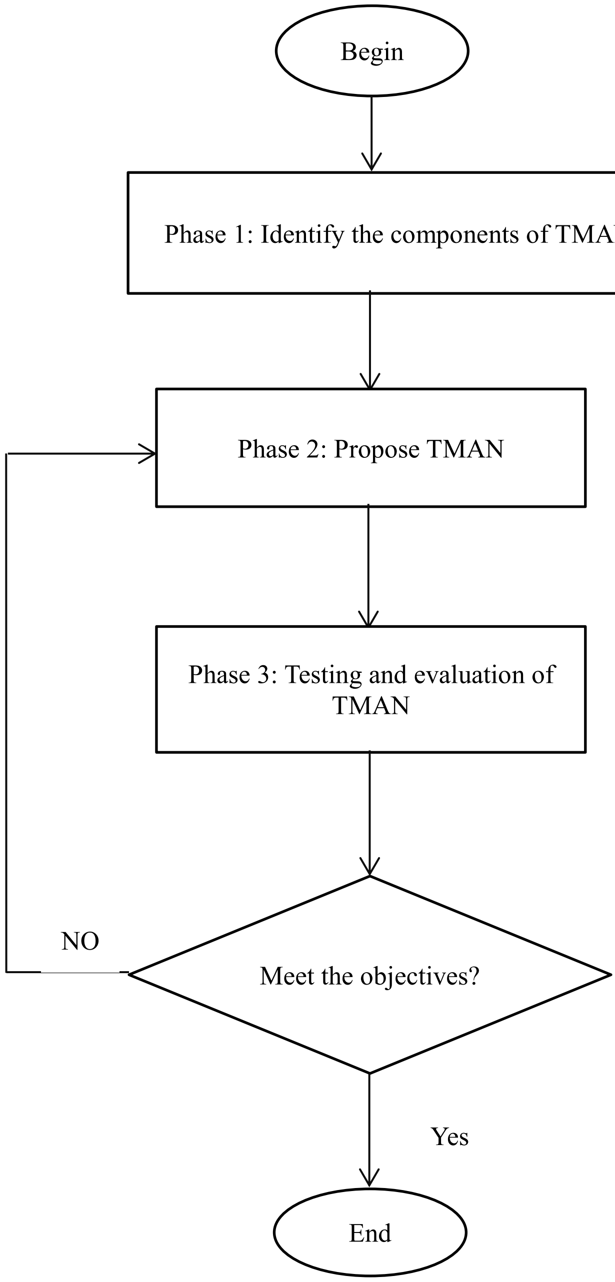


Figure 3.1: Research methodology phases

As shown in Figure 3.1, this research is based on three main phases to achieve the objectives which are necessary to complete the project plan. Each of these phases involves different steps as described in the following sections. The purpose of the first phase is identifying the main components which can be applied for designing TMAN, to accomplish this phase the most representative trust models were analyzed and the components which they used and their proposed methods for evaluating each component were compared. This phase helped to design TMAN according to the identified components. In the next phase, TMAN was designed based on the relationship between identified components using mathematical theory, Dezert-Smarandache Theory (Wang & Sun, 2009), and a mathematical method for selection the most trustworthy provider. This phase led to achieve the second objective of this study. Finally, in the last phase of research methodology TMAN was evaluated, the purpose of this phase was investigated the accuracy TMAN in different multi-agent environment. This phase has two sub activities as: random selection and trade network game that are two different methods used for evaluating the accuracy of TMAN. Each of these phases is explained in more details in the following sections.

3.2 Phase 1: Identify the components of TMAN

In this step, many trust models were searched for and investigated in multi-agent systems to collect the main components which should be considered when designing a trust model. At the end of this step, based on the review of the related literature, the main components of existing trust models in multi-agent systems were identified. Chapter 2 has presented the results of analyzing the existing trust models and has identified the main components which are essential for designing a trust model in a multi-agent environment. This chapter also investigated different methods of computing these identified components. According to Chapter 2, the identified components that are important for proposing TMAN are:

Similarity, Satisfaction, Dissatisfaction, Reliability, Unreliability, Reputation, Disrepute, Belief, Disbelief, Uncertainty, Conflict, and Trust Transitivity

The definition of each component has been discussed thoroughly in Chapter 2. In addition, Chapter 2 presented different methods that the most representative trust models provided for evaluating each component. In the next section of this chapter, the methods selected by TMAN according to these models are explained.

According to analysis existing trust models, methods of computing each selected components were collected, these methods applied different mathematical theory like probability theory and subjective theory. To select the proper method for evaluating each component the strong and weaknesses point of each method was investigated as described in the following sections.

3.2.1 Computing Similarity

As described in chapter 2, Dynamic Trust Model (Battiston et al., 2006) provides an applicable method in measuring the similarity between agents by computing the differences between preferences of two agents. Hence, the method provided by the Dynamic Trust Model in evaluating the similarity between requester and each advisor are adopted by TMAN.

3.2.2 Computing Satisfaction/Dissatisfaction

According to linguistic terms, the behavior of an agent in each interaction can have a different level of satisfaction or dissatisfaction, such as slightly good or slightly bad like TREPPS model (Li & Kao, 2009). It seems that rating each interaction using linguistic terms is meaningful according to the range of rating such as the rating between 0 and 1. If this range is considered between 0 and 1, then it seems that separating the range of dissatisfying interactions from neutral interactions and satisfying interactions is difficult. The FIRE (Huynh et al., 2006; Huynha et al., 2004) and REGRET (Sabater & Sierra, 2001a) models considered the range of rating between -1 and 1, the previous satisfying interactions is ranged in [1,0), and previous dissatisfying interactions is ranged between (0,-1], and 0 represents the neutral behavior of agents. In this case, presenting other computation formulas like reliability and unreliability that use satisfying and dissatisfying rates of the agent, respectively, can be proposed easily. Therefore, TMAN applies the range of [-1,1] for evaluating the rate of each interaction. In fact, TMAN considered four linguistic terms and four ranges to evaluate each linguistic term, as follows:

Linguistic term	**Range**
Good	[1,0.5)
Slightly good	[0.5,0)
Neutral	0
Slightly bad	(0,-0.5]
Bad	(-0.5,1]

Table 3.1: Proposed satisfaction and dissatisfaction rates by TMAN

3.2.3 Computing Reliability/Unreliability

As described in Chapter 2, the most representative trust models evaluated the reliability of each agent based on two factors; closeness and stability factors (Li & Kao, 2009). According to the definition of closeness factor, it is applied to examine the frequency of previous interactions between the agents. While the FIRE model evaluated the closeness factor based on a threshold, unfortunately it did not describe how to measure that threshold clearly; meanwhile, TREPPS presented a more appropriate and clear method, but its presented formula did not consider separate formulas for evaluating reliability and unreliability. In the proposed model, TMAN, the closeness factor is calculated based on the frequency of previous satisfying interactions; this is because of considering two separate formulas for evaluating reliability and unreliability. In fact, the closeness factor of reliability is measured based on the frequency of satisfying previous interactions of an agent relative to the total number of previous interactions.

Another factor is stability, which is used to define whether the result of interaction between requester and provider is stable or not. FIRE measured the stability factor based on the interaction rate in the range of [-1,1]; TREPPS proposed the same method, but it is based on interaction rate in the range of [0,1]. Two separate formulas were considered by TMAN; one formula evaluates reliability of agents based on its previous satisfying interactions in the range of (0,1] and another formula evaluates the unreliability based on previous dissatisfying interactions in the range of [-1,0), where 0 represents the neutral rates. Hence, for evaluating reliability, TMAN uses the method presented by the TREPPS model, in the range of (0,1] stability factor.

On the other hand, the unreliability is measured by evaluating closeness and stability factor. However, in this case, the closeness and stability factor are computed based on the dissatisfaction rates of previous interactions in the range of [-1,0).

3.2.4 Computing Reputation/Disrepute

Various methods have been presented for evaluating reputation; in fact, reputation is a component that has been considered more than other components by existing trust models. Each method has used several variables. The main variables that have been applied by the most representative models, as described in Chapter 2, are as follows:

i. Trustworthiness of rater agent (Rosaci et al., 2011)
ii. The rates that other agents give to the rated agent (Huynha et al., 2004; Rosaci et al., 2011; Sabater & Sierra, 2001b)
iii. The weight for each rating by assigning more weight to more recent interactions (Huynha et al., 2004)
iv. The weight for each aspect of service as an importance of that aspect of service (Sabater & Sierra, 2001b)
v. The interaction frequency of the rater agents with rated agent (Sabater & Sierra, 2001b)
vi. The number of rater agents (Sabater & Sierra, 2001b)

All above variables were applied by TMAN to evaluate the reputation of each agent. According to TRR model (Rosaci et al., 2011), which considered the trustworthiness of rater agents; TMAN used the reliability of rater agent instead of trustworthiness of those agents. Like TRR model, the belief is that, if the rater is reliable, the rate presented by that agent is considered as an accurate rate. Moreover, the reputation formula, presented by TMAN, applied the satisfaction rates that advisors gave to the rated agent, in the range of (0,1]; this includes the weight for each rating by assigning more weight to more recent interactions that advisor had with the rated agent.

Moreover TMAN considered the weight for each aspect of service as an importance of that service, and also the interaction frequency that rater advisors experienced with the rated agent.

In addition, TMAN considered the number of advisors that rate the rated agent. In fact, the belief is that the growth in the number of advisors that rated the specific agent increases the reputation value of that rated agent.

On the other hand, disrepute value of each agent should be also calculated together with reputation value. Therefore, disrepute of each advisor is computed by using the variables which applied for evaluating reputation as; reliability of rater agents, the rating that each rater advisor give to the rated agent, the weight for each rating by assigning more weight to more recent interactions that advisor had with the rated agent, the weight for each aspect of service as an importance of that service, the interaction frequency that rater advisors experienced with the rated agent, and also the number of advisors that rate the rated agent. But these variables are calculated based on the previous dissatisfaction rates that advisors gave to the rated agents, in the range of [-1,0).

3.2.5 Computing Belief/Disbelief

The existing trust models which used the belief theory to evaluate the trustworthiness of agents, calculated the belief and disbelief of agents based on the number of previous satisfying and dissatisfying interactions respectively. TMAN evaluates the belief of agents, which shows how well that agent can be trusted by using the weighted mean of the computed reliability and reputation value for that agent. On the other hand, the TRR model presented the weighted mean for integrating reliability and reputation of each agent to investigate how well that agent can be trusted. In fact, TRR model evaluated the trustworthiness of each agent as a weighted mean between reliability and reputation. This weighted mean is based on the number of previous interactions between requester and provider, and also expertise level that requester has in evaluating the specific service. TMAN calculates the belief of each agent based on reliability and reputation of the agent and uses the weighted mean between reliability and reputation of each agent. This weighted mean is based on the number of previous interactions and the knowledge of requester about each agent.

TMAN also evaluates disbelief of each agent based on the weighted mean of the computed unreliability and disrepute.

3.2.6 Computing Uncertainty

The trust models which used the Dempster-Shafer theory evaluated trustworthiness of the agent based on belief, disbelief and uncertainty of that agent. This means that these models evaluated the trustworthiness of agents based on three variables: how well the agent can be trusted (belief), how well the agent cannot be trusted (disbelief) and uncertainty in the agent's outcomes. Based on these models, two methods were presented for evaluating uncertainty; the first method uses the concept of the set theory and considered the value of conflict is always zero. As described in Chapter 2, this method seems not to be applicable in light of the new subjective logic theory, the Dezert-Smarandache theory which is able to handle both uncertainty and conflict. According to this theory, the value of conflict is not always zero. The other kinds of models like the Evidence-based trust model (Wang & Singh, 2010) as described in Chapter 2 presented an applicable method for evaluating uncertainty by using the posterior probability theory. According to this method, the value of conflict is not always zero.

Therefore, TMAN applies the method presented by Evidence-based trust model for evaluating uncertainty by using the posterior probability as explained in Chapter 2.

3.2.7 Computing Conflict

According to analysis of the most representative trust models, conflict is a concept which has been ignored by most of the existing trust models. Evidence-based trust model (Wang & Singh, 2010)presented a simple formula to evaluate the conflict in behaviors of agents. TMAN also uses the formula presented by Evidence-based trust model for evaluating the conflict based on the number of previous satisfying and dissatisfying interactions.

3.2.8 Computing Trust transitivity

As mentioned in Chapter 2, subjective logic defined two operators for transitivity of trust, which are combination and aggregation operators. However, there are two theories based on subjective logic that reflects trust transitivity based on those operators: Dempster-Shafer theory and Dezert-Smarandache theory. Since the Dezert-Smarandache theory is a new theory which can support conflict as well as uncertainty, most of the existing models applied the Dempster-Shafer theory like Evidence-based trust model (Wang & Singh, 2010). Nevertheless, there is a model known as New evidential trust model (Wang & Sun, 2009), which identified the advantage of the Dezert-Smarandache theory and also evaluated trust transitivity based on this theory.

Therefore,TMAN uses this new theory for evaluating trust transitivity based on belief, disbelief, uncertainty and also conflic, because this method can support conflict as well as uncertainty.

3.2.9 Computing Decision-making process

This concept has been investigated by a few existing trust models like (TREPPS) (Li & Kao, 2009). The most representative trust models presented a mechanism for evaluating the trustworthiness of agents; however, it did not indicate how the requester can select the most trustworthy agent if there are several trustworthy agents. It seems that TREPPS used a very applicable method. In fact, this model used one of the existing methods of multi-criteria decision-making methods known as FTOPSIS. In fact, this method is used specially for fuzzy numbers.

Thus, TMAN applies the TOPSIS method for normal numbers for selecting the most trustworthy provider among all evaluated providers. However, the method presented by TMAN is a little different from that of TREPPS. In fact, TREPPS introduced the weighted matrix according to the weight of each criterion, while TMAN used the entropy method to construct the weighted matrix.

At the end of this part of research methodology, the components involved in designing TMAN and the methods of computing each component were identified according to the most representative trust models that were described in Chapter 2. As explained earlier, this part addresses the first objective of this research by identifying the main components for designing TMAN based on the review of related literature.

In the next phase of research methodology, the structure of TMAN was proposed by using the identified components and the method of computing these components.

3.3 Phase 2: Design of TMAN

In the second phase, TMAN was designed based on the identified components. The methods of computing each component achieved from analyzing the most representative trust models in multi-agent environment as described in the first phase of research methodology.

The relationship between the identified components led to design TMAN. To create this relationship, the mathematical theories and also the relationship which proposed by trust models were applied. According to the most representative trust models like Dynamic Trust Model (Battiston et al., 2006) before evaluating trustworthiness of agents, similar advisor agents should be selected which have similar preferences with requester agents. Then, these models calculate the trustworthiness of similar agents.

Relationship between the components which used for computing trustworthiness of agents follows the Dezert-Smarandache Theory (Wang & Sun, 2009), Like New Evidential Trust Model (Wang & Sun, 2009), which is based on four main components belief, disbelief, uncertainty and conflict. Each of these components is consisted of other components which used for evaluating it. For instance for measuring the belief of each agent, the most representative trust models like TRR model (Rosaci et al., 2011) calculates the belief of how well an agent can be trusted by using two components as reliability and reputation. Thereby for computing trustworthiness of agents regarding toDezert-Smarandache Theory (Wang & Sun, 2009), belief of agents is computed based on reliability and reputation and disbelief is evaluated by using two components as unreliability and disrepute.

On the other hand, according to the most representative trust model likeEvidence-based trust model (Wang & Singh, 2010)uncertainty and conflict of agents measures by using probability theory. So the relationship between the components which used for evaluating trustworthiness of similar agents was based on Dezert-Smarandache Theory (Wang & Sun, 2009)

After evaluating trustworthiness of similar agents, it is necessary to select the most trustworthy one as TREPPS model(Li & Kao, 2009) used FTOPSIS method for selecting the most trustworthy agent.

Thereby, by analyzing the most representative trust models, the relationship between identified components were determined and TMAN designed in three stages; first similar agents selects by evaluating similarity of agents and then trustworthiness of agents evaluates based on Dezert-Smarandache Theory (Wang & Sun, 2009)and finally decision making process for selecting the most trustworthy agent is carried out by using TOPSIS method.

3.4 Phase 3: Test and evaluation of TMAN

By identifying the essential components, the advantages and disadvantages of each of the different methods of computing these components were described in Chapter 2. Therefore, the method of computing each component was selected according to the advantages of each method.

In the last phase of the research methodology, the effectiveness of TMAN was evaluated using two methods. The first was the evaluation method presented by Zhang and Cohen (2008) and Gorner et al. (2013) using random selection of benevolent and malicious agents based on random rating of the previous satisfying and dissatisfying interactions between benevolent and malicious agents. The second method was presented by Gray (2008) using the trust network game to collect the previous satisfying and dissatisfying rates of benevolent and malicious agents by simulating a simple auction environment. Each method used a special approach to evaluate the performance of TMAN. Figure 3.12 illustrates the methods of evaluation TMAN.

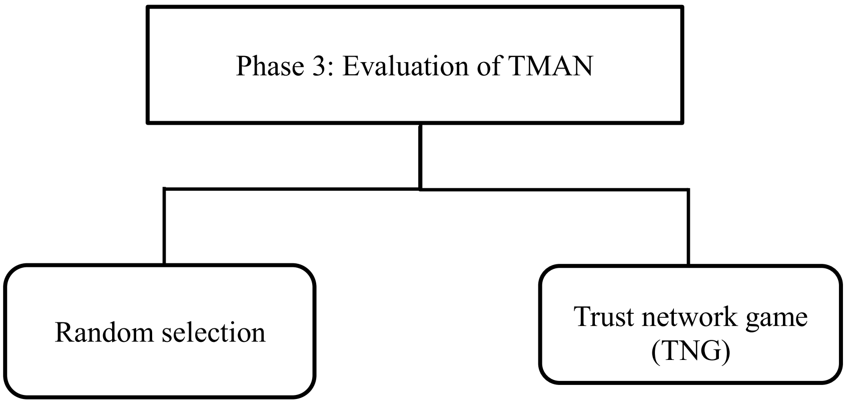


Figure 3.2: Phase 3 of research methodology

According to the random selection method, the average accuracy of TMAN in computing the main components, namely belief, disbelief, uncertainty, conflict, reliability, unreliability, reputation and also disrepute, were evaluated based on the random selection. Moreover, the performance of TMAN was compared with other existing models.

On the other hand, the trust network game method helped to simulate a simple auction environment in which agents can have transactions with each other, and the observations collected from these auctions were used as satisfaction and dissatisfaction rates for each agent and then the collected actual behaviors of agents from the trust network game compared with the results obtained by using TMAN.

3.4.1 Random selection

According to the result of analysis many articles and dissertations in proposing a trust model in multi-agent environments a method can be selected for evaluating TMAN, to investigate whether the proposed method of evaluating components are accurately, and whether TMAN can perform better than other trust models which used similar components. This method proposed by Zhang and Cohen (2008) and Gorner et al. (2013) and it is used the previous satisfying and dissatisfying interactions, considering preferences of agents to evaluate trustworthiness of agents by using real numbers, and the multi-agent environments consists of trustworthy and untrustworthy agents, thereby this method was applicable for TMAN.

Regarding this method,the requester, advisors and providers are selected randomly, the requester rated the advisors arbitrarily and also advisor agents rated the other advisors and providers arbitrarily as satisfying and dissatisfying. Moreover the random values are given to preferences of each agent. TMAN model defines the satisfaction rate to be between 0 and 1 (like Fire and REGRET models), whereas the dissatisfaction rate is between -1 to 0 (like Fire and REGRET models). In other words, the dissatisfying rate is represented by a negative rate.

In the first stage of evaluation, the accuracy of identified components which used for evaluating trustworthiness of agents was evaluated. According to (Li and Kao, 2009; Kaljahi *et al.*, 2013) model the accuracy of the components investigated after 100 times of interactions between requester, advisors and providers agents. Then the average value for each component after 100 interactions was recorded for trustworthy and untrustworthy agents. Then the accuracy of each component was investigated based on this fact that reliability and reputation of trustworthy agents should be higher that their unreliability and disrepute, while the reliability and reputation of untrustworthy agent should be less than their unreliability and disrepute.

In the second stage of evaluation, the performance of TMAN was compared with other existing models as the most of articles and researches carried out the comparison to evaluate whether their proposed model perform better that other models. To compare the performance of TMAN against other existing trust models, additional simulations were administered. To be precise, simulations were carried out for the four models described in this study, namelyEvidence-based trust model (Wang & Singh, 2010), and TREPPS model (Li & Kao, 2009), in addition to a basic model. All the models were tested using the same scenario.

The performance of models evaluated by using the method proposed by (Li and Kao, 2009; Kaljahi *et al.,* 2013). In this method accuracy in selecting the most trustworthy provider was determined by counting the number of times the model selects the most trustworthy provider in 100 times of interactions. As mentioned previously, the iterations were repeated ten times for each scenario; therefore the accuracies were averaged to produce the final.

3.4.2 Trade network game

In addition to evaluate the accuracy of each component and also comparing the performance of TMAN with other existing models, the method used by Gorner et al.

(2013) for the proposed reputation model in multi-agent environment was considered. This method is also applicable for the models which want to evaluate the performance of the models in e-commerce multi-agent environment by simulating a simple auction in a multi-agent environment. This simulator, named Trade Network Game (TNG), is a framework for studying the information and evolution of trade among interacting between agents as traders (requester, advisor, and providers). This simulator is based on the game theory that agents choose and refuse to trade with the agent partners. The trade outcomes to be presented in different levels: trader attributes, trade network formation it means that who was trading with, whom and with what regularity, trade behavior it means cooperative or cheating and individual and social welfare measures which should the agent utility during the trade.

Considering the proposed method by Gorner et al. (2013), the number of requester, advisors and providers, the type of multi-agent environment as consistent environment which agents do not change their behaviors during a trade or oscillating environment that agents can change their behavior, and the numbers of trades in each time of running were selected by user. Then TNG identifies the result of trading in each time of interactions. Thereby, this result can be used by TMAN to study whether TMAN can predict the behavior of agents in the next interaction and whether TMAN can selects the most trustworthy provider during the trades. Finally the obtained results from TMAN were compared with re result that TNG reported after trading.

To study whether TMAN can perform accurately in different multi-agent environments, TNG method was repeated for different number of agents in three different multi-agent environments, first consistent environment, then mild oscillating behavior, and finally oscillating environment.

3.5 Summary

In this chapter, the methodology of this research has been explained in three main phases. The first phase starts by analyzing of previous trust models, the essential components for designing TMAN were identified in this phase. In addition, the method of computing these components was described according to the analyzed models in chapter 2. In the second phase, TMAN was proposed using the selected components and identified methods of computing. In the final phase, the methods of evaluating TMAN were described by using two methods. First, TMAN was evaluated using the random selection method; in this method, the average accuracy of TMAN components were investigated, and the performance of TMAN in selecting the most trustworthy provider was compared with that of other existing trust models. Second, TMAN was evaluated by using the trade network game simulator. According to this method, the accuracy of TMAN in evaluating the trustworthiness of agents presented by TMAN was compared against the outcome scores of agents which presented by trade network game simulator, and the accuracy of TMAN in selecting the most trustworthy provider was also compared against the actual behavior of that provider.

CHAPTER 4: DESIGN AND IMPLEMENTATION OF TMAN

4.1 Introduction

This chapter describes the process of designing TMAN and then explains implementation of TMAN in multi-agent environments. The section 4.2 shows the TMAN mechanism consisting five main stages; selecting similar advisors which described in section 4.31, evaluating trustworthiness of similar advisors (section 43.2), calculating trustworthiness of suggested provides (section 4.3.3), computing trust transitivity among requester, similar advisors and suggested providers (section 4.3.4), decision-making process which led to select the most trustworthy suggested provider (section 4.3.5), and finally reward and punishment mechanism is explained in section 4.3.6.

In section 4.3 the methods of testing and evaluation TMAN have been described by using two methods of implementation. Each method evaluated first the accuracy of TMAN components to investigate whether TMAN calculate each proposed component accurately, then the performance of TMAN in selecting the most trustworthy agent was studied. Section 4.3.6 explains the random selection method in details that the accuracy of TMAN components in evaluating the trustworthiness of advisors and their suggested providers is investigated with different number of agents and various numbers of trustworthy and untrustworthy agents in a simulated multi-agent environment. Then the method of comparing the performance of TMAN against other models is described by using the random selection method in a simulated multi-agent environment. In section 4.4.2the method of testing the accuracy of TMAN components based on the trust network game (TNG) as a simulator is explained in details. According to TNG method the TNG outcomes after trades are compared with the results which obtained by using TMAN in a simulated auction by using TNG as a simulator.

4.2Design of TMAN

According to the problem statement, the existing trust models used advisor agent to select the trustworthy provider without considering that the advisors themselves can be malicious, and they may suggest an untrustworthy provider due to lack of information or for their own benefits. Hence, TMAN is a model proposed for evaluating the trustworthiness of advisors in regard to their suggested provider. Then according to the advisors' reports about their suggested providers, TMAN measures the trustworthiness of providers and finally selects the most trustworthy provider agent among all the suggested providers.

Moreover, TMAN reinforces dissimilarity existing in most of the other existing models by selecting similar advisors. TMAN also reduces the effect of uncertainty in agent's outcomes by evaluating uncertainty values of each advisor and its suggested provider; then, attempting to select the agent with less uncertainty in its outcomes.

TMAN computes the conflict in previous interaction outcomes of each advisor and its suggested provider and attempts to select the agent with less conflict, this leads to reduce the effect of unstable agents which had very conflict behaviors, and finally TMAN supports transitivity of trust between advisors and their suggested providers.

The remaining parts of this chapter provide a detailed description of how TMAN enables a requester agent to select the most trustworthy service provider according to the advice of benevolent advisors. Figure 4.1 illustrates a general flow chart of the TMAN mechanism.According to Figure 4.1, first, the similar agents are selected by TMAN, as advisors. The method of selecting the similar advisors is described in Section 4.3.1. Then the evaluation of trustworthiness of each advisor is explained in Section 4.3.2. In particular, within this section, the process of evaluating trustworthiness of each advisor is explained based on four components, namely belief, disbelief, uncertainty and conflict as shown in Figure 4.1. Section 4.3.3 explains the method of evaluating the trustworthiness of each suggested provider according to the report of advisors. The trust transitivity between advisors and their suggested provider is described in Section 4.3.4. Finally, the method of decision-making process for selecting the most trustworthy provider considering the evaluation of advisors in an advisor network is stated in Section 4.3.5. Section 4.3.6 describes how the reward and punishment method can encourage advisors to have a trustworthy behavior.

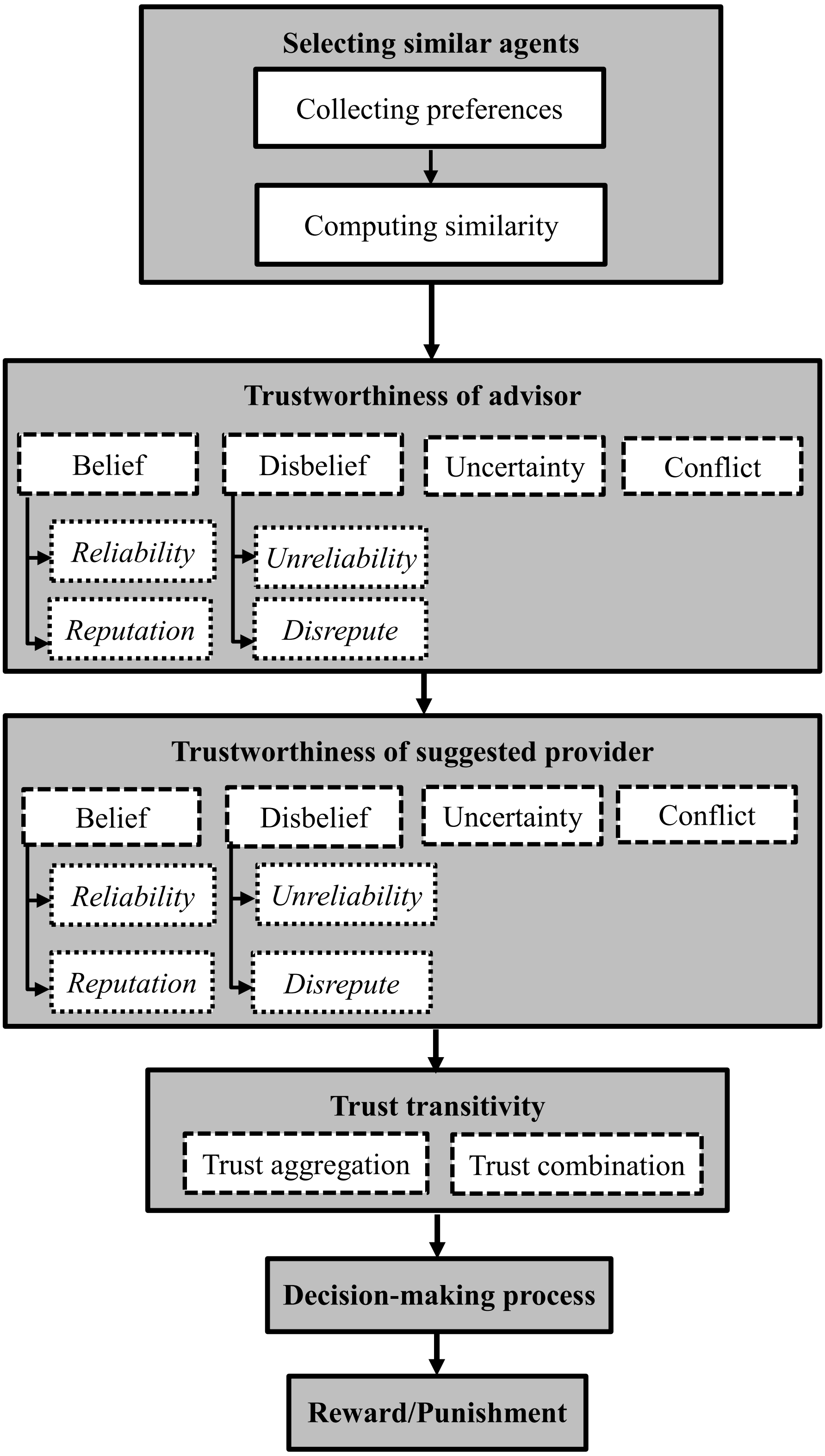


Figure 4.1: TMAN mechanism

4.2.1 Selecting similar agents

To select the similar agents and collect their suggestions about service providers, the requester agent sends a query in random order to other agents who have had previous interactions with them; the agents are asked to identify their preferences in different criteria of a specific service that they wish to buy and suggest a trustworthy service provider. The requester agent then receives a set of responses in return. The time limitation for each advisor to respond to the query is based on the average delay time that the advisor has had in its previous interactions with the requester agent. If the advisor does not respond within the time frame given, it will be ignored. It is assumed that each advisor suggests a provider, or if it cannot suggest any provider it will be ignored by the requester. Moreover, there is at least one advisor that suggests a trustworthy service provider.

For instance, the requester sends a query to its familiar agents and asks them to rate each of the criteria, such as product quality and product price, according to their preferences. After collecting all the responses, the requester calculates the similarity between itself and the familiar agents; the familiar agents that have more similarities with the requester are selected as a similar advisor. The query consists of the following:

1. The ID of the requester agent that has issued the query (*Req*).

2. The kind of service which the requester has chosen (*S*).

3. Preferences in different criteria of interaction on service (*S*).

4. The ID of all agents that were sent the query (*Adv*).

5. Ask the number of satisfying interactions, the total rating of previous satisfying interactions and also the last time that the responder agent experienced a satisfying interaction with other identified agents (only agents that have had previous interactions with any of the other identified agents will respond).

6. Ask the number of dissatisfying interactions, the total rating of previous dissatisfying interactions and also the last time that the responder agent experienced a dissatisfying interaction with other identified agents (only agents that have had previous interactions with any of the other identified agents will respond).

7. Ask the ID of a suggested trustworthy provider in providing the service (S).

8. Ask the number of satisfying interactions, total rating of previous satisfying interactions with suggested provider and also the last time that the responder agent experienced a satisfying interaction.

9. Ask the number of dissatisfying interactions, total rating of previous dissatisfying interactions with suggested provider and also the last time that the responder agent experienced a dissatisfying interaction.

A sample query is shown as follows:

(ID: Req; Service: S; Preference of product quality:_, Preference of product price:_, Preference of delivery time:_; Agents ID: A,B,C,D; No of satisfying interactions:_ Rate of satisfying interaction:_; Last time of satisfying interactions:_; No of dissatisfying interactions:_; Rate of dissatisfying interaction:_; Last time of dissatisfying interaction:_; Suggested provider:_; No of satisfying interactions:_ Rate of satisfying interactions:_; Last time of satisfying interaction:_; No of dissatisfying

interactions:_; Rate of dissatisfying interactions:_; Last time of dissatisfying interaction:_)

The response to the query consists of:

1. The ID of the agent which responds (*Res*).

2. The rating of each criterion according to the responder's preferences.

3. The number of satisfying interactions, the total rating of previous satisfying interactions with other identified agents, and also the last time it experienced a satisfying interaction (if it has had previous interactions with any of them).

4. The number of dissatisfying interactions, the total rating of previous dissatisfying interactions with other identified agents and also the last time it experienced a dissatisfying interaction (if it has had previous interactions with any of them).

6. The ID of the suggested provider in providing the service (S).

7. The number of satisfying interactions, total rating of previous satisfying interactions with suggested provider and also the last time it experienced a satisfying interaction.

8. The number of dissatisfying interactions, total rating of previous dissatisfying interactions with suggested provider and also the last time it experienced a dissatisfying interaction.

A sample reply is shown as follows:

(ID: A; Preference of product quality:0.8; Preference of product price:0.5; Preference of delivery time:0.1; No of satisfying interactions: B=3,D=7; Rate of satisfying interactions: A=0;, D=0.8; Last time of satisfying interaction: A= 10 days ago, D=4 days ago; No of dissatisfying interactions: A=1, D=3; Rate of dissatisfying interactions : A=-0.2, B=-0; Last time of dissatisfying interaction: A=7 days ago, B=10 days ago; Suggested provider: X; No of satisfying interactions: 5; Rate of satisfying interactions: 0.8; Last time of satisfyinginteraction:2 days ago; No of dissatisfying interactions:1; Rate of dissatisfying interactions:-0.2; Last time of dissatisfyinginteraction:9 days ago)

As a result, the requester agent receives a set of responses from agents. Then the requester calculates the similarity between its preferences and the responder's preferences through their collected preferences as shown in Figure 4.2.

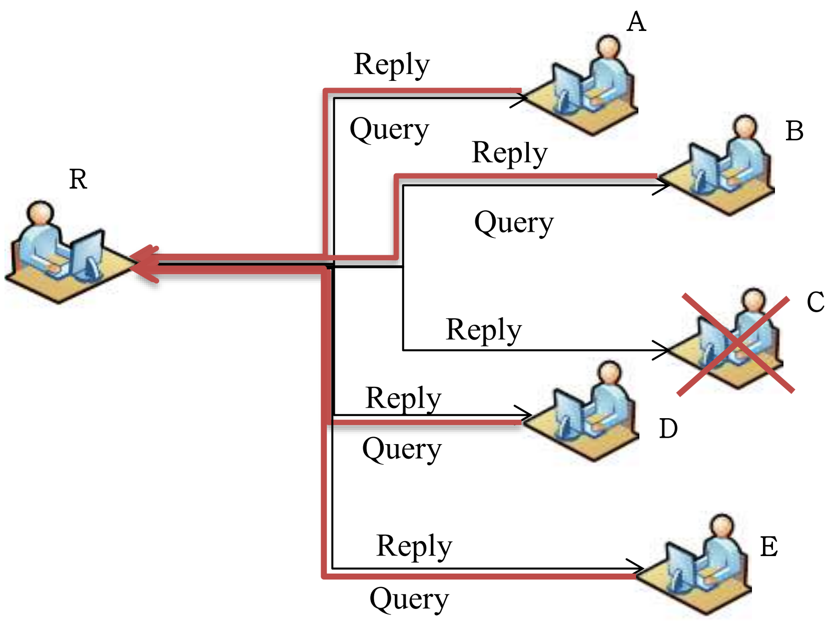


Figure 4.2: Sending query to familiar agents and collected the responses

As shown in Figure 4.2, requester R sent a query for agents A,B,C, D and E, and collected the responses which responded within the identified limitation of time. The responder C is eliminated, because it did not respond within the time limitation.

With reference to the TREPPS model (Li & Kao, 2009), preferences setting was assumed, as an importance weight of different criteria, which is expressed in seven linguistic terms: extremely unimportant (EU), unimportant (U), slightly unimportant (SU), average (A), slightly important (SI), important (I), extremely important (EI). Table 3.2 shows the meanings of these linguistic values.

Table 4.1: Linguistic values for importance weight of preferences criteria (Li & Kao, 2009)

Linguistic terms	**Range**
Extremely Unimportant (EU)	[0.0, 0.1]
Unimportant (U)	(0.1, 0.2]
Slightly Unimportant (SU)	(0.2, 0.4]
Average (A)	(0.4, 0.6]
Slightly Important (SI)	(0.6, 0.8]
Important (I)	(0.8, 0.9]
Extremely Important (EI)	(0.9, 1.0]

TMAN also used these seven linguistic terms as a preferences setting for evaluating similarity between requester and each responder agent.

According to the dynamic trust model (Battiston et al., 2006), the similarity between preferences of requester and each responder agent can be computed as follows:

$$Sim_{\mathrm{Re}q \to \mathrm{Re}s} = \frac{1}{c} \times \sum_{C} (1 - | f_{C_{\mathrm{Re}q}} - f_{C_{\mathrm{Re}s}} |) \tag{4.1}$$

Where:

$Sim_{\mathrm{Re}q \to \mathrm{Re}s}$ indicates the similarity between requester, *Req*, and responder, *Res*, and $Sim_{\mathrm{Re}q \to \mathrm{Re}s} \in [0,1]$

c shows the total number of criteria

$f_{C_{\mathrm{Re}q}}$ denotes the preference value of requester for criterion c which is presented in Table 4.1

$f_{C_{\mathrm{Re}s}}$ represents the preference value of responder for criterion c which is presented in Table 4.1

After calculating the similarity of each responder, TMAN proposed a method for selecting the similar advisors, according to this method the requester takes into account the average similarity of responders. The responders with similarity value higher than the average value will be selected as a similar advisor as follows:

$$\begin{cases} if \;\; Sim_{\mathrm{Re}q \to \mathrm{Re}s} \geq \dfrac{\sum_{\mathrm{Re}s} Sim_{\mathrm{Re}q \to \mathrm{Re}s}}{N} & will \;\; be \;\; selected \\ f \;\; Sim_{\mathrm{Re}q \to \mathrm{Re}s} \prec \dfrac{\sum_{\mathrm{Re}s} Sim_{\mathrm{Re}q \to \mathrm{Re}s}}{N} & will \;\; not \;\; be \;\; selected \end{cases} \tag{4.2}$$

Where:

$Sim_{\mathrm{Req}\to\mathrm{Res}}$ indicates the similarity between requester, *Req*, and responder, *Res*

N denotes the number of responders which their similarities are calculated

$\frac{\sum_{\mathrm{Res}} Sim_{\mathrm{Req}\to\mathrm{Res}}}{N}$ shows the average similarity of responders

Hence, the requester selects the similar agents and records their replies. Assuming that M is the total number of selected responders, the requester calculates the trustworthiness of each selected responder as an advisor agent, and also evaluates the trustworthiness of their suggested providers. Finally, based on the trust transitivity values for each provider, the requester selects an appropriate provider that can provide its needed services. Figure 4.3 shows a scenario in which responder D is eliminated, considering its similarity value is less than the average value.

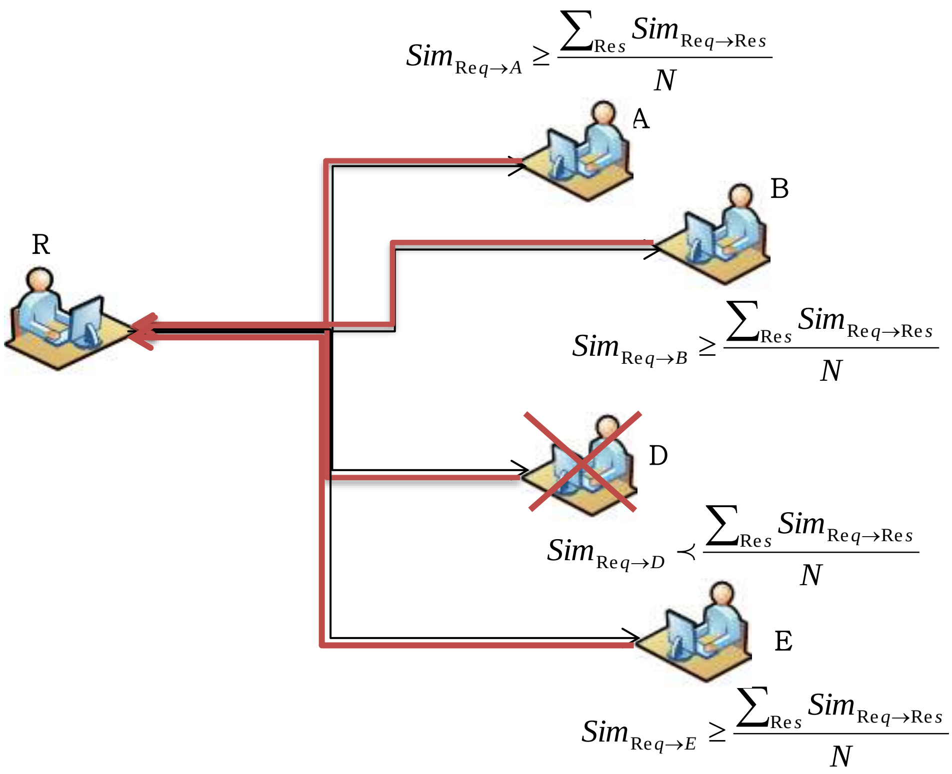


Figure 4.3: Evaluating similarity of responder agents

4.2.2 Trustworthiness of advisors

After selecting the similar agents as advisors, and recording their responders, the requester calculates the trustworthiness of these similar agents. The requester computes the trustworthiness of each advisor agent according to the four components, namely belief, disbelief, uncertainty, and conflict. The method of computing each of these components is described in the following sections.

4.2.2.1 Belief of each advisor

To evaluate the belief of an advisor that shows how well that advisor can be trusted, the requester computes a weighted mean between the reliability and reputation of that advisor. It calculates the value of reliability of advisor according to the opinion of the requester based on its previous interactions with that advisor. Meanwhile, the value of reputation of advisor can be evaluated based on the opinion of other selected advisors that have had any previous interaction with that advisor. Therefore, TMAN evaluates the belief of each advisor as follows:

$$\text{Belief} = (\alpha\,\text{Reliability} + (1-\alpha)\,\text{Reputation}) \tag{4.3}$$

Where:

α indicates the weighted mean between reliability and reputation

Computing reliability, reputation and the weighted mean of α is based on the satisfaction rates of previous interactions (Rosaci et al., 2011) between requester and each advisor. This is explained in further detail in the following sections.

4.2.2.1.1 Reliability of each advisor

As described in Part 1 of research methodology, the reliability of each advisor is measured by using two factors: closeness and stability factors. TMAN evaluates these two factors based on previous satisfying direct interactions between requester and each advisor.

The rating of satisfaction, as described in Part 1, is identified using two linguistic terms: slightly good (SG) and good (G) in the range of zero to one. The value of neutral interaction is 0. The meanings of these two linguistic variables are shown in Table 4.2.

Table 4.2: Linguistic values for rating of service satisfaction in different criteria

Linguistic terms	**Numbers**
Slightly good (SG)	(0, 0.5]
Good (G)	(0.5, 1]

Moreover, TMAN applies closeness factor to examine the frequency of previous satisfying interactions between the requester and advisor. As the number of satisfying interactions grows, the value of closeness factor increases; this relationship indicates the confidence degree of an advisor. The closeness factor has a direct relationship with the number of previous satisfying interactions between the requester and advisor. Thus, the method is employed by TMAN to measure the closeness factor is based on the proportion of the number of previous satisfying interactions between requester and advisor to the total number of previous interactions, as follows:

$$F_{CS_{Adv}} = \frac{\sum_{i \in S} j_{\mathrm{Re}q \to Adv}}{\sum_{i \in Interactions} i_{\mathrm{Re}q \to Adv}} \tag{4.4}$$

Where:

$F_{CS_{Adv}}$ indicates the closeness factor of advisor *Adv*

$\sum_{i \in S} j_{(\mathrm{Re}q \to Adv)}$ represents the total number of previous satisfying interactions between the requester, *Req*, and the advisor, *Adv*

$\sum_{i \in Interactions} i_{(\mathrm{Re}q \to Adv)}$ is the total number of previous interactions between the requester, *Req*, and the advisor, *Adv*

On the other hand, stability factor is used to define whether the results of previous interactions between the requester and the advisor are stable or not. The lower stability in previous interactions represents a lower confidence value for that specific advisor. According to the TREPPS model (Li & Kao, 2009), stability factor can be measured as follows:

$$F_{SF_{Adv}} = \frac{1}{c} \times 1 - \sum_{c \in C} \sum_{i \in Interactions} (w_{\mathrm{Re}q \to Adv}(i) \times | S^{c}_{\mathrm{Re}q \to Adv}(i) - \sigma_{Adv} |) \tag{4.5}$$

Where:

$F_{SF_{Adv}}$ indicates the stability factor of advisor, *Adv*

c showsthe total number of criteria

i denotesthe number of interaction

$S^{c}_{\mathrm{Req} \to Adv}(i)$ is the rate of previous satisfying interaction, i, in criterion, c

$w_{\mathrm{Re}q\to Adv}(i)=\frac{time_i}{\sum_{i\in Interactions} time_i}$ represents the weight factor which denotes the freshness weight of time. In fact, the weight factor of time places more value on interaction, i, which is closer to current time

σ_{Adv} is the initial reliability value calculated regarding to TREPPS model(Li & Kao, 2009)as:

$$\sigma_{Adv} = \frac{1}{c}\times\sum_{c\in C}\sum_{i\in Interactions} S^{c}_{\mathrm{Re}q\to Adv}(i)\times w_{\mathrm{Re}q\to Adv}(i) \tag{4.6}$$

Where:

c shows the total number of criteria

i denotesthe number of interaction

$S^{c}_{\mathrm{Re}q\to Adv}(i)$ is the rate of previous satisfying interaction, i, in criterion, c

$w_{\mathrm{Re}q\to Adv}(i)$ represents the weight factor of time

By integrating the closeness and stability factors like TREPPS model(Li & Kao, 2009), the final formula for computing the overall reliability value of each advisor is:

$$\Gamma_{Adv} = F_{CS_{Adv}}\times F_{SF_{Adv}} \tag{4.7}$$

Where:

Γ_{Adv} shows the reliability value of advisor, *Adv*

$F_{CS_{Adv}}$ is the closeness factor of advisor, *Adv*, obtaindeb by equation (4.4)

$F_{SF_{Adv}}$ represents the stability factor of advisor, *Adv*, obtaindeb by equation (4.5)

4.2.2.1.2 Reputation of each advisor

After calculating the reliability of the advisor, the requester computes the reputation of that advisor among other advisors. The reputation of each advisor is calculated based on the ratings of satisfaction that other advisors identified through their response to the query, the number of previous satisfying interactions and the last satisfying interaction reported by these responders. According to the TRR model (Rosaci et al., 2011), to reduce the effect of malicious advisors which may give a wrong value to other advisors, the requester should also consider the reliability of each rater advisor which rated the specific advisor.

According to this explanation, the initial reputation value of each advisor, which is proposed by TMAN,is measured as:

$$\Omega_{A \to Adv} = \frac{\sum_{a_i \in A-\{Adv\}} \sum_{c \in C} (\Gamma_{\mathrm{Re}q \to Adv} \times \xi^{c}_{a_i \to Adv} \times t_{a_i \to Adv} \times \mu_{a_i \to Adv} \times w^{c}_{\mathrm{Re}q})}{c \times \sum_{a_i \in A-\{Adv\}} \Gamma_{\mathrm{Re}q \to Adv}} \qquad (4.8)$$

Where:

$\Omega_{A \to Adv}$ indicates the initial reputation value for each advisor, *Adv*

$A = \{a_1, a_2, ..., a_m\}$ is the advisors that rated

c shows the total number of criteria

$\Gamma_{\mathrm{Req}\to Adv}$ is the reliability that requester considers for rated advisor agent, *Adv*

$\xi^{c}_{a_i\to Adv}$ is the total satisfaction rate which rater advisor agent, a_i, gives according to their previous interactions

$t_{a_i\to Adv}$ shows the weight for each rating by considering more weight to more recent interaction by *Adv*

$\mu_{a_i\to Adv} = \dfrac{\sum_{i\in S} j_{a_i\to Adv}}{\sum_{i\in Intractions} i_{a_i\to Adv}}$ denotes the proportion of the number of previous satisfying interactions to the total number of previous interactions between rater advisor, a_i, and rating advisor agent, *Adv*

w^{c}_{Req} is preferences of requester as an importance weight of each criterion, as shown in Table 4.1.

Moreover, the number of advisors, N, which sent their ratings affects the accuracy of the reputation value. As the number of advisors that participate in computing reputation of a specific advisor grows, the reputation value becomes more accurate.

Hence, the final formula is proposed by TMAN, for calculating the reputation of each advisor is:

$$\Pi_{Adv} = \frac{\sum_{n\in M} n}{M-1} \times \Omega_{A\to Adv} \tag{4.9}$$

Where:

Π_{Adv} indicates the reputation of advisor, *Adv*

$\sum_{n \in M} n$ is the total number of advisors that rated advisor, *Adv*, and participated in computing the reputation value of advisor, *Adv*

M is the total number of advisors

$M-1$ shows the total number of rater advisors minus the advisor that has been rated by others

$\Omega_{A \to Adv}$ is the initial reputation value of a specific advisor, *Adv*, obtained by equation (4.8).

In addition, according to TRR model (Rosaci et al., 2011)for integrating reliability and reputation, a weighted mean is considered as the number of satisfying and dissatisfying direct previous interactions between requester and each advisor, and also the knowledge of the requester about the advisor. In fact, the knowledge of requester about each advisor is taken into consideration according to the proportion of total number of previous interactions between specific advisor and requester to the total number of previous interactions that requester experienced with all advisors. The growth in the number of previous interactions with a specific advisor rather than other advisors illustrates that requester has more knowledge about that advisor through previous interactions. Therefore, the proposed weighted mean, considering to the presented method by TRR model(Rosaci et al., 2011), is measured as follows:

$$\alpha_{Adv} = \begin{cases} \dfrac{n_{Adv}}{K} \times \dfrac{i_{Adv}}{t_{Adv}} & if \quad \dfrac{i_{Adv}}{t_{Adv}} \le \dfrac{j_{Adv}}{t_{Adv}} \\ \dfrac{n_{Adv}}{K} & if \quad \dfrac{i_{Adv}}{t_{Adv}} \succ \dfrac{j_{Adv}}{t_{Adv}} \end{cases} \tag{4.10}$$

Where:

$\alpha_{\mathrm{Re}q \rightarrow Adv}$ indicates the weighted mean of reliability and reputation of advisors

n_{Adv} denotes the total number of previous interactions with advisor, *Adv*

K is the total previous interactions that requester had with all advisors

i_{Adv} represents the total number of previous satisfying interactions between advisor, *Adv*, and requester

j_{Adv} shows the total number of previous dissatisfying interactions between advisor, *Adv*, and requester

$t_{Adv} = i_{Adv} + j_{Adv}$ shows the total number of previous interactions between requester and advisor, *Adv*.

According to the TRR model (Rosaci et al., 2011), if the average value of previous satisfying interactions is higher than the average value of previous dissatisfying interactions, the weighted mean is equal to the knowledge of requester about advisor; otherwise, the weighted mean depends on the knowledge of requester about advisor and also the average value of previous satisfying interactions.

By considering the presented weighted meanwhich is used by TRR model(Rosaci et al., 2011), the final formula for evaluating the belief of each advisor by considering a weighted mean for reliability and reputation values, is as follows:

$$\mathrm{B}_{Adv} = \alpha_{Adv} \times \Gamma_{Adv} + (1 - \alpha_{Adv}) \times \Pi_{Adv} \qquad (4.11)$$

Where:

B_{Adv} shows the belief value of advisor, *Adv*

α_{Adv} is the weighted mean calculates by equation (3.10)

Γ_{Adv} shows the reliability of advisor, *Adv*, measured by equation (4.7)

Π_{Adv} represents the reputation of rated advisor, *Adv*,computed by equation (4.9)

4.2.2.2 Disbelief of each advisor

As described in Chapter 2, for selecting the most trustworthy agent, it is necessary to evaluate disbelief value of each agent, in addition to the belief value. TMAN considers two components for evaluating disbelief value: unreliability and disrepute of each advisor, which is based on the number and the rating of dissatisfying previous interactions. While belief of agent has a relationship with reliability and reputation, the value of disbelief of agent is measured based on the value of unreliability of advisor according to the opinion of requester, and the value of disrepute of advisor according to the opinion of other advisors which is presented by TMAN as follows:

$$\text{Disbelief} = (\alpha\ \text{Unreliability} + (1-\alpha)\ \text{Disrepute}) \qquad (4.12)$$

4.2.2.2.1 Unreliability of each advisor

The unreliability value of each advisor is computed with the same method used to calculate reliability, but it is based on the number and rating of previous dissatisfying interactions. As described in Part 1, the rating of dissatisfaction is presented as two linguistic terms: bad (B) and slightly bad (SB). The neutral interaction is evaluated as 0. Table 3.4 illustrates the meanings of these linguistic terms.

Table 4.3: Linguistic values for rating of service dissatisfaction in different criteria

Linguistic terms	**Range**
Slightly bad (SB)	(0.0, -0.5]
Bad (B)	(-0.5, -1]

According to the formula presented for reliability, the requester should also consider two critical factors, closeness factor and stability factor, for evaluating the unreliability of each advisor as follows:

$$dF_{CS_{Adv}} = \frac{\sum_{i \in S} h_{\mathrm{Req} \to Adv}}{\sum_{i \in Interactions} i_{\mathrm{Req} \to Adv}} \tag{4.13}$$

Where:

$dF_{CS_{Adv}}$ indicates the closeness factor of advisor,*Adv*

$\sum_{i \in S} h_{(\mathrm{Req} \to Adv)}$ shows the total number of previous dissatisfying interactions between the requester, *Req*, and the advisor, *Adv*

$\sum_{i \in Interactions} i_{(\mathrm{Req} \to Adv)}$ is the total number of previous interactions between the requester, *Req*, and the advisor, *Adv*

On the other hand, the stability factor is calculated as:

$$dF_{SF_{Adv}} = \frac{1}{c} \times 1 - \sum_{c \in C} \sum_{i \in Interactions} (w_{\mathrm{Re}q \to Adv}(i) \times \| dS^{c}_{\mathrm{Re}q \to Adv}(i) | - d\sigma_{Adv} |) \quad (4.14)$$

Where:

$dF_{SF_{Adv}}$ indicates the stability factor of advisor, *Adv*

C shows the total number of criteria

i denotesthe number of interaction

$| dS^{c}_{\mathrm{Req} \to Adv}(i) |$ is the positive value of previous dissatisfying interaction rate for criterion, c

$w_{\mathrm{Req} \to Adv}(i) = \frac{time_i}{\sum_{i \in Interactions} time_i}$ represents the weight factor of time

$d\sigma_{Adv}$ is the initial unreliability value calculated as:

$$d\sigma_{Adv} = \frac{1}{c} \times \sum_{c \in C} \sum_{i \in Interactions} | dS^{c}_{\mathrm{Req} \to Adv}(i) | \times w_{\mathrm{Req} \to Adv}(i) \quad (4.15)$$

Where:

C shows the total number of criteria

i denotesthe number of interaction

$| dS^{c}_{\mathrm{Req} \to Adv}(i) |$ is the positive value of previous dissatisfying interaction rate for criterion, c

$w_{\mathrm{Req}\to Adv}(i)$ represents the weight factor of time

By incorporating closeness factors and stability factors, the final formula for computing unreliability is:

$$d\Gamma_{Adv} = dF_{CS_{Adv}} \times dF_{SF_{Adv}} \tag{4.16}$$

Where:

$d\Gamma_{Adv}$ indicates the unreliability value of advisor, *Adv*

$dF_{CS_{Adv}}$ represents the closeness factor of advisor, *Adv*, for previous dissatisfying interactions, obtained from equation (3.13).

$dF_{SF_{Adv}}$ is the stability factor of advisor, *Adv*, for previous dissatisfying interactions, obtained from equation (3.14).

4.2.2.2.2 Disrepute of each advisor

The requester measures the disrepute value of each advisor agent according to the ratings of previous dissatisfying interactions collected from other advisors about the rated advisor, *Adv*. The presented method by TMAN for calculating disrepute of each advisor is as follows:

$$d\Omega_{A\to Adv} = \frac{\sum_{a_i \in A-\{Adv\}} \sum_{c \in C} (\Gamma_{\mathrm{Req}\to Adv} \times |\xi^{c}_{a_i\to Adv}| \times t_{a_i\to Adv} \times \mu_{a_i\to Adv} \times w^{c}_{\mathrm{Req}})}{c \times \sum_{a_i \in A-\{Adv\}} \Gamma_{\mathrm{Req}\to Adv}} \tag{4.17}$$

Where:

$d\Omega_{A\to Adv}$ indicates the initial disrepute of advisor, *Adv*, according to the rater advisors, *A*

$A=\{a_1,a_2,...,a_m\}$ is the advisors that rated other advisors

C shows the total number of criteria

$\Gamma_{\mathrm{Re}q\to Adv}$ is the reliability that requester considers for rated advisor agent, *Adv*

$\xi^{c}_{a_i\to Adv}$ is the total dissatisfaction value which rated advisor agent, a_i, gives to rating advisor, *Adv*, according to their previous interactions

$t_{a_i\to Adv}$ shows the weight for each rating by considering more weight to more recent interaction

$\mu_{a_i\to Adv}=\frac{\sum_{i\in S} j_{a_i\to Adv}}{\sum_{i\in Interactions} i_{a_i\to Adv}}$ denotes the proportion of the number of previous dissatisfying interactions to the total number of previous interactions between rater advisor, a_i, and rating advisor agent, *Adv*

$w^{c}_{\mathrm{Re}q}$ is preferences of requester as an importance weight of each criterion, as shown in Table 3.2.

Moreover, the number of agents that sent their ratings of dissatisfaction affects the credibility of the disrepute value. As the number of advisors that participate in computation of the disrepute grows, the disrepute value will be more accurate. Hence, the final formula for calculating the disrepute of advisor, *Adv*, is:

$$d\Pi_{Adv} = \frac{\sum_{m \in M} m}{M - 1} \times d\Omega_{A \to Adv} \qquad (4.18)$$

Where:

$d\Pi_{Adv}$ indicated disrepute of advisor, *Adv*

$\sum_{m \in M} m$ represents the total number of rater advisor, a_i, which participated in computing the disrepute value of advisor, *Adv*

M is the total number of advisors

$M - 1$ shows the total number of rater advisors minus the advisors that has been rated by others

$d\Omega_{A \to Adv}$ indicates the initial disrepute value of a specific advisor, *Adv*, obtained by equation (3.17).

According to the identified weighted mean for evaluating belief value of each advisor, to integrate unreliability and disrepute, a weighted mean is considered as the number of satisfying and dissatisfying direct previous interactions between requester and each advisor, in addition to the knowledge of the requester about the advisor.

The proposed weighted mean for evaluating disbelief is as follows:

$$\alpha_{\mathrm{Re}q \to Adv} = \begin{cases} \dfrac{m_{Adv}}{K} \times \dfrac{j_{Adv}}{t_{Adv}} & if \quad \dfrac{j_{Adv}}{t_{Adv}} \leq \dfrac{i_{Adv}}{t_{Adv}} \\ \dfrac{m_{Adv}}{K} & if \quad \dfrac{j_{Adv}}{t_{Adv}} \succ \dfrac{i_{Adv}}{t_{Adv}} \end{cases} \tag{4.19}$$

Where:

α_{Adv} indicates the weighted mean between requester and advisor

n_{Adv} denotes the total number of previous interactions with advisor, *Adv*

K is the total previous interactions that requester had with all advisors

i_{Adv} represents the total number of previous satisfying interactions

j_{Adv} shows the total number of previous dissatisfying interactions between advisor, *Adv*, and requester

$t_{Adv} = i_{Adv} + j_{Adv}$ shows the total number of previous interactions between requester and advisor, *Adv*.

If the average value of dissatisfying interactions is higher than the average value of satisfying interactions, the weighted mean is equal to the knowledge of requester about advisor; otherwise, the weighted mean depends on the knowledge of requester about advisor and also the average value of dissatisfying interactions.

By considering the presented weighted mean between unreliability and disrepute values, the final formula for evaluating the disbelief of each advisor, is as follows:

$$DB_{Adv} = \alpha_{Adv} \times d\Gamma_{Adv} + (1 - \alpha_{Adv}) \times d\Pi_{Adv} \tag{4.20}$$

Where:

$D\mathrm{B}_{Adv}$ shows the disbelief value of advisor, *Adv*

α_{Adv} is the weighted mean calculated by equation (4.19)

$d\Gamma_{Adv}$ shows the unreliability of rater advisor, *Adv*, measured by equation (4.16)

$d\Pi_{Adv}$ represents the disrepute of rated advisor, *Adv*, computed by equation (4.18)

4.3.2.3 Uncertainty of each advisor

The method of calculating uncertainty is presented based on the Evidence-based trust model (Wang & Singh, 2010). According to this model, the uncertainty in the previous behaviors of advisors is measured based on the binary event of previous satisfying and dissatisfying interactions. Thus, uncertainty is calculated as follows:

$$U_{Adv} = 1 \quad C_{Adv} \tag{4.21}$$

Where:

U_{Adv} indicates the uncertainty in outcomes of advisor, *Adv*

$C_{Adv} = \frac{1}{2}\int_0^1 \left| \frac{x^s(1 \quad x)^{ds}}{\int_0^1 x^s(1 \quad x)^{ds}} \right| dx$ represents the certainty of binary evidence (s, ds),

Where:

s shows the total number of previous satisfying interactions between specific advisor and requester and also other advisors

ds represents the total number of previous dissatisfying interactions between specific advisor and requester and also other advisors.

4.2.2.4 Conflict of each advisor

Conflict in the evidence means that some evidences are positive (satisfying interactions) and some are negative (dissatisfying interactions), which shows the inconsistency in the previous behaviors of the agent. According to Evidence-based trust model (Wang & Singh, 2010), the value of conflict for each advisor is evaluated as:

$$C_{Adv} = \min(\alpha = \frac{s}{t}, 1 - \alpha) \tag{4.22}$$

Where:

C_{Adv} indicates the conflict in behaviors of advisor, *Adv*

s representsthe total previous satisfying interactions between specific advisor, *Adv,* and requester and also other advisors

t isthe total previous interactions between specific advisor, *Adv,* and requester and also other advisors

Finally, the trustworthiness of each advisor is evaluated, by using Dezert theory (Wang & Singh, 2010), based on belief, disbelief, uncertainty and conflict value, as explained in previous sections, as follows:

$$T_{Adv} = (B_{Adv}, DB_{Adv}, U_{Adv}, C_{Adv}) \tag{4.23}$$

Where:

T_{Adv} indicates the trustworthiness of advisor, *Adv*, and $T_{Adv} \in [0,1]$.

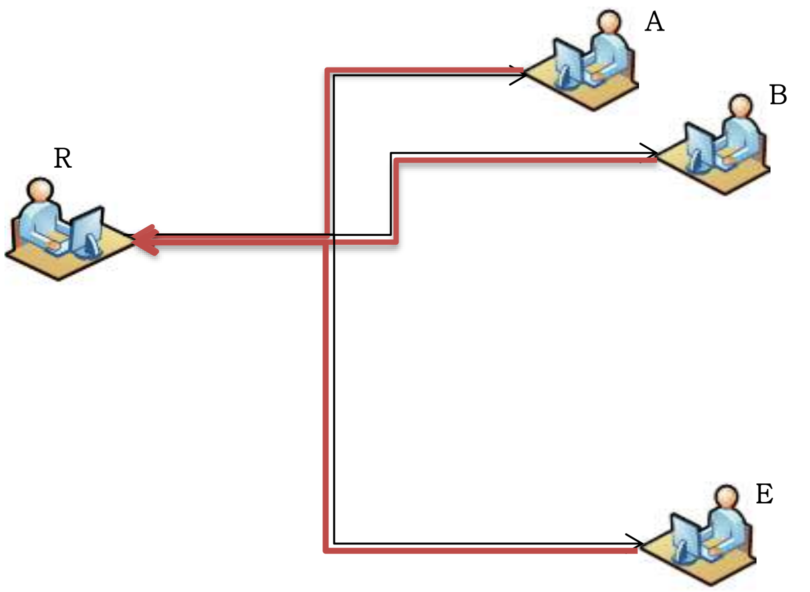
B_{Adv} represents the belief of advisor, *Adv*.

DB_{Adv} shows the disbelief of advisor, *Adv*.

U_{Adv} is uncertainty in outcomes of advisor, *Adv*.

C_{Adv} denotes conflict in behaviors of advisor, *Adv*.

Figure 4.4 showshow belief, disbelief, uncertainty, and conflict are represented for each advisor.



$$(B_A, DB_A, U_A, C_A)$$

Figure 4.4: Evaluating trustworthiness of each advisor

4.2.3 Trustworthiness of each provider

After evaluation of trustworthiness for each advisor, the requester should evaluate the trustworthiness of the suggested provider according to the information that each advisor reported through the query. In fact, each advisor sent the numbers, rating and also the last time of satisfying or dissatisfying interaction for its suggested provider. Therefore, requester can evaluate the trustworthiness of each provider by considering the recorded information collected from advisors. The trustworthiness of each provider is also calculated based on belief, disbelief, uncertainty, and conflict.

The method of computing belief and disbelief of provider is different from calculating the trustworthiness of advisors; as advisors have direct interaction with requester, the requester can evaluate the reliability of the advisor according to its own experiences. In the next sections, the method of computing each component of trustworthiness of provider is explained.

4.2.3.1 Belief of each provider

After calculating the trustworthiness of each advisor, the belief of each suggested provider should be calculated according to the responses collected from advisors. Because the requester does not have any previous direct interactions with providers, the reliability and unreliability values of the providers are zero; hence, the belief value of each provider should be evaluated by reputation values which are calculated based on the rates collected from the advisors. In regard to the sent query, each advisor suggested a trustworthy provider and identified the number and the rating of previous satisfying and dissatisfying interactions that it experienced with its suggested provider. The reputation value of each suggested provider is calculated based on the ratings of satisfaction that advisors identified through their response to the query, the number of previous satisfying interactions and the last time of satisfying interaction reported by advisors and the reliability of each advisor that suggested and rated the provider. In addition to the number of advisors that suggested the specific provider, it seems that the growth in the number of advisors that suggested the specific provider will increase the confidence degree of selecting the provider. Thus, the reputation value of each provider is computed as follows:

$$\Omega_{A \to \mathrm{Pro}} = \frac{\sum_{a_i \in A} \sum_{c \in C} (\Gamma_{\mathrm{Req} \to Adv} \times \xi^{c}_{a_i \to \mathrm{Pro}} \times t_{a_i \to \mathrm{Pro}} \times \mu_{a_i \to \mathrm{Pro}} \times w^{c}_{\mathrm{Req}})}{c \times \sum_{a_i \in A} \Gamma_{\mathrm{Req} \to \mathrm{Pro}}} \qquad (4.24)$$

Where:

$A = \{a_1, a_2, ..., a_m\}$ is the advisors that rated the suggested provider, *Pro.*

$\Omega_{A \to Adv}$ indicates the initial reputation value of provider, *Pro*, according to the rates which reported by advisors, *A.*

$\Gamma_{\mathrm{Re}q \to Adv}$ is the reliability that requester evaluates for rater advisor agent, *Adv.*

C shows the total number of criteria.

$\xi^{c}_{a_i \to \mathrm{Pr}o}$ is the total satisfaction value which rater advisor agent, a_i, gives to its suggested provider, *Pro*, according to their previous interactions

$t_{a_i \to Adv}$ shows the weight for each rating by considering more weight to more recent interaction with suggested provider, *Pro*

$\mu_{a_i \to \mathrm{Pr}o} = \frac{\sum_{i \in S} j_{a_i \to \mathrm{Pr}o}}{\sum_{i \in Intractions} i_{a_i \to \mathrm{Pr}o}}$ denotes the proportion of the number of previous satisfying interactions to the total number of previous interactions between rater advisor, a_i, and provider, *Pro*

$w^{c}_{\mathrm{Re}q}$ isthe preferences of requester as an importance weight of each criterion, as shown in Table 3.2.

The final formula for calculating the reputation of each provider is as follows:

$$\Pi_{\mathrm{Pr}o} = \frac{\sum_{n \in M} m}{M} \times \Omega_{A \to \mathrm{Pr}o} \qquad (4.25)$$

Where:

Π_{Pro} indicated the reputation value of provider, *Pro*

m is the total number of advisors that rated provider, *Pro*

M is the total number of advisors

$\Omega_{A\to\mathrm{Pro}}$ is the initial reputation value of a specific provider, *Pro*, obtained by equation (4.24).

4.2.3.2 Disbelief of each provider

Disbelief values of suggested providers are computed based on their disrepute value; their unreliability is zero when they do not have any direct interaction with requester. Thus, disbelief value of each provider is measured as:

$$d\Omega_{A\to\mathrm{Pro}} = \frac{\sum_{a_i\in A}\sum_{c\in C}(\Gamma_{\mathrm{Req}\to Adv}\times|\xi^c_{a_i\to\mathrm{Pro}}|\times t_{a_i\to\mathrm{Pro}}\times\mu_{a_i\to\mathrm{Pro}}\times w^c_{\mathrm{Req}})}{c\times\sum_{a_i\in A-\{Adv\}}\Gamma_{\mathrm{Req}\to Adv}} \qquad (4.26)$$

Where:

$A=\{a_1,a_2,...,a_m\}$ is the advisors that rated other advisors

$d\Omega_{A\to Adv}$ indicates the initial disrepute of provider, *Pro*, according to the rate of advisors, *A*

$\Gamma_{\mathrm{Req}\to Adv}$ is the reliability that requester evaluates for rater advisor agent, *Adv*

C shows the total number of criteria

$\xi^{c}_{a_i \to \Pr o}$ is the total dissatisfaction value which rater advisor agent, a_i, gives to provider, *Pro,* according to their previous interactions

$t_{a_i \to \Pr o}$ shows the weight for each rating by considering more weight to more recent interaction with suggested provider, *Pro*

$\mu_{a_i \to \Pr o} = \frac{\sum_{i \in S} j_{a_i \to \Pr o}}{\sum_{i \in Intractions} i_{a_i \to \Pr o}}$ denotes the proportion of the number of previous dissatisfying interactions to the total number of previous interactions between rater advisor, a_i, and provider, *Pro*

$w^{c}_{\mathrm{Re}q}$ isthe preferences of requester as an importance weight of each criterion, as shown in Table 4.1.

Moreover, the number of agents that sent their ratings of dissatisfaction affects the accuracy of the disrepute value. As the number of advisors that participate in computation of the disrepute grows, the disrepute value will be more accurate. Hence, the final formula for calculating the disrepute of advisor, *Adv*, is:

$$d\Pi_{Adv} = \frac{\sum_{m \in M} m}{M} \times d\Omega_{A \to Adv} \tag{4.27}$$

Where:

$d\Pi_{Adv}$ indicates disrepute of advisor, *Adv*

$\sum_{m \in M} m$ is the total number of advisors that rated advisor, *Adv,* and participated in computing the reputation value of advisor, *Adv*

M is the total number of advisors

$d\Omega_{A \to Adv}$ is the initial disrepute value of a specific advisor, *Adv*, obtained by equation (4.26).

4.2.3.3 Uncertainty of each provider

Considering the Evidence-based trust model (Wang & Singh, 2010), the uncertainty of each suggested provider is calculated based on the number of previous satisfying and dissatisfying interactions between advisors and their suggested provider. Therefore, the requester takes into account the uncertainty of predicting the future behavior of each provider according to the rating reported by advisors as follows:

$$U_{Adv} = 1 \quad C_{Adv} \tag{4.28}$$

Where:

U_{Adv} indicates the uncertainty in outcomes of advisor, *Adv*

$C_{Adv} = \frac{1}{2}\int_0^1 \left| \frac{x^s (1-x)^{ds}}{\int_0^1 x^s (1-x)^{ds}} \right| dx$ shows the certainty of binary evidence (s, ds).

Where:

s shows the total number of previous satisfying interactions between advisors and providers

ds represents the total number of previous dissatisfying interactions between advisors and providers.

4.2.3.4 Conflict of each provider

Moreover, conflict in previous behaviors of each provider, is computed with the same formula as computing conflict in behaviors of advisors, as follows:

$$C_{\Pr o} = \min(\alpha = \frac{s}{t}, 1 - \alpha) \qquad (4.29)$$

Where:

$C_{\Pr o}$ indicates the conflict in behaviors of provider, *Pro*

s representsthe total previous satisfying interactions between advisors and an specific suggested provider, *Pro*

t isthe total previous satisfying and also dissatisfying interactions between advisors and an specific suggested provider, *Pro*

Ultimately the requester evaluates the trustworthiness of each provider as:

$$T_{\Pr o} = (B_{\Pr o}, DB_{\Pr o}, U_{\Pr o}, C_{\Pr o}) \qquad (4.30)$$

Where:

$T_{\Pr o}$ indicates the trustworthiness of provider, *Pro*, and $T_{Adv} \in [0,1]$

$B_{\Pr o}$ represents the belief of provider, *Pro*

$DB_{\Pr o}$ shows the disbelief of provider, *Pro*

U_{Pro} is uncertainty in outcomes of provider, *Pro*

C_{Pro} denotes conflict in behaviors of provider, *Pro*

Figure 4.5 represents that the requester R evaluated the trustworthiness of each providera and b, based on the reports collected from advisors A, B, and E.

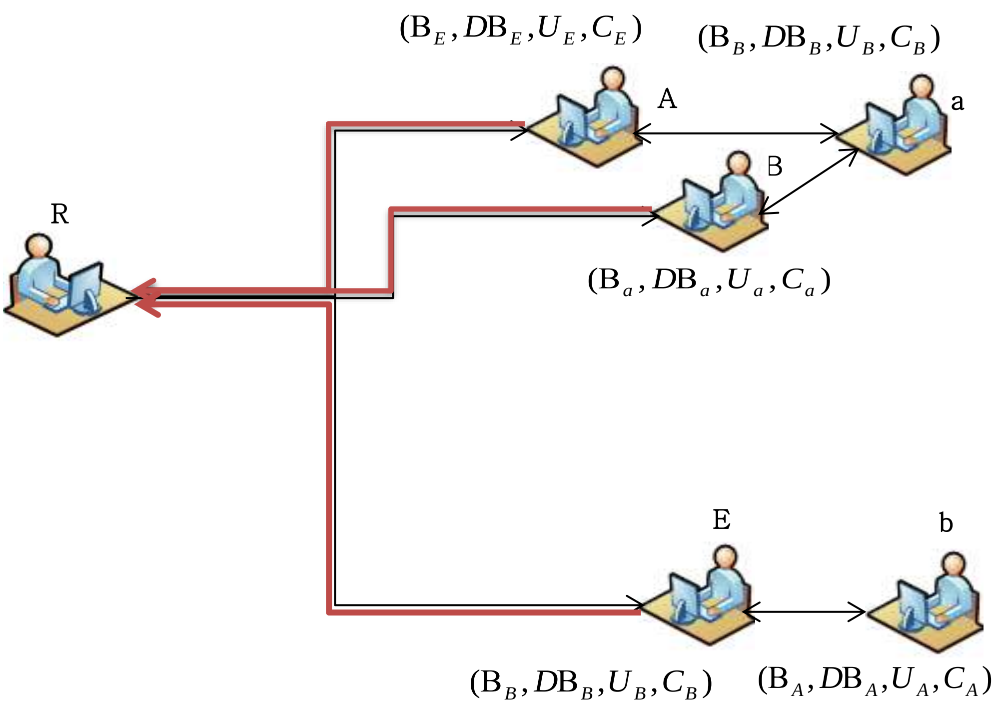


Figure 4.5: Evaluating trustworthiness of each provider

4.2.4 Trust transitivity

To select the trustworthy provider, the trust transitivity between each requester and its suggested provider should be evaluated. For evaluating the trust transitivity in the multi-agent environments, the Dezert-Smarandache theory (Wang & Sun, 2009) is applied. According to the Dezert-Smarandache theory (Wang & Sun, 2009), the general frame of discernment of the problem under consideration is $\Theta = \{B, DB\}$, which is based on two hypotheses: B (agent, A, trusts agent, B) and DB (agent, A, distrusts agent, B). In addition, the hyper-power set D^{Θ} is defined as:

$$D^{\Theta} = \{\phi, B, DB, B \cap DB, B \cup DB\} \tag{4.31}$$

Where:

B shows the belief value of the agent in the set, D^{Θ}.

DB represents the disbelief value of the agent in the set, D^{Θ}.

$B \cup DB = U$ indicates the uncertainty value of the agent in the set, D^{Θ}.

$B \cap DB = C$ denotes the conflict value of the agent in the set, D^{Θ}.

and a general basic belief assignment (gbba) is a function as:

$$m : D^{\Theta} \to [0,1] \tag{4.32}$$

Where:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subseteq D^{\Theta}} m(A) = 1 \end{cases}$$

In fact, the trust evaluation of one agent to another one can be described by the gbba m(.) as:

$m(\{B\})$ describes value of belief.

$m(\{DB\})$ represents the value of disbelief.

$m(\{B \cup DB\}) = m(\{U\})$ identifies the value of uncertainty

$m(\{B \cap DB\}) = m(\{C\})$ is the value of conflict caused by paradoxical behaviors

Then, the trust combination happens when one advisor suggested a specific provider, *Pro*.

Suppose that the trust evaluation of requester, *Req*, to advisor agent, *Adv*, is:

$$T_{\mathrm{Re}q \to Adv} = (m_{\mathrm{Re}q \to Adv}(\{B\}), m_{\mathrm{Re}q \to Adv}(\{DB\}), m_{\mathrm{Re}q \to Adv}(\{U\}, m_{\mathrm{Re}q \to Adv}(\{C\})) \qquad (4.33)$$

andAdv's trust evaluation of provider, *Pro* is as follows:

$$T_{Adv \to \mathrm{Pr}o} = (m_{Adv \to \mathrm{Pr}o}(\{B\}), m_{Adv \to \mathrm{Pr}o}(\{DB\}), m_{Adv \to \mathrm{Pr}o}(\{U\}, m_{Adv \to \mathrm{Pr}o}(\{C\})) \qquad (4.34)$$

Then the trust transitivity evaluation through this referral chain is calculated as:

$$T_{\mathrm{Re}q \to \mathrm{Pr}o} = T_{\mathrm{Re}q \to Adv} \otimes T_{Adv \to \mathrm{Pr}o} \qquad (4.35)$$

Where:

$$m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{B\}) = (m_{\mathrm{Re}q \to Adv}(\{B\}) + m_{\mathrm{Re}q \to Adv}(\{C\})) \times m_{Adv \to \mathrm{Pr}o}(\{B\})) \qquad (4.36)$$

$$m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{DB\}) = (m_{\mathrm{Re}q \to Adv}(\{B\}) + m_{\mathrm{Re}q \to Adv}(\{C\})) \times m_{Adv \to \mathrm{Pr}o}(\{DB\})) \qquad (4.37)$$

$$m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{C\}) = (m_{\mathrm{Re}q \to Adv}(\{B\}) + m_{\mathrm{Re}q \to Adv}(\{C\})) \times m_{Adv \to \mathrm{Pr}o}(\{C\})) \quad (4.38)$$

$$m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{U\}) = 1 - m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{B\}) - m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{DB\}) - m_{\mathrm{Re}q \to \mathrm{Pr}o}(\{C\}) \quad (4.39)$$

Another approach in transitivity of trust is trust aggregation, when more than one advisor suggests the same provider.

Suppose m_1 and m_2 are two independent gbba then trust aggregation is calculated as:

$$T_{\mathrm{Re}q \to \mathrm{Pr}o} = T_{\mathrm{Re}q \to Adv} \oplus T_{Adv \to \mathrm{Re}q} \quad (4.40)$$

Where:

$$m(C) = m_1(A) \oplus m_2(B) = \sum_{\substack{A,B \in D^{\Theta} \\ A \cap B = C}} m_1(A) m_2(B) \quad (4.41)$$

$$m_1(A) = (m_{Adv1 \to \mathrm{Pr}o}(\{B\}), m_{Adv1 \to \mathrm{Pr}o}(\{DB\}), m_{Adv1 \to \mathrm{Pr}o}(\{U\}), m_{Adv1 \to \mathrm{Pr}o}(\{C\})) \quad (4.42)$$

$$m_2(B) = (m_{Adv2 \to \mathrm{Pr}o}(\{B\}), m_{Adv2 \to \mathrm{Pr}o}(\{DB\}), m_{Adv2 \to \mathrm{Pr}o}(\{U\}), m_{Adv2 \to \mathrm{Pr}o}(\{C\})) \quad (4.43)$$

Therefore, trust transitivity of each chain is evaluated according to trust combination and trust aggregation.

Figure 4.6 shows the trust transitivity between requester and the suggested providers was evaluated by requester R.

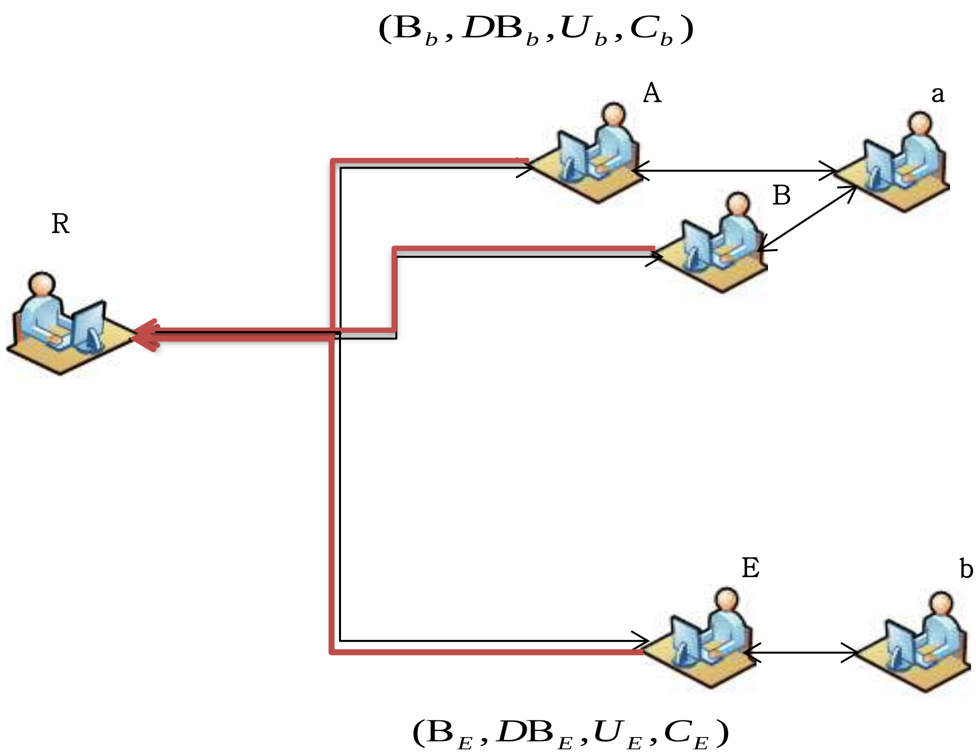


Figure 4.6: Evaluating trust transitivity

4.2.5 Making a decision

By computing the trust transitivity for each chain between requester and the suggested provider, a requester agent should select the most trustworthy provider to interact with based on the advisors' suggestion. In order to make a decisionthe TOPSIS multi-criteria decision-making method proposed by Chen (2000) is considered to implement the decision support process method in selecting the most trustworthy provider according to the advice of the benevolent advisors. In this case, the requester should store all of the trust transitivity values in a decision matrix as well as construct a weighted decision matrix. The decision matrix should be constructed based on the belief, disbelief, uncertainty, and conflict obtained from evaluating the trust transitivity. The decision matrix is formulated as follows:

$$D = \begin{array}{c c} & \begin{array}{cccc} \mathit{Belief} & \mathit{Disbelief} & \mathit{Uncerta}\,\text{int}\,y & \mathit{Conflict} \end{array} \\ \begin{array}{c} \Pr o_A \\ \Pr o_B \\ \Pr o_C \\ \Pr o_D \end{array} & \begin{bmatrix} B_{\Pr o_A} & D_{\Pr o_A} & U_{\Pr o_A} & C_{\Pr o_A} \\ B_{\Pr o_B} & D_{\Pr o_B} & U_{\Pr o_B} & C_{\Pr o_B} \\ B_{\Pr o_C} & D_{\Pr o_C} & U_{\Pr o_C} & C_{\Pr o_C} \\ B_{\Pr o_D} & D_{\Pr o_D} & U_{\Pr o_D} & C_{\Pr o_D} \end{bmatrix} \end{array} \quad (4.44)$$

Hence to make a decision according toTOPSIS method, the following steps should be carried out according to the constructed decision matrix.

Stage 1: Make a decision matrix from the trust transitivity values (D).

Stage 2: Normalize the decision matrix through inclusion of the trust transitivity.

Stage 3: Construct the weighted matrix by using entropy method.

Stage 4: Make the weighted normalized decision matrix using entropy method

Stage 5: Determine the shortest distance from the positive ideal rate (PIS) and the farthest distance from the positive ideal rate (NIS), respectively.

Stage 6: Calculate the distance of each alternative from PIS and NIS, respectively.

Stage 7: Calculate the closeness coefficient of each alternative.

Stage 8: The ranking order of all alternatives is determined in the final stage according to the closeness coefficient. The most trustworthy service provider can be chosen accordingly.

The example in Figure 4.7 illustrates that requester R selects provider b based on the decision-making process.

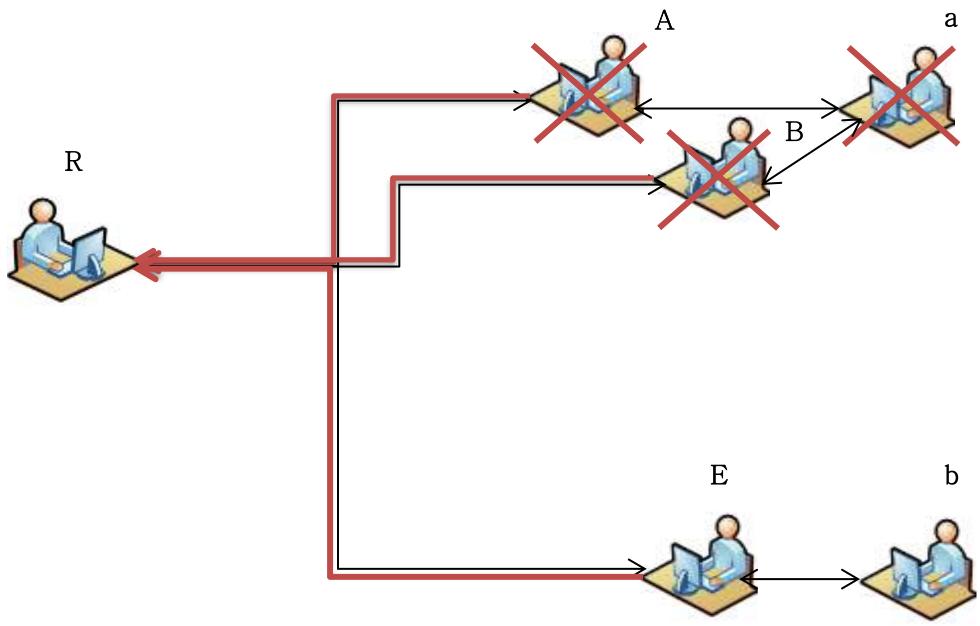


Figure 4.7: Decision-making process

4.2.6 Reward and punishment

After an interaction with the selected service provider, the requester will rate the service provider and consider reward or punishment for advisors that have advised that service provider. In this case, if interaction was successful and the rating of service provider given by the advisors was close to the real rating given by the requester, the requester considers a reward for these advisors, and gives the satisfaction rate to that advisor. Depending on the closeness of the rating the advisor offered for a service provider to the real rating given by the requester, the rate of satisfaction with the advisor, in terms of reward, is identified using two linguistic terms: slightly good (SG) and good (G). The meanings of these linguistic variables are shown in Table 3.3.

On the other hand, if the rating given by advisors was far from the real rating given by the requester after interaction, the requester considers a punishment for these advisors and gives the rate of dissatisfaction. The rate of dissatisfaction depends on the gap between the rate of the advisor and the real rate; it is defined using two linguistic terms: slightly bad (SB) and Bad (B), as shown in Table 4.2. This reward or punishment for these advisors has an impact on calculating belief and disbelief values of each advisor in the future interactions.

Figure 4.8 shows the requester R interacted with the provider b suggested by advisor E. After this interaction, the requester can decide whether to give a reward or punishment to advisor E.

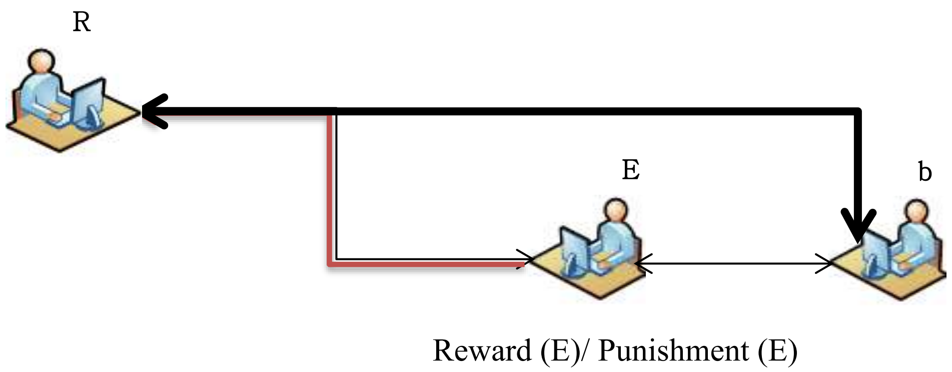


Figure 4.8: Reward or punishment for the final selected advisors

4.2.7 TMAN schema

Figure 4.9 illustrates the overall schema of the proposed model, TMAN. According to this figure, the process of finding the trustworthy advisors and selecting the best service provider is described in seven steps: sending the query and collecting the responses; calculating the similarity between responses and the requester; choosing the similar responders as advisors and recording their responses; computing the trustworthiness of each advisor, according to belief, disbelief, uncertainty, and conflict; calculating the trustworthiness of each suggested provider based on the reports that advisors sent about their suggested provider; evaluating the trust transitivity between advisors and their suggested provider to obtain the accurate trustworthiness value of each suggested provider; making a decision to select the most trustworthy service provider and finally considering reward or punishment for advisors that suggested the selected provider.

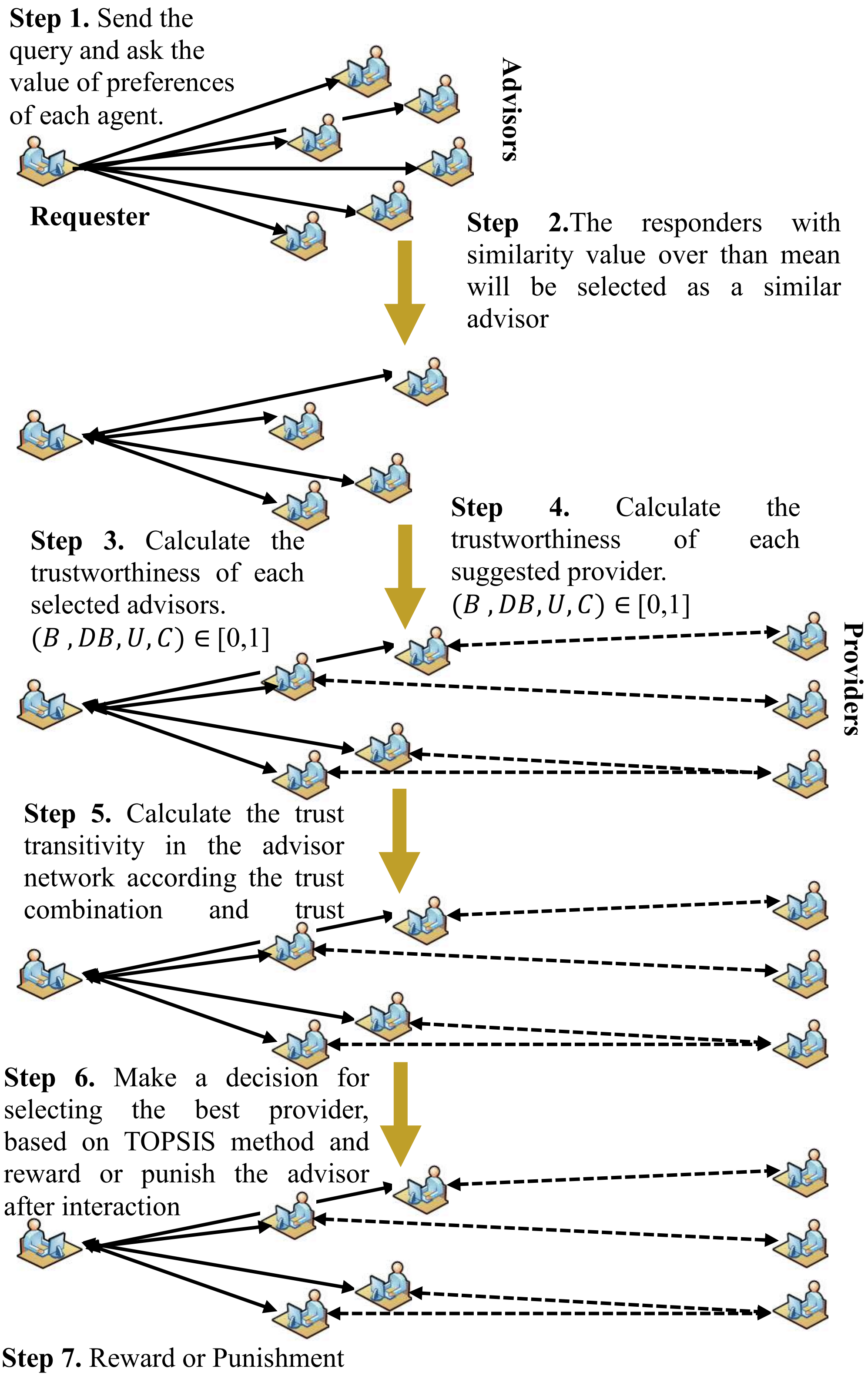


Figure 4.9: TMAN schema

4.3Evaluation method of TMAN

After designing TMAN, the accuracy of TMAN was evaluated by using two methods; random selection method and trade network game method. In the following sections, each method is described in more details.

4.3.1 Random selection method

In this method, the requester, advisors, and providers were selected randomly and also the agents rated the advisors arbitrarily using satisfying and dissatisfying ratings, for each simulation. In this part of evaluation, the simulation environment was constructed using the MATLAB (R2012a) simulator, according to the following settings:

i) Composition: The analysis was performed for three distributions with two different percentages of malicious advisors according to Gorner et al. (2013), in addition to one more distribution in which the percentage of malicious and benevolent advisors is equal, as shown in Table 3.5. Each analysis were repeated ten times for each group by referring to the evaluation method presented by Gray (2008), to investigate whether TMAN generally has the same results. Then the average results of ten times repeated for each distribution were recorded.

Table 4.4Distributions of experiments

No of	Distribution 1	Distribution 2	Distribution 3
Benevolent Advisors/providers	40	50	70
Malicious Advisors/providers	60	50	30
Total	100	100	100

On the other hand, to test the scalability of this approach according to the TREPPS model (Li & Kao, 2009), further experiments were carried out with different numbers of advisors and providers in four groups, as shown in Table 3.6.

Table 4.5Parameters of experiments

No. of	Group 1	Group 2	Group 3	Group 4
Requester	1	1	1	1
Advisor	10	20	30	40
Provider	10	20	30	40
Total	21	41	61	81

ii) Structure: The experiments were designed using the simulations approach presented in Zhang and Cohen (2008) and Gorner et al. (2013) to verify the performance of TMAN. According to this approach, the requester, advisors, and providers were selected randomly and also the agents rate the advisors arbitrarily as satisfying or dissatisfying. Each advisor and provider were selected as a benevolent one if their random satisfying rating were in the range of (0,1], otherwise they were labeled as a malicious one. Moreover, the preferences values of requester and advisors were selected randomly. The total numbers of criteria, as described in Chapter 3, was considered as four criteria consists of product quality, product price, customer service and delivery time.

Moreover, the total times of interactions in this simulation was 100 with 10 iterations, where the results were recorded after each iteration like the evaluation method used by Li and Kao (2009).

iii) Behavior: First, the requester agent sent a query randomly to its neighbors. When the neighbors,whichwere the advisor agents received a query, they replied based on the related providers which have had a relationship with them. Then, the requester recorded the responses of the queries and evaluated the trustworthiness of each responder. After each interaction between agents, the relationship between agents was updated.

4.3.1.1 Average accuracy of TMAN

The average accuracy of TMAN was evaluated to calculate the performance of TMAN. The aim of this step is to study the average accuracy of TMAN in determining the trustworthiness of advisors and providers and also study the average accuracy of TMAN in evaluating trust transitivity among agents. According to the evaluation method used by Li and Kao (2009), the average accuracy can be calculated as the average timesof calculating the belief, disbelief, reliability, unreliability, reputation and disrepute of benevolent and malicious agent accurately in the iteration.

4.3.1.2 Comparing the performance of the TMAN with other existing models

In this step, we compared the performance of TMAN in comparison with the approaches employed in other existing models: Evidence-based trust model (Wang & Singh, 2010), and TREPPS model (Li & Kao, 2009), in addition to a basic model. The performance of each trust model in this experiment was determined as the average times of selecting a benevolent provider. Based on TREPPS model, the average accuracy was calculated as the average times of choosing benevolent providers, as advised by the selected benevolent advisors in the iteration. The expectation was that the average accuracy of performance of TMAN in selecting the benevolent providers can be better than that of other models in different iterations with various numbers of malicious and benevolent advisors.

The performance of TMAN was compared to the models which used for proposing it. Among all models were applied for computing Reliability and finally integration these three components to select the most trustworthy agent, Evidence-based Trust Model and TREPPS Model selected as a benchmark because these models have more similarity with TMAN. The mathematical method of TMAN and Evidence-based Trust Model are both based on subjective logic. Moreover Evidence-based Trust Model considered three conditions, as a selection method, for selecting the most trustworthy agent and TREPPS model applied FTOPSIS method to select the most trustworthy provider. Whereas other models presented an evaluation method for trustworthiness of agent but they did not propose the selection method to select the agent with highest trustworthiness. Hence, to compare TMAN with other models and investigate whether

TMAN can select trustworthy agents in different multi-agent environments with various numbers of agents, Evidence-based Trust Model and TREPPS can be used as comparable models.

4.3.2 Evaluation plan with trust network game approach

In the second method of evaluation, the performance of TMAN was evaluated by simulating an auction behavior,referring to Gray (2008). According to this method, a series of experiments was carried out in which an auction behavior was simulated, using a version of the trade network game simulator (McFadzean & Tesfatsion 1999) that has been used to simulate a simple auction environment. However, this method did not consider the similarity between agents because the preferences of advisors were not clarified and the preference of agent was considered as one, in addition the advisors could not rate each other so this is the specific case that the reputation of advisors is zero. According to TNG method each advisor can suggest a similar provider; it means that the advisor with consistent behavior suggests the provider with consistent behavior, also the advisor with mild oscillating behaviors can suggest the provider with the mild oscillating behaviors, because their profile settings are the same

Trade Network Game (TNG) is a framework for studying the formation and evolution of trade among strategically interacting traders (buyers, sellers, and dealers) operating under different specified market protocols. In this study, the buyer was considered as requester agent, seller as provider agent and dealer as advisor agent.

TNG blends and extends the standard matching theory and sequential game theory, where each trader must jointly determine over time whom to seek trades with (partner selection) and how to behave in any trade interactions that take place (strategy selection). Each TNG trader in a bilateral trade can either play the role of C (cooperate) or D (defect). The TNG GUI screen permits the user to specify arbitrary payoffs for the four situations that a trader could find itself in as a result of a bilateral trade: CC (both cooperate); DD (both defect); DC (temptation, i.e. the trader defects against a cooperating partner); and CD (sucker, i.e. the trader is cooperating but its partner defects against it). Thereby, for evaluating the accuracy of TMAN by using TNG method, the payoffs of each advisor and provider was set according to identified satisfaction and dissatisfaction rates by TMAN, as described in Chapter 3. After running TNG, observations of advisors and also provider's auction behaviors in each interaction were recorded.

In order to evaluate TMAN in relation to TNG, the following parameters were specified in the TNG simulations. First, the number of interactions between requester, provider and advisor was configurable. Next, the behavior profile of the agents was set. When agent's behavior profile was set, the agent acts randomly in each interaction according to that profile.

Gray (2008)applied the TNG method for evaluating its proposed trust model based on two cases, consistently behavior and oscillating behaviors. With reference to Gray (2008), TMAN was evaluated based on three different cases; consistently behavior, mild oscillating behavior, and strong oscillating behavior.

In this part of evaluation, the intent was to see how well TMAN performs in each of the following three cases: case one, in which agents displayed **consistently behavior** in simulated auction; case two, in which agents showed **mild oscillating behavior**; case three, in which agents represented **strong oscillating behaviors**.

The purpose of this analysis was to evaluate how well TMAN calculates the trustworthiness of advisors and providers based on the observation of their behaviors in past interactions, which leads to selecting the most trustworthy provider.

The pattern that was applied for the evaluation of case one with consistently normal behavior is as follows: This experiment simulates the case in which advisors' and providers' behaviors over time are consistent for theiteration. The parameters used for this experiment are as follows.

Parameter specification:

Total number of interactions: 16

One Advisor, one provider, and one requester– each gent had the same role as follows for all interactions.

Behavior setting of advisor A: $\begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$

Behavior setting of provider A: $\begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$

Agent's behavior profile remains constant: ***mutation rate=0***.

This parameter specification presents the payoffs for cooperation, defection, temptation and sucker situations were determined considering the satisfaction and dissatisfaction rates which identified in Chapter 3. According to this setting, if two agents cooperated (*Cooperation*), then the scores presented by TNG were between 1 and 0.5. These scores were consideredas the satisfying interactions with the linguistic term of good.If the trader agents defected against their cooperating partner (*Temptation*), then the scores presented by TNG were between 0.5 and 0. These scores were considered as the satisfying interactions with the linguistic term of slightly good. If the trader agents cooperated but their partner defected against them (*Sucker*), then the score presented by TNG were between 0 and -0.5. These scores were considered as the dissatisfying interactions with the linguistic term of slightly bad; and finally if both agents defected (*Defection*), then the score presented by TNG were between -0.5and -1. This indicated the dissatisfying interactions with the linguistic term of bad.

Moreover, in this case mutation rate is zero which represents that the agents displayed consistently normal behavior without any oscillating behavior.

The pattern that was used for the evaluation of case two with oscillating behavior is the same as the pattern which used by case one but in this case the agents can change their behaviors during the interactions. This pattern is explained as follows:

In this experiment, providers and advisors oscillate their behaviors during the auction. This experiment was also based on one advisor and one provider as follows.

Parameter Specification:

Total number of interactions: 16

One Advisor, one provider, and one requester– each gent had the same role as follows for all interactions.

$$\text{Behavior setting of advisor A:} \begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$$

$$\text{Behavior setting of provider A:} \begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$$

Agent's behavior profile remains with mild oscillating: ***mutation rate=0.05***.

Finally in case three, the pattern was used with strong oscillating behavior. In this experiment, providers and advisors change their behaviors a lot during the interactions. This experiment was also based on one advisor and one provider agents as follows:

Parameter Specification

Total number of interactions: 16

One Advisor, one provider, and one requester– each gent had the same role as follows for all interactions.

$$\text{Behavior setting of advisor C:} \begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$$

$$\text{Behavior setting of provider C:} \begin{cases} Cooperation: 1 \\ Defection: -1 \\ Temptation: 0.5 \\ Sucker: -0.5 \end{cases}$$

Agent's behavior profile remains with strong oscillating: ***mutation rate=0.5***.

4.3.2.1 Accuracy of TMAN components

In this step, the outcome scores for each advisor and provider collected from TNG were usedby TMAN as the rate of previous satisfying or dissatisfying interactions. By using these recorded ratings, the trustworthiness of advisors and providers were computed for the first fifteen interactionsby applying TMAN. Finally, the outcome scoresof advisors and providers, presented by TNG were compared with the trustworthiness which calculated by TMAN.

4.3.2.2 Performance of TMAN in decision-making process

By running TNG and recording the outcome scores of advisors and providers, as the rate of satisfaction or dissatisfaction for providers and advisors, the trustworthiness of each advisor and provider was computed. Then, the trust transitivity between requester and the suggested providers was calculated before selecting the most trustworthy provider by TMAN. In this step, the most trustworthy provider selected by TMAN was compared with the presented scores by TNG for each provider in the last interaction, to illustrate that the suggested provider that TMAN selected according to previous interactions had the best scores in the last interaction presented by TNG.

4.4 Summary

In this chapter the process of designing TMAN has been described based on the identified components. The design of TMAN was based on six main stages. First the similar advisor agents have been selected (stage one), then trustworthiness of each similar advisor was evaluated (stage two), in the next step the trustworthiness of suggested provider which suggested by advisors were computed according to the report of advisors about their suggested provider (stage three). Next transitivity of trust between requester, similar advisors and their suggested providers were measured (stage four), then the most trustworthy provider was selected using TOPSIS method (stage five). After description of TMAN design, the methods of evaluation of the accuracy of TMAN in computing each component and also the performance of TMAN in multi-agent environments have been explained in details. The first method of evaluation was random selection in which the average accuracy of TMAN in computing the identified components have been studied, then by using random selection the performance of TMAN have been compared against three other models. Second the evaluation of TMAN in computing the identified components have been investigated by using TNG method and finally the performance of TMAN in different multi-agent environments have been studied according to TNG method.

CHAPTER 5:RESULTS AND DISCUSSION

5.1 Introduction

This chapter describes the evaluation results of the proposed model, TMAN, which was discussed in Chapter 3. This chapter consists of two parts. The first part discusses the results collected from the random selection method of evaluation through four experiments; first the average accuracy of the TMAN components in computing the trustworthiness of each **advisor**isinvestigated based on the results of Experiment 1.1, in Section 5.2.1.Second, the average accuracy of the TMAN components in computing the trustworthiness of each **provider** is described, in Section 5.2.2 by using Experiment 1.2. Then, the average accuracy of TMAN in evaluation of **trust transitivity**is discussed based on the results of Experiment 1.3, in Section 5.2.3. On the other hand, the performance of TMAN is compared with that of other existing models by using Experiment 1.4, in Section 5.2.4.

Second part discusses the performance of TMAN based on the trust network game (TNG) as a simulator. In this part the accuracy of TMAN components in evaluating the trustworthiness of advisors and their suggested providers is investigated by Experiment 2.1, in Section 4.3.1.Finally the accuracy of TMAN in selecting the most trustworthy provider is described by Experiment 2.2, in Section 4.3.2.

5.2 Part 1: Evaluation of TMAN with random selection

The random selection method consists of four experiments as discussed in the following sections. The experiments are:

I. Assessment of the main components used in computing the trustworthiness of each **advisor.**

II. Assessment of the main components applied in calculating the trustworthiness of each **provider**.

III. Evaluation of the trust transitivity between **advisors and their suggested provider**.

IV. Comparison of the performance of TMAN with other existing trust models.

The evaluation setting and the simulation environment of TMAN was described in Phase 3, which is part of the research methodology, in Chapter 3. According to this setting, three distributions with different percentages of benevolent and malicious agents in four different groups with different number of advisors were considered.

According to Evidence-based trust model, the belief of benevolent agents is higher than their disbelief. Hence, the average accuracy of TMAN in evaluating its main components was based on this expectation that reliability, reputation, and in overall belief values of benevolent advisors should be higher than their unreliability, disrepute and overall disbelief, respectively. Therefore, TMAN should accurately calculate these components, and the results should denote reliability, reputation and belief values of benevolent advisors that are calculated by TMAN are higher than their unreliability, disrepute and disbelief values, respectively.

In contrast, according to Evidence-based trust model, the belief of malicious agents islower than their disbelief. Thereby, the expectation was that reliability, reputation and belief values of malicious advisors should be lower than their unreliability, disrepute and also disbelief values, respectively. Hence, TMAN should also compute these components accurately; this means that results reported by TMAN should represent lower reliability, reputation and belief values of malicious advisors than their unreliability, disrepute and disbelief values.

The results obtained from running TMAN for all the distributions and groups are described and discussed as follows.

5.2.1. Experiment 1.1: Evaluation of the advisors' trustworthiness

In this experiment, a requester sent a query to advisors in a simulatedenvironment; then the trustworthiness of benevolent and malicious advisors were calculated, as described in Chapter 4.

For instance, the distribution one,as shown in Table 4.4, consisted 40% of trustworthy and 60% untrustworthy agents and the group one, as shown in Table 4.5, involved 10 agents. Figure 5.1 shows a sample of simulated environment for distribution one, group one.

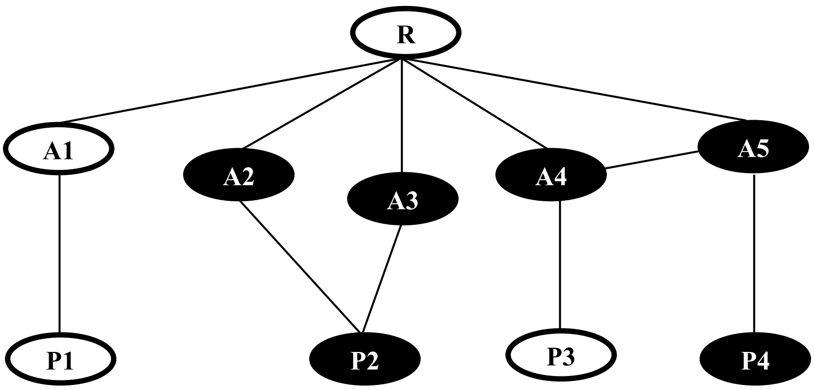


Figure 5.1: An example for experiment 1.1

As shown in Figure 5.1, each agent labeled as R means requester, A means Advisor, and P means Provider. According to Table 4.5, group one was consisted of

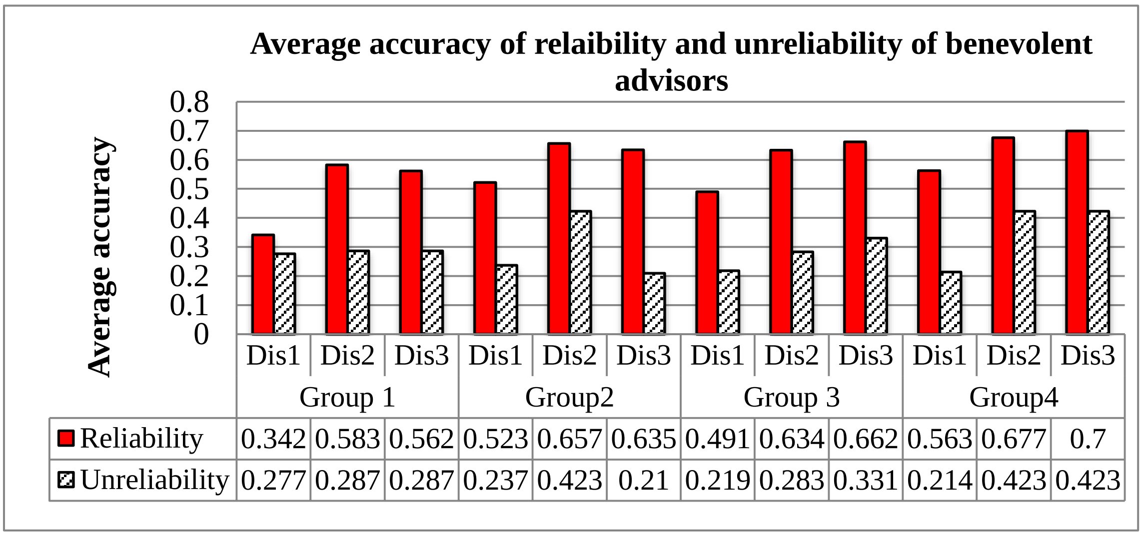
1requester, 5 advisors and 4 providers. The relationship between requester, advisors and providers were randomly, so the requester had randomly relationship with advisors during the running program, advisors also had relationship with each other randomly, and each advisor had randomly relationship with one provider which was its suggested provider. By running the program, the satisfying, dissatisfying rates gave randomly to each cycle as shown in Table 5.1.

Table 5.1: An example of experiment 1.1

Type of agent	No of Interaction	Rate of interaction
R-A1	1	0.875
R-A2	1	-0.523
R-A3	1	-0.637
R-A4	1	0.786
R-A5	1	0.515
A4-A5	1	0.489

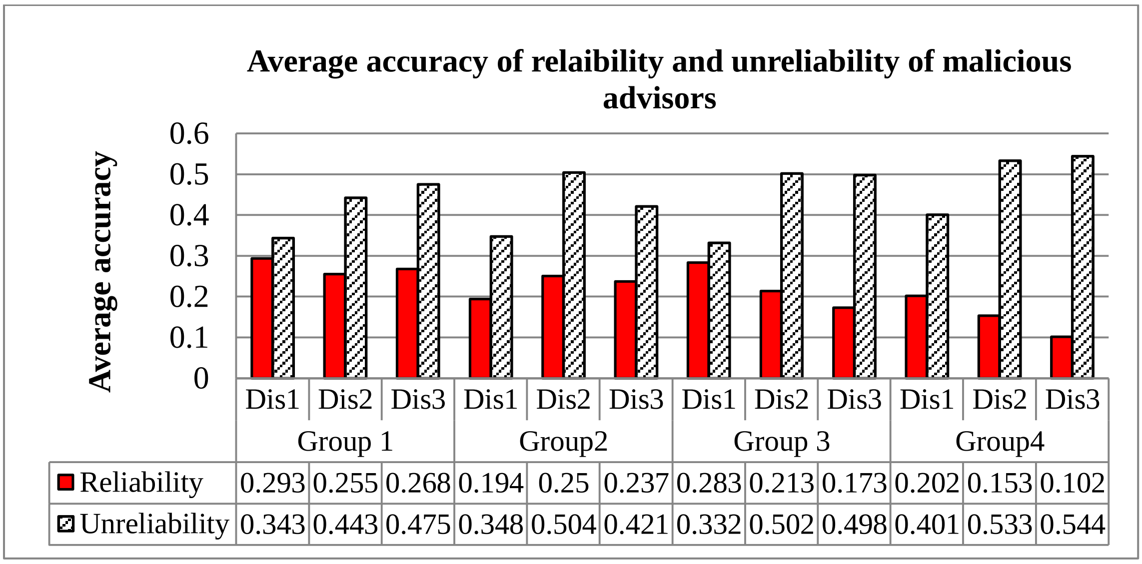
Table 5.1 illustrates the first time of interaction that the rate of satisfying and dissatisfying interactions were identified by the system. These random rates identified the color of cycles. If the rate which gave to cycle was satisfying the color of that cycle was white and if the rate was dissatisfying the color of that cycle was black. These random ratesused by presented formulas for computing the trustworthiness of advisors. In each time of running, this scenario repeated until 100 times, and each time, the trustworthiness of advisors was evaluated according to random satisfying and dissatisfying rates. The result of these 100 times of interactions was recorded. The system revealed the average result as the average accuracy of TMAN after each ten times of interactions.

This simulation experiment was run 10 times, for all the distributions and groups as identified in Tables 4.3 and 4.4 of Chapter 4. The average aggregated results of 10 times running for calculating the reliability and unreliability values ofthe benevolent and malicious advisors are illustrated in Figure 5.2 and Figure 5.3, respectively.



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Reliability	0.342	0.583	0.562	0.523	0.657	0.635	0.491	0.634	0.662	0.563	0.677	0.7
Unreliability	0.277	0.287	0.287	0.237	0.423	0.21	0.219	0.283	0.331	0.214	0.423	0.423

Figure 5.2: Average accuracy of reliability and unreliability values for benevolent advisors across all groups and distributions

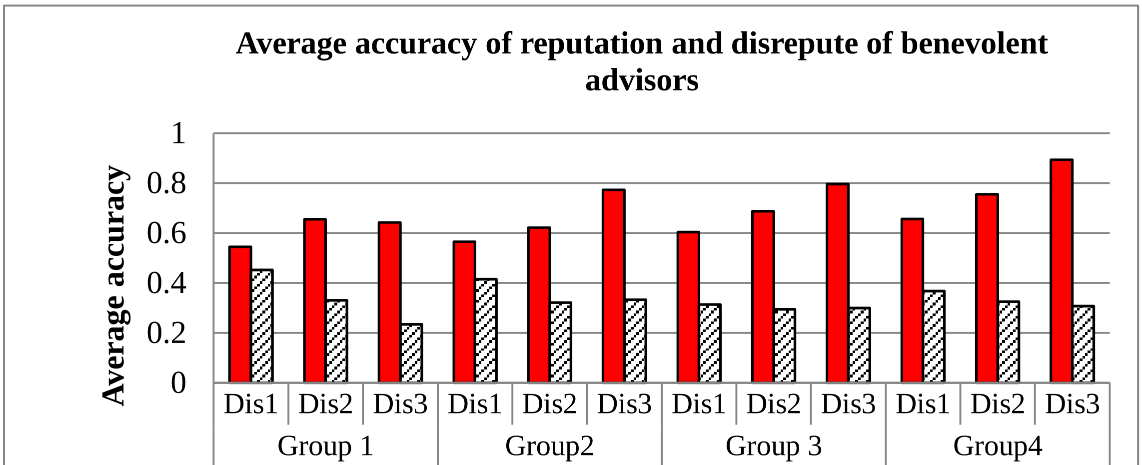


	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Reliability	0.293	0.255	0.268	0.194	0.25	0.237	0.283	0.213	0.173	0.202	0.153	0.102
Unreliability	0.343	0.443	0.475	0.348	0.504	0.421	0.332	0.502	0.498	0.401	0.533	0.544

Figure 5.3: Average accuracy of reliability and unreliability values for malicious advisors across in each group and distribution

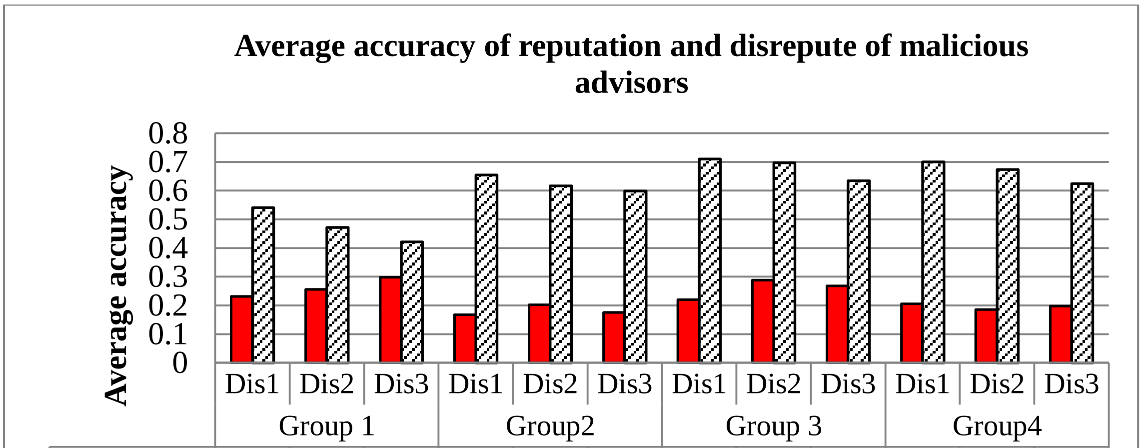
Figure 5.2 and Figure 5.3 show the average accuracy of TMAN in computing reliability and unreliability for different categories of simulation, involving three distributions of benevolent and malicious agents with four groups of agents. As shown in Figure 5.2, the average accuracy of reliability for benevolent advisors is higher than their unreliability,wherever Figure 5.3 illustrates that the average accuracy of reliability for malicious advisors is lower than their unreliability across all groups.

Figures 5.4 and Figure 5.5show the average accuracy of reputation and disrepute for benevolent and malicious advisors.



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Reputation	0.544	0.654	0.642	0.565	0.622	0.773	0.603	0.687	0.795	0.656	0.755	0.893
Disrepute	0.452	0.33	0.234	0.415	0.321	0.333	0.313	0.294	0.3	0.368	0.325	0.307

Figure 5.4: Average accuracy of reputation and disrepute values for benevolent advisors in each group and distribution



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Reputation	0.231	0.256	0.298	0.168	0.203	0.176	0.22	0.288	0.268	0.206	0.186	0.198
Disrepute	0.541	0.472	0.422	0.656	0.617	0.6	0.711	0.698	0.635	0.701	0.674	0.625

Figure 5.5: Average accuracy of reputation and disrepute values for malicious advisors across in each group and distribution

Figure 5.4 denotes that the average accuracy of reputation of benevolent advisors is higher than the average accuracy of their disrepute, while Figure 5.5 shows that average accuracy of reputation of malicious advisors is lower than their average accuracy of disrepute.

After investigating the simulation results for evaluating reliability, unreliability, reputation and disrepute of advisor, the evaluation results for all distributions and groups on average accuracy of the disbelief and belief of benevolent and malicious advisors are examined as shown in Figure 5.6, and 5.7, respectively.

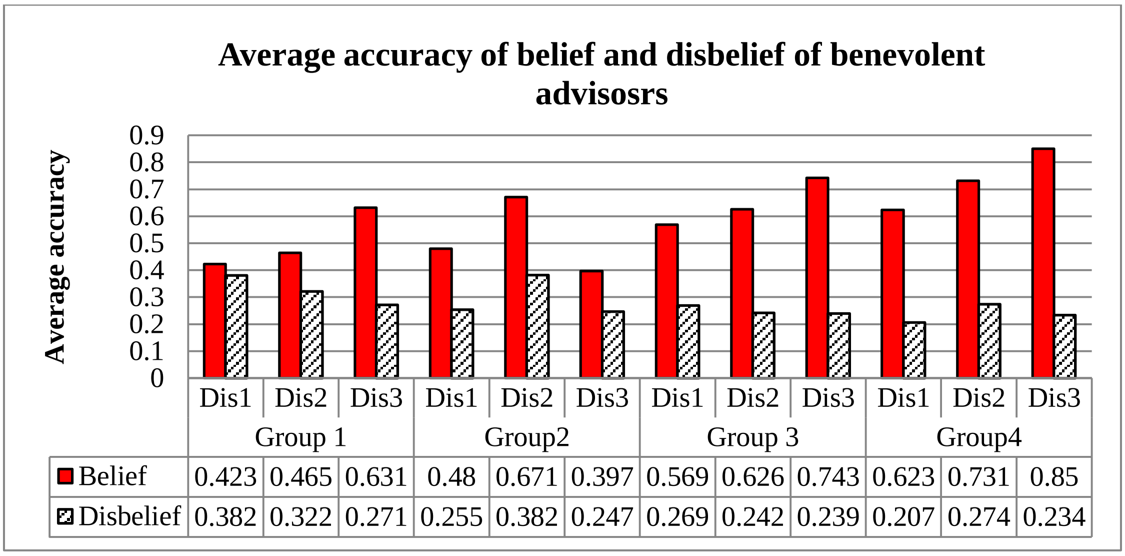


Figure 5.6: Average accuracy of belief and disbelief of benevolent advisors across in each group and distribution

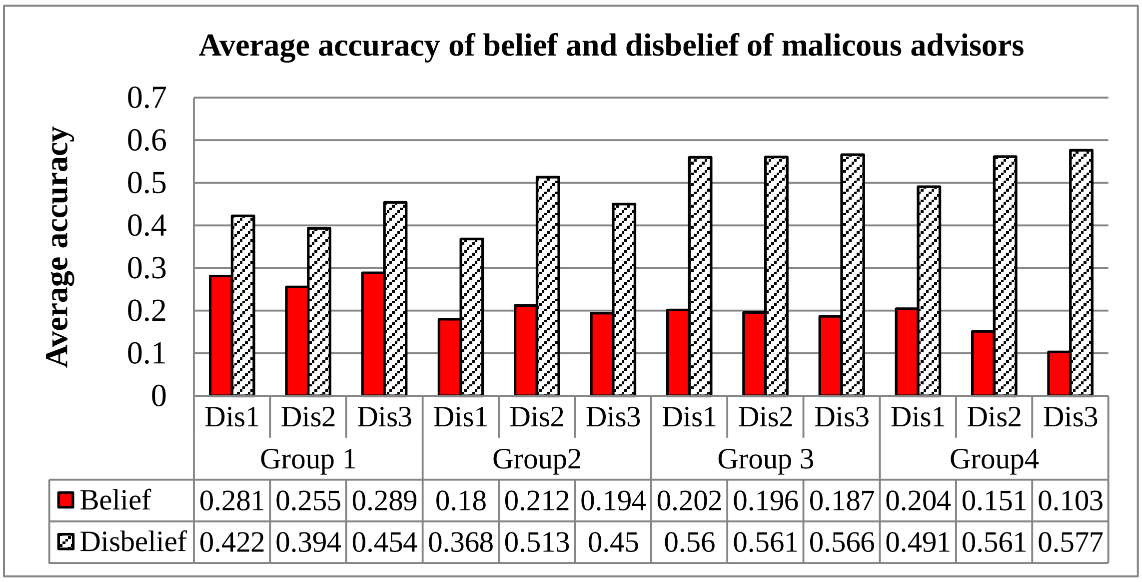


Figure 5.7: Average accuracy of belief and disbelief of malicious advisors in each group and distribution

In fact, Figure 5.6 and Figure 5.7 show that TMAN can accurately evaluate the belief and disbelief of advisors, since the average accuracy of belief value for benevolent advisors is higher than their average accuracy of disbelief, as shown in Figure 5.6. On the other hand, the average accuracy of belief for malicious advisors is less than their average accuracy of disbelief, as shown in Figure 5.7.

Figure 5.8, Figure 5.9 and Figure 5.10 illustrate the total average accuracy of TMAN in computing reliability, unreliability, reputation, disrepute, belief and disbelief across all groups and distributions.

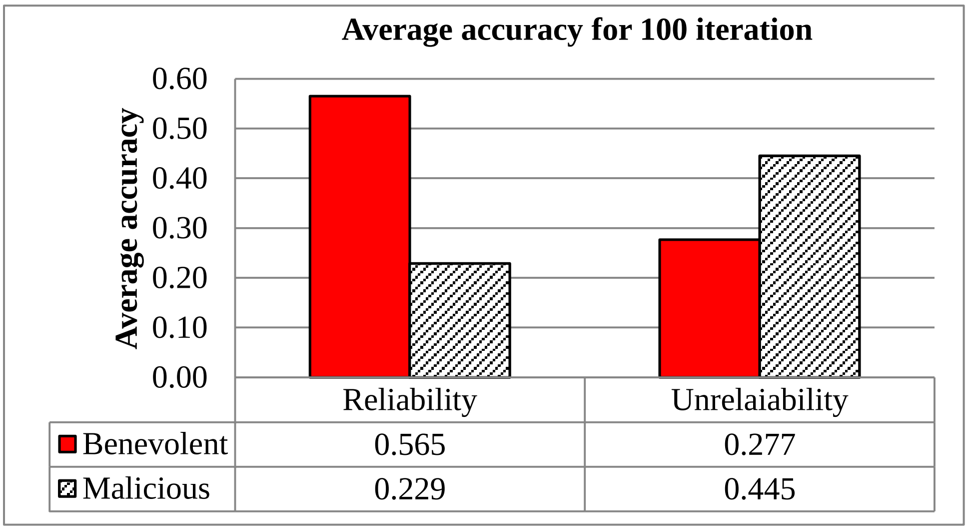


Figure 5.8: Average accuracy of reliability and unreliability for all groups and distributions of benevolent and malicious advisors

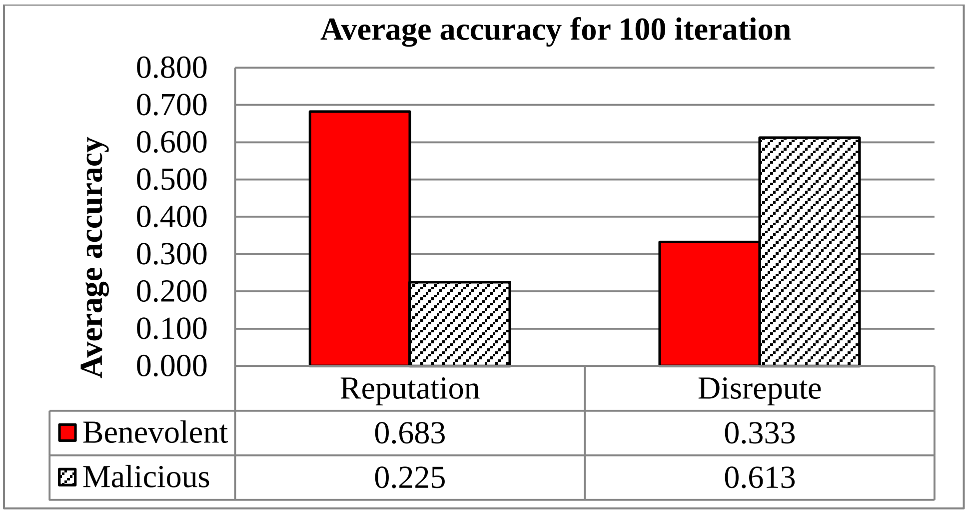


Figure 5.9: Average accuracy of reputation and disrepute for all groups and distributions of benevolent and malicious advisors

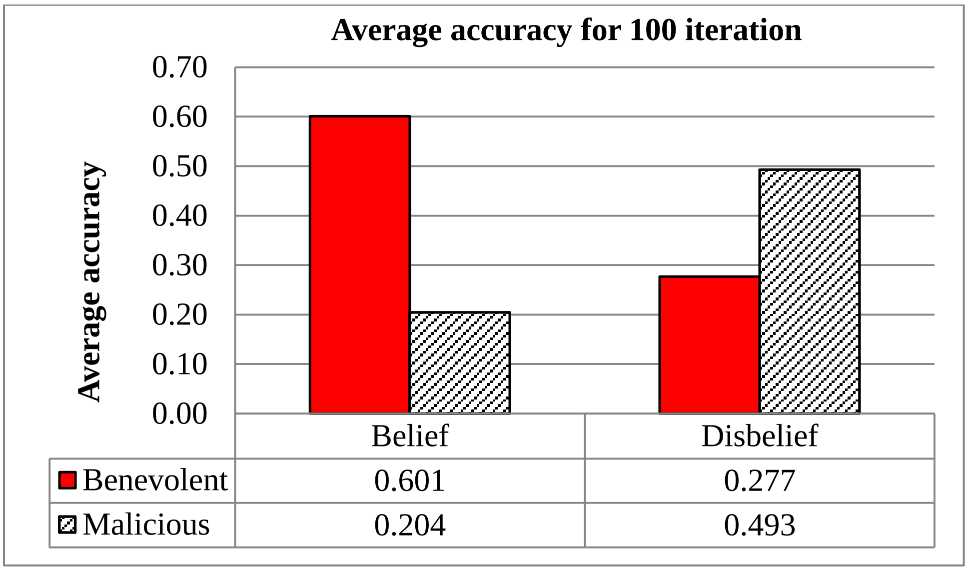


Figure 5.10: Average accuracy of belief and disbelief for all groups and distributions of benevolent and malicious advisors

Figures 5.8, 5.9, and 5.10 indicate TMAN met the research expectations in regard to calculating reliability, unreliability, reputation, disrepute belief and disbelief accurately.

In fact, experiment one studied the average accuracy of the TMAN components used in evaluating the trustworthiness of advisors. The results showed that TMAN can manage the expectations of these components in computing the reliability, unreliability, reputation, disrepute, belief and also disbelief of advisors. Thereby the proposed formulas for evaluating belief and disbelief of advisors can accurately calculate the trustworthiness of advisors

5.2.2 Experiment 1.2: Evaluation of the trustworthiness of providers

The trustworthiness of each provider is also based on belief, disbelief, uncertainty, and conflict. According to TMAN, the reliability and unreliability values of providers are zero, because the providers do not have any direct interactions with requester. Therefore, the value of belief for provider is calculated solely based on reputation, and disbelief is measured based on disrepute. In this experiment, the average accuracy of TMAN in evaluating the belief and disbelief of providers was examined. For instance, distribution two involved 50% trustworthy and 50% untrustworthy agents and the group one had 10 agents. Figure 5.11 shows a sample of simulated environment for distribution two, group one.

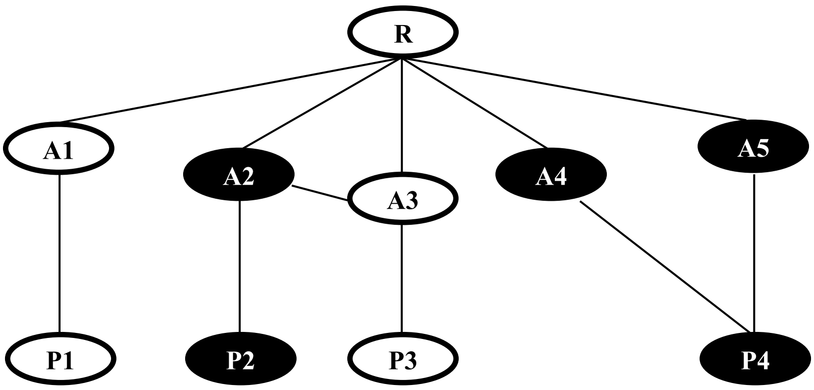


Figure 5.11:An example for experiment 1.1

As shown in Figure 5.11 trustworthy agents shows by the cycle white color, which selected randomly and untrustworthy agents selected by cycle black color. As shown in Table 4.5, group one was consisted of 1 requester, 5 advisors and 4 providers that was labeled in Figure 5.11. Requester had randomly relationship with advisors, advisors also had relationship with each other randomly, and each advisor had randomly relationship with one provider which was its suggested provider. By running the program, the satisfying, dissatisfying rates were given to each cycle randomly as shown in Table 5.2.

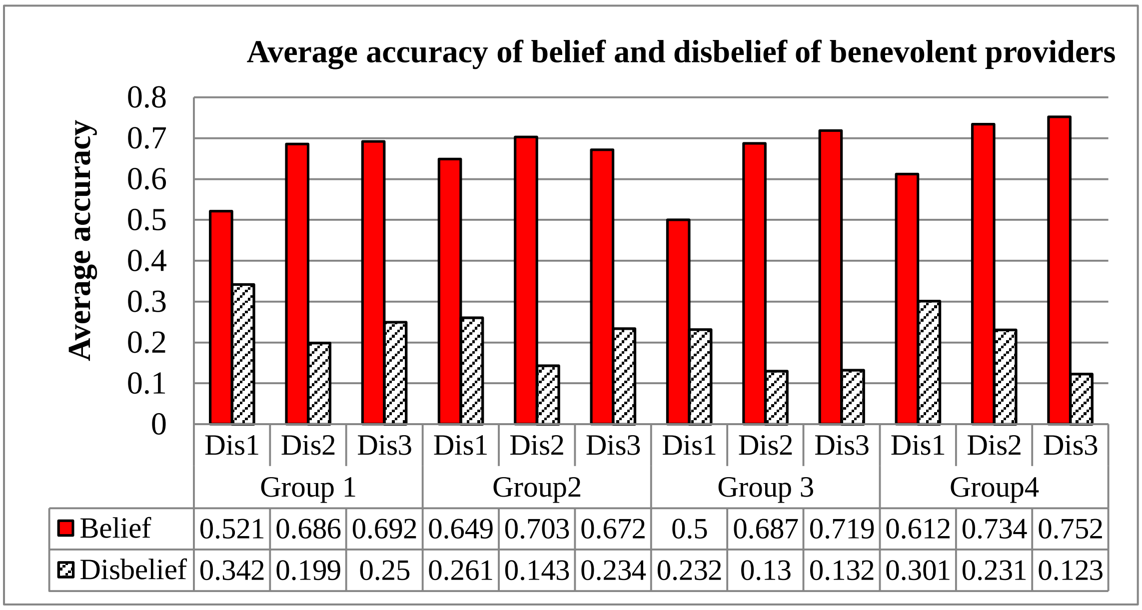
Table 5.2:An example of experimentation 1.1

Type of agent	**No of Interaction**	**Rate of interaction**
P1	1	0.675
P2	1	-0.432
P3	1	0.813
P4	1	-0.667

Table 5.2 shows random rate of satisfying and dissatisfying rates for providers used by presented formulas for calculating the trustworthiness of providers. In each time of running, this scenario was repeated 100 times, and the trustworthiness of providers wascomputed according to random satisfying and dissatisfying rates. The system proposed the average result after each ten times.

Similar to experiment one, the expectation in this evaluation is that the average accuracy of belief of benevolent providers is higher than the average accuracy of their disbelief. This experiment examined whether TMAN can address this expectation and compute the average accuracy of belief and disbelief for both benevolent and malicious providers accurately.

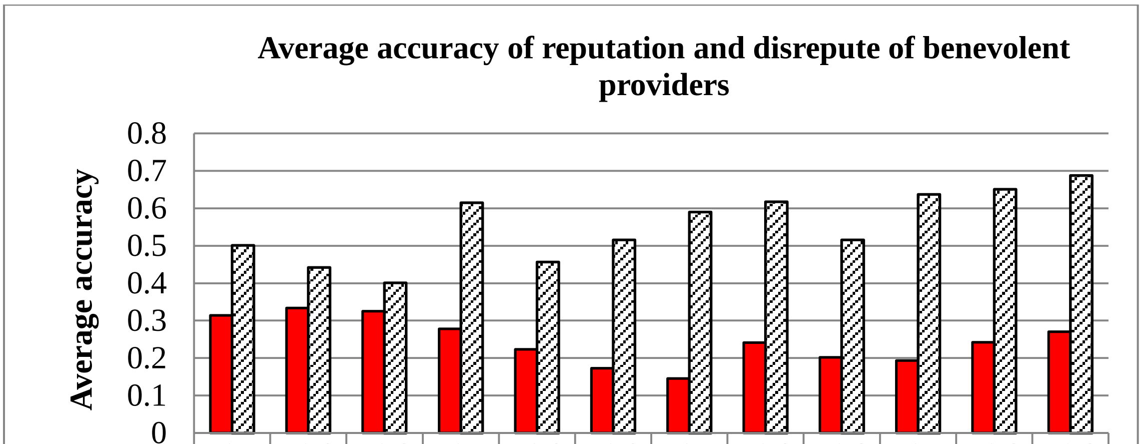
The evaluation result of belief and disbelief of benevolent providers is shown in Figure 5.12.



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Belief	0.521	0.686	0.692	0.649	0.703	0.672	0.5	0.687	0.719	0.612	0.734	0.752
Disbelief	0.342	0.199	0.25	0.261	0.143	0.234	0.232	0.13	0.132	0.301	0.231	0.123

Figure 5.12: Average accuracy of belief and disbelief of benevolent providers in each group and distribution

Moreover, the summary of the average accuracy of belief and disbelief of malicious agents is shown in Figure 5.13.



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Belief	0.314	0.333	0.325	0.278	0.224	0.173	0.146	0.241	0.202	0.193	0.243	0.271
Disbelief	0.501	0.443	0.401	0.616	0.457	0.516	0.59	0.618	0.516	0.638	0.651	0.688

Figure 5.13: Average accuracy of belief and disbelief of malicious providers in each group and distribution

Considering the expectation that the average accuracy of belief for benevolent providers should be higher than the average accuracy of disbelief, Figure 5.12 illustrates that TMAN achieved the expectation for benevolent providers. While the average accuracy of belief for malicious providers should be less than the average accuracy of their disbelief, Figure 5.13 shows that TMAN also managed to meet the expectation for malicious providers.

The total average accuracy of belief and disbelief for providers across all groups and distributions is denoted in Figure 5.14.

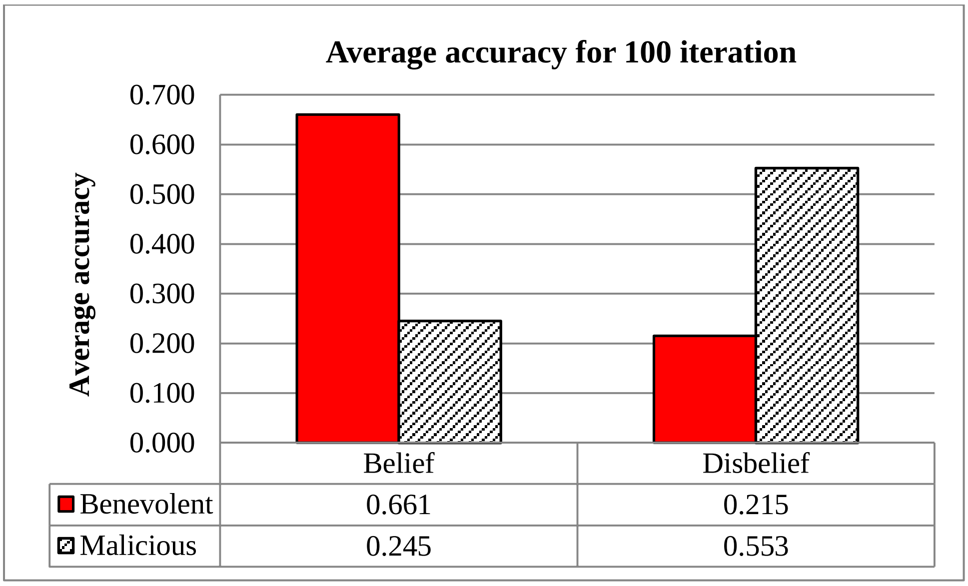


Figure 5.14: Total average accuracy of belief and disbelief across all groups

As shown in Figure 5.14, the total average accuracy of belief for benevolent providers is higher. Moreover, Figure 5.14 indicates that the total average accuracy of belief for malicious providers is less than the total average accuracy of their disbelief. Thus, this figure verifies that TMAN also evaluated the belief and disbelief of providers accurately.

5.2.3 Experiment 1.3: Trust transitivity between advisors and providers

Trust transitivity should evaluate the referral trust between advisors and their suggested provider. As discussed in Chapters 2 and 4, trust transitivity can combine and aggregate trustworthiness of advisors and providers. Thus, for assessing the average accuracy of trust transitivity in an advisor network by using TMAN, the combination and aggregation of advisors and their suggested provider were measured. The expectation was that just like experiments one and two, after transitivity of trust, the belief of benevolent providers should be higher than their disbelief, while the belief of malicious providers should be less than their disbelief values.

In this experiment, trust transitivity between advisors and providers was evaluated based on the average accuracy of TMAN in calculating trust transitivity.

For instance, distribution three, as shown in Table 4.4, consisted 70% of trustworthy agents, 30% untrustworthy ones and the group one involved 10 agents including 1 requester, 5 advisors and 4 providers. Figure 5.15 shows a sample of this simulated environment for distribution three, group one.

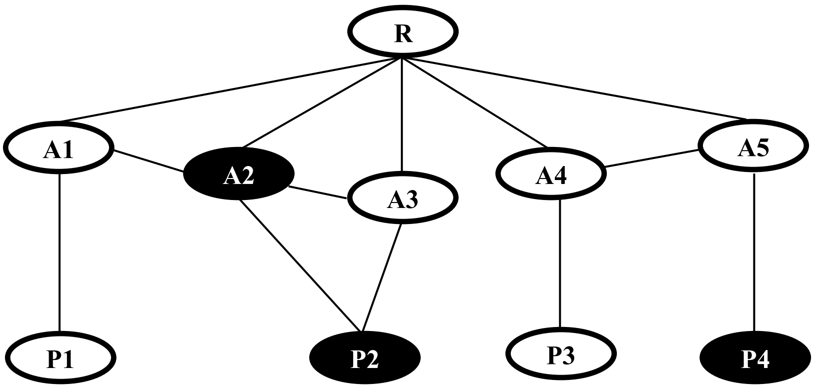


Figure 5.15: An example for experiment 1.3

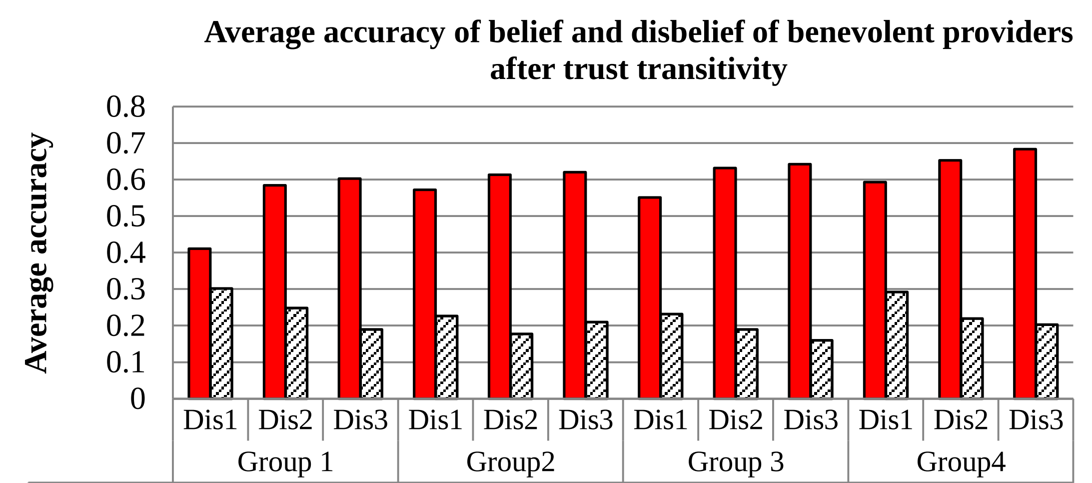
As shown in Figure 5.15 trustworthy agents were selected randomly and the system rated each cycle as satisfying and dissatisfying interactions which the white cycles show the trustworthy agents with satisfying rates, while black cycles illustrate dissatisfying interactions. Requester had randomly relationship with advisors, advisors also had random relationship with each other, and each advisor had random relationship with one provider which was its suggested provider. By running the program, the satisfying, dissatisfying rates randomly give to each advisor and provider as shown in Table 5.3.

Table 5.3:An example of experimentation 1.1

Agent	Interaction	Trustworthiness	Untrustworthiness	Uncertainty	Conflict
A1	1	0.865	0.342	0.216	0.853
A2	1	0.287	0.764	0.748	0.479
A3	1	0.765	0.354	0.248	0.736
A4	1	0.436	0.789	0.931	0.129
A5	1	0.783	0.327	0.878	0.256
P1	1	0.902	0.297	0.769	0.392
P2	1	0.459	0.643	0.527	0.748
P2	1	0.392	0.135	0.658	0.329
P3	1	0.482	0.768	0.842	0.118
P4	1	0.369	0.538	0.467	0.253

Table 5.3 shows trustworthiness, untrustworthiness, uncertainty and conflict of each agentTMAN used byrandom rate of satisfying and dissatisfying for each agents as were illustrated in Table 5.1 and 5.2. The calculated values for trustworthiness, untrustworthiness, uncertainty and conflict of agents were applied by presented formulas for calculating the trust transitivity of providers. This scenario was repeated 100 times. The result of trust transitivity of each provider in 100 times of interactionswas recorded and the system presented the average result after each ten times.

Figure 5.16 represents the average accuracy of belief and disbelief for benevolent providers achieved by transitivity of trust between advisors and their suggested providers.



	Group 1			Group2			Group 3			Group4		
	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3	Dis1	Dis2	Dis3
Belief	0.411	0.584	0.602	0.572	0.613	0.621	0.551	0.631	0.642	0.593	0.652	0.683
Disbelief	0.302	0.249	0.19	0.227	0.178	0.21	0.232	0.19	0.16	0.292	0.22	0.203

Figure 5.16: Average accuracy of belief and disbelief of benevolent providers after trust transitivity in each group and distribution

As shown in Figure 5.16, the average accuracy of belief for benevolent providers is higher than the average accuracy of their disbelief after trust transitivity. On the other hand, the average accuracy of belief and disbelief value for malicious providers after trust transitivity is illustrated in Figure 5.17.

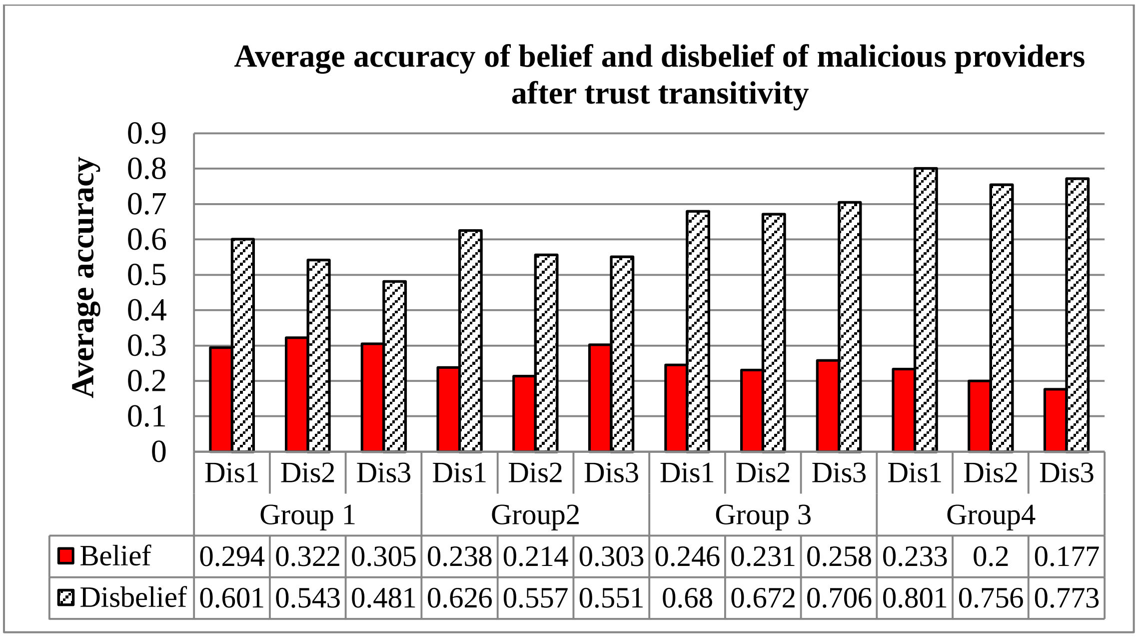


Figure 5.17: Average accuracy of belief and disbelief of malicious providers after trust transitivity in each group and distribution

Figure 5.17 denotes that the average accuracy of belief for malicious provider agents after trust transitivity is less than the average accuracy of disbelief.

Thereby, TMAN achieved the expectation for computing belief and disbelief of providers after trust transitivity, where it calculated belief value of malicious providers to be less than their disbelief values.

Comparing the differences between belief and disbelief in each group and distribution for benevolent and malicious agents is shown in Figure 5.18.

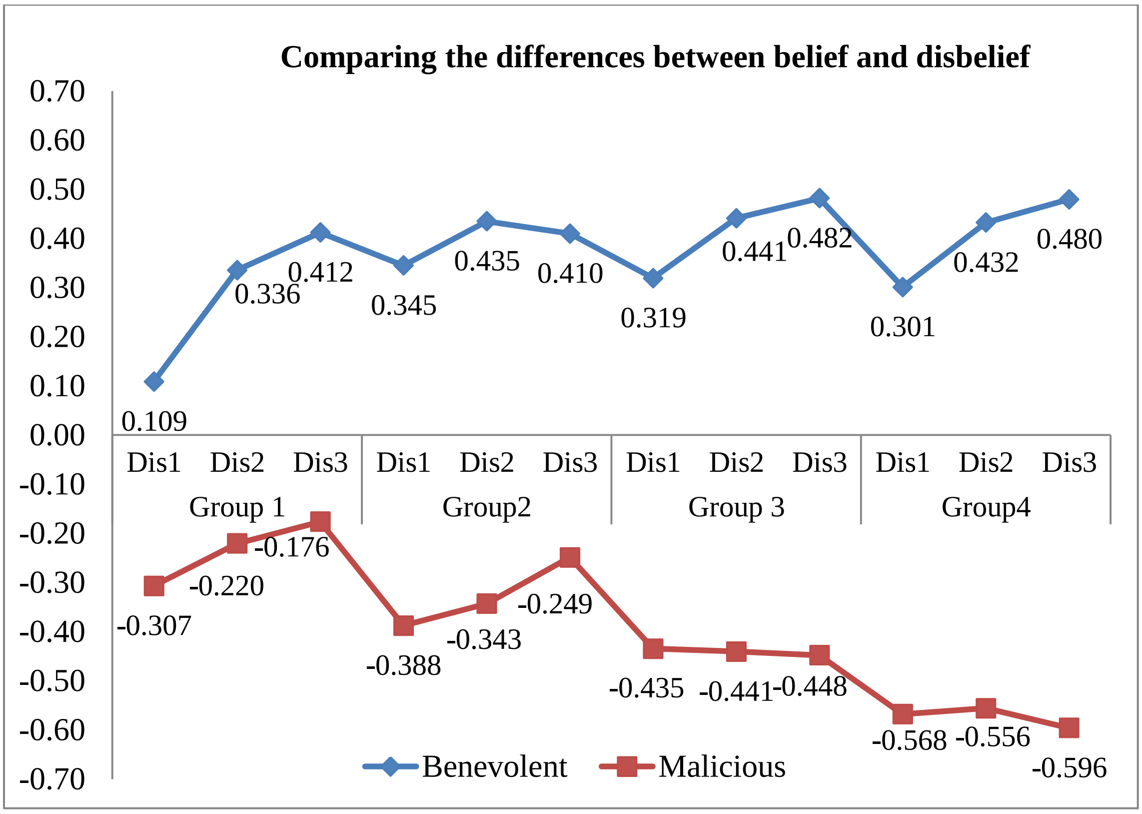


Figure 5.18: Comparing the differences between belief and disbelief of benevolent and malicious providers

As shown in Figure 5.18, the differences between belief and disbelief of benevolent advisors increased by growing the number of agents; group 4 with 20 advisors shows the highest differences between belief and disbelief values. However this increase is not steady. In fact, the peak points of this increase, which identified in Figure 5.18, happened in distribution three and two for benevolent agents with the same percentage of 50 percentages and 70 percentages benevolent, respectively, it is obvious that in these two distributions the numbers of benevolent agents were more than malicious ones, thereby the average accuracy of benevolent agents in these two groups are higher. In contrast, the peak points of malicious advisors happened in distribution one with 60 percentages malicious agents and 40 percentages benevolent, it is clear that because the number of malicious agents in this distribution was more than benevolent ones, the average accuracy in these points is higher. On the other hand the differences between belief and disbelief of malicious advisors increased by growing the number of agents. Thereby TMAN represents better performance in bigger multi-agent systems. In fact by increasing the number of agents in the simulated multi-agent environment, the accuracy of TMAN was more significant.

Figure 5.19 shows the comparison between the total average accuracy of belief and disbelief for benevolent providers and malicious ones across all groups and distributions.

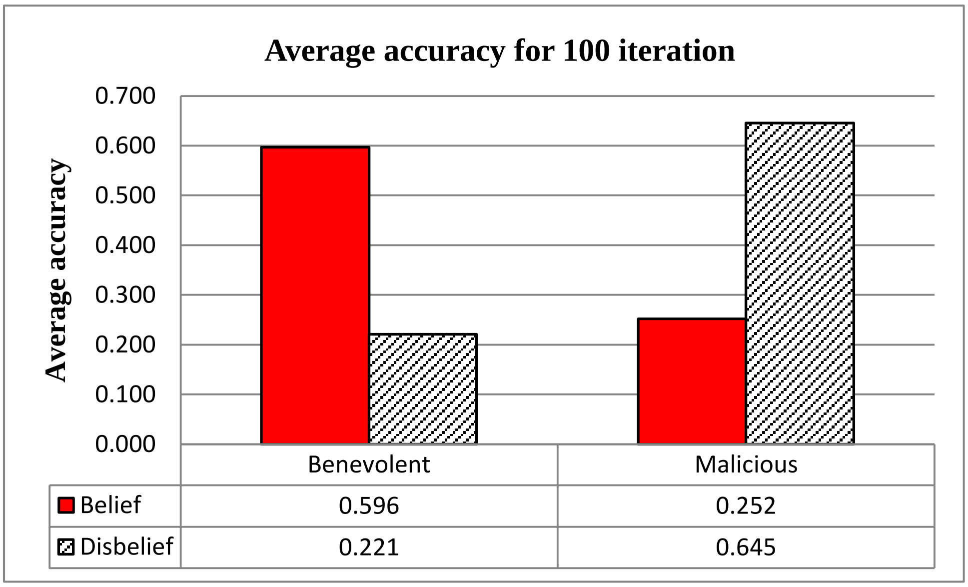


Figure 5.19: Total average accuracy of belief and disbelief after trust transitivity across all groups and distributions

Figure 5.19 verifies that TMAN accurately evaluated the belief and also disbelief of providers after trust transitivity. As shown in Figure 5.16, the average accuracy of belief for trustworthy providers is higher than the average accuracy of their disbelief, since the average accuracy of malicious providers is less than the average accuracy of their belief in all groups and distributions after trust transitivity.

Moreover, the differences between trustworthiness values of providers before and after trust transitivity are illustrated in Figure 5.20.

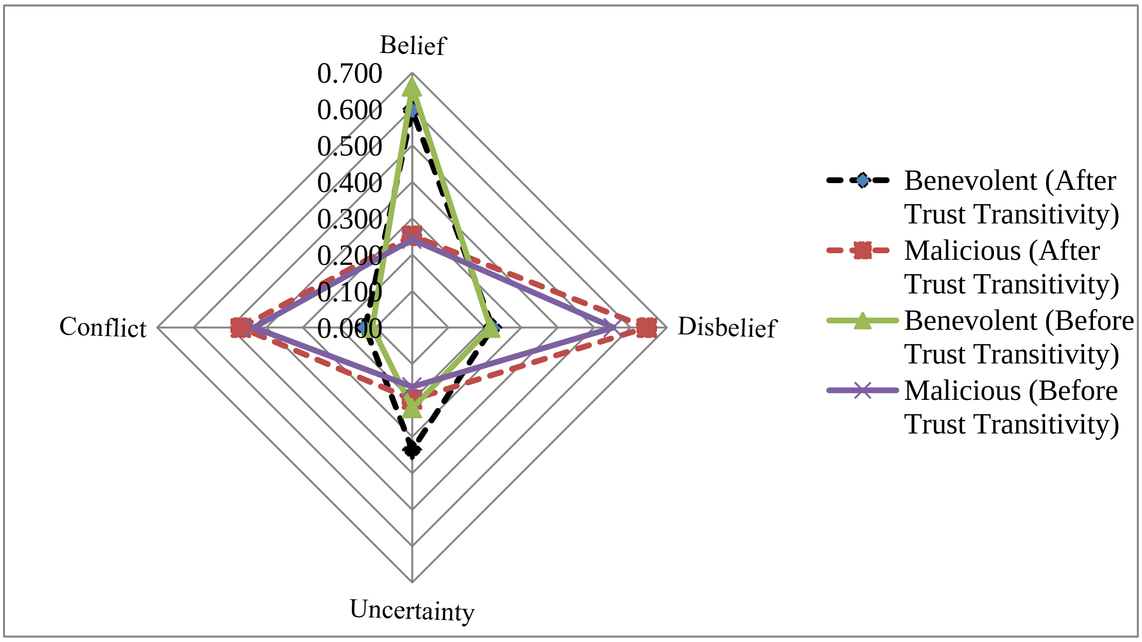


Figure 5.20: Differences in trustworthiness of providers before and after trust transitivity

Figure 5.20 illustrates that the trustworthiness of providers is affected by transitivity of trust, and the level of belief increased for benevolent provider while the level of disbelief increased for malicious provider agents. This result show that trust transitivity led to better recognition of benevolent and malicious providers, because the level of belief for benevolent providers increased while their level of belief for malicious advisors decreased.

5.2.4 Experiment 1.4: Comparing the performance of TMAN with other existing models

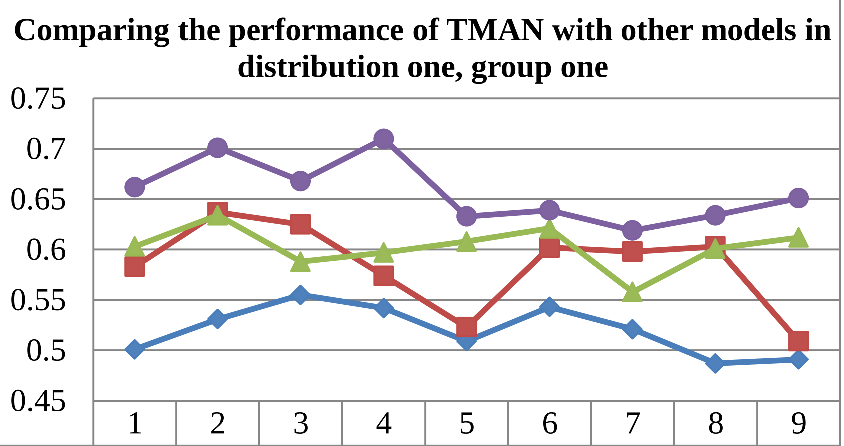
In the final part, the overall performance of TMAN was compared with the performance of the basic model and two other alternative models: Evidence-based trust model (Wang & Singh, 2010), and TREPPS (Li & Kao, 2009). The basic model is a model without a specific trust mechanism. In this case, requester sends a query to advisors; if an advisor has had previous interactions with providers, it will respond to the requester and recommends a suitable provider. The basic model is the model that does not apply any trust mechanism; the requester makes a decision based on the number of recommendations for each provider and selects the provider which has the most number of recommendations.

On the other hand, the Evidence-based trust model (Wang & Singh, 2010) and TREPPS model (Li & Kao, 2009) are two selected models which were appropriate for comparison with TMAN. The method of computing several identified components that presented by these two models were described in Chapter 2.

5.2.4.1 Experiment 1.4.1: Comparing the performance of TMAN with other comparable models according to group one

In this experiment, the aggregated results of comparing the performance of TMAN with three other comparable models, namely the basic model, TREPPS model, and Evidence-based trust model are presented for group one with five advisors, as shown in Table 4.4.

For instance, for comparing TMAN against Evidence-based trust model (Wang & Singh, 2010), TREPPS model(Li & Kao, 2009), and basic model in distribution one, group one with 60% untrustworthy agents and 1 requester, 5 advisors, and 4 providers the satisfying and dissatisfying rates, in addition to the preferences for agents were given randomly by the system. Then these random values were used by TMAN, Evidence-based trust model, TREPPS model, and basic model to select the most trustworthy agents in 100 times of interaction. The average result of comparing in each ten interactions was recorded and presented by system. Figure 5.21 shows a sample of result for distribution one group one.



	1	2	3	4	5	6	7	8	9
BASIC	0.501	0.531	0.555	0.542	0.509	0.543	0.521	0.487	0.491
Evidence-Based Trust	0.583	0.637	0.625	0.574	0.523	0.602	0.598	0.603	0.509
TREPPS	0.603	0.634	0.588	0.597	0.608	0.621	0.558	0.601	0.612
TMAN	0.662	0.701	0.668	0.71	0.633	0.639	0.619	0.634	0.651

Figure 5.21 An example for experiment 1.4

As shown in Figure 5.21, TMAN had better performance than other compared models. This scenario repeated ten times for distribution one group one and the average of these results are revealed as the comparison of TMAN performance than other compared models.

Table 5.4 illustrates the summary results that compare TMAN with other models in group one with three different distributions.

Table 5.4: Results of comparing TMAN with other comparable models in group one

Distribution one										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.411	0.522	0.481	0.573	0.585	0.498	0.479	0.51	0.511	0.586
TREPPS	0.621	0.59	0.632	0.587	0.603	0.591	0.623	0.578	0.582	0.614
Evidence-based trust	0.59	0.579	0.531	0.561	0.601	0.569	0.499	0.568	0.531	0.61
TMAN	0.63	0.588	0.671	0.645	0.62	0.635	0.641	0.634	0.621	0.61
Distribution two										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.531	0.456	0.487	0.528	0.501	0.505	0.547	0.581	0.493	0.517
TREPPS	0.589	0.613	0.643	0.59	0.641	0.564	0.598	0.61	0.645	0.61
Evidence-based trust	0.546	0.578	0.621	0.578	0.531	0.499	0.561	0.61	0.587	0.568
TMAN	0.61	0.624	0.64	0.593	0.672	0.598	0.614	0.658	0.672	0.689
Distribution three										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.514	0.498	0.417	0.531	0.587	0.521	0.601	0.571	0.521	0.49
TREPPS	0.607	0.651	0.598	0.61	0.674	0.631	0.647	0.603	0.631	0.598
Evidence-based trust	0.542	0.567	0.593	0.621	0.573	0.497	0.531	0.578	0.612	0.542
TMAN	0.631	0.678	0.613	0.687	0.704	0.638	0.653	0.614	0.678	0.702

As shown in Table 5.4, the average accuracy of TMAN in selecting the trustworthy provider in almost all iterations is higher than that of other selected models.

Additionally, the analysis of variance (ANOVA) was applied for comparing the performance of TMAN with that of the comparable models. Table 5.5 shows the results of the ANOVA test for investigating the significant of the TMAN performance than the performance of the other comparable models.

Table 5.5: The result of the ANOVA test in comparing the significance of TMAN performance with the performance of other comparable models

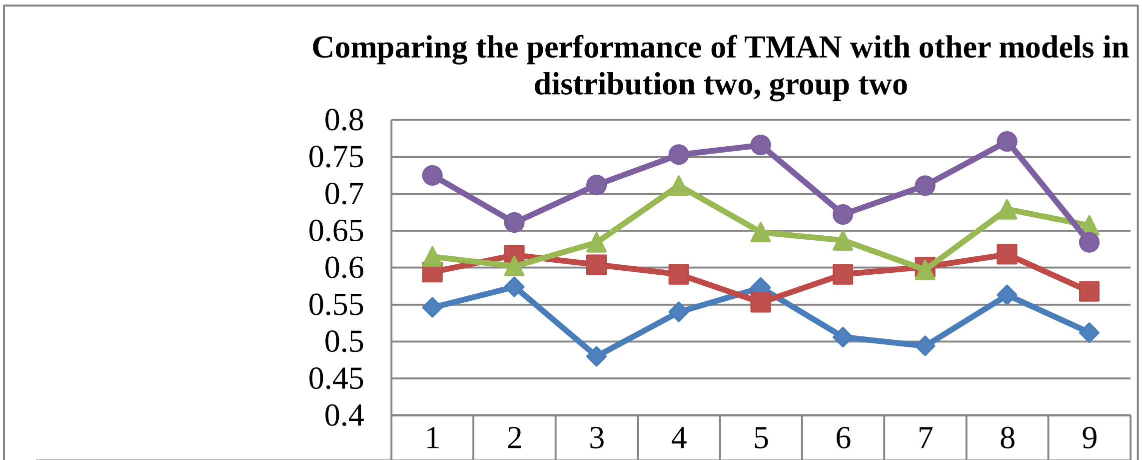
Models	**F**	**P-value**
Basic model	140.5439	P<0.001
TREPPS model	15.53804	0.00022
Evidence-based trust model	75.02138	P<0.001

Table 5.5 denotes that the difference in P-value between the comparable models and TMAN is less than 0.05. Overall, these results can verify that TMAN performed significantly better than all comparable models across group one.

5.2.4.2 Experiment 1.4.2: Comparing the performance of TMAN with other comparable models according to group two

In this experiment, the aggregated results of comparing the performance of TMAN with that of three other models are examined using the three types of distributions, For instance, for comparing TMAN against Evidence-based trust model

(Wang & Singh, 2010), TREPPS model, and basic model in distribution two, group two with 50% untrustworthy agents and 1 requester, 10 advisors, and 9 providers the satisfying and dissatisfying interactions as shown, in addition to the preferences for agents selected randomly by the system. Then these random values used by the formulas which presented by TMAN, Evidence-based trust model, TREPPS model, and basic model to select the most trustworthy agents in 100 times of interactions result of comparing TMAN against other models in each ten interactions recorded and presented by system. Figure 5.22 shows a sample of result for distribution two, group two.



	1	2	3	4	5	6	7	8	9
BASIC	0.546	0.574	0.48	0.54	0.573	0.506	0.494	0.563	0.512
Evidence-Based Trust	0.594	0.617	0.604	0.591	0.553	0.591	0.601	0.618	0.5677
TREPPS	0.615	0.602	0.634	0.711	0.648	0.637	0.597	0.679	0.657
TMAN	0.725	0.661	0.712	0.753	0.766	0.672	0.711	0.771	0.634

Figure 5.22 An example for experimentation

As shown in Figure 5.22, TMAN had better performance than other compared models. This scenario repeated ten times for distribution one, group one and the average of these results are revealed as the comparison result of TMAN performance than other compared models.

The summary of results for each distribution in group two is shown in Table 5.6.

Table 5.6: Results of comparing TMAN with other comparable models in group two

Distribution one										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.502	0.543	0.568	0.532	0.498	0.543	0.528	0.497	0.423	0.553
TREPPS	0.657	0.698	0.621	0.655	0.598	0.601	0.542	0.591	0.654	0.634
Evidence-based trust	0.543	0.657	0.647	0.574	0.502	0.612	0.598	0.613	0.489	0.599
TMAN	0.672	0.721	0.671	0.71	0.653	0.62	0.61	0.634	0.671	0.632
Distribution two										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.557	0.546	0.574	0.476	0.54	0.593	0.432	0.498	0.563	0.512
TREPPS	0.675	0.642	0.671	0.654	0.587	0.675	0.613	0.597	0.632	0.629
Evidence-based trust	0.568	0.589	0.568	0.498	0.597	0.61	0.587	0.547	0.598	0.549
TMAN	0.67	0.69	0.713	0.678	0.654	0.679	0.71	0.621	0.675	0.687
Distribution three										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.497	0.534	0.506	0.478	0.519	0.567	0.589	0.499	0.518	0.583
TREPPS	0.61	0.625	0.667	0.612	0.627	0.598	0.622	0.638	0.643	0.597
Evidence-based trust	0.576	0.601	0.578	0.633	0.614	0.589	0.61	0.558	0.651	0.579
TMAN	0.621	0.631	0.685	0.619	0.622	0.637	0.681	0.714	0.698	0.61

Table 5.6 shows that the simulation results for ten advisors also revealed that TMAN has better performance than other comparable models. Moreover, the ANOVA test was done to discover the significance of TMAN performance in comparison with other selected models. Tables 5.7 illustrate the results of the ANOVA test for TMAN and three other comparable models.

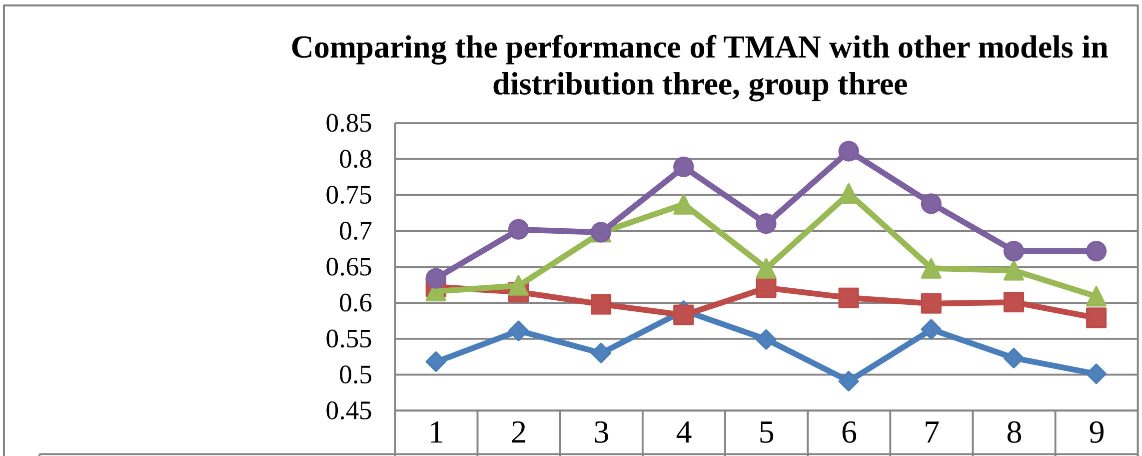
Table 5.7: Results of the ANOVA test in comparing the performance of TMAN with the other comparable models

Models	F	P-value
Basic model	189.3486	P<0.001
TREPPS model	15.04805	0.00027
Evidence-based trust model	62.75906	P<0.001

Table 5.7 shows that the difference in P-value between the significance of the compared models and TMAN is less than 0.05; hence, TMAN also performed significantly better than the other comparable models in group two.

5.2.4.3 Experiment 1.4.3: Comparing the performance of TMAN with other comparable models according to group three

In experiment 1.4.3, the aggregated results of comparing the performance of TMAN with that of three other comparable models in group three. For instance, for comparing TMAN against Evidence-based trust model (Wang & Singh, 2010), TREPPS model, and basic model in distribution one group one with 30% untrustworthy agents and 1 requester, 15 advisors, and 14 providers the satisfying and dissatisfying interactions as shown, in addition to the preferences for agents selected randomly by the system. Then these random values used by the formulas which presented by TMAN, Evidence-based trust model, TREPPS model, and basic model to select the most trustworthy agents in 100 times of interactions result of comparing TMAN against other models in each ten interactions recorded and presented by system. Figure 5.23 shows a sample of result for distribution three, group three.



	1	2	3	4	5	6	7	8	9
BASIC	0.518	0.561	0.53	0.589	0.549	0.491	0.563	0.523	0.501
Evidence-Based Trust	0.622	0.615	0.598	0.583	0.621	0.607	0.599	0.601	0.579
TREPPS	0.616	0.624	0.698	0.737	0.648	0.752	0.648	0.645	0.609
TMAN	0.634	0.702	0.698	0.789	0.71	0.811	0.738	0.672	0.672

Figure 5.23 An example for experimentation

As shown in Figure 5.23, TMAN had better performance than other compared models. This scenario repeated ten times for distribution three, group three and the average of these results are revealed as the comparison result of TMAN performance than other compared models. The summary of results for group three is illustrated in Table 5.8.

Table 5.8: Results of comparing TMAN with other comparable models in group three

Distribution one										
Iteration / **Models**	10	20	30	40	50	60	70	80	90	100
Basic	0.452	0.561	0.558	0.469	0.561	0.601	0.519	0.589	0.567	0.504
TREPPS	0.593	0.572	0.587	0.595	0.57	0.597	0.579	0.601	0.595	0.6
Evidence-based trust	0.578	0.569	0.619	0.577	0.591	0.517	0.61	0.623	0.578	0.637
TMAN	0.631	0.657	0.761	0.701	0.721	0.711	0.742	0.719	0.802	0.761
Distribution two										
Iteration / **Models**	10	20	30	40	50	60	70	80	90	100
Basic	0.541	0.587	0.501	0.453	0.531	0.546	0.511	0.471	0.423	0.538
TREPPS	0.554	0.589	0.601	0.536	0.52	0.501	0.55	0.547	0.571	0.543
Evidence-based trust	0.595	0.602	0.634	0.661	0.598	0.617	0.577	0.59	0.571	0.601
TMAN	0.615	0.713	0.765	0.81	0.792	0.783	0.795	0.681	0.71	0.801
Distribution three										
Iteration / **Models**	10	20	30	40	50	60	70	80	90	100
Basic	0.517	0.568	0.537	0.593	0.517	0.498	0.565	0.541	0.502	0.481
TREPPS	0.59	0.542	0.602	0.537	0.531	0.598	0.604	0.597	0.611	0.572
Evidence-based trust	0.567	0.603	0.578	0.617	0.631	0.584	0.638	0.61	0.573	0.617
TMAN	0.634	0.702	0.698	0.791	0.71	0.811	0.748	0.672	0.63	0.698

This experiment was carried out for group three with fifteen advisors as shown in Table 5.8. Similar to the results of experiments 1.4.1 and 1.4.2, the performance of

TMAN was better than that of other models. The ANOVA test results show the significance of TMAN rather than other comparable models as shown in Tables 5.9.

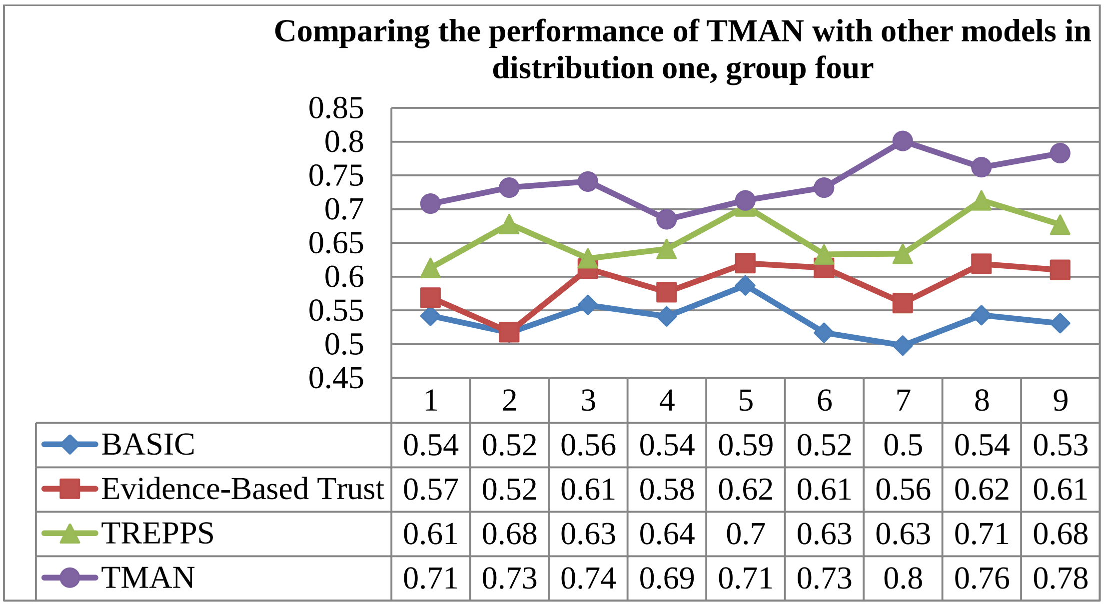
Table 5.9: The result of the ANOVA test in comparing the performance of TMAN with the other comparable models

Models	**F**	**P-value**
Basic model	215.5812	P<0.001
TREPPS model	74.56117	0.000276
Evidence-based trust model	113.131	P<0.001

As shown in Tables 5.9, the P-value of all compared models is less than 0.05. Therefore, TMAN performed significantly better than other comparable models in group three.

5.2.4.4 Experiment 1.4.4: Comparing the performance of TMAN with other comparable models according to group four

In the final experiment, the aggregated results of comparing the performance of TMAN with that of three other comparable models by employing twenty advisors were examined. For instance, for comparing TMAN against Evidence-based trust model (Wang & Singh, 2010), TREPPS model, and basic model in distribution one, group four with 60% untrustworthy agents and 1 requester, 20 advisors, and 19 providers the satisfying and dissatisfying interactions as shown, in addition to the preferences for agents selected randomly by the system. Then these random values used by the formulas which presented by TMAN, Evidence-based trust model, TREPPS model, and basic model to select the most trustworthy agents in 100 times of interactions result of comparing TMAN against other models in each ten interactions recorded and presented by system. Figure 5.24 shows a sample of result for distribution one, group four.



	1	2	3	4	5	6	7	8	9
BASIC	0.54	0.52	0.56	0.54	0.59	0.52	0.5	0.54	0.53
Evidence-Based Trust	0.57	0.52	0.61	0.58	0.62	0.61	0.56	0.62	0.61
TREPPS	0.61	0.68	0.63	0.64	0.7	0.63	0.63	0.71	0.68
TMAN	0.71	0.73	0.74	0.69	0.71	0.73	0.8	0.76	0.78

Figure 5.24 An example for experimentation

As shown in Figure 5.24, TMAN had better performance than other compared models. This scenario repeated ten times for distribution four, group four and the average of these results are revealed as the comparison result of TMAN performance than other compared models.

The summary of results for final group is illustrated in Table 5.10.

Table 5.10: Results of comparing TMAN with other comparable models in group four

Distribution one:										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.583	0.524	0.574	0.511	0.561	0.518	0.497	0.527	0.539	0.498
TREPPS	0.583	0.524	0.574	0.511	0.561	0.518	0.497	0.527	0.539	0.498
Evidence-based trust	0.563	0.634	0.598	0.567	0.598	0.61	0.528	0.601	0.632	0.587
TMAN	0.702	0.721	0.692	0.689	0.718	0.729	0.776	0.738	0.8	0.797
Distribution two										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.501	0.498	0.509	0.542	0.511	0.579	0.551	0.491	0.589	0.505
TREPPS	0.501	0.498	0.509	0.542	0.511	0.579	0.551	0.491	0.589	0.505
Evidence-based trust	0.599	0.614	0.599	0.658	0.578	0.608	0.593	0.562	0.601	0.579
TMAN	0.689	0.731	0.703	0.678	0.684	0.679	0.71	0.621	0.675	0.752
Distribution three										
Iteration / Models	10	20	30	40	50	60	70	80	90	100
Basic	0.409	0.581	0.552	0.538	0.586	0.487	0.54	0.527	0.587	0.409
TREPPS	0.409	0.581	0.552	0.538	0.586	0.487	0.54	0.527	0.587	0.409
Evidence-based trust	0.551	0.591	0.605	0.609	0.598	0.571	0.614	0.612	0.565	0.61
TMAN	0.678	0.721	0.755	0.801	0.778	0.693	0.653	0.705	0.789	0.725

In overall, TMAN shows better performance than the other comparable models in almost all iterations. The results of the ANOVA test for the group four are illustrated in Table 5.11.

Table 5.11: The result of the ANOVA test in comparing the performance of TMAN with the other comparable models

Models	F	P-value
Basic model	290.8012	P<0.001
TREPPS model	165.3442	P<0.001
Evidence-based trust model	171.5978	P<0.001

Tables 5.11 denote that TMAN performed significantly better than other models in group four, because the P-value of all compared models is less than 0.05.

In fact, the Basic model selected the trustworthy provider without considering the following main components: similarity, trust transitivity as well as the belief and disbelief of agents established based on satisfying and dissatisfying previous interactions. Similarly, the performance of the Evidence-based trust model is also significantly poorer than the performance of TMAN, in all distributions and groups. The model presented a proper formula for evaluating the uncertainty and conflict in behaviors of agents based on the satisfying and dissatisfying previous interactions of each agent, and it also measured trust transitivity between agents; however, it did not compute reliability, reputation, unreliability, and disrepute of agents established based on satisfying and dissatisfying previous interactions. Moreover, Evidence-based trust model ignored the similarity between two agents. In contrast, TREPPS computed reliability, satisfaction, similarity and trust transitivity; however, the computations are based on previous satisfying interactions only, and hence the unreliability, disrepute and uncertainty of each agent were not evaluated. Moreover, it measured the similarity of the recommendations of agents by computing the similarity between two fuzzy variables, without noting the preferences between advisors and requester.

Therefore, the overall results indicated that TMAN model's accuracy is significantly better than that of the other comparable models, across all groups. This is because the proposed model focus has been to propose a trust model for advisor agents. In fact evaluates the trustworthiness of advisors and try to select the most trustworthy provider according to advice of benevolent advisors, especially when the requester has no relationship with providers. On the other hand, the proposed model evaluates vital components, which are: i) similarity between agents based on the preferences of each agent in different criteria; ii) trust transitivity between agents; iii) unreliability and disrepute of agents based on dissatisfying previous interactions separating from the formulas which used for evaluating reliability and reputation, respectively; and v) incorporation of these components and selection of the most trustworthy provider by using the TOPSIS method.

5.3 Part 2: Evaluation of TMAN with the trust network game method

As described in Section 4.4.2, TNG was run on different parameter settings. In fact, the scores that TNG identified after each interaction for each agent were recorded and used as satisfaction and dissatisfaction ratings for that agent. Then by running TMAN, the trustworthiness of each advisor and provider was calculated, and the most trustworthy provider was selected. The scores presented by TNG after iteration and the trustworthiness computed by TMAN were compared to investigate how well TMAN can calculate the trustworthiness of each advisor and also its suggested provider. As described in Section 4.4.2, three different behaviors were considered for agents to investigate the performance of TMAN. In fact, two agents, one advisor and its suggested provider, behaved consistently during iteration and two agents behaved mild oscillating and two others had strong oscillating behaviors.

5.3.1 Experiment 2.1: Accuracy of TMAN in evaluating the trustworthiness of agents

As described in Section 4.4.2, TNG was run on different parameter settings. In fact, the scores that TNG identified after each interaction for each agent were recorded and used as satisfaction and dissatisfaction ratings for that agent. Then by running TMAN, the trustworthiness of each advisor and provider was calculated, and the most trustworthy provider was selected. The scores presented by TNG after iteration and the trustworthiness computed by TMAN were compared to investigate how well TMAN can calculate the trustworthiness of each advisor and also its suggested provider. As described in Section 4.4.2, three different behaviors were considered for agents to investigate the performance of TMAN. In fact, two agents, one advisor and its suggested provider, behaved consistently during iteration and two agents behaved mild oscillating and two others had strong oscillating behaviors.

5.3.1.1 Experiment 2.1.1: Consistent behaviors

In this experiment, the trustworthiness for one advisor and its suggested provider are investigated in light of the results obtained from TNG and TMAN after iteration. For instance the behavior of advisor in consistent environment presented by TNG, after running it for fifteen trades between requester and advisor as shown in Table 5.12

Table 5.12: A sample of advisor behavior in consistent TNG environment

Number of interactions	Actual behavior of advisor
Interaction 1	0.02
Interaction 2	0.02
Interaction 3	0.02
Interaction 4	0.02
Interaction 5	0.02
Interaction 6	0.02
Interaction 7	0.02
Interaction 8	0.02
Interaction 9	0.02
Interaction 10	0.02
Interaction 11	0.02
Interaction 12	0.02
Interaction 13	0.02
Interaction 14	0.02
Interaction 15	0.02

Table 5.12 illustrates that the advisor had satisfying interactions in all fifteen trades because the presented results by TNG were positive. Since the experiment 2.1.1 was based on the consistent multi-agent environment, the advisor could not change its behavior during fifteen trades. In fact,TNG outcomes showed that the actual behavior of the advisor during these trades and TMAN used these outcomes, which presented in Table 5.12, as satisfying rates, while dissatisfying rates were zero because advisor had positive outcomes during all interactions, so the advisor traded without cheating. By applying these outcomes through TMAN, the expectation was that TMAN can propose the accurate results in calculated belief and disbelief of the advisor. Thereby the belief value of this advisor which was computed by TMAN should be consistent during fifteen interactions while disbelief valued of the advisor should be zero.

Figures 5.25 illustrate the comparison between the scores presented by TNG and trustworthiness of **advisors A** with consistent behavior during the all interactions.

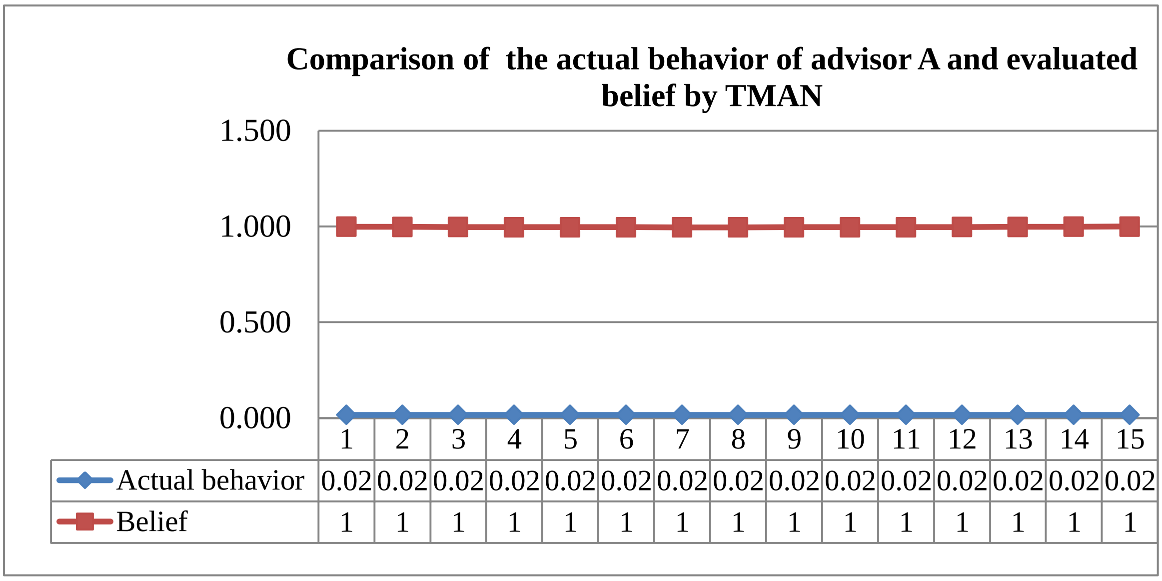


Figure 5.25: Comparison of the actual behavior of advisor A and its belief computed by TMAN (Oscillating rating =0)

According to Figure 5.25, the score of advisor A during interactions with requester wasstable and it gained the same score in iteration,because the advisor A had consistent behavior, the belief values for this advisor also remained approximately steady with the standard deviation of 0.001, and mean absolute difference between actual behavior and the belief computed by TMAN is 0.001. Thereby, Figure 4.18 revealed that the calculation mechanism of TMAN calculated belief that reflects the likelihood of actual behavior with approximately 100% accuracy for iteration.

Moreover, Figure 5.26 shows the comparison result for provider A which has consistent behavior with zero oscillate rating. The advisor which suggested this provider also behaved consistently during the interactions.

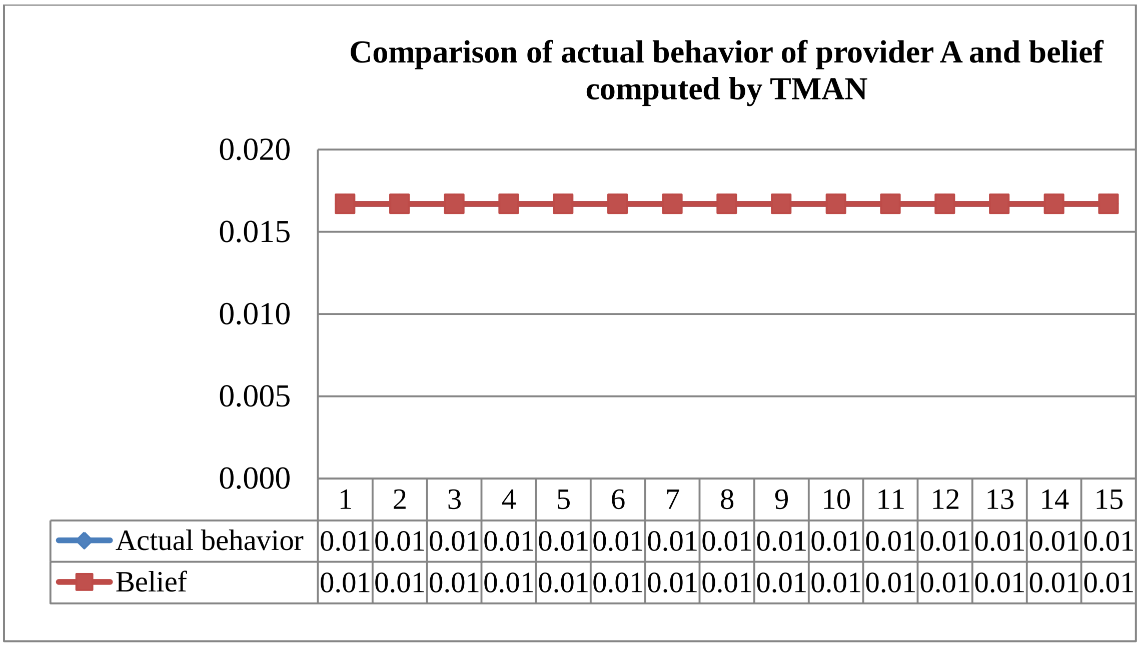


Figure 5.26: Comparison of the actual behavior of advisor A and its belief computed by TMAN (Oscillating rating =0)

Figure 5.26 also demonstrated that the calculation mechanism of TMAN proposed belief that reflects the likelihood of actual behavior of 100% accuracy for provider A. In fact the mean absolute difference between actual behavior and belief calculated by TMAN is zero.

Moreover, because the advisor A and its suggested provider A displayed satisfying behavior in all iterations, disbelief values of them are zero.

5.3.1.2 Experiment 2.1.2: Slightly oscillating behaviors

In this experiment, the trustworthiness for one advisor and its suggested provider are examined in light of the results obtained from TNG and TMAN for mild oscillating behaviors of agents.

For instance the behavior of advisor in mild oscillating environment, which were presented by TNG, for fifteen trades between requester and advisor had mildly changes, as shown in Table 5.13

Table 5.13: A sample of advisor behavior in mild oscillating TNG environment

Number of interactions	Actual behavior of advisor
Interaction 1	1
Interaction 2	1
Interaction 3	1
Interaction 4	1
Interaction 5	1
Interaction 6	1
Interaction 7	1
Interaction 8	1
Interaction 9	1
Interaction 10	1
Interaction 11	1
Interaction 12	0.099
Interaction 13	1
Interaction 14	-0.016
Interaction 15	-0.016

Table 5.13shows that the advisor had negative outcomesin thirteen trades. These trades illustrate the satisfying interactions, then the advisor changed its behaviormildly to negative outcomes means dissatisfying interactions in the last two trades. In fact, TNG outcomes revealed the actual behavior of the advisor during the fifteen trades and TMAN used these outcomes, which presented in Table 5.13, as satisfying and dissatisfying rates for the advisor and calculated the belief and disbelief of that advisor in each interaction.

Figure 5.27represents comparison of actual behavior of advisor B with mild oscillating behavior with belief and disbelief computed by TMAN.

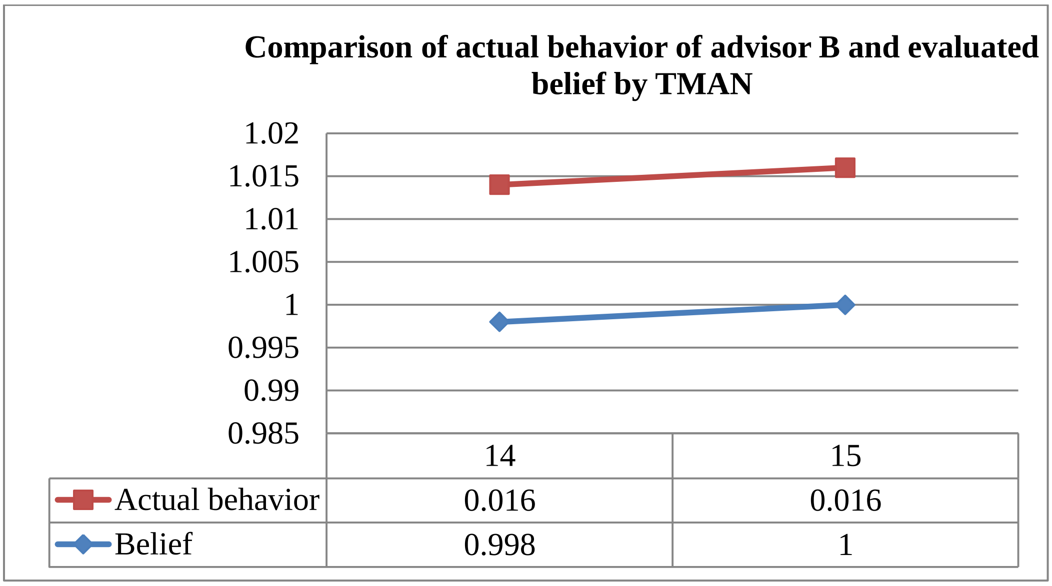
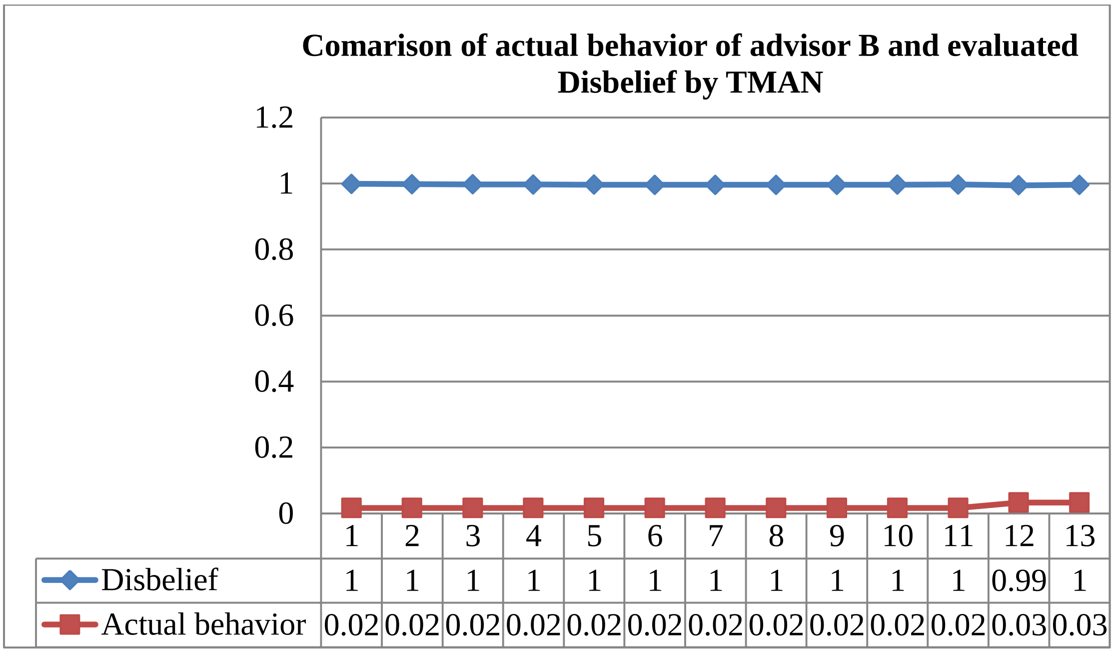


Figure 5.27: Comparison of the actual behavior of advisor B and its belief computed by TMAN (Oscillating rating =0.05)

As shown in Figure 5.27advisor B had mild oscillating behaviors in iteration 14 and 15. This figure illustrated that the calculation mechanism of TMAN calculated belief that reflects the likelihood of actual behavior with approximately 100% accuracy for iteration with mean absolute difference of 0.001.

On the other hand, Figure 5.28 denotes the comparison of actual behavior of advisor B and disbelief computed by TMAN



	1	2	3	4	5	6	7	8	9	10	11	12	13
Disbelief	1	1	1	1	1	1	1	1	1	1	1	0.99	1
Actual behavior	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03

Figure 5.28: Comparison of the actual behavior of advisor B and its disbelief computed by TMAN (Oscillating rating =0.05)

The mean absolute difference between actual behavior of advisor B and its disbelief computed by TMAN is 0.004, which indicates that TMAN computed disbelief reflects the likelihood of actual behavior with approximately 100% accuracy for iteration.

Figure 5.29 shows the comparison for the suggested provider B with mild oscillating behaviors.

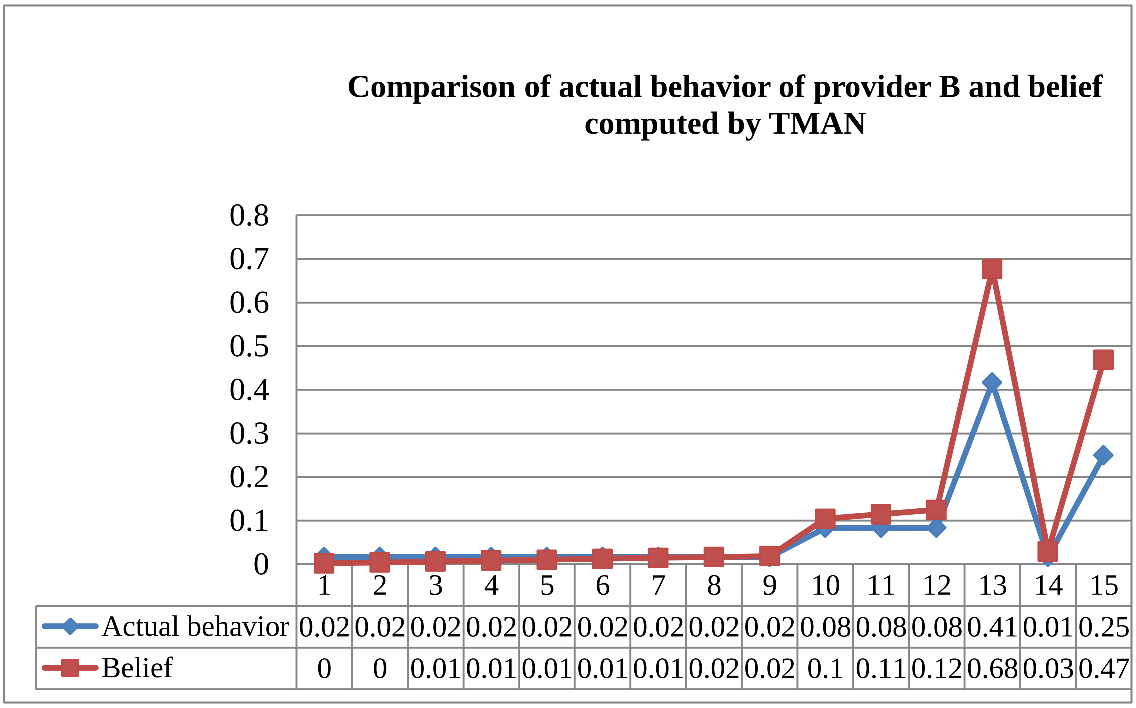


Figure 5.29: Comparison of the behavior of provider B and its belief computed by TMAN (Oscillating rating =0.05)

As shown Figure 5.29, when the provider B changed its satisfying behavior highly between interaction 12 and interaction 14, TMAN calculated the belief value with approximately similar increasing and decreasing as the actual behavior of advisor B between interaction 12 and interaction 14. In overall, the mean absolute difference between actual behavior and belief computed by TMAN is 0.03. Thereby, in the case that the agents oscillate their behavior TMAN can approximately calculate their belief and disbelief similar to their actual behaviors.

5.3.1.3 Experiment 2.1.3: Oscillating behaviors

In this experiment, the actual behavior of one advisor and one provider with oscillating behaviors is compared with the trustworthiness calculated by TMAN.

For instance the behavior of advisor in oscillating environment changed rapidly, Table 5.14 illustrates the behavior of the advisor in oscillating behavior

Table 5.14: A sample of advisor behavior in oscillating TNG environment

Number of interactions	Actual behavior of advisor
Interaction 1	-1
Interaction 2	0.996
Interaction 3	-0.99
Interaction 4	-1
Interaction 5	0.996
Interaction 6	-0.99
Interaction 7	-0.99
Interaction 8	-0.99
Interaction 9	-0.99
Interaction 10	-0.99
Interaction 11	0.996
Interaction 12	-0.99
Interaction 13	-1
Interaction 14	0.0998
Interaction 15	-1

Table 5.13 shows that the advisor changed its behavior from negative outcomes in trade number 1, 3, 4, 6, 7, 8, 9, 10, 12, 13, and 15 which means that these trades were dissatisfying to positive outcomes in trade number 2, 5, 11, and 14 which determines that the advisor had cooperative behavior in these trades, so these trade were satisfying. TMAN used the actual behaviors of the advisors which presented by TNG, which presented in Table 5.13, as satisfying and dissatisfying rates for that advisor and computed belief and disbelief of the advisor in each interaction.

Figures 5.30 illustrate the result of comparison for advisor C that had strong oscillating behavior rating.

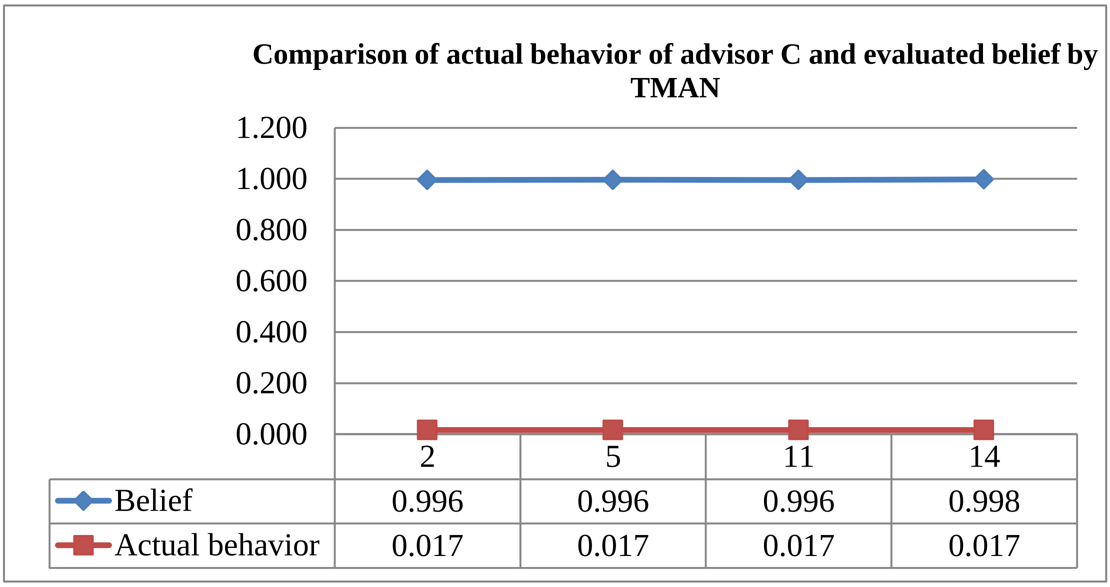


Figure 5.30: Comparison of the behavior of advisor C and its belief computed by TMAN (Oscillating rating =0.5)

Figure 5.30shows that advisor C had oscillating satisfying behavior in iterations 2, 5, 11, and 14. The mean absolute difference between actual behavior of advisor C and the belief computed by TMAN is 0.008. Thereby, TMAN computed belief reflects the likelihood of actual behavior with approximately 100% accuracy for iteration

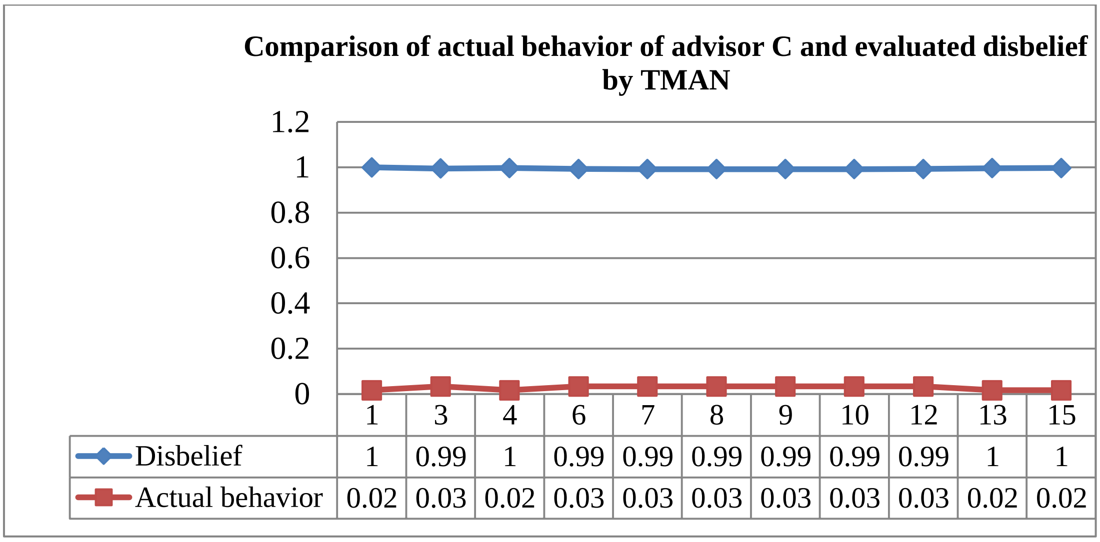
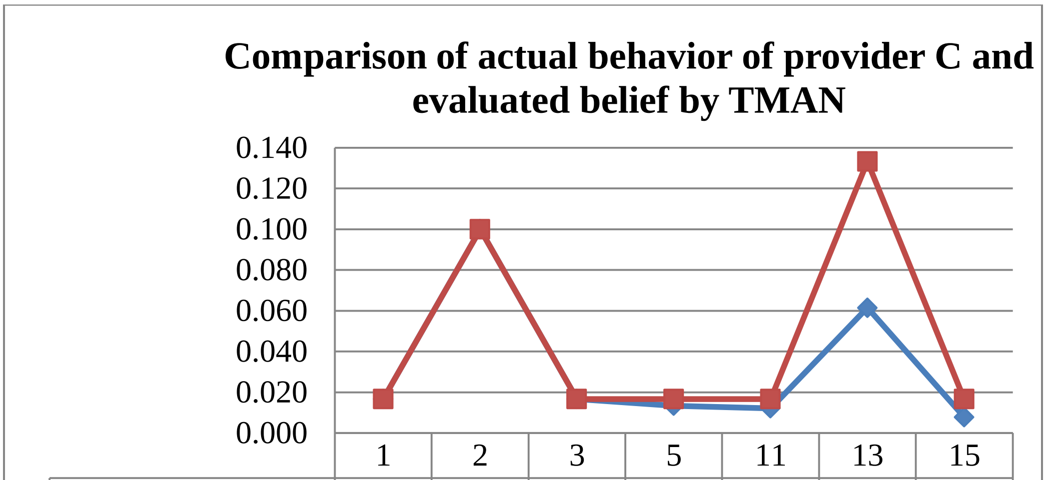


Figure 5.31: Comparison of the behavior of advisor C and its disbelief computed by TMAN (Oscillating rating =0.5)

Moreover as shown in Figure 5.31 TMAN calculated disbelief reflects the likelihood of actual behavior with approximately 100% accuracy for iteration while the mean absolute difference between actual behavior of advisor C and disbelief calculated by TMAN is 0.009

Finally Figure 5.32 and Figure 5.33 illustrate the result of comparison for provider C that had strong oscillating behavior rating of 0.5.



	1	2	3	5	11	13	15
Belief	0.017	0.100	0.017	0.013	0.012	0.062	0.008
Actual behavior	0.0167	0.1	0.0167	0.0167	0.0167	0.1333	0.0167

Figure 5.32: Comparison of the behavior of provider C and its belief computed by TMAN (Oscillating rating =0.5)

Figure 5.32 denotes that, provider C displayed highly changes in iteration 2 and also iteration 13. In fact, TMAN calculated the belief values in these iterations with approximately similar increasing and decreasing as the actual behavior of provider C. According to Figure 5.32, the mean difference between actual behavior of provider C and belief computed by TMAN is 0.001 which shows that TMAN computed belief reflects the likelihood of actual behavior with approximately 100% accuracy for iteration.

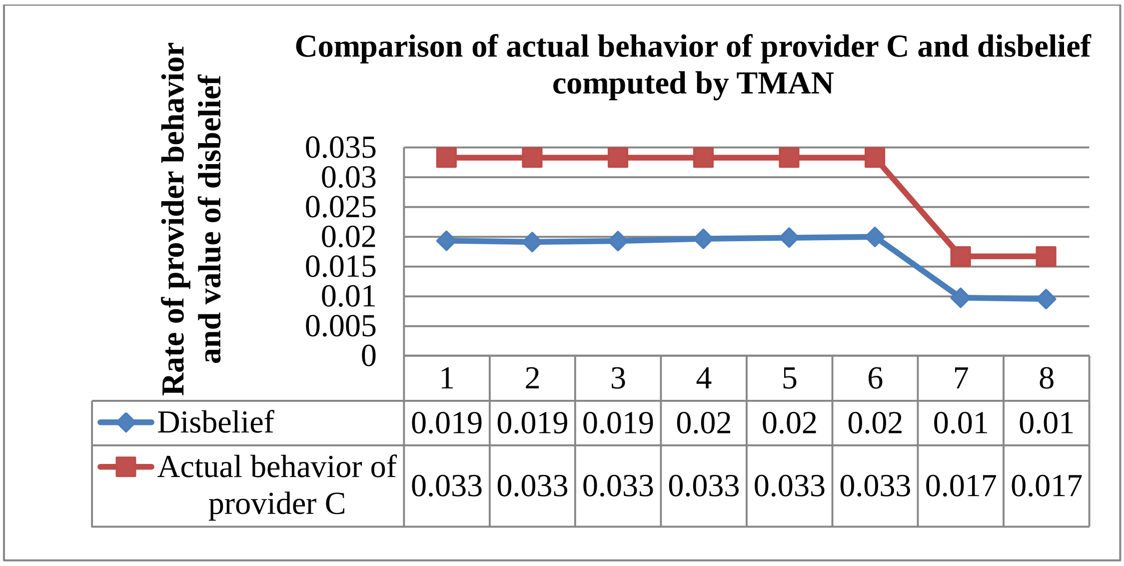


Figure 5.33: Comparison of the behavior of provider C and its disbelief computed by TMAN (Oscillating rating =0.5)

As shown in Figures 5.33, the mean difference between actual behavior of provider C and disbelief calculated by TMAN is 0.002 which reveals that the calculation mechanism of TMAN also calculated disbelief of provider C that reflects the likelihood of actual behavior with approximately 100% accuracy for strong oscillating behaviors of provider C.

The experiment 1.1, 1.2 and 1.3 verified that the TMAN mechanism can produce and evaluate the belief and disbelief of agents in different types of multi-agent environment accurately.

5.3.2 Experiment 2.2: Performance of TMAN in selecting the provider

In this step, the most trustworthy provider selected after evaluating the trust transitivity between each advisor and its suggested provider.

For instance, in oscillating TNG environment TMAN predicted the behavior of provider C,according to the first fifteen trade outcomes, as shown in Table 5.13, will be less than provider B from mild oscillating environment. In fact the first fifteen trades outcomes which presented by TNG used by TMAN as previous satisfying and dissatisfying interactions and TMAN applied TOPSIS method to select the most trustworthy provider, then the selected provider compared by the TNG outcome for sixteen interaction which showed the actual behaviors of providers.

Figure 5.34 shows the comparison of the rate of selected provider by TMAN with actual behaviors of that provider as presented by TNG in the last iteration.

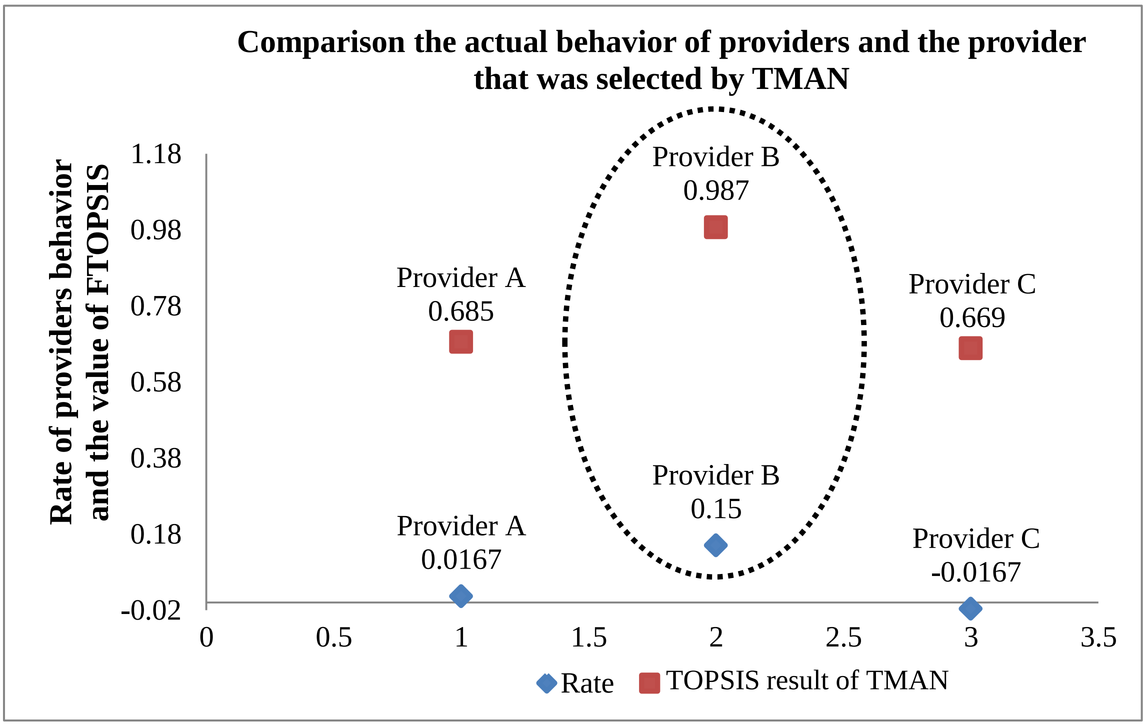


Figure 5.34: comparing the actual behavior of providers which presented by TNG and the final rate of selected provider by TMAN

As shown in Figure 5.34, TMAN can accurately select the provider which has better behavior than other providers, and the result of TOPSIS method for provider B is

0.15. This result can also verify the accuracy of TMAN in computing the trustworthiness of agents and selecting the most trustworthy provider.

5.4 Summary

By simulating the advisor network based on different numbers of agents and different densities of benevolent and malicious advisors with the MATLAB (R2012a) simulator, the mechanisms of TMAN were evaluated. Two different methods were used to evaluate TMAN. They consist of the random selection method as described in Section 5.2 and the TNG method as explained in Section 5.3.

In the random selection method, first, the accuracy of TMAN in evaluating the main components of TMAN was examined. The results verified that TMAN can accurately measure the reliability, unreliability, reputation, disrepute and also belief and disbelief of advisors and the belief and disbelief of providers. Moreover the accuracy of TMAN in evaluating trust transitivity between advisors and their suggested provider was evaluated. In fact, the results showed that TMAN can accurately calculate belief and disbelief of providers after trust transitivity.

Then, the performance of TMAN in decision-making process of selecting the trustworthy provider was studied by comparing the performance of TMAN with that of three other models: basic model, Evidence-based trust model, and TREPPS model. The result of simulation showed that in different times of running, the performance of TMAN in selecting the benevolent providers is better than that of other compared models.

According to the TNG method, the accuracy of TMAN in computing the main components has been evaluated by comparing the actual behaviors of agents collected from a simulated auction environment based on multi-agents with the presented results by TMAN. The results showed that TMAN can accurately evaluate the trustworthiness of advisors and also providers in this method. In the final stage of experiment, the performance of TMAN has been studied by using TNG outcomes. In this case TMAN could identify the most trustworthy suggested provider among all other providers.

CHAPTER 6:CONCLUSIONS, LIMITATIONS AND FUTURE WORKS

6.1 Introduction

This chapter provides a summary of the research carried out and presents a number of avenues for future research. In fact, this chapter discusses how to achieve the research objectives, answer the research questions that have been formulated in Chapter 1 and enumerate the key research achievements. The chapter concludes with a number of future research areas and addresses some of the main limitations of this research.

In this dissertation, the main focus has been to propose a trust model for advisor agents which make up an advisor network in a multi-agent system especially in e-commerce environment. TMAN is necessary because malicious advisors may take advantage of others by behaving in an untrustworthy manner.Assume a B2B scenario for a fictitious food manufacturer who has an online system. In an event where the manufacturer is looking for a packaging supplier, he may perform a search via his system which contains a potential list of suppliers (assumption). Additionally, assume the manufacturer specifies his criteria, such as price of service (10%), quality of service (30%) and response time (60%). The percentage indicates the weightage given for each criterion. In this example, response time is highly important to him compared to the price of service. When the manufacturer did not familiar with any supplier which can provide his demanded services, he will ask other manufacturer that it may familiar with those suppliers to advise him. In this case manufacturer should select the best supplier among all advices which can provide his demanded service. So, the successful interactions require selecting a trustworthy supplier agent according to advice of benevolent advisors. Taking advisors into consideration is essential, especially when the requester has had no previous interactions with providers, and it needs to find a trustworthy provider according to the advice of other agents. In this case, the agents that have had previous interactions with providers can play the role as an advisor to help the requester select the most trustworthy provider. However, if these advisors act maliciously, it will cause an unsuccessful interaction, especially in e-commerce areas, where the safety of interaction is vital. Thus, this proposed model can help to enhance the likelihood of a successful interaction in e-commerce-based multi-agent systems.

In the state-of-the-art concept of multi-agent systems, an advisor network and trust in multi-agent systems have been discussed along with analysis of different related work in Chapter 2.

The architecture of the proposed model, TMAN, has been clearly explained in Chapter 3 according to the following steps: i) select agents that are similar to requester as an advisor; ii) calculate the trustworthiness of advisors and suggested providers; iii) evaluate the trust transitivity in the advisor network by measuring the transitivity of trust between advisors and their suggested provider; and iv) the decision-making process for selecting the most trustworthy provider.

TMAN was tested in each stage and compared with three other alternative models with two different methods of evaluation: random selection and trust network game, the results of these evaluations were discussed in Chapter 4.

6.2 Summary of findings and research objectives accomplished

The architecture of TMAN was based on six main stages as explained in Chapter 4, Section 4.2. First the similar advisor agents have been selected (stage one), then trustworthiness of each similar advisor was evaluated (stage two), in the next step the trustworthiness of suggested provider which suggested by advisors were computed according to the report of advisors about their suggested provider (stage three). Next transitivity of trust between requester, similar advisors and their suggested providers were measured (stage four), then the most trustworthy provider was selected using TOPSIS method (stage five). Finally the requester, after interacting with the suggested provider, considers reward or punishment for the selected advisors (stage six).

The research objectives, as defined in Chapter 1, have been used as a guideline throughout this dissertation and formed the basis of our research questions. The summary of how these objectives have been achieved is summarized in the subsequent subsections. The full details have been discussed in earlier chapters.

6.2.1 Summary of the first research objective

The first objective of this research is to identify the main components that can be used to present a trust model for advisor networks in a multi-agent environment.

This objective was achieved in chapter 2, section 2.8 by analyzing the most representative trust models,such as, TREPPS (Li & Kao, 2009), Evidence-based trust model (Wang & Singh, 2010) and TRR model (Rosaci et al., 2011), and was explained in more details in chapter 3, section 3.2. A total twelve components were identified, namely: satisfaction, similarity, reliability, unreliability, disrepute, reputation, belief, disbelief, uncertainty, conflict, trust transitivity, and decision-making process.

6.2.2 Summary of the second research objective

The second objective of this research is to build a trust model based on the identified components to recognize a trustworthy provider agent which achieved in chapter 3, section 3.3.

By identifying the main components, TMAN was proposed based on the integration of the identified components to select a trustworthy provider according to the advice of the benevolent advisors, which are as follows:

First, the requester selects the similar advisors that have similar preferences to the requester. Then, the belief of how well the advisors can be trusted as well as disbelief value that shows how much the advisors cannot be trusted is evaluated. After that, the uncertainty in outcomes of each advisor and also conflict in previous behaviors of each advisor are measured to define the level of trust for each one. Based on this computation, the trustworthiness of malicious advisors should be less than that of the benevolent ones. Moreover, the belief, disbelief, uncertainty and conflict in previous behaviors of each suggested provider is evaluated based on the ratings reported by advisors. To calculate the accurate value of trust for providers, trust transitivity should be also evaluated in an advisor network. Then, the requester can make a decision based on the evaluated trustworthiness of each provider after trust transitivity and selects the most trustworthy one. Finally the requester considers reward or punishment for advisors that suggested the trustworthy provider.

6.2.3 Summary of the third research objective

The final objective is the evaluation of the accuracy of the components of TMAN and also performance of TMAN in a multi-environment. This objective achieved in chapter 5, section 5.2 and 5.3.

To evaluate the accuracy of TMAN, two methods were applied: the random election and also rust network game. According to the random selection, the average accuracy of TMAN in calculating reliability, unreliability, reputation, disrepute, belief and also disbeliefof agents were examined; then the average accuracy of TMAN in computing these main components after trust transitivity were investigated; finally, the performance of TMAN was compared with a basic model, which selects a suggested provider without computing the trustworthiness of the agents. This research also took into consideration two other representative trust models: the Evidence-based trust model(Wang & Singh, 2010) and TREPPS model(Li & Kao, 2009). These two models were selected to be compared with TMAN because they have many similarities to it. Moreover, several methodspresented by these two models were used in proposing TMAN.

6.3 Research Contributions

In this research,the major challenge is the malicious advisors, which affect the decision of requester agents and cause them to interact with malicious provider agents. To solve this problem, a trust model called TMAN is proposed. TMAN selected the similar agents as an advisor and calculated the trustworthiness of each similar advisor as well as computing the trustworthiness of their suggested provider, then the trustworthiness of requester to each suggested provider was evaluated by transitivity of trust, and the most trustworthy provider selected based on the computed trust transitivity value of each suggested provider. Finally, rewardthe advisors hat it can lead to increased reliability and reputation of those advisors, or punishmentthem that it can cause to increase the level of unreliability and disrepute of those advisors.

The above steps show that the evaluation of trustworthiness of advisors and their suggested provider can avoid the wrong decision made by requester agents about advisors and help them to interact with trustworthy provider agents.

Moreover TMAN can overcome to the following problems which were indicted in Chapter 1 as dissimilarity between requester and advisors, inaccurate trust value, the effect of unpredictable behavior of agents, and transitivity of trust among agents.

In overall, TMAN reduces the risk of interaction with an untrustworthy provider, and increases the accuracy of selecting an appropriate provider. On the whole, it enriches the safety for business-to-business trade in e-commerce.

TMAN is able to limit the risk of interaction with malicious providers. It provides a decision-making mechanism that is able to make an accurate decision of which provider to interact with by selecting the most trustworthy suggested provider. In fact, TMAN addresses each of the issues highlighted above. It selects the similar agent for interaction, it presents a method for reducing the effect of uncertainty of future behavior of agents on the decision-making process, it presents a method for decreasing the chance of selecting agents which have high contradictory behaviors, and finally, it considers a method for computing trust transitivity between agents. In summary, the proposed model of this study is expected to benefit the academic and commercial sectors that use e-commerce.

6.4 Research implications

This study has important implications for electronic business-to-business commerce which is based on multi-agent systems. In a multi-agent environment, the agents are autonomous and behave in a self-interested way towards one another(Kyriakarakos et al., 2013). Such environments require the presence of a system of trust and distrust in order to ensure the fulfilment of a contract(Hoogendoorn et al., 2014), especially for commercial tasks which must be securely performed and where vital information must be protected. More specifically, in the situation where the requester agent has had no previous interactions with providers, it needs to seek the advice of advisor agents. However, it is a challenge to find trustworthy advisors; if an advisor provides exaggerated or wrong advice; this can lead to an unsuccessful interaction and cause leakage of vital information(Zhang & Cohen, 2013). This issue has motivated this research to find a computational trust model, TMAN, which can be applied in multi-agent systems. In e-commerce multi-agent environments, TMAN enables an agent to make effective and sound decisions in light of the uncertainty that exists in multi-agent environments. TMAN calculates uncertainty and conflict of the agent's behavior to reduce the effect of unpredictable behaviors of agents.

The main benefit of using TMAN is that it provides a set of mechanisms, to assess the trustworthiness of advisors (section 4.3.2 explained the trustworthiness of advisors), in addition to the trustworthiness of the provider (section 4.3.3 explained the trustworthiness of providers), and make a decision based on the advice of benevolent advisors to select the most trustworthy provider (section 4.3.5 decision-making process and selecting the most trustworthy provider).

6.5 Limitations and future research

The findings presented in this dissertation provide a basis for further research. The following subsections discuss avenues for further research, in which TMAN can be applied as the base trust model to explore other related areas. It is important to note that this study has a number of limitations, and the results cannot be generalized to all other situations. These limitations can be overcome in future studies.

6.5.1 Storage space limitation

The TMAN mechanism records all the ratings from previous interactions and all the ratings reported by advisors; however, there is limited storage space for each agent. This problem can be solved by proposing a method that uses an update function to store the satisfaction and dissatisfaction ratings of previous interactions; this will reduce the storage overhead and decrease the relative time to select a trustworthy provider.

6.5.2 Level of advisor in an advisor network

With regard to the TMAN referral mechanism, one level for advisor agents is considered; it is assumed that each advisor suggests a provider, or if it cannot suggest any provider it will be ignored by the requester. It may be better if the requester can ask the advisor that cannot suggest any provider, to pass the query to another advisor which it assumes can suggest a trustworthy provider. In this case, the level of advisors will increase until the advisors which can suggest a trustworthy provider are found. The researcher believes that the trustworthiness of other levels of advisors can also be evaluated based on the formulas presented for evaluating the trustworthiness of the provider agents. However, the number of levels can affect the level of trustworthiness of agents. As the number of levels of advisors in an advisor network increases, the level of trustworthiness also decreases.

6.5.3 Time consumed for calculation

TMAN is based on a different mathematical computation which takes time to be calculated, and the time consumed for calculation can decrease the tendency to apply this computational trust model. At present, other computational trust models also ignore the time consumed for calculation. Hence, there is a need for a method that measures the approximate time consumed for calculation of trustworthiness of agents and selection of the most trustworthy provider.

6.5.4 Cost of agents

TMAN evaluates the trustworthiness of advisors and providers according to previous satisfying and dissatisfying interactions; it makes a decision based on the level of trust for each agent, without considering the transaction cost of wrong advice and also transaction cost when dealing with each malicious provider. Evaluating the risk of trust for an advisor or suggested provider in relation to the amount of cost that the requester may pay for that transaction can enhance the accuracy of the decision-making process for selecting the most appropriate provider. Future research can consider proposing a method for evaluating the transaction cost of each agent.

6.5.5 Other components

TMAN proposed the trust model based on the main components collected from the most representative models and the methods that those models presented for computing each of those components. Future studies can improve on TMAN by exploring other components to enhance the trustworthiness of agents and integrate them with the approach presented in this study.

6.5.6 Other domains of application

Finally, TMAN is presented and evaluated in the context of an e-commerce environment, especially electronic business-to-business commerce. It would be useful to consider how application of TMAN in the domain under consideration can be extended to different domains; an investigation can be done on the usefulness of the proposed methods in different domains.

6.6 Summary

This chapter has provided a summary of all the key findings in this research. The findings and research objectives, as identified in Chapter 1, have been summarized, and the methods used to achieve the research objectives have been explained. This chapter also recaps the proposed solutions to the problem statement,described in Chapter 1. The chapter has also discussed contributions of this research, determination of the research implications and identification of the research limitations. Finally, recommendations to overcome these limitations have been presented, which can be explored by future studies.

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APPENDIX A: MATLAB PROGRAMMING

```
clearall
closeall
clc

agent_no = 1;
% 1 --> 5 advisors
% 2 --> 10 advisors
% 3 --> 15 advisors
% 4 --> 20 advisors
p_type_mean = [];

[rec_rec, rec_p, req_rec, no_m_rec, no_b_rec, no_m_p, no_b_p] =
makegraph2(agent_no);

graph = [0, req_rec, zeros(1, (no_m_p + no_b_p)); zeros((no_m_rec + no_b_rec), 1),...
   rec_rec, rec_p; zeros((no_m_p + no_b_p), (no_m_rec + no_b_rec)+(no_m_p +
no_b_p)+1)];

for l = 1:11
iter = [1, 10:10:100];
best_p = [];
p_type = [];

for z = 1:iter(l)

indx = randi((no_m_rec + no_b_rec), 1, no_m_rec);
rec_m = zeros(1, (no_m_rec + no_b_rec));
rec_m(1, indx) = 1;

indx = randi((no_m_p + no_b_p), 1, no_m_p);
p_m = zeros(1, (no_m_p + no_b_p));
p_m(1, indx) = 1;

IDs(Abedinzadeh & Sadaoui) = 'Req';

for i = 1:(no_m_rec + no_b_rec)
if rec_m(1,i) == 1
IDs{i+1} = ['Rec_m', num2str(i)];
else
IDs{i+1} = ['Rec_b', num2str(i)];
end
end

tmp = (no_m_rec + no_b_rec) + 1;

for i = 1:(no_m_p + no_b_p)
if p_m(1,i) == 1
IDs{i+tmp} = ['P_m', num2str(i)];
```

```
else
IDs{i+tmp} = ['P_b', num2str(i)];
end
end

bg = biograph(graph, IDs);

Nodes = bg.nodes;

for i = 1:((no_m_rec + no_b_rec)+(no_m_p + no_b_p))+1
Nodes(i).Label = num2str(i);
end

dolayout(bg);
% bg.view;

%-----------------------------------------------------------------------
[best_p(z, 1) p_type(z, 1)] = model1(rec_rec, rec_p, req_rec, no_m_rec, no_b_rec,
no_m_p, no_b_p, bg, rec_m, p_m);
%-----------------------------------------------------------------------
[best_p(z, 2) p_type(z, 2)] = model2(rec_rec, rec_p, req_rec, no_m_rec, no_b_rec,
no_m_p, no_b_p, bg, rec_m, p_m);
%-----------------------------------------------------------------------
[best_p(z, 3) p_type(z, 3)] = model3(rec_rec, rec_p, req_rec, no_m_rec, no_b_rec,
no_m_p, no_b_p, bg, rec_m, p_m);
%-----------------------------------------------------------------------
[best_p(z, 4) p_type(z, 4), mean_out{z}, mean_out2{z}] = model4(rec_rec, rec_p,
req_rec, no_m_rec, no_b_rec, no_m_p, no_b_p, bg, rec_m, p_m);
%-----------------------------------------------------------------------
end

p_type_mean(1, l) = (1 - mean(p_type(:,1)));
p_type_mean(2, l) = (1 - mean(p_type(:,2)));
p_type_mean(3, l) = (1 - mean(p_type(:,3)));
p_type_mean(4, l) = (1 - mean(p_type(:,4)));

mean_final{l} = zeros(7, 2);
mean_final2{l} = zeros(4, 2);

for t = 1:size(mean_out, 2)
   mean_final{l} = mean_final{l} + mean_out{t};
   mean_final2{l} = mean_final2{l} + mean_out2{t};
end

mean_final{l} = mean_final{l} ./ size(mean_out, 2);
mean_final2{l} = mean_final2{l} ./ size(mean_out2, 2);

end

bg.view;
%-----------------------------------------------------------------------
x = [1, 10:10:100]
```

```
y = p_type_mean
t = ['accuracy for 'num2str((no_m_rec + no_b_rec + no_m_p + no_b_p + 1)) ' agents'];
figure;
plot(x, y(1, :), '-^', x, y(2, :), '--*', x, y(3, :), ':+', x, y(4, :), '-.o', 'LineWidth', 2)
legend('Basic model', 'Evidence-based trust model', 'TREPPS model', 'TMAN');
xlabel('Iterations'); ylabel('Accuracy');
title(t);
%-----------------------------------------------------------------------
t = ['Before trust transitivity for advisor'num2str((no_m_rec + no_b_rec + no_m_p +
no_b_p + 1)) ' agents after 100 times run'];
y = mean_final{11}(1:4, :);
figure;
bar(y)
legend('Benevolent', 'Malicious');
set(gca, 'XTickLabel', {'Reliability', 'Unreliability', 'Reputation', 'Disrepute', 'Belief',
'Disbelief'});
ylabel('Mean');
title(t);
%-----------------------------------------------------------------------
t = ['Before trust transitivity for provider'num2str((no_m_rec + no_b_rec + no_m_p +
no_b_p + 1)) ' agents after 100 times run'];
y = mean_final{11}(5:end, :);
figure;
bar(y)
legend('Benevolent', 'Malicious');
set(gca, 'XTickLabel', {'Belief', 'Disbelief'});
ylabel('Mean');
title(t);
%-----------------------------------------------------------------------
t = ['After trust transitivity for 'num2str((no_m_rec + no_b_rec + no_m_p + no_b_p +
1)) ' agents after 100 times run'];
y = mean_final2{11};
figure;
bar(y)
legend('Benevolent', 'Malicious');
set(gca, 'XTickLabel', {'Belief', 'Disbelief'});
ylabel('Mean');
title(t);
%-----------------------------------------------------------------------
```