

TREPPS: A Trust-based Recommender System for Peer Production Services

Yung-Ming Li*, Chien-Pang Kao

Institute of Information Management, National Chiao Tung University, 1001 Ta-Hsueh Road, Hsinchu 30010, Taiwan

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.

© 2008 Elsevier Ltd. All rights reserved.

Keywords: Peer production; Recommender systems; Trust computing; Fuzzy inference systems

1. Introduction

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 (Kolbitsch & Maurer, 2006; Lindahl & Blount, 2003). 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 (Benkler, 2006), is gradually shifting the traditional capital-intensively wealth production to a new model which heavily depends on information creating and sharing (Gillmor, 2006). 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 captured the attentions of almost 45% of active Web users (Bausch & Han, 2006). 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

* Corresponding author. Tel.: +886 3 5712121.

E-mail addresses: yml@mail.nctu.edu.tw (Y.-M. Li), java.gang@gmail.com (C.-P. Kao).

accelerate the probe and organization of peers' contributions, two new emerging approaches have been extensively incorporated in SNS. Folksonomy (Folksonomy, 2007), 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 (Doctorow, 2007), and fake news (Web 2.0 Television, 2006) 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 (Watchlist (Internet), 2007) 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 (O'Donovan & Smyth, 2005; Wei, Moreau, & Jennings, 2005). 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. We present a recommender system based on the trust of social networks instead of the conventional recommender systems and aforementioned approaches. 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 (Zadeh, 1965) 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.

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

2.1. Trust computing and trust-based recommender systems

The trust referred in this study can be classified as *interpersonal trust* (McKnight & Chervany, 1996) which means that people more than two trust each other in a certain situation. In general, interpersonal trust, a directional relationship, requires at least an involvement of two parties called *trustor* and *trustee*. It expresses that *trustor* expects *trustee* to behave the way she/he wants (Jøsang, 1996). Since the groundbreaking Internet technologies are being developed, many trust computing model has been proposed and applied in emerging core technologies such as Web Semantic, Peer-to-Peer and Multi-Agent systems. Several studies provide surveys and reviews of trust computing model and relevant applications (Artz & Gil, 2007; Jøsang, Ismail, & Boyd, 2007; Sabater & Sierra, 2005).

Essentially, trust network is an online social network in which peers are interlinked by trust relationship (Ding, Kolari, Ganjugunte, Finin, & Joshi, 2004). It can be represented by directed graph as shown in Fig. 1, where vertices 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 (Abdul-Rahman & Hailes, 1998; Ding, Zhou, & Finin, 2003), the trust values along the chain of connected trust networks can be inferred and be formulated as follows:

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

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. 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 $T_{\alpha,\beta} = (0.3 \times 1 + 0.8 \times 0.5) / (0.3 + 0.8) = 0.636$.

Trust can be used to estimate the quality of a peer's beliefs, and furthermore to reduce the information search

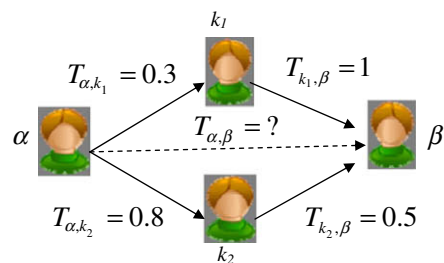


Fig. 1. Graph theory based representation of trust network.

complexity (Ding et al., 2004). Trust networks prefilter not only the like-minded peers but also the credible recommendation sources (Ziegler & Golbeck, 2007). The results of Sinha and Swearingen’s research (Sinha & Swearingen, 2001, 2002) indicate that users like to know why an item was recommended and prefer recommendation from others who know and trust. By utilizing trust computing, trust-based recommender system allows people to be aware that the sources of recommendation were produced from the people they know (Golbeck, 2006). Thus, the concerns stated above can be properly dealt with. It can, moreover, improve the accuracy of recommendation and decrease the error when compared with common Collaborative Filter technology (Golbeck, 2006; Massa & Bhattacharjee, 2004; O’Donovan & Smyth, 2005).

2.2. Fuzzy numbers, arithmetic, and operations

Fuzzy set and logic introduced by Zadeh (1965) 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. From an end-user perspective, its linguistic term expression provides a rich and natural way to express a personal judgment and knowledge. Therefore, the fuzzy logic is employed in this study to capture the knowledge of trust, to express the extent of service satisfaction, and to model the users’ preferences. Based on the fuzzy set theory, a set of rules which takes account of trust and critical factors pointed out in literatures are investigated to construct a fuzzy inference system for evaluating the confidence of recommendation. The brief definitions of the specific fuzzy number and the necessary fuzzy arithmetic operations may be introduced for later discussion.

Let \tilde{A} be a triangle fuzzy number (TFN) on the real line \mathfrak{R} 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 $a_1 \leq a_2 \leq a_3$. The membership function $\tilde{A}(x)$ of TFN defining the degree of membership of element $x \in \mathfrak{R}$ to \tilde{A} :

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

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 (Dubois & Prade, 1980), three essential arithmetic operations are necessary in this study:

$$\begin{aligned} \tilde{A}(+) \tilde{B} &= (a_1, a_2, a_3)(+)(b_1, b_2, b_3) \\ &= (a_1 + b_1, a_2 + b_2, a_3 + b_3) \end{aligned} \quad (3)$$

$$\begin{aligned} \tilde{A}(-) \tilde{B} &= (a_1, a_2, a_3)(-)(b_1, b_2, b_3) \\ &= (a_1 - b_3, a_2 - b_2, a_3 - b_1) \end{aligned} \quad (4)$$

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

where k is a real number. The distance measure between two TFNs according to the vertex method stated in Chen (2000) can be calculated as

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

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 (Kuo, Tzeng, & Huang, 2007; Li, 2007). 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 (1970), is an appropriate approach to effectively cope with the inherent vagueness, uncertainty, and subjectiveness of human decision making process (Kuo, Yeh, & Chau, 2003). 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 (1981), has been extensively extended (Chen, 2000; Chen & Tzeng, 2004; Chen & Hwang, 1992; Li, 2007) 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 (2000) is chosen in this study to implement the decision support process. However, we do not elaborate on the approach here since Chen’s (2000) approach is already adopted widely 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.

3. TREPPS: Trust-based REcommender 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. 2. *Service requestor* initiates the service request process by offering the keywords that define the topics of interested services. *Service providers*

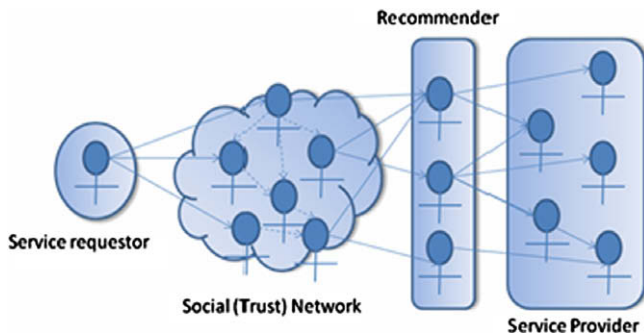


Fig. 2. Roles participated in peer production services.

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.

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 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. However, we will not elaborate the practices of topic matching here since it is out of the scope of this study and fairly depend on what the type of peer production services underlaid. 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,¹ 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 1, is obviously an indispensable mechanism for social media annotation, and is good for services probing.

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.

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, Motta, and Petre (2006) 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 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 she/he cares about the *timeliness* of news. In addition, there may be one concerning about the *completeness* of content, but she/he does not care about whether the news is on time or not. Moreover, some people may mind the *accuracy* of

¹ Apache Lucene, <http://lucene.apache.org/>.

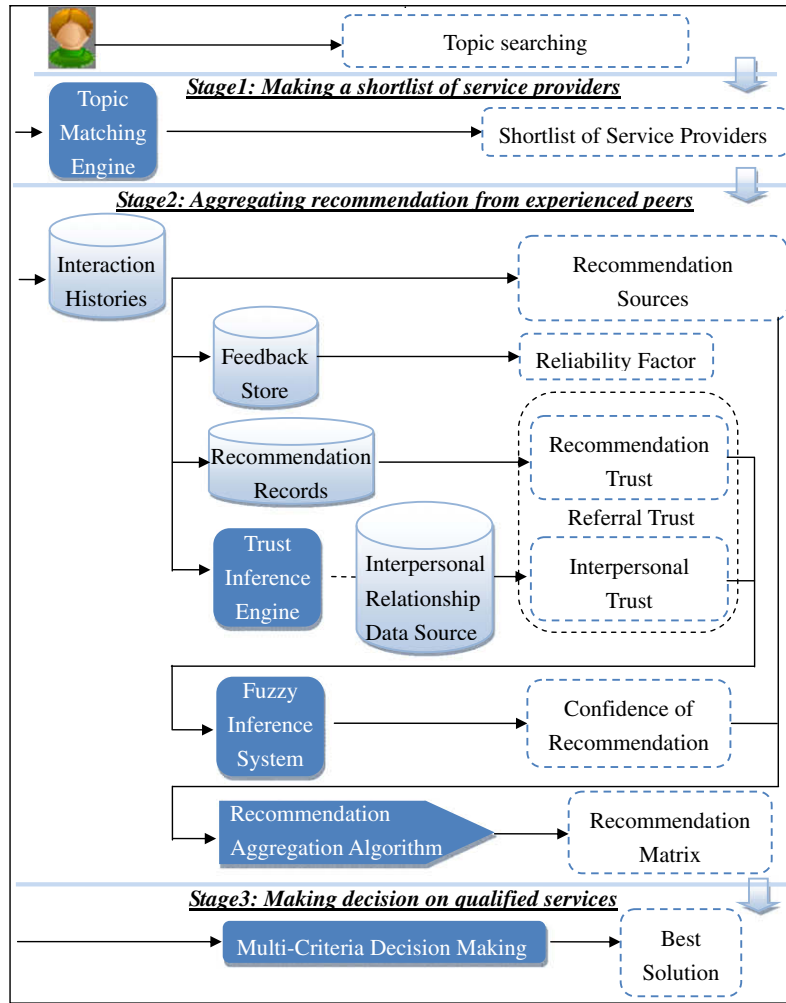


Fig. 3. Three stages of peer production service recommendation process and the core tasks and necessary system components.

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*. 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. 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

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

where $f_w(i) = \text{fresh}(i) / \sum_{i \in k} \text{fresh}(i)$ and $\text{fresh}(i) = \text{time}(i) / \text{time}(t)$. Weight factor f_w , firstly introduced by Sabater and Sierra (2001), 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 Tables 1 and 2, while the membership functions are depicted in Figs. 4 and 5 respectively. 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 $s_c^1 \leq s_c^2 \leq s_c^3$. Expert trust denoted as

Table 1
Linguistic values and fuzzy numbers for service satisfaction and trust

Linguistic terms		Fuzzy numbers
Service satisfaction	Interpersonal and 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 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)

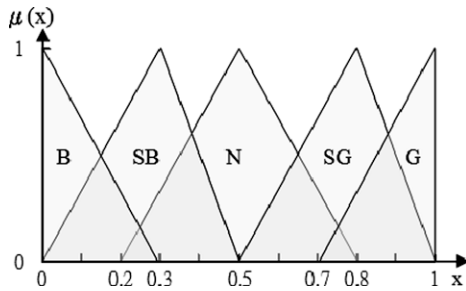


Fig. 4. Membership functions for service satisfaction.

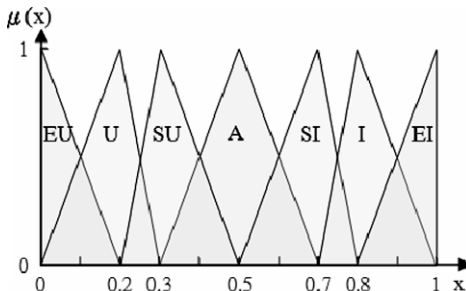


Fig. 5. Membership functions for importance weight of performance criteria.

$\tilde{T}e_c = (Te_c^1, Te_c^2, Te_c^3)$. According to Eqs. (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.

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 (Huynh, Jennings, & Shadbolt, 2006; Sabater & Sierra, 2001; Song, Hwang, Zhou, & Kwok, 2005). These two factors both are derived from feedback store as shown in Fig. 3.

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 (2001), 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:

$$Fs_{r,p}^c = \tilde{P} - \sum_{i \in k} fw(i) \cdot |S_{rp}^c(i) - Te_{rp}^c| \tag{10}$$

where $\tilde{P} = (1, 1, 1)$ denoted as an ideal value of stability factor. $Fs_{r,p}^c$ 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:

$$RL_{r,p}^c = Fc_{r,p} \times Fs_{r,p}^c, \tag{11}$$

and the corresponding membership functions that contain three fuzzy numbers – *low* (L), *medium* (M), and *high* (H) are depicted in Fig. 6.

The participants in social network naturally have reputations gained from providing good services and referrals (Singh, Yu, & Venkatraman, 2001). 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. (2003), 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 2.1. 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 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 (1992), let A_1, A_2, \dots, A_n , and W_1, W_2, \dots, W_n be the fuzzy numbers defined on the universes X_1, X_2, \dots, X_n , and Z_1, Z_2, \dots, Z_n , respectively. If f is a function which maps from $X_1 \times X_2 \times \dots \times X_n \times Z_1 \times Z_2 \times \dots \times Z_n$ to the universe Y , then the fuzzy weighted average y is defined as

$$y = f(x_1, x_2, \dots, x_n, w_1, w_2, \dots, w_n) = \frac{w_1x_1 + w_2x_2 + \dots + w_nx_n}{w_1 + w_2 + \dots + w_n} \tag{12}$$

where for each $i = 1, 2, \dots, n$, $x_i \in X_i$ and $w_i \in Z_i$. An algorithm – *Alternative Fuzzy Weight Average* (AFWA) proposed by Chang, Hung, Lin, and Chang (2006) 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. (2006) 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 2.1. Supposing there exist a trust relationship expressed in linguistic terms as depicted in Fig. 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: $T_{\alpha,\beta} = (SD \times T + ST \times N) / (SD + ST) = (0.2, 0.636, 0.9)$. The result is characterized in Fig. 8.

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 (Golbeck, 2005) 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

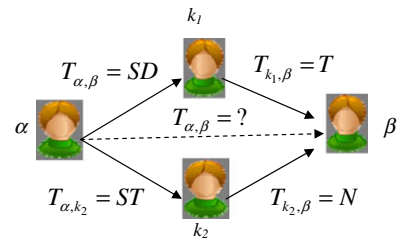


Fig. 7. Linguistic terms representation of trust network.

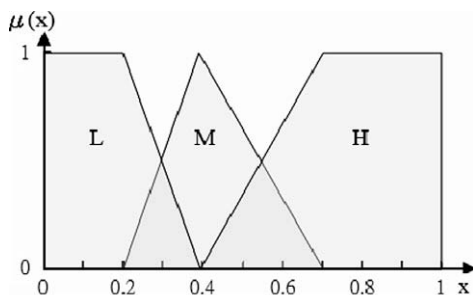


Fig. 6. Membership functions for reliability factor.

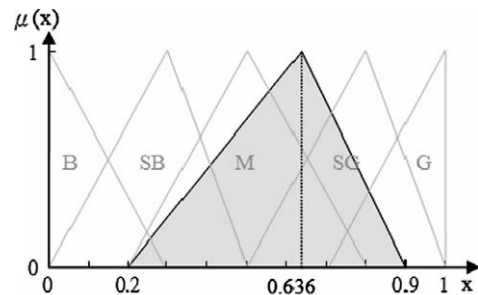


Fig. 8. Fuzzy number of trust $T_{\alpha,\beta}$ calculated by AFWA.

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:

$$Ra_{s,r,p} = \sum_c Cw_c \times sim(Te_{r,p}^c, S_{s,p}^c) \tag{13}$$

where Cw_c is a important weight (with normalized) of service criterion c defined by requestor r , and the function $sim(\cdot)$ is used to calculate the similarity between two fuzzy numbers. Based on the geometric-mean averaging operator, Chen (2006) 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 (2006) study:

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

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 $sim(\cdot)$, 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_A^* and y_B^* are calculated by the following equation:

$$y_A^* = \begin{cases} \frac{a_3 - a_2 + 2}{a_4 - a_1}, & \text{if } a_1 \neq a_4 \\ 1/2, & \text{if } a_1 = a_4 \end{cases} \tag{15}$$

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 (Castellano, Fanelli, & Mencar, 2003). 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

Table 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

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.

Mamdani type fuzzy inference system (Mamdani & Assilian, 1999) is adopted to infer the confidence level of recommendation. The proposed rule base contains 11 rules to evaluate the CF is shown in Table 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.

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:

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

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:

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

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. 9. 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

RecommendationAggregation (a shortlist of service providers P , requestor me)	1
For each p in P	2
Collect the set R where each peer r in R has ever interacted with p .	3
If R is not empty then	4
Initiate vectors num_f , num_e , den_f , and den_e , and set each one’s size to lcl .	5
For each r in R	6
Calculate expert trust $Te_{r,p}^c$.	7
Evaluate reliability $Rl_{r,p}^c$ of expert trust.	8
If r is me then assign a default trust value T_{me}^{def} to T .	9
Else	10
Infer the interpersonal trust $Tf_{me,r}$ as the value of T .	11
If T is null then calculate recommendation trust Tr_r as the value of T .	12
If T is null then set a default referral trust T_{ref}^{def} to T .	13
Apply T and $Rl_{r,p}^c$ to FIS to evaluate the confidence level $CF_{r,p}^c$.	14
If T is T_{me}^{def} or T belongs to the type of interpersonal trust then	15
For each service criterion c	16
$num_f(c) = num_f(c) + (Te_{r,p}^c \times CF_{r,p}^c)$.	17
$den_f(c) = den_f(c) + CF_{r,p}^c$.	18
Else // i.e., T belongs to the type of recommender trust or T is T_{ref}^{def} .	19
For each service criterion c	20
$num_e(c) = num_e(c) + (Te_{r,p}^c \times CF_{r,p}^c)$.	21
$den_e(c) = den_e(c) + CF_{r,p}^c$.	22
For each criterion c , calculate $RC_p^c = \delta \frac{num_f(c)}{den_f(c)} + (1 - \delta) \frac{num_e(c)}{den_e(c)}$	23
Else for each criterion c , set $RC_p^c = R_{def}$.	24

Fig. 9. Recommendation aggregation algorithm.

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 just 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.

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 (2000) 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 (2000), 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 (2000) 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 (2000) small world generator provided by JUNG² (Java Universal Network/Graph) framework is utilized to generate a small world featured network for simulation. The underlying structure of Kleinberg's model 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 α is the clustering exponent (JUNG, 2007).
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, 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

² JUNG is a JAVA API for modeling, analyzing, and visualizing the data that can be represented as graph or network.

Table 4
Service sensitivity distribution for simulations

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

A and B. The initial interpersonal trusts between direct connected peers are also established based on this assumption.

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 does not 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 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 1000 when 10 iterations reach.

As illustrated in Fig. 10, 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. 11 shows that TREPPS dominates all other models when recommendation 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

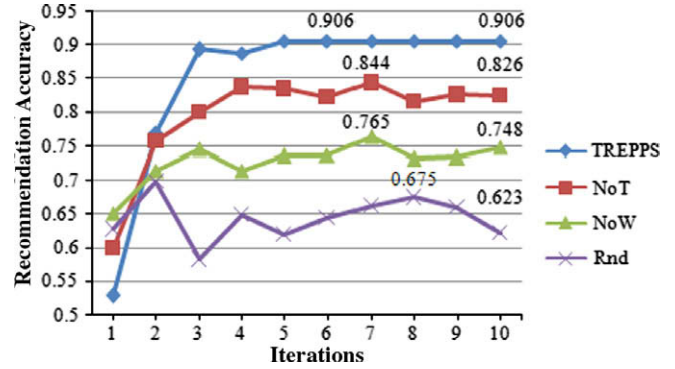


Fig. 10. Average recommendation accuracy of sensitivity distribution Dist. 1 per iteration.

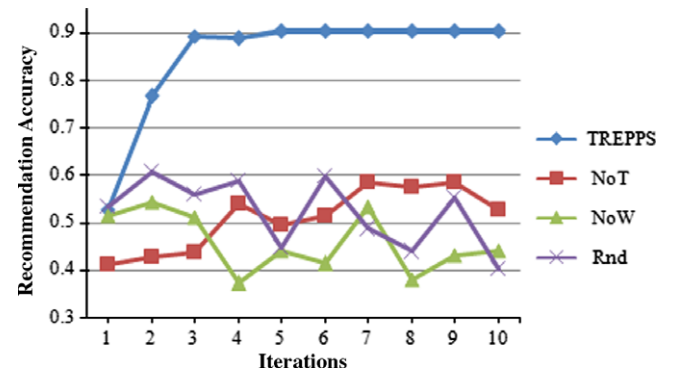


Fig. 11. Average recommendation accuracy of sensitivity distribution Dist. 1 for group G2 per iteration.

interactions) average recommendation accuracy for each group (i.e., G1 to G3) corresponding to each model is depicted in Fig. 12. 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. 13 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 0.4–0.6 and 0.3–0.55, respectively.

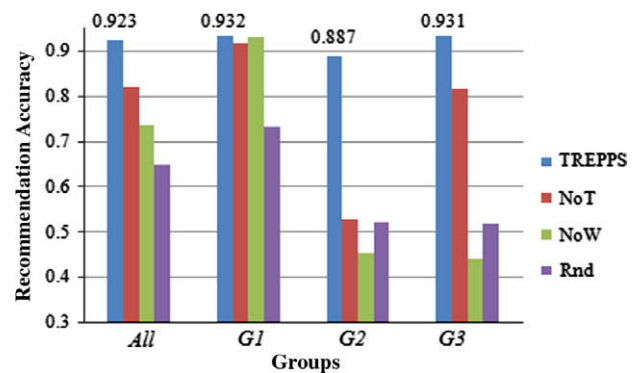


Fig. 12. Total (all iterations) average recommendation accuracy for all groups.

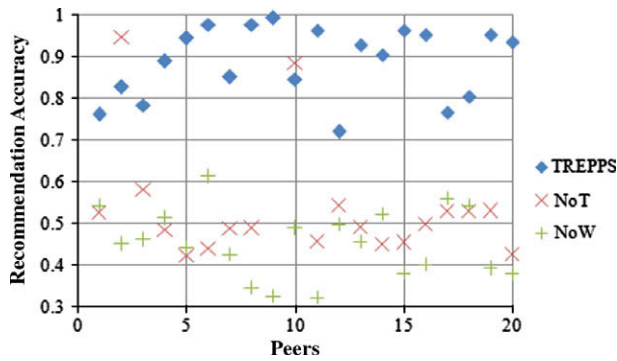


Fig. 13. The distribution of average recommendation accuracy for peers in group G2.

We extend the size of network to 400 peers and conduct experiments with the same sensitivities distribution setting. Table 5 summarizes the results of average accuracy for all experiment settings. Fig. 14 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 5 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.

Table 5
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

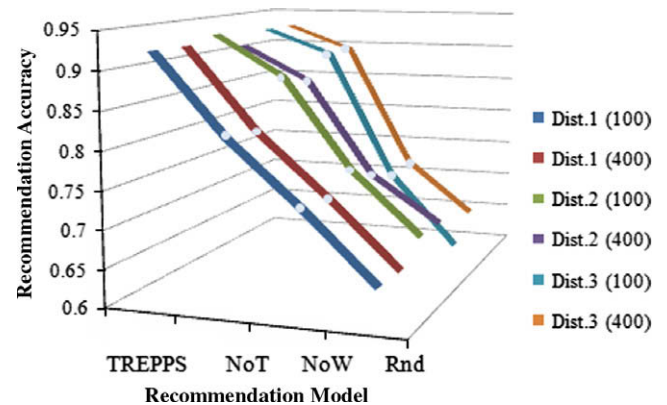


Fig. 14. The comparison of the average recommendation accuracy of network size 100 and 400.

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.

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 (Social bookmarking, 2007) 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 (Doctorow, 2007). Therefore, we proposed a trust-based social news system

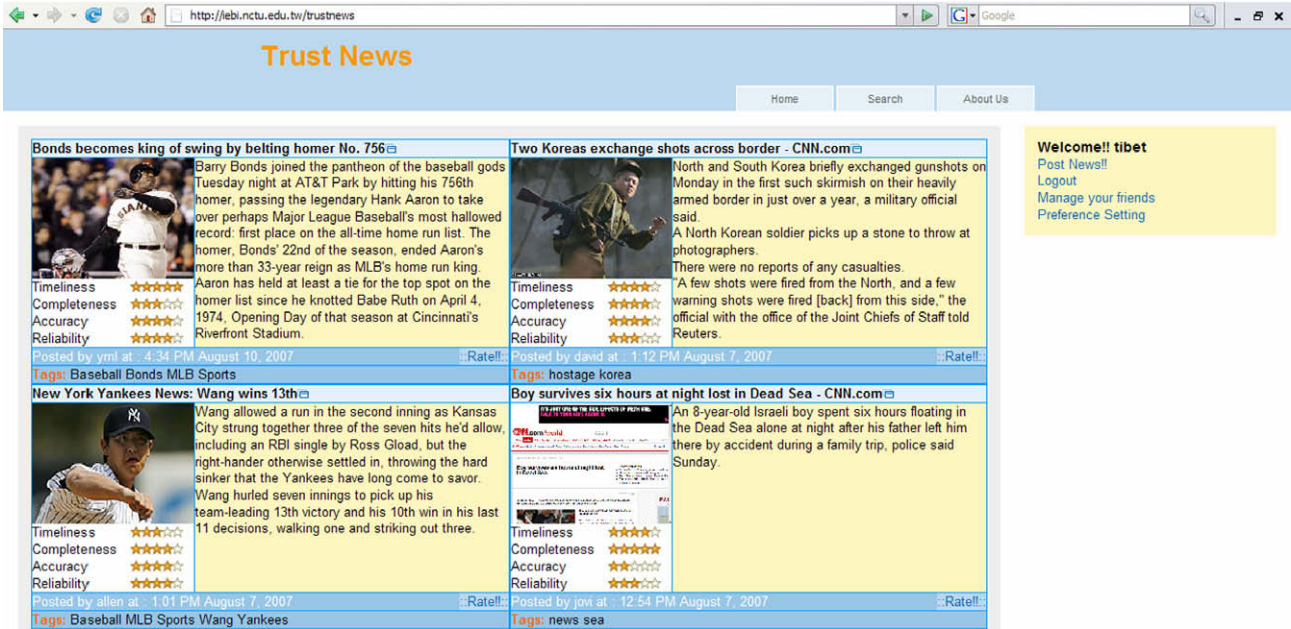


Fig. 15. The portal of trust news system.



Fig. 16. The news block in the main area of portal.



Fig. 18. The interface to manage the trust relationship.



Fig. 17. The feedback interface for satisfaction rating.

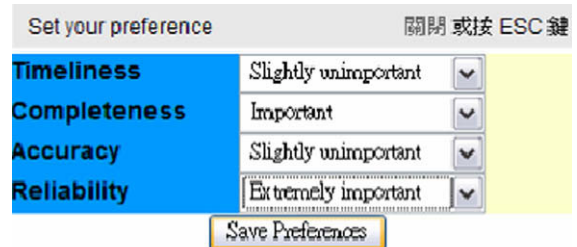


Fig. 19. The interface to set the user's preferences.

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. 15 contains a main display area for the recently submitted news. Each block as shown in Fig. 16 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 feed-

Table 6
Using the fuzzy similarity measure to choice 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

#	Title	Rank
1	MLB/胡金龍上大聯盟? 這奇官網: 9月才會上-Yahoo!奇摩新聞	0.538
2	Bonds becomes king of swing by belting homer No. 756	0.429
3	New York Yankees News: Wang wins 13th	0.395
4	關震弱勢青少年 熱愛運動 統一歸球星簽名會	0.352

Fig. 20. The ranking of search results.

back interface. As shown in Fig. 17, 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 Figs. 18 and 19, respectively.

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. 16. 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 1, the nearest linguistic term – *neutral* (N) will be chosen as shown in Table 6. Secondly, we implement a tag-based topic matching engine to help the news searching. As shown in Fig. 20, the search results are ranked by proposed recommendation aggregation algorithm with FTOPSIS MCDM method.

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. This can also 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.

6. Conclusion

As the prediction of IDC (Gantz et al., 2007), 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. From the perspective of computer science (precisely say, an aspect of intelligent expert systems), this study intends to deal with the informa-

tion 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.

Although a series of controlled experiments which simulates the structures and behaviors of SNS is conducted and shows that the proposed system outperforms the conventional mechanisms, the real users' experiences of proposed trust-based social news system need to be further investigated. Moreover, the potential applications of proposed recommender system should be exploited. For example, the previous researches such as Li, Li, and Chen (2006) which develop a trust based information diffusion system based on instant messenger to enlarge the message accessibility without the overflow of messages. In a later study, they apply the trust model to evaluate the trustworthiness of blog articles (Li, Chen, & Li, 2007). All of these studies will be extended to real social networks to provide empirical studies to understand the benefits of trust computing and improve the proposed model.

Acknowledgement

This research was supported by the National Science Council of Taiwan under the Grant NSC 94-2416-H-009-030.

References

- Abdul-Rahman, A., & Hailes, S. (1998). A distributed trust model. In *Proceedings of the 1997 workshop on new security paradigms* (pp. 48–60). Langdale, Cumbria, United Kingdom: ACM Press.
- Artz, D., & Gil, Y. (2007). A survey of trust in computer science and the semantic web. *Web Semantics: Science, Services and Agents on the World Wide Web*, 5(2), 58–71.

- Bausch, S., & Han, L. (2006). Social networking sites grow 47 percent, year over year, reaching 45 percent web users, according to Nielsen/NetRatings. New York: Nielsen/NetRatings.
- Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science*, 17(4), B141–B164.
- Benkler, Y. (2006). *The wealth of networks: How social production transforms markets and freedom*. Yale University Press.
- Castellano, G., Fanelli, A. M., & Mencar, C. (2003). Design of transparent Mamdani fuzzy inference systems. *Design and Application of Hybrid Intelligent Systems*, 468–476.
- Chang, P.-T., Hung, K.-C., Lin, K.-P., & Chang, C.-H. (2006). A comparison of discrete algorithms for fuzzy weighted average. *IEEE Transactions on Fuzzy Systems*, 14(5), 663–678.
- Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 114, 1–9.
- Chen, M.-F., & Tzeng, G.-H. (2004). Combining grey relation and TOPSIS concepts for selecting an expatriate host country. *Mathematical and Computer Modelling*, 40, 1473–1490.
- Chen, S.-J. (2006). *A new similarity measure of generalized fuzzy numbers based on geometric-mean averaging operator*. *IEEE International Conference on Fuzzy Systems*. BC, Canada: Vancouver (pp. 1879–1886).
- Chen, S.-J., & Hwang, C. L. (1992). *Fuzzy multiple attribute decision making: Methods and applications*. New York: Springer-Verlag.
- Ding, L., Kolari, P., Ganjugunte, S., Finin, T., Joshi, A. (2004). Modeling and evaluating trust network inference. In *Proceedings of the 7th international workshop on trust in agent societies*. New York.
- Ding, L., Zhou, L., Finin, T. (2003). Trust based knowledge outsourcing for semantic web agents. In *Proceedings of the 2003 IEEE/WIC international conference on web intelligence* (pp. 379–387).
- Doctorow, C. (2007). *Tricking the social voting sites*. Boing Boing <http://www.boingboing.net/2007/03/01/tricking_the_social_.html> (Retrieved 11.08.07).
- Dubois, D., & Prade, H. (1980). *Fuzzy sets and systems: Theory and applications*. New York: Academic Press.
- Folksonomy. (2007). Wikipedia: <<http://en.wikipedia.org/wiki/Folksonomy>> (Retrieved 11.08.07).
- Gantz, J. F., Reinsel, D., Chute, C., Schlichting, W., McArthur, J., Minton, S., et al. (2007). *The expanding digital universe: A forecast of worldwide information growth through 2010*. EMC. IDC.
- Gillmor, D. (2006). Networking for fun and profit. CIO Insight: <<http://www.cioinsight.com/article2/0,1540,2000646,00.asp>> (Retrieved 31.05.07).
- Golbeck, J. (2006). Generating predictive movie recommendations from trust in social networks. In *Proceedings of the 4th international conference on trust management*. Pisa, Italy.
- Golbeck, J. (2005). Personalizing applications through integration of inferred trust values in semantic web-based social networks. In *Proceedings of the semantic network analysis workshop at the 4th international semantic web conference*.
- Heath, T., Motta, E., Petre, M. (2006). Person to person trust factors in word of mouth recommendation. In *Proceedings CHI2006 workshop on reinventing trust, collaboration, and compliance in social systems*.
- Huynh, T. D., Jennings, N. R., & Shadbolt, N. R. (2006). An integrated trust and reputation model for open multi-agent systems. *Journal of Autonomous Agents and Multi-Agent Systems*, 13(2), 119–154.
- Hwang, C.-L., & Yoon, K. (1981). *Multiple attribute decision making: methods and applications: A state-of-the-art survey*. Berlin: Springer-Verlag.
- Josang, A. (1996). The right type of trust for distributed systems. In *Proceedings of the 1996 workshop on new security paradigms* (pp. 119–131). Lake Arrowhead, CA, United States: ACM Press.
- Josang, A., Ismail, R., & Boyd, C. (2007). A survey of trust and reputation systems for online service provision. *Decision Support Systems*, 43(2), 618–644.
- JUNG. (2007). KleinbergSmallWorldGenerator (JUNG 1.7.6 API). JUNG – Java Universal Network/Graph Framework: <<http://jung.sourceforge.net/doc/api/edu/uci/ics/jung/random/generators/KleinbergSmallWorldGenerator.html>> (Retrieved 18.05.07).
- Kleinberg, J. (2000). Navigation in a small world. *Nature*, 406, 845.
- Kolbitsch, J., & Maurer, H. (2006). The transformation of the web: How emerging communities shape the information we consume. *Journal of Universal Computer Science*, 12(2), 187–213.
- Kuo, M.-S., Tzeng, G.-H., & Huang, W.-C. (2007). Group decision-making based on concepts of ideal and anti-ideal points in a fuzzy environment. *Mathematical and Computer Modelling*, 45(3–4), 324–339.
- Kuo, Y.-L., Yeh, C.-H., & Chau, R. (2003). A validation procedure for fuzzy multiattribute decision making. *The 12th IEEE International Conference on Fuzzy Systems*, 2, 1080–1085.
- Li, D.-F. (2007). Compromise ratio method for fuzzy multi-attribute group decision making. *Applied Soft Computing*, 7(3), 807–817.
- Li, Y.-M., Chen, J.-C., Li, T.-Y. (2007). A Blog system with trust mechanism. In *Proceedings of the 18th international conference on information management*. Taipei, Taiwan (in Chinese).
- Li, Y.-M., Li, T.-Y., Chen, J.-C. (2006). Trust based instant messaging system. In *Proceedings of the 9th conference on information management practice*. Yunlin, Taiwan (in Chinese).
- Lindahl, C., & Blount, E. (2003). Weblogs: Simplifying web publishing. *Computer*, 36(11), 114–116.
- Liou, T.-S., & Wang, M.-J. J. (1992). Fuzzy weighted average: An improved algorithm. *Fuzzy Sets and Systems*, 49(3), 307–315.
- Mamdani, E. H., & Assilian, S. (1999). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Human-Computer Studies*, 51(2), 135–147.
- Massa, P., & Bhattacharjee, B. (2004). Using trust in recommender systems: An experimental analysis. *Lecture Notes in Computer Science*, 2995.
- McKnight, D. H., Chervany, N. L. (1996). *The meanings of trust*. Technical Report WP9604. University of Minnesota Management Information Systems Research Center.
- O'Donovan, J., & Smyth, B. (2005). Trust in recommender systems. In *Proceedings of the 10th international conference on intelligent user interfaces* (pp. 167–174). San Diego, CA, USA: ACM Press.
- Sabater, J., Sierra, C. (2001). REGRET: A reputation model for gregarious societies. In *Proceedings of the 4th workshop on deception fraud and trust in agent societies* (pp. 61–70). Montreal, Canada.
- Sabater, J., & Sierra, C. (2005). Review on computational trust and reputation models. *Artificial Intelligence Review*, 24(1), 33–60.
- Singh, M. P., Yu, B., & Venkatraman, M. (2001). Community-based service location. *Communications of the ACM*, 44(4), 49–54.
- Sinha, R., Swearingen, K. (2001). Comparing recommendations made by online systems and friends. In *Proceedings of the DELOS-NSF workshop on personalization and recommender systems in digital libraries*. Dublin, Ireland.
- Sinha, R., & Swearingen, K. (2002). *The role of transparency in recommender systems*. Conference on human factors in computing systems. Minneapolis, MN, USA: ACM Press (pp. 830–831).
- Social bookmarking. (2007). Wikipedia: <http://en.wikipedia.org/wiki/Social_bookmarking> (Retrieved 11.08.07).
- Song, S., Hwang, K., Zhou, R., & Kwok, Y.-K. (2005). Trusted P2P transactions with fuzzy reputation aggregation. *IEEE Internet Computing*, 9(6), 24–34.
- Watchlist (Internet). (2007). Wikipedia: <[http://en.wikipedia.org/wiki/Watchlist_\(Internet\)](http://en.wikipedia.org/wiki/Watchlist_(Internet))> (Retrieved 11.08.07).
- Web 2.0 Television. (2006). Phony Digg stories show iterative Web 2.0 problem. Web 2.0 Television: <<http://www.web2.0television.com/blog/2006/11/21/phony-digg-stories-show-iterative-web-20-problem/>> (Retrieved 07.05.07).
- Wei, Y. Z., Moreau, L., & Jennings, N. R. (2005). A market-based approach to recommender systems. *ACM Transactions on Information Systems*, 23(3), 227–266.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8, 338–353.
- Ziegler, C.-N., & Golbeck, J. (2007). Investigating interactions of trust and interest similarity. *Decision Support Systems*, 43(2), 460–475.