國立交通大學

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以信任為基礎之個人產出服務推薦系統

A Trust-based Recommender System for Peer Production Services

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摘　要

個人產出服務(Peer Production Services)逐漸地將傳統的資產密集生產模式轉變成重度依賴資訊創造與分享的模式。越來越多的線上使用者依賴此類服務，例如：新聞、文章、書籤，以及眾多分散於全球資訊網上的使用者產出內容(User-generated content)。然而，這些使用者產出的品質以及可信度並未有效的管理，如果沒有適當的機制來衡量使用者產出的品質，結果將導致資訊過載(Information overload)。本研究提出一個基於社會網路信任的推薦系統，藉由信任運算，使用者產出的品質與可信度得以適當的衡量。本研究並整合了兩種著名的模糊邏輯應用-「模糊推論系統」以及「模糊多準則決策方法」用以支援服務選擇的決策制定。實驗結果顯示，本研究提出的系統能夠有效的提升使用者產出服務的品質，進而克服資訊過載的問題。最後，本研究建置了一個以信任為基礎的「個人產出新聞系統(Social news system)」用以呈現系統的可能性應用。

A Trust-based Recommender System for Peer Production Services

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ABSTRACT

Peer Production, a new mode of production, is gradually shifting the traditional, capital-intensive wealth production to a model which heavily depends on information creating and sharing. More and more online users are relying on this type of services, such as news, articles, bookmarks, and various user-generated contents, around World Wide Web. However, the quality and the veracity of peers' contributions are not well managed. Without a practical means to assess the quality of peer production services, the consequence is information-overloading. In this study, we present a recommender system based on the trust of social networks. Through the trust computing, the quality and the veracity of peer production services can be appropriately assessed. Two prominent fuzzy logic applications - fuzzy inference system and fuzzy MCDM method are utilized to support the decision of service choice. The experimental results showed that the proposed recommender system can significantly enhance the quality of peer production services and furthermore overcome the information overload problems. In addition, a trust-based social news system is built to demonstrate the application of the proposed system.

誌　　謝

這本論文的完成，意味著兩年的碩士學習，要在炙熱的七月劃下句點。套一句奧斯卡頒獎常聽到的話：感謝你們，沒有你們就沒有這個獎。雖然這不是一個獎，而是本多年後仍塵封在圖書館角落的論文，但無論在完成論文這件事情上，亦或是取得碩士學位的過程中，必須感謝的人真的很多。感謝你們，讓我有這麼一次成長的機會，並且給予我最大的鼓勵與支持。

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高建邦

2008 年 6 月 謹誌於 新竹 國立交通大學光復校區

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1. Introduction

1.1 Research Background and Motivation

Historically, Internet has followed the separation of consumer and producer roles in which most information are offered by professional service providers due to the technological obstacles [36][43]. With the ubiquitous networking and cheap computing, Internet starts to give the production power back to people and thereby let the lines between producers and consumers are blurred. A new mode of production called Peer Production [5], is gradually shifting the traditional capital-intensively wealth production to a new model which heavily depends on information creating and sharing [21]. The beginning of creating and sharing information between people worldwide greatly contributes to the emergence of social network sites/services (SNS). SNS are online communities where people are sharing similar interest with each other based on the social relationship between them. In April 2006, SNS have capatured the attentions of almost 45% of active Web users [3]. Enormous services and communities allow individuals to contribute over SNS. For instance, the social bookmarking services, including Del.icio.us and Spurl.net, provide users an easy way to share their online discovery. Other social media services, such as YouTube.com and Flickr.com, provide a platform for online users to contribute their collections based on originality. Social news sites, such as Digg.com and Newsvine.com, allow the citizens of the community to share, vote for, and comment on news. Wikipedia, the well-known collaborative online encyclopedia, lets anyone create and edit encyclopedia articles without the intervention of formal review process. What's more, online users are relying on these services around World Wide Web. In order to accelerate the probe and organization of peers' contributions, two new emerging approaches have been extensively incorporated in SNS. Folksonomy [19], a combination of the words *folk* and *taxonomy*, is a collaborative categorization framework using the freely-chosen keywords called tags to help the information easily to be discovered, navigated, and organized. Social voting, a simple but widely used mechanism, is applied to reflect what the contents are popular and what the things the communities most care about. However, the tricking incidents include vote-buying, vote-exchanging [16], and fake news [66] reveal that the popularity are not closely aligned with the quality and cannot sufficiently reflect the trustworthiness of sources. None of two mechanisms can function as the role to improve the quality and the veracity of peer production services. Wikipedia integrates both centralized revision control system and real-time peer review mechanisms, such as IRC (Internet Relay Chat) Channels and Watchlists [65], to alleviate the concerns of quality control. But it is not appropriate for the most peer production services which are huge and continuously refreshed, such as news, articles, bookmarks, and various user-generated contents.

Without a practical means to assess the quality of peer production services, the consequence is information-overloading. Recommender systems have been widely advocated as a viable solution to the information overload problems [51][67]. However, the conventional recommender system, oriented to support the products that are produced (or sold) by a particular and limited number of manufacturers, is inapplicable for peer production services which are diversified and without specific features to capture. Therefore, how to strengthen the capability and to leverage the use of social networking technology to enhance the quality and the veracity of peer production services becomes the aim of this research.

1.2 Research Objectives

Instead of the conventional recommender systems and aforementioned approaches, this study intends to present a recommender system based on the trust of social networks. Through the trust computing, the quality and the veracity of peer production services can be appropriately assessed. To model subjective information, such as trust knowledge, service satisfaction, and user preferences, the fuzzy set theory [69] and its linguistic terms representation are employed. Moreover, two prominent applications of fuzzy logic - fuzzy inference system and fuzzy MCDM method are utilized to support the decision of services choice. We also build a trust-based social news system to demonstrate the utilization of proposed system.

1.3 Research Structure

This study is to be organized and structured as follows. At first, we introduce the research background and methodologies of this study in Section 2, followed by the proposed recommender system in Section 3. A series of controlled experiments demonstrates the advantage and the performance of proposed system is conducted in Section 4. The trust-based social news system implemented on the proposed approach is presented in Section 5. At last, Section 6 offers conclusions and future works.

2. Related Literature

This section will discuss the related works, including the core properties of computational trust model, fuzzy number with its arithmetic operations, and the methodologies for decision making problem.

2.1 The Computational Trust Model

Trust has been a main research topic across many disciplines, such as sociology, philosophy, psychology, economics, management, marketing, and computer science [12][24][57]. Since the objective of this study is to apply the computational concept of trust to Internet services (i.e., peer production services), it is proper to turn to the related literature in computer science. Fields in computer science, such as web semantic, peer-to-peer (P2P), multi-agent systems, and human-computer interaction [2][12][24][26][31][34][46][49][54][57][70], have studies providing comparisons and reviews of the computational trust models. Further application and its use ranged from network systems to e-marketplaces can be found in Grandison & Sloman [25] and Song et al. [63]. In this work, attention should be placed according to philosophical relations between security and trust followed by the benefits of computational trust applied into the domain of information filtering. A trust network is presented at last to illustrate the computational concept of trust model.

2.1.1 Trust as Social Control Mechanism for Security Issues

Security mechanism can be classified into *hard* and *soft* paradigms [53]. By hard security mechanism, it usually focuses on private capital and resources protection. By soft security, it refers to a social control mechanism, such as trust and reputation system, being advocated to create secure open systems where the participants are responsible for the security. The following examples were used to illustrate the different orientation of each paradigm. In the

P2P file sharing network, hard security mechanism were proposed [52][71] to ensure content authenticity and integrity as well as to enforce appropriate access control policies. But, trust and reputation system, as a soft security mechanism, were designed [33][64][68] to protect against malicious user who may distribute corrupted files or disseminate virus-infected files for notoriety. Then, in e-marketplace, digital signatures/certificates and SET (Secure electronic transaction [58]) are applied as hard security to protect buyers against privacy, integrity, authentication, and non-repudiation issues [18], while online reputation management such as eBay's feedback system, as a soft security mechanism, provides the simplest form to facilitate the online transaction decision. Another relevant example refers to applications of information filtering. Signatures and encryption mechanisms integrated as hard security to validate the owner or the source of web information [2], whereas the computational model of trust, as a vital soft security component, is incorporated into standard collaborate filtering framework to guide the measurement of source trustworthiness [22][27][47][51].

2.1.2 Trust in Information Filtering

From the perspective of information filtering, trust and reputation systems can be used to estimate the quality of a peer's beliefs and further to reduce the information search complexity [14] because the systems pre-filter not only the like-minded peers but also the credible recommendation sources [72]. While *collaborative filtering* (CF) systems collect opinions from experienced users and provide recommendation result to the users with similar taste, trust and reputation management as *collaborative sanctioning* (CS) [31][48] systems, provide mechanism for tracking source reliability and therefore can be used to weight the reliability of opinion pool. CS systems can discourage (give an incentive for) service providers to provide low (high) quality resources and misrepresentive (unmisleading) information due to the poor performance sanctioning. It can, moreover, improve the accuracy of recommendation and decrease the error when compared with common collaborative filter technology [22][47][51].

The results of Sinha and Swearingen's research [60][61] indicate that users like to know why an item was recommended and prefer recommendation from others who know and trust. CS responds to this call by utilizing computational trust model since a trust-based recommender system allows people to be aware that the sources of recommendation were produced from the people they know [22]. Thus, the concerns stated above can be properly dealt with.

2.1.3 Trust Inference in Social Network

According to the definitions in several dictionaries[1], *'reputation'* could be described as a public known characteristic held by someone or something. *'Trust'*, on the other hand, can represent a relationship that requires an involvement of at least two parties called *trustor* and *trustee*. It is expressed as trustor expecting trustee to behave the way s/he wants [30]. Jøsang et al. [31] illustrated the difference between reputation and trust by the following statement:

(1) I trust you because of your good reputation.

(2) I trust you despite your bad reputation.

Put differently, the trustor has some private knowledge about the trustee (either through direct experience or interpersonal relationship and referral) that might overrule the public reputation that the trustee holds. The properties of computational trust model applied in this work are essentially inherited from such implication.

Trust network is an online social network in which peers are interlinked by trust relationship [14]. It can be represented by directed graph as shown in Fig. 2.1, where vertices

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[1] The word *'reputation'* defined in compact Oxford English dictionary as a *widespread belief* that someone or something has a particular characteristic. In Webster's online dictionary, reputation is a *general estimation* that the public has for a person. In Collins English dictionary, reputation is the opinion *generally held* of a person or thing.

are denoted as peers in social network, and directed solid edges along with trust value represent the degree of direct trust relationship between two peers. Due to the transitivity properties of trust [1][15], the trust values along the chain of connected trust networks can be inferred and be formulated as follows [24]:

$$T_{\alpha,\beta} = \frac{\sum_{k \in neighbors(\alpha)} T_{\alpha,k} \times T_{k,\beta}}{\sum_{k \in neighbors(\alpha)} T_{\alpha,k}} \tag{1}$$

where α and β are two distinct peers in trust network, and k is denoted as the neighbors of α, from which a one-way trust relationship exists. As depicted in Fig. 2.1, the indirect trust relationship (denoted as dotted edge) between peers α and β can be inferred, although the peer α does not have direct trust relationship to β. According to Eq. (1), the value of $T_{\alpha,\beta}$ is calculated as: $T_{\alpha,\beta} = (0.3 \times 1 + 0.8 \times 0.5)/(0.3 + 0.8) = 0.636$.

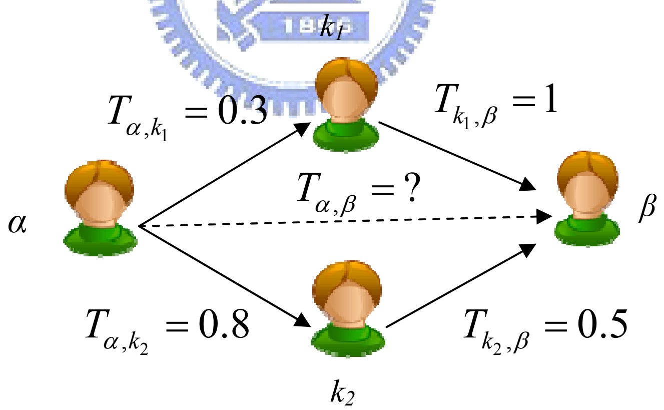

Fig. 2.1 Graph theory based representation of trust network

2.2 Fuzzy Numbers, Arithmetic, and Operations

Fuzzy set and logic introduced by Zadeh [69] is another powerful tool to deal with uncertainties in addition to the probability theory. It is especially appropriate to deal with the subjective and vague information. Lately, researchers are making use of fuzzy logic for trust and reputation modeling since they always involve subjectivity as well as uncertainty and vagueness. Schmidt et al. [55] proposed a fuzzy trust evaluation system to support service selection in the automatic e-commerce markets. They evaluated the trustworthiness of recommending agent's experiences by feeding related interaction attributes include timeslots, counts, and agent's credibility into the proposed fuzzy inference system. Song et al. [64] utilized fuzzy inference system to infer the local trust scores as well as the weights of global reputation. Local transaction parameters such as payment method, goods quality, and deliver time are taken into account to determine the local trust scores, while transaction amount, interaction time, and peer's reputation are aggregated to obtain the weights of global reputation. Sabater and Sieraa [56] proposed a fuzzy reputation model to evaluate the reliability degree of information comes from the third sources. The antecedent of each fuzzy rule is the type and the corresponding degree of a social relation such as, cooperative and competitive relation. These rules were proposed to ensure that the recommendations about an agent are not biased or incorrect. Griffiths [50] introduced the concept of distrust and insufficient trust in their fuzzy trust model. Six fuzzy terms of trust can be determined by experience and confidence of past interactions. In contrast to crisp trust inference algorithm proposed by Golbeck [24], Lesani and Bagheri [39] proposed a fuzzy trust inference system to aggregate trust value from social networks. The corresponding fuzzy rule was proposed to determine the stronger inference paths to infer the more accurate result. Their experimental results indicated that fuzzy trust model reports richer expressions matched with the existed information in the trust network graph, especially when contradictory information is composed for the trust inference. In this study, the fuzzy logic is employed not only to capture the knowledge of trust, but also to support the representation of service satisfaction and users' preferences. Users participated in peer production services can express above knowledge easily since linguistic term expression provides a rich and natural way for personal judgment.

We also investigate a set of rules which takes account of trust and critical factors which have pointed out in literatures to construct a fuzzy inference system for determining the confidence of recommendation.

The brief definitions of the specific fuzzy number and the necessary fuzzy arithmetic operations may be introduced for latter discussion. Let $\tilde{A}$ be a *Triangle Fuzzy number* (TFN) on the real line $\Re$ and can be represented as $\tilde{A} = (a_1, a_2, a_3)$, where a_1, a_2, and a_3 are real numbers with $a_1 \le a_2 \le a_3$. The membership function $\tilde{A}(x)$ of TFN defining the degree of membership of element $x \in \Re$ to $\tilde{A}$:

$$\tilde{A}(x) = \begin{cases} 0, & x < a_1, \\ (x - a_1)/(a_2 - a_1), & a_1 \le x \le a_2, \\ (a_3 - x)/(a_1 - a_2), & a_2 \le x \le a_3, \\ 0, & x > a_3, \end{cases} \tag{2}$$

Let $\tilde{A}$ and $\tilde{B}$ be two TFNs parameterized by the triplet (a_1, a_2, a_3) and (b_1, b_2, b_3) respectively. According to the nature of TFN and the extension principle [17], three essential arithmetic operations are necessary in this study:

$$\tilde{A}(+)\tilde{B} = (a_1, a_2, a_3)(+)(b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{3}$$

$$\tilde{A}(-)\tilde{B} = (a_1, a_2, a_3)(-)(b_1, b_2, b_3) = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{4}$$

$$k\tilde{B} = (kb_1, kb_2, kb_3) \tag{5}$$

where *k* is a real number. The distance measure between two TFNs according to the vertex method stated in Chen [8] can be calculated as:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{6}$$

2.3 Multi-Criteria Decision Making on Fuzzy Environment

A Multi-Criteria Decision Making (MCDM) problem is to find a best/compromise/optimal solution from all feasible alternatives evaluated on multiple and usually conflicting criteria, both quantitative and qualitative [37][40]. As depicted in Fig. 2.2, to choose the qualified peer production services in terms of several user defined preferences from various possible providers is a MCDM problem. Therefore, a fuzzy MCDM method can be applied to the end of proposed recommendation process to support the decision for end users from complex and unintelligible information. Fuzzy MCDM, firstly introduced by Bellman and Zadeh [4], is an appropriate approach to effectively cope with the inherent vagueness, uncertainty, and subjectiveness of human decision making process [38]. Since then, an increasing number of published studies on solving Fuzzy MCDM problems has been developed in the recent decade. The technique for order preference by similarity to an ideal solution (TOPSIS), the well-known and proven MCDM methods proposed by Hwang and Yoon [29], has been extensively extended [8][9][11][40] to deal with fuzzy MCDM problems. It is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution (PIS) and the farthest from the negative-ideal solution (NIS). One of notable Fuzzy TOPSIS (FTOPSIS) methods proposed by Chen [8] is chosen in this study to implement the decision support process. Chen's [8] approach as elaborated in Appendix A has already been extensively adopted in several studies. It is also noted that the choice of FMCDM methods is not constrained in FTOPSIS as long as it can appropriately help the best services decision.

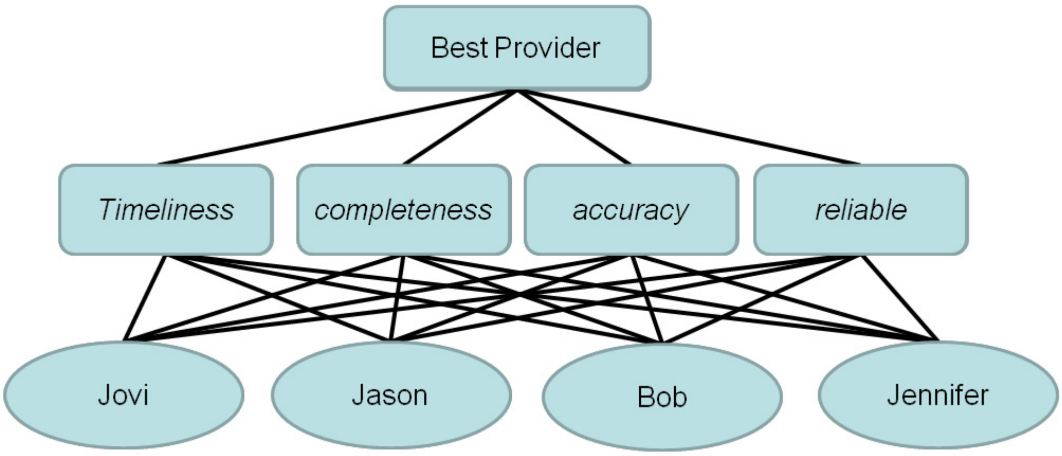

Fig. 2.2 The MCDM problem in this study

3. Trust-Based Recommender System for Peer Production Services

In this section, we present the proposed recommendation system for peer production services called *TREPPS* (Trust-based REcommender for Peer Production Services). To build an efficient recommender system for peer production services, it is necessary to identify the key participating roles at the beginning. Most peer production services in SNS contain three roles: *requesting*, *recommending* and *providing* services as shown in Fig. 3.1 *Service requestor* initiates the service request process by offering the keywords that define the topics of interested services. *Service providers* are peers who have capability of *fulfilling* the service request. Under this circumstance, the definition of service fulfillment should not only match the topics the requestors need but also satisfy their preferences. Therefore, the *service recommenders* who have ever interacted with service providers should be clearly identified. The experiences of them will be aggregated as recommendations in addition to the topic matching.

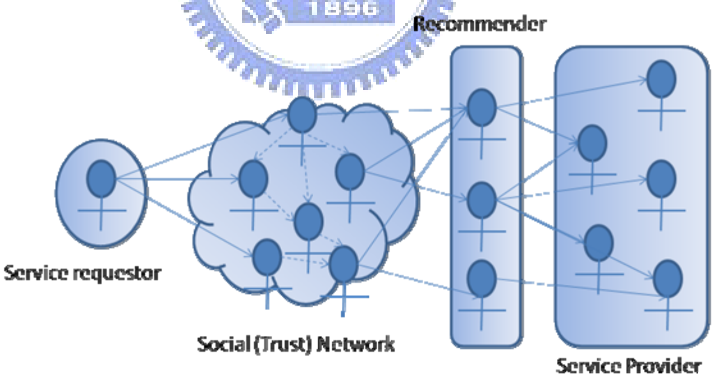

Fig. 3.1 Roles participated in peer production services

To understand the proposed recommender system, three major stages that carry out the whole recommendation process are:

Stage 1: Making a shortlist of service providers. Find out the shortlist of service providers who can (or already have) provide services that match the topic the requestor needs.

Stage 2: Aggregating recommendation from experienced peers. Identify trustworthy recommenders who not only have experiences with service providers but also reliable. Aggregate their experiences and construct a recommendation matrix for service decision.

Stage 3: Making decision on qualified services. Generate a recommendation ranking that the end users can easily understand and make decision on which service meets their preferences.

Fig. 3.2 characterizes the core tasks and the necessary system components. The following sections explain the purpose and the implementation of these stages.

3.1 The First Stage: Making a Shortlist of Service Providers

The objective of this stage is to retrieve user interesting services through the topic matching and offer a shortlist of service providers who are eligible for evaluation in second stage. The practices of topic matching depend on what type of peer production services is. For instance, the underlying mechanism of topic matching may be a full-texted search engine for text-based contents sharing. Rather than build from scratch, many well-made and mature frameworks of search engine may be considered to facilitate the task completion in this stage. Apache Lucene[2], for example, is a high performance, full-featured and scalable search engine that written in Java. It has already been ported to other programming language, such as Perl, Python, C++ and .NET, and could be a good approach to accomplish the task of topic matching. Tagging, as mentioned in Section 0, is obviously an indispensable mechanism for social media annotation, and is good for services probing. Two approaches provided for topic matching in the proposed social news system are described in Section 5. One is content search engine supported by MySQL[3] full-text search functions; and the other is searchable tagging mechanism.

Consequently, the output of this stage is a shortlist of service providers who can (or already) provide relevant services matching the topic the requestor needs.

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[2] Apache Lucene, http://lucene.apache.org/

[3] MySQL is the world's most popular open source database. http://www.mysql.com/

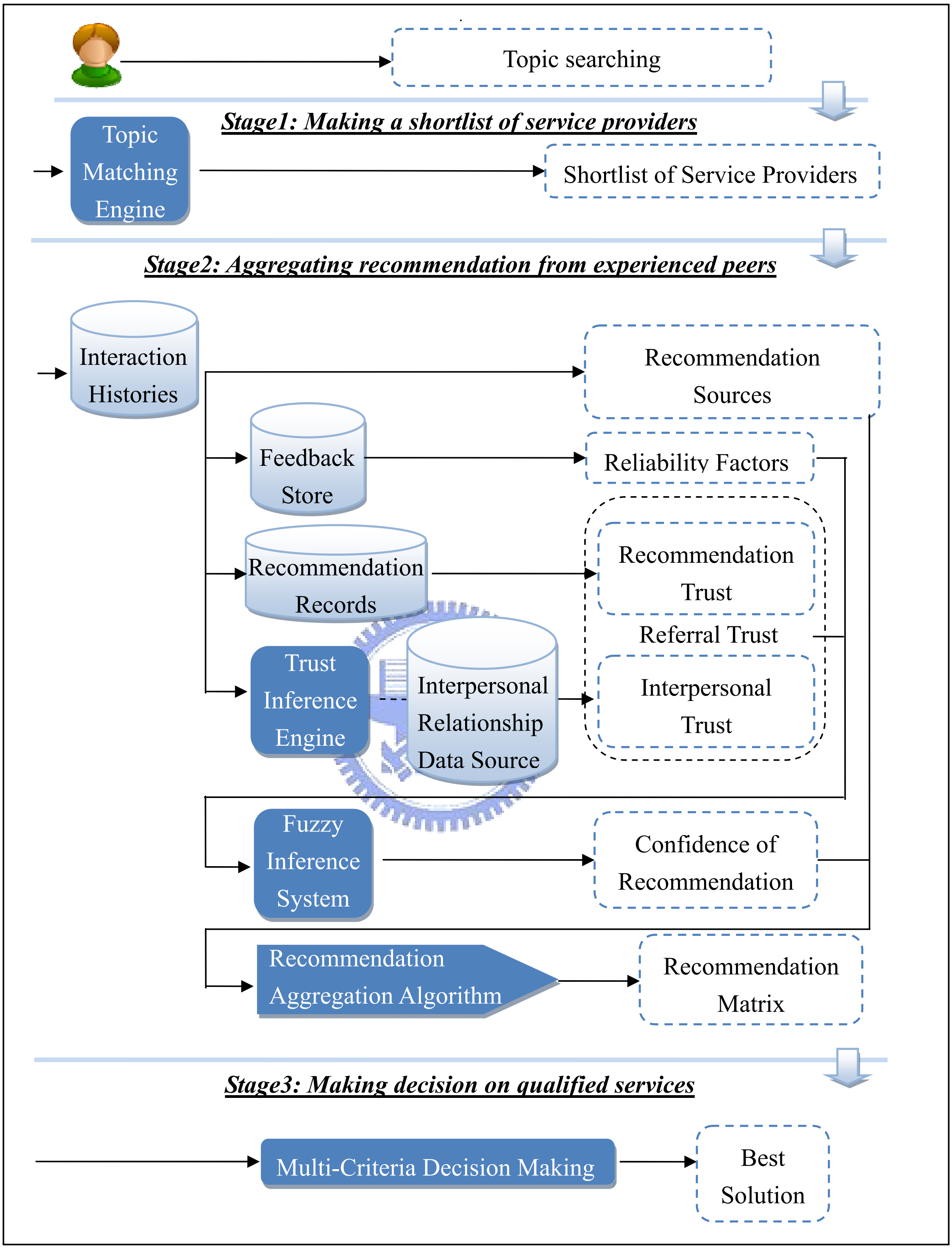

Fig. 2.2 Three stages of peer production service recommendation process and the core tasks and necessary system components

3.2 The Second Stage: Aggregating Recommendation from Experienced Peers

The short-listed service providers made in the first stage are just peers whose services match to the topics the requestor needs. The performance needs to be evaluated such that the unsuitable ones who do not meet requestor's preferences could be filter out. This is the core stage in the whole recommendation process to reach the goal of service fulfillment.

3.2.1 Design an Appropriate Feedback Mechanism for Service Satisfaction Representation

A suitable recommendation sources has a significant effect on the correctness of recommendation. Heath et al. [27] identify 'experience' is one of the most important factors that could influence the choice of recommender. In this study, an aggregation of one's experiences to a specific service provider is defined as one's trust to that provider. We name this type of trust as *expert trust* and use it as the recommendation source to evaluate provider's performance. As illustrated in Fig. 3.2 the recommendation sources are retrieved through interaction histories. When completing an interaction, service requestor needs to rate provider's performance through the feedback interface in order to respond his satisfaction of current interaction. Typically, rating the satisfaction for a service provision is more complex than just according to success or failure of interaction. This is because the criteria of qualified services depend on what the requestor care about the most, while everyone has dissimilar sensitivities on different perspectives of provider's performance. Simply gauge the satisfaction of service performance in a single dimension with binary only rating (i.e., yes or no) as the recommendation source will lead to the wrong prediction. For example, in the case of social news services, one hopes the contents added to the site are continuously refreshed since s/he cares about the *timeliness* of news. In addition, there may be one concerning about the *completeness* of content, but s/he does not care about whether the news is on time or not.

Moreover, some people may mind the *accuracy* of the contents, while others prefer specific editors or publisher but are careless about what the content is since the readers have good experiences with them and believe the services they provided are always *reliable*. As we can see, while single dimension rating mechanism provides information regarding a provider's *overall* performance, a multi-criteria rating mechanism can reveal some insights about *why* a requestor dis/satisfies the interaction. Therefore, to design an appropriate feedback mechanism so that users can express their experience effectively is a critical task. We take two mechanisms- *multi-dimensional representation* and *linguistic term expression* into account to relieve the aforementioned concerns.

For the consideration of multi-dimensional representation, suppose that the criteria of the service satisfaction denoted as c and user's preferences are defined in $|c|$ criteria. Each time when users request a service, they can set the preferences by assigning important weights for each criterion in advance. Then, the system will recommend services according to the preference setting. After completing interaction, requestors rate provider's performance of current interaction in terms of these criteria as the feedbacks of service satisfaction. These feedbacks are recorded in the feedback store as depicted in Fig. 3.2 The service satisfaction (i.e., feedback of service) denoted as S. $S_{s,p}^{c}(i)$ represents the requestor s' satisfaction of provider p' service in terms of criterion c at a particular interaction i. Deriving from the feedback store, $Te_{s,p}^{c}$ represents requestor s' *expert trust* to provider p in terms of criterion c for the past transactions k and be formulated as:

$$Te_{s,p}^{c} = \sum_{i \in k} S_{s,p}^{c}(i) \times fw(i) \tag{7}$$

where $fw(i) = fresh(i) / \sum_{i \in k} fresh(i)$ and $fresh(i) = time(i) / time(t)$. Weight factor fw, firstly introduced by Sabater and Sierra [56], represents the freshness weight of time to give higher value for interaction i that is closer to current time t.

Linguistic term expression provides a rich and natural way for end users to express the knowledge and personal judgments thereby let them feel more comfortable than binary only or numeric values rating. From this perspective, we define the extents of *service satisfaction* in five linguistic terms- *bad* (*B*), *slightly bad* (*SB*), *neutral* (*N*), *slightly good* (*SG*), and *good* (*G*). For the user preferences setting, an *importance weight of criterion* is expressed in seven linguistic terms- *extremely unimportant* (*EU*), *unimportant* (*U*), *slightly unimportant* (*SU*), *average* (*A*), *slightly important* (*SI*), *important* (*I*), and *extremely important* (*EI*). The meaning of linguistic values can be interpreted as fuzzy sets. We parameterized these two linguistic variables with TFNs as shown in Table 3.1 and Table 3.2, while the membership functions are depicted in Fig. 3.3 and Fig. 3.4 respectively.

Table 3.1 Linguistic values and fuzzy numbers for service satisfaction and trust

Linguistic terms		Fuzzy numbers
Service satisfaction	Interpersonal & Recommendation Trust	
Bad (B)	Distrust (D)	(0, 0, 0.3)
Slightly bad (SB)	Slightly distrust (SD)	(0, 0.3, 0.5)
Neutral (N)	Neutral (N)	(0.2,0.5,0.8)
Slightly good (SG)	Slightly trust (ST)	(0.5,0.8,1)
Good (G)	Trust (T)	(0.7,1,1)

Table 3.2 Linguistic values and fuzzy numbers for importance weight of performance criteria

Linguistic values	Fuzzy numbers
Extremely unimportant (EU)	(0, 0, 0.2)
Unimportant (U)	(0, 0.2, 0.3)
Slightly unimportant (SU)	(0.2,0.3,0.5)
Average (A)	(0.3,0.5,0.7)
Slightly important (SI)	(0.5,0.7,0.8)
Important (I)	(0.7,0.8,1)
Extremely important (EI)	(0.8,1,1)

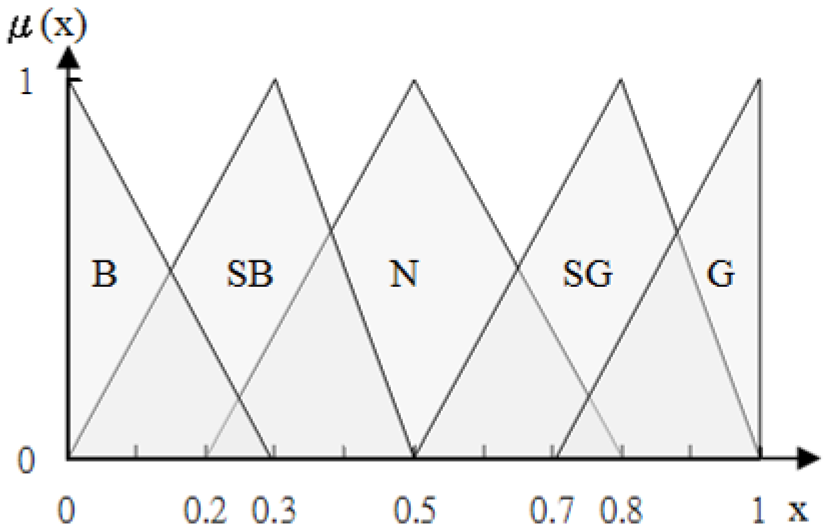

Fig. 3.3 Membership functions for service satisfaction

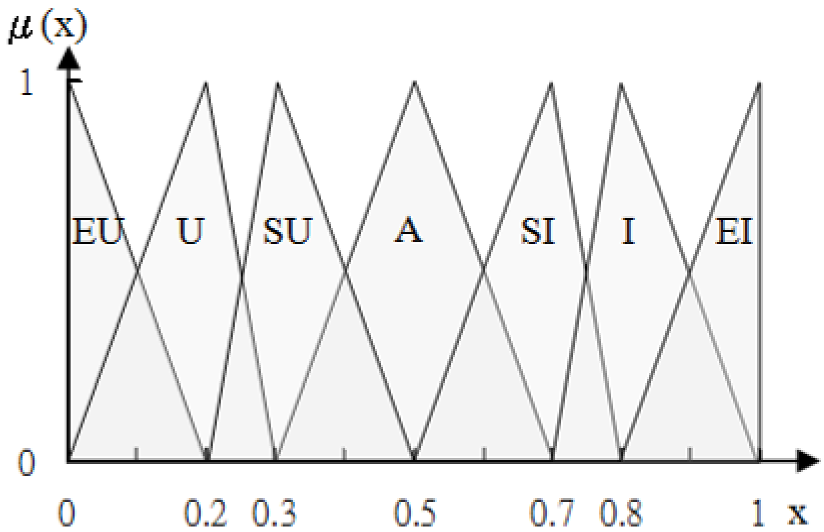

Fig. 3.4 Membership functions for importance weight of performance criteria

Supposing $\tilde{s}_c$ is a TFN of satisfaction in terms of criterion c, denoted as $\tilde{s}_c = (s_c^1, s_c^2, s_c^3)$, where s_c^1, s_c^2 and s_c^3 are real numbers with $s_c^1 \le s_c^2 \le s_c^3$. Expert trust denoted as $\tilde{Te}_c = (Te_c^1, Te_c^2, Te_c^3)$. According to Eq. (3), (5), and (7), we can calculate expert trust as:

$$Te_c^m = \sum_{i \in k} fw(i) \times s_c^m \tag{8}$$

where m=1,2,3, and k denotes the number of past transactions. Fig. 3.5 summarized the required procedures to derive expert trust.

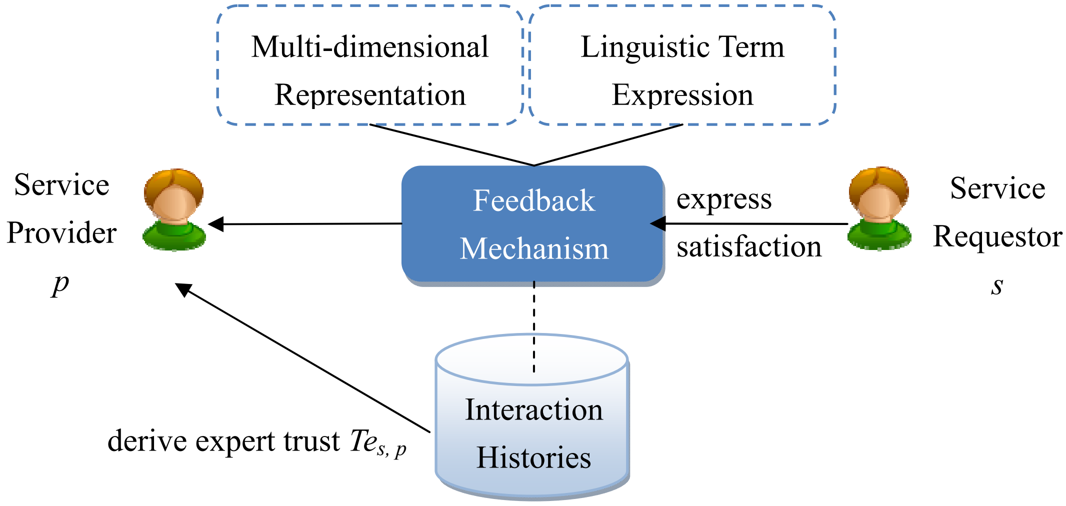

Fig. 3.5 Required mechanisms designed to derive expert trust

3.2.2 Confidence of Recommendation

Unlike the conventional approaches such as social voting treating all recommenders' experiences identically, two crucial factors affect the reliability of recommendation sources, and the referral trust that used to assess the trustworthiness of recommendation sources are both taken into account to evaluate the *confidence* (*CF*) of recommendation.

Although there are many factors may be taken into account to measure the reliability of recommendation sources, we will address on two critical factors whose related concepts are already stressed and discussed in several studies [28][56][64]. These two factors both are derived from feedback store as shown in Fig.3.2.

Closeness factor is used to examine the frequency of interactions between a recommender and a service provider. As the number of interaction grows, the degree of closeness factor increases until it reaches the certain number (denoted as l) of interactions. Intuitively, this factor is considered because people prefer to adopt the recommendation from peers whose interaction with certain object is more frequent. In addition to a transformed function proposed by Sabater and Sierra [56], an alternative function to normalize the numbers of interaction to [0,1] is given to calculate the degree of closeness factor Fc :

$$Fc_{r,p} = \begin{cases} e^{\frac{(k-l)\ln s}{l}} & \text{, if } k < l \\ 1 & \text{, otherwise} \end{cases} \tag{9}$$

where k denotes the number of interactions between a recommender r and a service provider p, s is the minimum degree of closeness factor for k=0. The definition of value l depends on the scale of underlying social network. We set $l=5$ for the proposed social news system as the default value.

Stability factor functions to determine whether the result of interactions between a recommender and a provider is stable or not. The lower the stability of past interactions, the more volatile the provider is likely to be in fulfilling service. Stability factor is denoted as Fs and is calculated as follows:

$$Fs^c_{r,p} = \tilde{P} - \sum_{i \in k} fw(i).\left| S^c_{rp}(i) - Te^c_{rp} \right| \tag{10}$$

where $\tilde{P} = (1,1,1)$ denoted as an ideal value of stability factor. $Fs^c_{r,p}$ represents the stability of interactions between recommender r and provider p in terms of service criterion c in past transactions k.

By incorporating these two crucial factors, the definition of reliability becomes:

$$RL^c_{r,p} = Fc_{r,p} \times Fs^c_{r,p} \tag{11}$$

, and the corresponding membership functions that contain three fuzzy numbers– *low* (L), *medium* (M), and *high* (H) are depicted in Fig. 3.6.

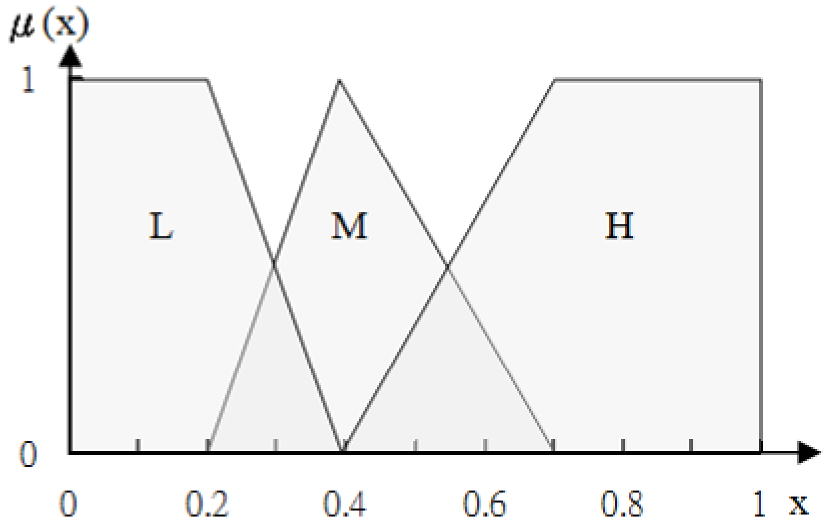

Fig. 3.6 Membership functions for reliability factor

The participants in social network naturally have reputations gained from providing good services and referrals [59]. In this study, aforementioned *expert trust* played a role in former, and is used to evaluate service provider's performance. The latter one is classified as *referral trust* according to 'agent knowledge taxonomy' defined by Ding et al. [15], which is user's belief about the trustworthiness of other users' referral knowledge. It can be seen as a user's belief of recommender's past experiences (i.e., recommender's expert trust to service provider.). Therefore, two types of referral trust described as follows are both taken into account to provide a more robust mechanism to cope with the situation that one of the sources may not be available.

The primary source of referral trust used in proposed system is *interpersonal trust* which we have mentioned in Section 1. Like the service satisfaction, the extent of interpersonal trust is *explicitly assigned* by users and is represented in five linguistic terms– *distrust* (*D*), *slightly distrust* (*SD*), *neutral* (*N*), *slightly trust* (*ST*), and *trust* (*T*) for users to express their trust relationships in social network. The corresponding fuzzy numbers are equivalent to the definition of service satisfaction as shown in Table 3.1.

To model the trust knowledge and apply the trust inference to linguistic expressed trust values, *Fuzzy Weight Average* (FWA), a computation for performing weighted average operations on fuzzy numbers, is discussed. Algorithms for FWA computing have been proposed in many studies. To generalize the FWA according to the definition of Liou and Wang [44], let $A_1, A_2, ..., A_n$, and $W_1, W_2, ..., W_n$ be the fuzzy numbers defined on the universes $X_1, X_2, ..., X_n$, and $Z_1, Z_2, ..., Z_n$, respectively. If f is a function which maps from $X_1 \times X_2 \times ... X_n \times Z_1 \times Z_2 \times ... Z_n$ to the universe *Y*, then the fuzzy weighted average *y* is defined as:

$$y = f\left(x_1, x_2, \cdots, x_n, w_1, w_2, \cdots, w_n\right) = \frac{w_1 x_1 + w_2 x_2 + \cdots + w_n x_n}{w_1 + w_2 + \cdots + w_n} \tag{12}$$

where for each *i*=1,2,…,*n*, $x_i \in X_i$ and $w_i \in Z_i$. An algorithm – Alternative Fuzzy Weight Average (AFWA) proposed by Chang et al. [7] is adopted in this study because of its performance being more efficient compared to other discrete algorithms. The reader is referred to the work of Chang et al. [7] to see the implementation detail of AFWA. Here we give an example to explain how the FWA applied to the trust network which is expressed in linguistic terms instead of the real number as discussed in Section 1. Supposing there exist a trust relationship expressed in linguistic terms as depicted in Fig. 3.7. According to trust inference function Eq. (1) and the definition of FWA in Eq. (12), the indirect trust between peer *α* and *β* can be calculated by AFWA as: $T_{\alpha,\beta} = \left(SD \times T + ST \times N\right) / \left(SD + ST\right) = (0.2, 0.636, 0.9)$. The result is characterized in Fig. 3.8.

In this study, it is notable that the implementation of interpersonal trust inference is follows Breadth-first search (BFS) approach. The Java interface 'java.util.Set[4]' is also applied to avoid computational cycling (node revisited) problem while inferring the trust value.

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[4] 'java.util.Set' is a collection that contains no duplicate elements.

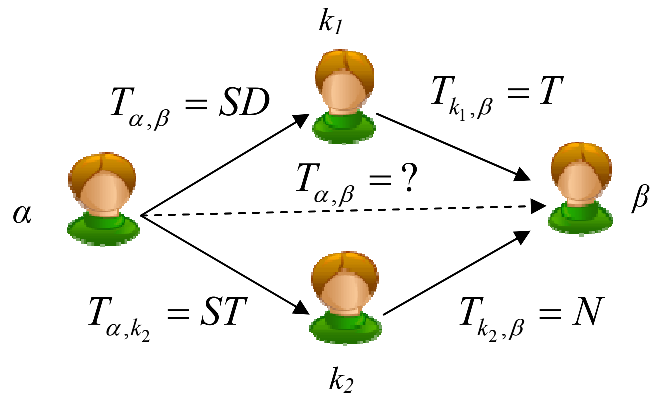


Fig. 3.7 Linguistic terms representation of trust network

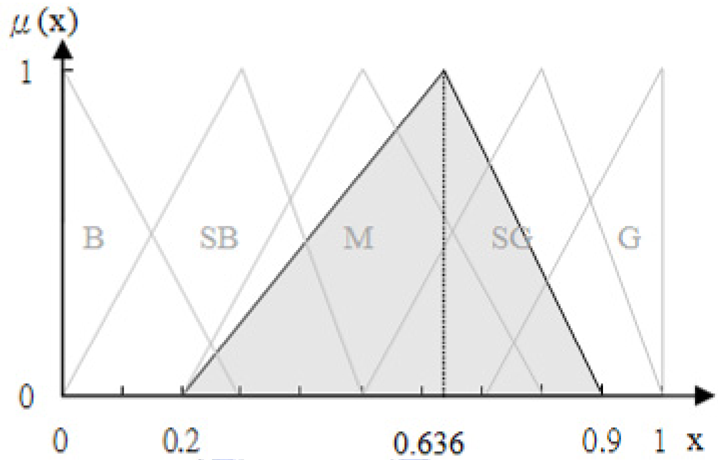


Fig. 3.8 Fuzzy number of Trust $T_{\alpha,\beta}$ calculated by AFWA

The computing of trust inference needs to consume many system resources, such as CPU times and memory spaces, especially when the underlying social network is large and highly connected. In order to preserve sufficient resources to serve the main activities under SNS and to improve the accuracy of trust inference, the trust inference mechanism may be constrained by path length and trust value threshold [23] and thereby interpersonal trust may not always be available. Therefore, *Recommendation trust* is proposed to complement the lack of interpersonal trust in this situation. While the value of interpersonal trust is *subjectively assigned* by peer's personal judgment, the value of recommendation trust is *objectively derived* from the accuracy of past recommendations. Given an interaction between a requestor *s* and a service provider p, the accuracy of recommendation provided by recommender r for a current interaction is measured by comparing the similarity between r' recommendation and s' satisfaction as follows:

$$Ra_{s,r,p} = \sum_{c} Cw_c \times sim(Te^{c}_{r,p}, S^{c}_{s,p}) \qquad (13)$$

where Cw_c is an important weight (with normalized) of service criterion c defined by requestor r, and the function *sim(.)* is used to calculate the similarity between two fuzzy numbers. Based on the geometric-mean averaging operator, Chen [10] indicates that the measure of proposed fuzzy numbers similarity successfully overcomes the limitations of the existing methods and can correctly obtain the similarity measurement result. The simplified equation applied to this study is shown as follows, the complete operations and comparison results could be found in Chen's [10] study:

$$sim(\tilde{A}, \tilde{B}) = \left[\sqrt[4]{\prod_{i=1}^{4} (2 - |a_i - b_i|)} - 1 \right] \times \frac{\min(y^*_{\tilde{A}}, y^*_{\tilde{B}})}{\max(y^*_{\tilde{A}}, y^*_{\tilde{B}})} \qquad (14)$$

where $sim(\tilde{A}, \tilde{B})$ is goes from 0 to 1. The larger the value of $sim(\tilde{A}, \tilde{B})$, the greater the similarity between the fuzzy numbers $\tilde{A}$ and $\tilde{B}$. Both $\tilde{A}$ and $\tilde{B}$ should be transformed first to trapezoidal fuzzy numbers from TFNs before being applied to the function *sim(.)*, i.e., $\tilde{A} = (a_1, a_2, a_3 (= a_2), a_4)$ and $\tilde{B} = (b_1, b_2, b_3 (= b_2), b_4)$ respectively. $y^*_{\tilde{A}}$ and $y^*_{\tilde{B}}$ are calculated by equation:

$$y^*_{\tilde{A}} = \begin{cases} \dfrac{\dfrac{a_3 - a_2}{a_4 - a_1} + 2}{6}, & \text{if } a_1 \neq a_4 \\ 1/2, & \text{if } a_1 = a_4 \end{cases} \qquad (15)$$

For a given recommender r, Tr_r denoted the *recommendation trust* of r. It is aggregated by all past recommendation accuracy of r. It also be parameterized by TFNs which has the same definition as interpersonal trust as another source of referral trust.

3.2.3 Fuzzy Inference System for Evaluating Recommender Confidence

Based on the fuzzy set theory, fuzzy inference systems have been applied in many fields, such as pattern recognition, decision analysis, and data classification, successfully due to their intuitive handling and simplicity, as well as closeness to human perception and reasoning [6]. After deriving two critical elements (i.e., reliability factors and referral trust) which considerably affect the reliability and the trustworthiness of recommendation sources, a fuzzy inference system is built to determine the recommendation confidence. The measurement to determine the confidence level of recommendation under the conditions of the referral trust and reliability factor is expressed as a fuzzy rule with the following format:

*If referral trust is **X** and reliability is **Y** then confidence is **Z***

where ***X*** could be the value of interpersonal trust or recommendation trust, the value of ***Y*** is calculated by Eq. (11), and ***Z*** is the output (result) of recommendation confidence.

Table 3.3 Rule base for recommendation confidence

If referral trust is good and reliability is low then confidence is good
If referral trust is good and reliability is medium then confidence is very good
If referral trust is good and reliability is high then confidence is extremely good
If referral trust is bad and reliability is low then confidence is extremely bad
If referral trust is bad and reliability is medium then confidence is very bad
If referral trust is bad and reliability is high then confidence is bad
If referral trust is medium and reliability is low then confidence is slightly bad
If referral trust is medium and reliability is high then confidence is slightly good
If referral trust is medium and reliability is medium then confidence is medium
If referral trust is slightly bad then confidence is slightly bad
If referral trust is slightly good then confidence is slightly good

Mamdani type fuzzy inference system [45] is adopted to infer the confidence level of recommendation. The proposed rule base contains eleven rules to evaluate the *CF* is shown in Table 3.3. The intuition behinds these rules is that the referral trust is the major factor that could significantly influence the extent of *CF*. For instance, the rules from one to six reflect that if referral trust is *good* (*bad*) then the confidence level is at least equal or better (worse) than *good* (*bad*). Given a referral trust, the reliability factor adjusts the extent of *CF* somewhat according to the degree of reliability. The following figure summarizes the necessary factors mentioned above.

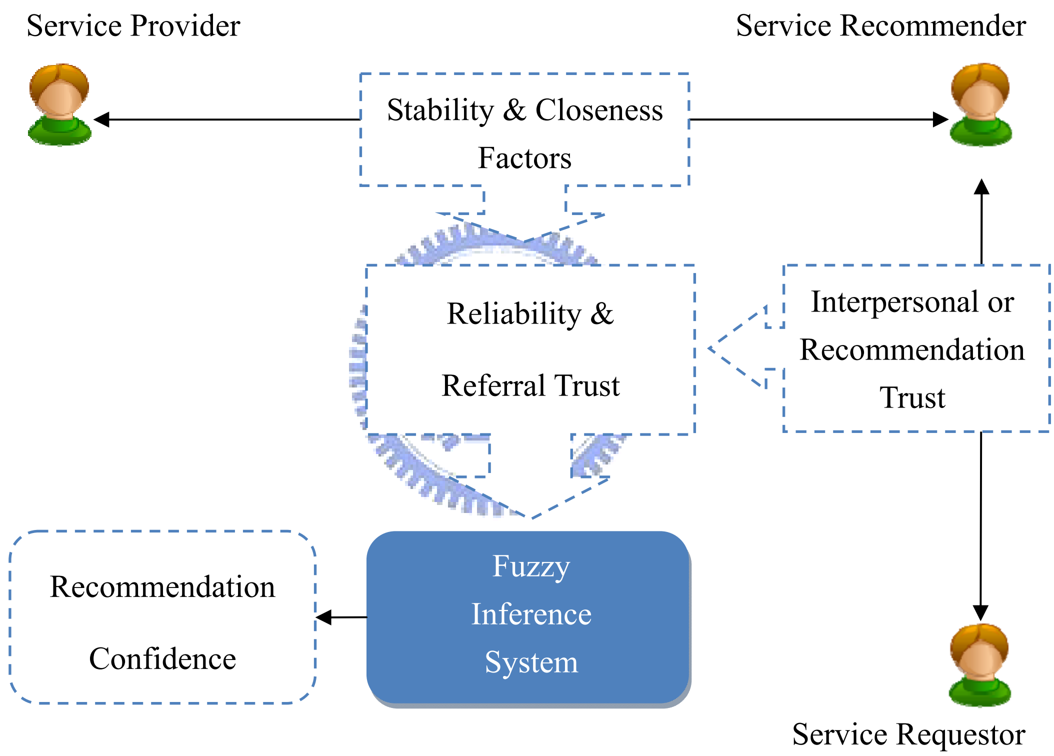


Fig. 3.9 Required factors to evaluate the recommendation confidence

3.2.4 An Algorithm to Construct a Recommendation Matrix

We have introduced how to derive recommendations and proposed a fuzzy inference system to determine the confidence level of these sources. Here we introduce an algorithm to construct a recommendation matrix from the collected information. Suppose a shortlist of service providers P has been collected according to the topic the requestor- *me* needs. The recommendation matrix R is constructed to support the decision making at the final stage and is formulated as follows:

$$R = \begin{array}{c} \\ p_1 \\ p_2 \\ \vdots \\ p_m \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & & c_n \end{array} \\ \begin{bmatrix} RC_1^1 & RC_1^2 & \cdots & RC_1^n \\ RC_2^1 & RC_2^2 & \cdots & RC_2^n \\ \vdots & \vdots & \vdots & \vdots \\ RC_m^1 & RC_m^2 & & RC_m^n \end{bmatrix} \end{array} \tag{16}$$

where $p \in P$, m=|P|, n=|c|, and c as mentioned is denoted as the criterion of the service satisfaction. The recommendation score of provider p in terms of criterion c denoted as RC_p^c is the constituent element of recommendation matrix and is determined by the equation below:

$$RC_p^c = (\delta)\frac{\sum_{r\in R, T\in F} Te_{r,p}^c CF_{r,p}^c}{\sum_{r\in R, T\in F} CF_{r,p}^c} + (1-\delta)\frac{\sum_{r\in R, T\in E} Te_{r,p}^c CF_{r,p}^c}{\sum_{r\in R, T\in E} CF_{r,p}^c} \tag{17}$$

where recommender set R means peers who have ever interacted with service provider p, expert trust Te is the recommendation source used to evaluate provider's performance, and recommendation confidence CF is used to assess reliability and trustworthiness of the recommendation sources. $T \in F$ indicates that the referral trust T belongs to the type of interpersonal trust, while $T \in E$ indicates that the referral trust T belongs to the type of recommendation trust. Thus it follows that the score of recommendation, RC, can be calculated by having the expert trust multiplied by recommendation confidence. In a mathematical form, $RC = \sum(Te \times CF) / \sum CF$. As for the value of δ, this is the weighting factor of the score of recommendation for the two types of referral trust – interpersonal trust and recommendation trust. The complete procedure of proposed algorithm to construct the recommendation matrix is shown in Fig. 3.10. The following describes how the algorithm works:

- For each service provider p in P, do the following actions.
- *Line 3* collects recommender set R from peers who have ever interacted with service

provider *p*. If *R* is not empty then do the following actions, otherwise executes *line 24* to set the recommendation of *p* to default recommendation score R_{def}. The value of R_{def} set to (1,1,1) to give a novice incentive to contribute the services.

- *Line 5* initiates four vectors with size |c| for storing the numerators and denominators (i.e., the summation of $Te \times CF$ and the summation of *CF* respectively) which will be used to aggregate the recommendation score.
- For each recommender *r* in set *R*, do the procedures from *line 7* to *line 22*.
- *Line 7* and *line 8* calculate recommender *r*' expert trust to service provider *p* in terms of criterion *c*, and to evaluate the reliability of expert trust respectively.
- *Line 9* to *line 13* calculate the referral trust *T*. If *me* in *R* (i.e., *me* has ever interacted with service provider *p*) the default trust T_{me}^{def} will be assigned to *T* (The value of T_{me}^{def} also set to (1,1,1) to indicate that *me* believes self experiences absolutely.), otherwise the interpersonal trust $Tf_{me,r}$ will be inferred as a primary source of referral trust *T*. If in the condition as we mentioned in Section 3.2.2 that interpersonal trust is unavailable, the recommendation trust of *r* will be calculated instead of the interpersonal trust. In the worst case that recommender *r* has no record on recommending (e.g., *r* is a new citizen jus join the community recently), the default referral trust T_{ref}^{def} will be assigned to *T*. The value of T_{ref}^{def} set to (1,1,1) to give a new user more chance to promote recommendation.
- By calculating the value of reliability and the referral trust to recommender (from *line 8* to *line 13*), *line 14* applies the values to fuzzy inference system to evaluate the confidence of recommendation.
- *Line 15* to *line 22* take the recommendation confidence *CF* to weight the recommendation score by storing the summation of $Te \times CF$ to the numerator vector and the summation of CF to the denominators. If referral trust *T* is T_{me}^{def} or belongs to

the type of interpersonal trust, the results are added to vectors *num_f* and *den_f* respectively. Otherwise, the results are added to vectors *num_e* and *den_e.*

- After computing each expert trust Te and recommendation confidence CF for current provider *p*, the recommendation scores for each criterion are calculated at *line 23*.

1 ***RecommendationAggregation*** (a shortlist of service providers *P*, requestor *me*)
2 For each *p* in *P*
3 Collect the set *R* where each peer *r* in *R* has ever interacted with *p*.
4 If *R* is not empty then
5 Initial vectors *num_f*, *num_e*, *den_f*, and *den_e*, and set each one's size to |c|.
6 For each *r in R*
7 Calculate expert trust $Te^{c}_{r,p}$.
8 Evaluate reliability $Rl^{c}_{r,p}$ of expert trust.
9 If *r* is *me* then assign a default trust value T^{def}_{me} to *T*.
10 Else
11 Infer the interpersonal trust $Tf_{me,r}$ as the value of *T*.
12 If *T* is null then calculate recommendation trust Tr_r as the value of *T*.
13 If *T* is null then set a default referral trust T^{def}_{ref} to *T*.
14 Apply *T* and $Rl^{c}_{r,p}$ to FIS to evaluate the confidence level $CF^{c}_{r,p}$.
15 If *T* is T^{def}_{me} or *T* belongs to the type of interpersonal trust then
16 For each service criterion *c*
17 $num\_f(c) = num\_f(c) + (Te^{c}_{r,p} \times CF^{c}_{r,p})$.
18 $den\_f(c) = den\_f(c) + CF^{c}_{r,p}$.

Else // i.e., T belongs to the type of recommender trust or T is T_{ref}^{def}.

For each service criterion c

$num\_e(c) = num\_e(c) + (Te_{r,p}^{c} \times CF_{r,p}^{c})$.

$den\_e(c) = den\_e(c) + CF_{r,p}^{c}$.

For each criterion c, calculate $RC_{p}^{c} = \delta \dfrac{num\_f(c)}{den\_f(c)} + (1-\delta)\dfrac{num\_e(c)}{den\_e(c)}$

Else for each criterion c, set $RC_{p}^{c} = R_{def}$.

Fig. 3.10 Recommendation aggregation algorithm

3.3 The Third Stage: Making Decision on Qualified Services

The recommendation matrix constructed in the end of second stage is essentially a decision matrix where the elements (i.e., recommendation scores) constituted are parameterized by fuzzy numbers corresponding to all possible solutions (i.e., service providers) evaluated on multiple criteria (i.e., user's preferences). Therefore, to transform a decision matrix that contains fuzzy and unintelligible information to a comprehensible form so that the end users can easily understand the meaning of recommendation is a crucial stage in the end of recommendation process. A FTOPSIS- fuzzy multi-criteria decision making method proposed by Chen [8] is chosen to implement the decision support process in the end stage of recommendation process to help end users make the best service decision.

Referred to the procedure of FTOPSIS method proposed by Chen [8], six steps are summarized 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 FPIS and FNIS respectively.

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

Step 5: Calculate 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. The best service solution could be chosen accordingly.

Again, the reader is advised to review the work of Chen [8] for additional details of implementation.

4. Experimental Results

In this section, a simulation of the peer production services recommendation is conducted as a controlled experiment. The proposed recommender system is then evaluated in comparison with other three approaches.

4.1 Experiment Setting and Design

In order to imitate a real social network community to support peer production services recommendation, the runtime environment is constructed based on following settings:

1. Structure: Kleinberg's [35] small world generator provided by JUNG[5] (Java Universal Network/Graph) framework is utilized to generate a small world featured network for simulation. The underlying structure of Kleinberg's [35] model as depicted in Fig. 4.1 is an $n \times n$ toroidal lattice in which each node *p* (represented a peer) connected with four adjacent neighbors. Additionally, one long range connection to a random node *v* which is chosen according to probability proportional to *d^-alpha* where *d* is the lattice distance between *p* and *v* and *alpha* is the clustering exponent [32].

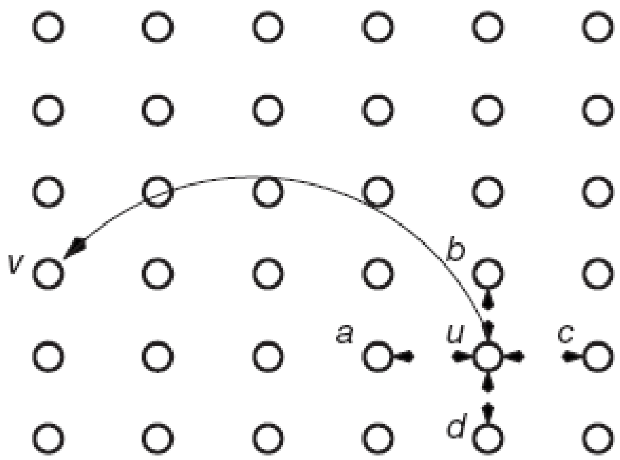


Fig. 4.1 The underlying structure of Kleinberg's model [35]

[5] JUNG is a JAVA API for modeling, analyzing, and visualizing the data that can be represented as graph or network.

2. Composition: Consider a heterogeneous composition in the simulated network where peers have dissimilar valuation in terms of service criteria. We assume that each peer has the highest sensitivity to one of criteria - *C1*, *C2*, and *C3* to represent their preferences. Three groups *G1*, *G2*, and *G3* corresponds to the criteria *C1* to *C3* are initialized as the population composition according to three controlled sensitivity distributions - *Dist. 1*, *Dist. 2*, *and Dist. 3* as shown in Table 4.1, where the proportions (%) defined in each group indicates the percentage of peers to whole network have the highest sensitivity/performance to the corresponding service criterion.
3. Behavior: Peer's preferences reflect her service performance. That is, we suppose that if a peer cares about the criterion *c* the most, she will do the best performance on criterion *c* when receiving the service request. For example, a peer *A* provides a service to the peer *B*, the satisfaction of peer *B* in current transaction will be measured by the similarity calculated between preferences of *A* and *B*. The initial interpersonal trusts between direct connected peers are also established based on this assumption.

Table 4.1 Service sensitivity distribution for simulation

	G1	*G2*	*G3*
Dist. 1	60%	20%	20%
Dist. 2	60%	30%	10%
Dist. 3	50%	30%	20%

Base on above settings, three alternative but meaningful recommendation models– NoT, NoW, and Rnd are set to compared with the proposed model TREPPS in this study. Essentially, the NoT model is the same as TREPPS but *without trust* mechanism. Practitioner may treat the NoT model as a conventional social voting mechanism which is applied in present SNS that treat all the recommendation sources equally without trustworthiness validation. The NoW model aggregates the recommendation sources equivalent to TREPPS but doesn't support the important weight setting for end users at the stage of decision making. It follows that the criteria are equally emphasized without considering user preferences. The last comparison model - Rnd is set for experimental baseline in which service providers are chosen arbitrarily. Recommendation accuracy described in Section 3 is calculated as experimental index to evaluate the performance of each model and the higher is better.

4.2 Results and Analysis

The first experimental configuration contains 100 peers with sensitivity/performance distribution *Dist. 1* as shown in Table 4.1 in which 60%, 20%, and 20% population in terms of criteria *C1* to *C3* respectively corresponding to groups *G1* to *G3*. This is to say, the peers in majority (60%) population of the community - group *G1* have the highest sensitivity to *C1*, while the peers in minority (20%) groups *G1* and *G2* have the highest sensitivity to *C2* and *C3* respectively. Each peer is randomly selected to perform a service requesting an iteration, and the best service provider is chosen to conduct an interaction according to a respective model. The total number of interactions in the simulation is 1,000 when 10 iterations reach.

As illustrated in Fig. 4.2, an average recommendation accuracy of TREPPS for each iteration tends to be stable when the value approaching 0.9 after three iterations and is by far the best approach among others. Fig. 4.3 shows that TREPPS dominates all other models when recommended to users whose highest sensitivity of service criterion is different from most peers in community such as group *G2* in *Dist. 1*. The recommendation accuracy of TREPPS stays steadily at 0.9 after 3 iterations, while the performances of other three models are mostly under 0.6 and fluctuate, making comparing difficult. The total (all interactions) average recommendation accuracy for each group (i.e., *G*1 to *G3*) corresponding to each model is depicted in Fig. 4.4. We can see that an accuracy of TREPPS remains at 0.9 overall regardless of which group is compared, while the accuracy of other compared models drops substantially for groups *G2* and *G3*. Fig. 4.5 illustrates the distribution of average recommendation accuracy for peers in group *G2*. Half of recommendation accuracy of TREPPS lies above 0.9, while the distributions of models NoT and NoW are mostly in the regions of 0.4 to 0.6 and 0.3 to 0.55 respectively.

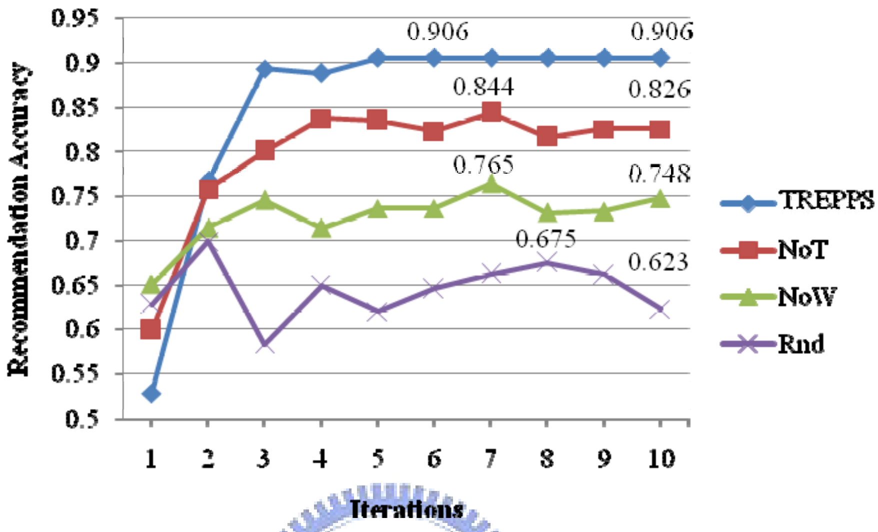


Fig. 4.2 Average recommendation accuracy of sensitivity distribution *Dist. 1* per iteration

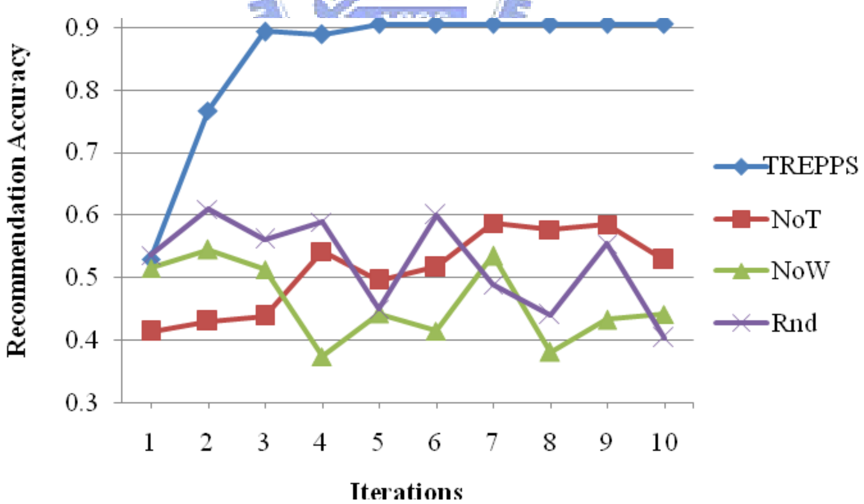


Fig. 4.3 Average recommendation accuracy of sensitivity distribution *Dist. 1* for group *G2* per iteration

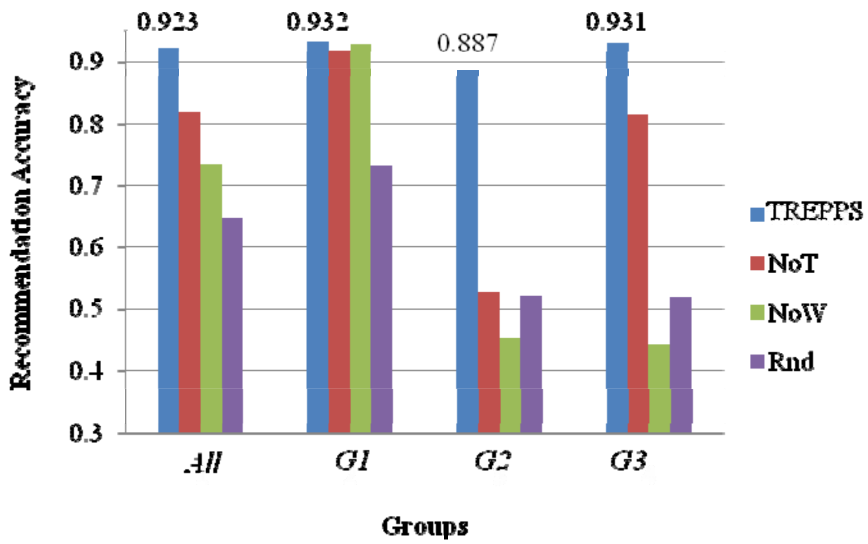


Fig. 4.4 Total (all iterations) average recommendation accuracy for all groups

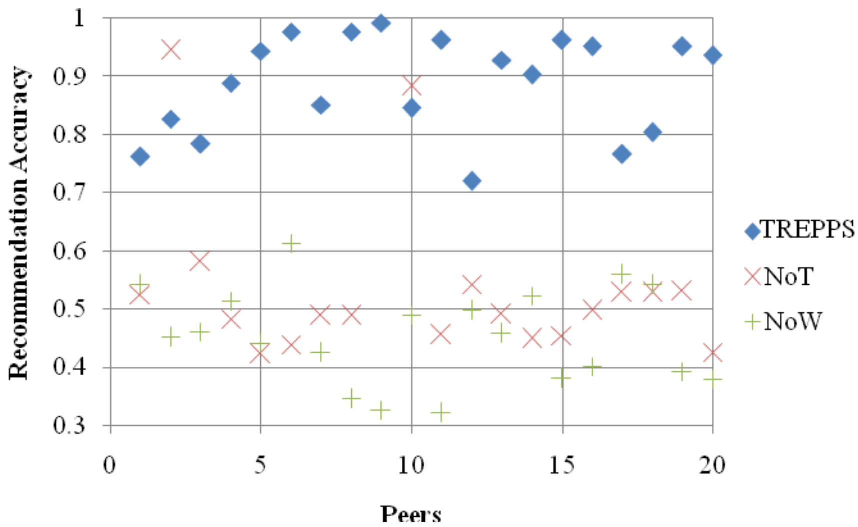


Fig. 4.5 The distribution of average recommendation accuracy for peers in group *G2*

We extend the size of network to 400 peers and conduct experiments with the same sensitivities distribution setting. Table 4.2 summarizes the results of average accuracy for all experiment settings. Fig. 4.6 depicts the comparison of the average recommendation accuracy of two networks (size 100 and size 400) and shows that the experimental results conducted in two network size are similar. The superior proposed system TREPPS functions well in both network sizes. Additionally, as highlighted in Table 4.2 that the three compared models are poor especially for the groups whose proportion to whole network is relative small such as group *G3* in *Dist. 2*, the performance of Models NoT and NoW is even worse than the baseline model - Rnd.

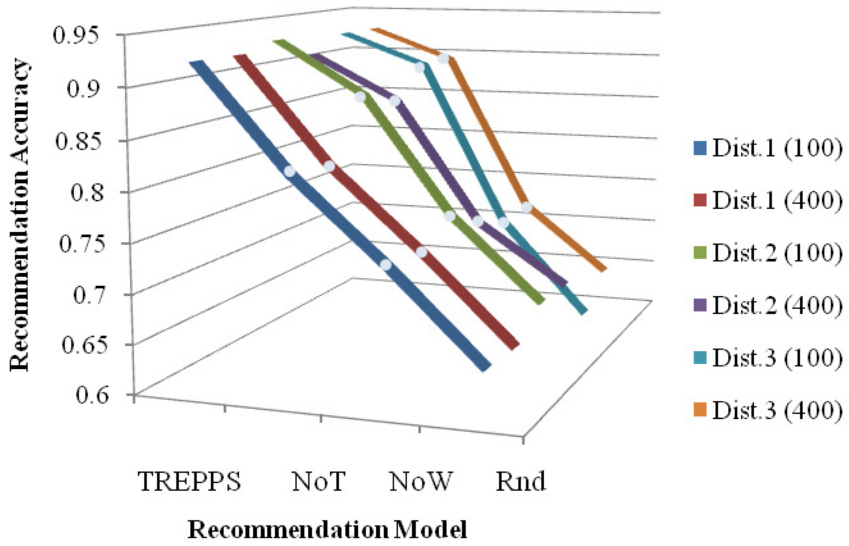


Fig. 4.6 The comparison of the average recommendation accuracy of network size 100 and 400

Information overload is a problematic situation where an exposure to too much information makes a decision unable to be made in a clear way. An appropriate recommender system could function as a filter to prevent online users from information pollution by recommending services that meet their preferences. From the experimental results, we realize that the conventional social voting could not be a viable recommendation approach since the services recommended for everyone are identical and less accurate. In contrast to three compared models, the services provided by TREPPS are not only personalized but also with high quality. Therefore, by taking both the trustworthiness of recommendation sources and the user preferences into account, we argue that the proposed recommender system could be a considerable solution to overcome the information overload problems.

Table 4.2 Summary of the results of average recommendation accuracy for all experiment settings.

# of peers	Distribution	Average				Model
		Total	*G1*	*G2*	*G3*	
100	*Dist. 1* (60%, 20%, 20%)	0.923	0.932	0.887	0.931	TREPPS
		0.818	0.918	0.527	0.816	NoT
		0.736	0.929	0.453	0.441	NoW
		0.646	0.732	0.522	0.518	Rnd
	Dist. 2 (60%, 30%, 10%)	0.931	0.946	0.930	0.838	TREPPS
		0.876	0.940	0.902	0.418	NoT
		0.752	0.943	0.470	0.452	NoW
		0.667	0.742	0.587	0.458	Rnd
	Dist. 3 (50%, 30%, 20%)	0.927	0.941	0.918	0.905	TREPPS
		0.893	0.920	0.873	0.858	NoT
		0.714	0.906	0.563	0.459	NoW
		0.613	0.669	0.587	0.515	Rnd
400	*Dist. 1* (60%, 20%, 20%)	0.922	0.930	0.913	0.907	TREPPS
		0.814	0.911	0.675	0.660	NoT
		0.732	0.915	0.470	0.444	NoW
		0.643	0.724	0.531	0.511	Rnd
	Dist. 2 (60%, 30%, 10%)	0.909	0.934	0.926	0.708	TREPPS
		0.862	0.920	0.900	0.398	NoT
		0.729	0.910	0.475	0.401	NoW
		0.666	0.744	0.571	0.484	Rnd
	Dist. 3 (50%, 30%, 20%)	0.927	0.937	0.922	0.910	TREPPS
		0.893	0.920	0.880	0.846	NoT
		0.718	0.899	0.543	0.528	NoW
		0.644	0.691	0.602	0.591	Rnd

5. Application: A Trust-Based Social News System

Social news system is one of the most popular applications of peer production services. The word -'social' suggests that the citizens of community share the news based on the social relationships between them. The 'news' is defined to be any type of user-generated contents around World Wide Web. Hence the sources of news published or linked to social news site are not constrained to the news edited by particular professional journalists but could be the Weblog articles written by Bloggers, the videos created by amateur videographers, and the opinions commented on any online resources by community citizens, etc. Due to the property of susceptibility to corruption and collusion [62] of bookmarking type services, the veracity of the sources of these services cannot be discriminated and the quality of these services is unpredictable. The commonly susceptible case is that the online users submit their contents or links with a lot of popular but irrelevant tags to make their sites visible. The worst cases include the aforementioned phenomena, such as vote-buying and vote-exchanging [16]. Therefore, we proposed a trust-based social news system called '*Trust News,*' which not only demonstrate the utilization of proposed recommender system but also intend to relieve these concerns.

The portal of proposed trust news system as shown in Fig. 5.1 contains a main display area for the recently submitted news. Each block as shown in Fig. 5.2 contains brief information of the individual news, such as title, snapshot image, short description, and tags. In addition, a 'rate' link allows users to respond their satisfactions through the feedback interface. As shown in Fig. 5.3, the feedback interface allows users to express the degree of satisfactions corresponding to four criteria – timeliness, completeness, accuracy, and reliability with linguistic terms. The linguistic expression also applied to trust management interface and service preference setting as shown in Fig. 5.4 and Fig. 5.5 respectively.

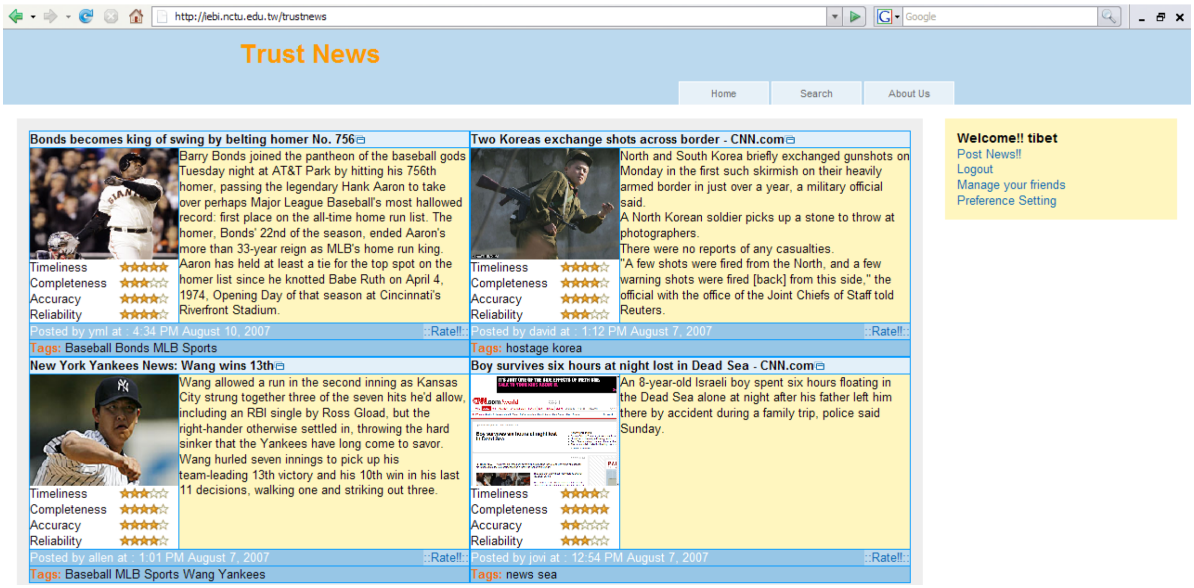


Fig. 5.1 The portal of trust news system

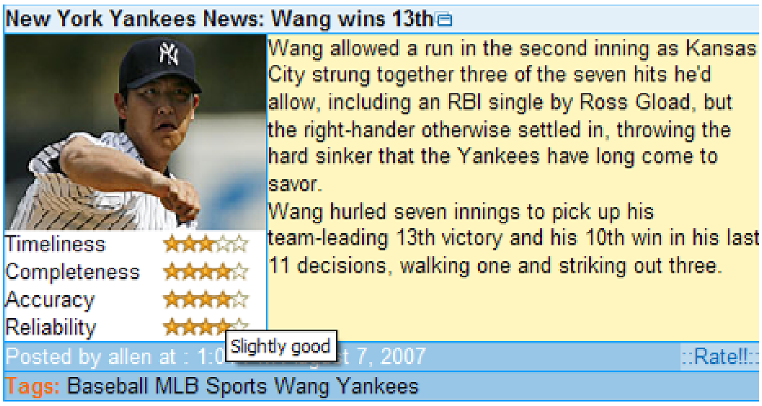


Fig. 5.2 The news block in the main area of portal

Fig. 5.3 The feedback interface for satisfaction rating

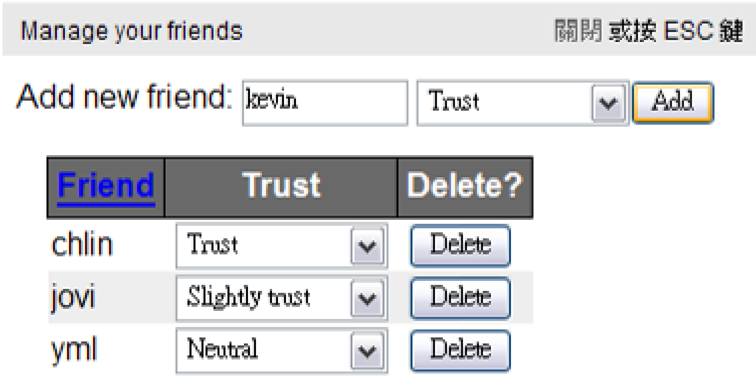


Fig. 5.4 The interface to manage the trust relationship

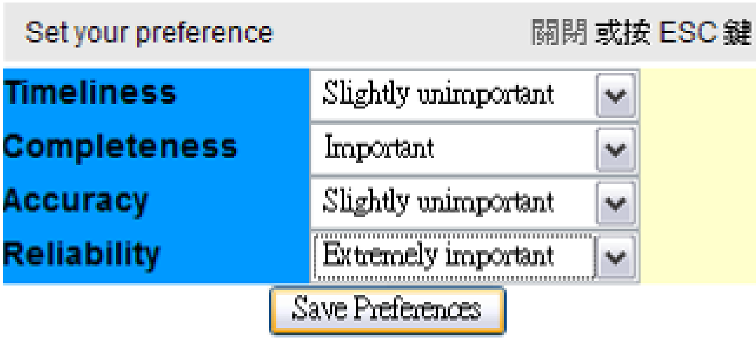


Fig. 5.5 The interface to set the user's preferences

Two different dimensions are taken into account to gain more understanding of the proposed system. Firstly, a five-star symbol which corresponds to five linguistic terms expression of service satisfaction is displayed in individual news block. Together they form the recommendation information as shown in Fig. 5.2. The fuzzy number similarity measure discussed in Section 3 is used to transform the computed recommendation score *RC* to a comprehensible five-star symbol. For example, suppose *RC* is parameterized with a TFN as (0.1, 0.4, 0.7) originally. By computing the similarity between the recommendation score *RC* and the fuzzy numbers of service satisfaction defined in Table 3.1, the nearest linguistic term – *neutral (N)* will be chosen as shown in Table 5.1. Secondly, we implement a tag-based topic matching engine to help the news searching. As shown in Fig. 5.6, the search results are ranked by proposed recommendation aggregation algorithm with FTOPSIS MCDM method.

Fig. 5.6 The ranking of search results

Table 5.1 Using the fuzzy similarity measure to choose the nearest linguistic term

Linguistic terms of satisfaction	Similarity
Bad (B)	0.6702
Slightly bad (SB)	0.8745
Neutral (N)	***0.9***
Slightly good (SG)	0.6244
Good (G)	0.4696

We provide an example to illustrate the underlying process of social news system which follows the three stages as discussed in Section 3. Suppose a scenario where user *A* intends to search the related social news about movie. She enters the keyword “movie” in search field as depicted in Fig. 5.6. The personal preference is also set in advance through a user interface as depicted in Fig. 5.5. The preference setting is shown in Table 5.2 where criteria from *C1* to *C4* are corresponding to timeliness, completeness, accuracy, and reliability. In order to provide a comprehensive description of underlying process, we assume that there are only 10 registered users in the social news system. Fig. 5.7 illustrates the corresponding trust network of these users. Table 5.3 shows the related tags of the services the users have provided.

Table 5.2 The preference setting of user *A*

Criteria	C1	C2	C3	C4
Importance Weight	EI	A	EU	A

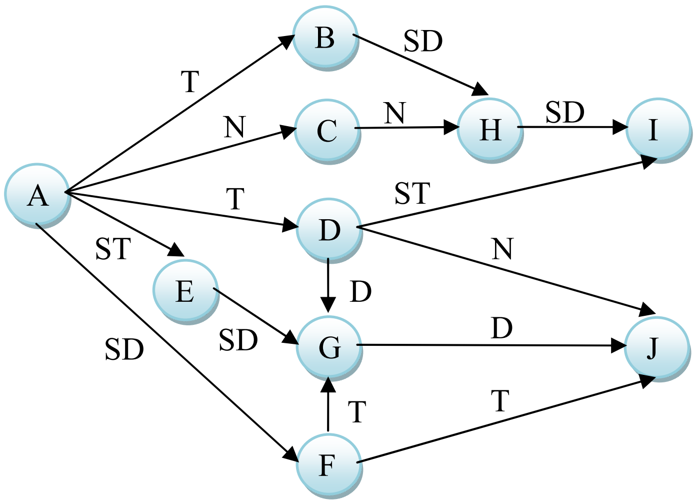


Fig. 5.7 The underlying trust network of social news system

Table 5.3 The tags of the services the users have provided

Users	Tags
A	Novel, Artists
B	Travel, Web Design
C	Typography, Artists
D	Sport, Computer Science
E	Comic, Typography
F	Sport, Entertainment
G	Novel, Sport
H	Sport, Entertainment
I	Movie, Travel, Artists,
J	Comic, Novel, Movie

The following describes the full process of recommendation:

Stage 1: According to Table 5.2, we can find out a shortlist of service providers *P* consists of users *I* and *J* who can provide services that match the topic 'movie'.

Stage 2: The recommendation matrix is obtained by following the recommendation aggregation algorithm (Fig. 3.10).

- *Line 2* to *line 3* of the algorithm indicates that the first step is to collect a recommendation set *R* where each one *r* in *R* has ever interacted with user *A*. Table 5.4 shows that users *H* and *D* have ever interacted with service provider *I* while users *D*, *G*, and *F* have ever interacted with service provide *J*. Interaction histories store the interaction time and the satisfaction feedbacks in terms of criteria *C1* to *C4* respectively.

Table 5.4 Recommender set *R* and the corresponding interaction histories

Service Provider	Recommender	Interaction Histories				
p in *P*	*r* in *R*	C1	C2	C3	C4	Time
I	H	B	N	N	G	3
		N	G	SB	SG	8
		N	SB	N	N	11
	D	N	N	SB	SG	8
		B	SG	N	SG	9
J	D	SG	G	G	N	5
	G	N	G	SG	SB	3
		SB	SG	G	B	5
	F	N	SG	B	SB	6
		N	N	B	G	8

- Follows the *line 7* of the algorithm, we calculate the value of expert trust *Te* according to Table 5.4 and Eq. (7) as Table 5.5 shows.

Table 5.5 Recommender *r*' expert trust to provider *p*

Service Provider	Recommender	Expert Trust *Te*			
p in *P*	*r* in *R*	C1	C2	C3	C4
I	H	(0.173, 0.432, 0.732)	(0.282, 0.582, 0.723)	(0.127, 0.427, 0.691)	(0.377, 0.677, 0.9)
	D	(0.094, 0.235, 0.535)	(0.359, 0.659, 0.906)	(0.106, 0.406, 0.659)	(0.5, 0.8, 1.0)
J	D	(0.5,	(0.7,	(0.7,	(0.2,

		0.8, 1.0)	1.0, 1.0)	1.0, 1.0)	0.5, 0.8)
	G	(0.075, 0.375, 0.613)	(0.575, 0.875, 1.0)	(0.625, 0.925, 1.0)	(0, 0.112, 0.375)
	F	(0.2, 0.5, 0.8)	(0.329, 0.629, 0.886)	(0, 0, 0.3)	(0.4, 0.7, 0.786)

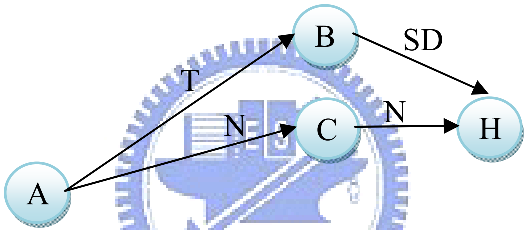
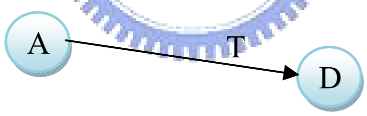
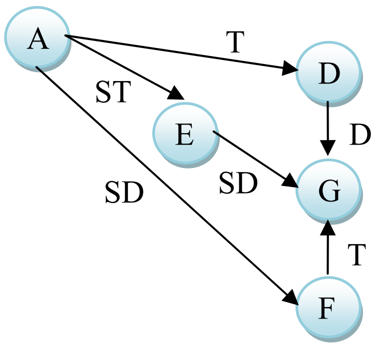
- According to *line 8* of the algorithm, we need to evaluate the reliability *Rl* of expert trust. Two factors as shown in Eq. (9) and Eq. (10) are incorporated as *Rl* according to Eq. (10). Table 5.6 shows the result.

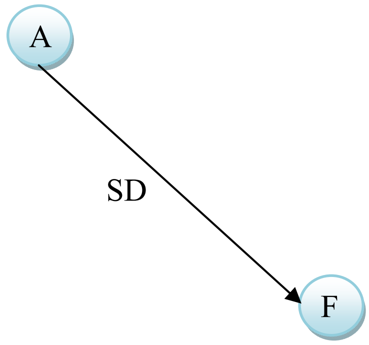
Table 5.6 Reliability factors of expert trust

Service Provider *p* in *P*	Recommender *r* in *R*	Reliability Factors *Fc*	 *Fs* for C1 to C4	 *Rl*
I	H	0.398	(0.882,0.882,0.953) (0.696,0.696,0.777) (0.861,0.907,0.907) (0.823,0.823,0.9)	(0.351,0.351,0.379) (0.277,0.277,0.309) (0.343,0.361,0.361) (0.328,0.328,0.358)
	D	0.251	(0.751,0.751,0.9) (0.851,0.851,0.9) (0.851,0.9,0.9) (1.0,1.0,1.0)	(0.189,0.189,0.226) (0.214,0.214,0.226) (0.214,0.226,0.226) (0.251,0.251,0.251)
J	D	0.158	(1.0,1.0,1.0) (1.0,1.0,1.0) (1.0,1.0,1.0) (1.0,1.0,1.0)	(0.158,0.158,0.15) (0.158,0.158,0.15) (0.158,0.158,0.15) (0.158,0.158,0.15)
	G	0.251	(0.859,0.906,0.906) (0.906,0.906,1.0) (0.906,0.906,1.0) (0.859,0.906,1.0)	(0.216,0.228,0.228) (0.228,0.228,0.251) (0.228,0.228,0.251) (0.216,0.228,0.251)
	F	0.251	(1.0,1.0,1.0) (0.853,0.853,0.902) (1.0,1.0,1.0) (0.657,0.657,0.755)	(0.251,0.251,0.251) (0.214,0.214,0.227) (0.251,0.251,0.251) (0.165,0.165,0.190)

- The referral trust T is calculated by following the algorithm from *line 9* to *line 13*. As we can see in Fig. 5.7, while user A has direct trust between users D and F, he does not have direct relationship with users H and G. However, we observe that the interpersonal trust between them can be inferred through the direct trust between users B, C and users D, E, F respectively. Thus, according to Eq. (1) and the AFWA [7] method, we can calculate the referral trust T of each recommender r. Table 5.7 shows the values of referral trust T and the corresponding trust networks.

Table 5.7 Referral trust T of each recommender and the corresponding trust network

Recommender r in R	Trust Network	Referral Trust T
H		(0.033,0.367,0.66)
D		(0.7, 1.0, 1.0)
G		(0,0.257,0.565)

F	 	(0, 0.3,0.5)

- Follows the *line 14* of the algorithm, we can evaluate the confidence *CF* of recommendation by applying the calculated values of two factors- reliability *Rl* and referral trust *T* to the proposed fuzzy inference system (Table 3.3). Table 5.8 shows the evaluated confidence *CF* of each criterion.

Table 5.8 Confidence of recommendation for each recommender and the corresponding service provider

Service Provider *p* in *P*	Recommender *r* in *R*	Confidence *CF*			
		C1	C2	C3	C4
I	H	0.380	0.354	0.38	0.374
	D	0.75	0.749	0.747	0.740
J	D	0.751	0.751	0.751	0.751
	G	0.289	0.301	0.301	0.301
	F	0.294	0.277	0.294	0.257

- Since the expert trust *Te* and confidence level *CF* are obtained, the recommendation matrix *R* as shown in Table 5.9 can be constructed by following the algorithm from *line 15* to *line 23*.

Table 5.9 Recommendation matrix for user *A*

	Evaluated Criterion *c*				
	RC_p^c	C1	C2	C3	C4
Provider *p* in *P*	I	(0.121, 0.301,	(0.334, 0.634,	(0.113, 0.413,	(0.459, 0.759,

		0.601)	0.847)	0.670)	0.966)
	J	(0.342, 0.642, 0.872)	(0.594, 0.894, 0.976)	(0.530, 0.765, 0.847)	(0.193, 0.450, 0.700)

Stage 3: Refer to the procedure of FTOPSIS method as shown in Appendix A [8], the ranking order and the corresponding scores of providers *I* and *J* are determined as shown in Table 5.10. According to the ranked recommendation result, user *A* can determine that the best service provider is *J*.

Table 5.10 Ranking order of the recommendation result

Rank	Service Provider *p* in *P*	Score
1	J	0.382
2	I	0.325

Trust-based social news system demonstrates a practical application based on the proposed recommender system. In the system, the recommendation provided along with the services is personalized according to individual preference. This mechanism has significantly reduced the traditional effort to find the right services and also mitigated information overload problem. Further, the trust-based social news is a great start to borrow the concepts and spirits of peer production services.

While the proposed system can be a framework for developing future application of peer production related services since the core participated roles are identical and the underlying processing mechanism is similar, some additional modifications as following may be possible in applying this study to different context or application domain:

- As mentioned in Section 3.1, the practices of topic matching depend on what type of peer production services is and how do they be organized. Some peer production services may be organized with more attributes and the corresponding features, not only full-text descriptions. Therefore, it is possible to provide more property filters for topic searching as long as it can make a shortlist of service providers in the first stage.

- The definitions of criteria (i.e., user preferences) are adjustable on your needs. You may define fewer or more criteria for user preference setting and do not need to set four dimensions as demonstrated in this study. Some criteria may correlate to the specific service features and properties according to the application context.
- The user-defined interpersonal trust may be constrained to certain application context and therefore not portable and inconsistence between different domains. The definition of the trust expressions is also domain-dependent. However, it does not affect the process and the related practices of the proposed system.
- As we noted in Section 2.3, the choice of FMCDM methods to support the decision process on the third stage is not constrained in FTOPSIS as long as the applied method can appropriately help the best services decision.

6. Conclusions and Future Work

6.1 Conclusions

Based on the prediction made by IDC [20], nearly 70% of 988 billion gigabytes digital information will be created by individuals in 2010. However, the issues of peers' contributions, such as quality and veracity, are not well managed and treated seriously. This study intends to deal with the information overload problems that occur in peer production services. Through the development of personal recommender system which is mainly based on the incorporation of prominent artificial intelligent methodology – fuzzy logic and promising social networking technology – trust computing, the quality and the veracity of peer production services can be significantly enhanced. In addition, we presented an appropriate practice on dealing with the subjective judgments, such as trust knowledge, personal preferences, and service satisfactions, based on fuzzy logic and its linguistic terms expression. The fuzzy inference system is also built to determine the recommendation confidence based on the explicitly expressed fuzzy rules which imitate the expert's knowledge. The fuzzy MCDM method which usually applied in operational researches and management sciences is employed and advance the peer production services decision making.

6.2 Future Work

Although a series of controlled experiments is conducted based on a reasonable setting (i.e., imitated social network structure, heterogeneous population composition, and intuitive reactive behaviors), some feature works can be continued and extended based on the following suggestions:

1. The referred quality functions in this work include closeness, and freshness factors may be investigated further either through more dynamic simulated experiment or via

empirical investigation in real applications. These factors reflect the dynamic nature of peer production services and have already been validated in the literature [28][56][64], but they are not well examined in this work due to the restriction of relative static simulation.

2. It is interesting to investigate the real users' experiences of proposed trust-based social news system. The empirical results may provide more implication of the proposed model in the field of information filtering. In addition, the impact of quality functions as mentioned could be observed in such dynamic runtime environment.
3. There are innovative works proposed based on simple trust model such as "Trust-based instant messenger [42]" which enlarges the message accessibility without the overflow of messages and "Trust-based blog system [41]" which aim at evaluate the trustworthiness of blog articles. If these applications can be extended based on this work, the potential benefits of proposed recommender system can be exploited.
4. Computational trust model is implemented by the manipulation of matrix multiplication where the matrix represents the underlying trust network. Hadoop[6], an open source platform which implement Google's MapReduce distributed programming model [13], provides a feasible solution for parallel programming on such massive matrix. If the proposed recommender system can be implemented on Hadoop platform, it will be relative easy to realize the second and the third future works.

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[6] Hadoop, http://hadoop.apache.org/

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Appendix A

Supposing a Fuzzy MCDM problem has *m* alternatives from which decision makers have to choose, and also *n* decision criteria with which alternative performance are measured, denoted as $A_1, A_2, ..., A_m$ and $C_1, C_2, ..., C_n$ respectively. A typical Fuzzy MCDM problem can be expressed in matrix format as below:

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & & \tilde{x}_{mn} \end{bmatrix} \end{array}, \qquad (18)$$

$$\tilde{W} = [\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n]$$

where $\tilde{x}_{ij}$, $\forall i, j$ is the rating of alternative A_i with respect to criterion C_j, and $\tilde{w}_j$, *j=1,..,n* is the weight of criterion C_j. $\tilde{x}_{ij}$ and $\tilde{w}_j$ are linguistic variables which can be parameterized by triangular fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$.

In order to transform the various criteria scales into a comparable scale, a normalized fuzzy decision matrix $\tilde{R}$ is obtained through the linear scale transformation:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}, \quad i = 1, 2, ..., m, \; j = 1, 2, ..., n \qquad (19)$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \; j \in B \qquad (20)$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \; j \in C \qquad (21)$$

$$c_j^* = \max_i c_{ij} \qquad , \text{ if } j \in B \qquad (22)$$

$$a_j^- = \min_i a_{ij} \qquad , \text{ if } j \in C \qquad (23)$$

where B and C are the set of benefit criteria and cost criteria respectively. The normalized method above preserves the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1].

Considering the different importance of each criterion, we can construct the weighted normalized fuzzy decision matrix as below:

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, \quad i = 1, 2, ..., m, \ j = 1, 2, ..., n \tag{24}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)\tilde{w}_j$. Because the positive triangular fuzzy numbers are included in the interval [0, 1], the fuzzy positive-ideal solution (FPIS, A^*) and fuzzy negative-ideal solution (FNIS, A^-) hence are defined as

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, ..., \tilde{v}_n^*) \tag{25}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_n^-) \tag{26}$$

where $\tilde{v}_j^* = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$.

The distance of each alternative from A^* and A^- can be currently calculated as below:

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right) \tag{27}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right) \tag{28}$$

where $d(\cdot,\cdot)$ is the distance measurement between two fuzzy numbers.

Once d_i^* and d_i^- of each alternative A_i have been calculated, a closeness coefficient of each alternative can be determined:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \tag{29}$$

in order to rank the order of all alternatives, and the best solution is therforely can be choosen from among a set of feasible alternatives.