Fuzzy multicriteria decision-making approach for Collaborative recommender systems

K. Palanivel* and R. Sivakumar

***Abstract*—The Collaborative Recommender Systems provide personalized recommendations to users using the rating profiles of different users. These systems should maintain accurate model of user's interests and needs by collecting the user preferences either explicitly or implicitly using numerical scale. Although most of the current systems maintain single user ratings in the user-item ratings matrix, these single ratings do not provide useful information regarding the reason behind the user's preference. However, the *multicriteria* based systems provide an opportunity to compute accurate recommendations by maintaining the details of user preferences in multiple aspects. Apart from this, the user ratings are usually subjective, imprecise and vague in nature, because it is based on user's perceptions and opinions. Fuzzy sets seem to be an appropriate paradigm to handle the uncertainty and fuzziness of human decision making behavior and to effectively model the natural complexity of human behavior. Because of these reasons, this paper adopts the Fuzzy linguistic approach to efficiently represent the user ratings and the Fuzzy Multicriteria Decision Making (FMCDM) approach to accurately rank the relevant items to a user. This work empirically evaluates the proposed approach's performance through a Music Recommender system developed for this research. The proposed approach's performance is compared to traditional user-based and item-based recommendation algorithms. From the evaluation results, it is observed that the proposed approach shows improvement in recommendations than the traditional algorithms.**

***Index Terms*— Collaborative filtering, E-commerce, Fuzzy linguistic, Fuzzy multicriteria decision making, Recommender systems.**

I. INTRODUCTION

Wide application of the Internet creates foundation for the fast development of E-commerce. An E-commerce website contains enormous amount of product information. The basic question here is that how can the users of the website acquire the required product information conveniently, quickly and accurately. The development of personalized Recommender system is an important method to solve this problem. *Recommender systems* are the tools that use the opinions of members of a community to help individuals in that community by identifying the products most likely to be interesting to them [7]. These systems provide recommendations only based on the accurate modeling of user's interests and needs. In E-commerce field, many recommender systems have emerged in the past few years to help the users in their search process to find out the most suitable items (such as movies, songs, CDs, books and so on) according to their preferences [8]. Using this kind of personal assistance, the commercial websites achieve higher selling rates.

A. The problem and proposed method: Collaborative filtering is one of the most frequently used techniques in Recommender systems. This technique helps the users to find the items of interest from an overwhelming number of available items. It is based on the idea that a set of like-minded users can help each other to find useful information. Most of the collaborative recommender systems collect the relevance feedback explicitly in the form of user ratings in a numerical scale and store this user preference information in user-item ratings matrix to compute future recommendations. The recommendation quality depends on the quality of data available in this matrix. In the current literature, most of the studies use the user-item ratings matrix with single ratings. However, maintaining ratings in multiple aspects (criteria) of items give more information about the user's preferences. These multiple criteria information of items provides an opportunity to compute accurate recommendations [1]. The recommender systems can utilize this additional information and can potentially increase the recommendation accuracy. Limited systems have begun to use the multicriteria ratings. However, these systems are not used in the personalization context. Therefore, taking the complete advantages of the multicriteria ratings in personalization applications require new recommendation techniques [2]. The improved recommendation algorithms predict the user preferences accurately using multicriteria ratings and provide better recommendations. The limited number of studies in integrating multiple components of ratings to improve the quality of recommendations is one of the motivations behind this work.

The collaborative recommender systems need the user's preference data in the form of ratings to compute new recommendations. The performance of these systems depends on the representation of user preferences and the reasoning on user-item relationships. The information collected by these systems involves uncertainty because it is based on user's perceptions, opinions and tastes. Collecting the user's relevance feedback, representing the user's preferences and reasoning on user-item relationship are the major challenges in Recommender systems, because the ratings are subjective, imprecise and vague [13]. Soft computing seems to be an appropriate paradigm to handle the uncertainty and fuzziness on user preference and to

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efficiently model the natural complexity of human behavior [10]. In order to solve this problem, this paper adopts Fuzzy linguistic approach to represent the user preferences in user-item ratings matrix and Fuzzy Multicriteria Decision Making method to rank the appropriate, relevant items to a user in a collaborative recommendation context. It provides an opportunity to express the user's preference information using linguistic assessments instead of numerical ones. In a recent study [13], the work explores the fuzzy set theoretic method in content-based recommender context. In another work [9], fuzzy linguistic approach is proposed to capture the uncertainty in user preferences in a knowledge-based recommender system. In order to evaluate the proposed approach, a Music Recommender System is developed and a set of user submitted multicriteria ratings are collected both in fuzzy and crisp value format. The performance of the proposed approach is compared with traditional user-based and item-based recommendation approaches [11] in order to evaluate the recommendation accuracy of proposed approach.

II. Multicriteria Collaborative Recommendation Approach

Multicriteria ratings provide information about user preferences on multiple aspects of items. For example, the overall (single) user rating for a movie gives the general user preference on that movie. However, the multicriteria ratings of a movie, such as ratings for Action, Direction, Story and Music, provide in-depth knowledge about the user preferences on that movie. The Recommender systems should benefit from leveraging this additional information and potentially increase the recommendation accuracy [2].

Table I: Multicriteria (*music, lyric and voice*) user-item ratings matrix

Single(overall) rating   Multicriteria rating

	Item 1	Item 2	Item 3	Item 4
User 1	**0** (0, 0, 0)	**2** (2, 3, 1)	**0** (0,0,0)	**4** (5, 3, 4)
User 2	**3** (1, 3, 5)	**3** (1, 3, 5)	**4** (5, 4, 3)	**?** (?, ?, ?)
User 3	**3** (5, 1, 3)	**3** (5, 2, 2)	**4** (2, 5, 5)	**3** (5, 1, 3)
User 4	**2** (2, 1, 3)	**2** (1, 1, 4)	**3** (3, 2, 4)	**4** (3, 5, 4)
User 5	**2** (2, 2, 2)	**2** (1, 2, 3)	**3** (2, 3, 4)	**4** (4, 4, 4)
Content features ***Music*** ***Lyric*** ***Voice***	Rahman(M_1) Muthu(L_1) Doss(V_1)	MSV(M_2) Muthu(L_1) Balu(V_2)	Rahman(M_1) Vijay(L_2) Balu(V_2)	MSV(M_2) Vijay(L_2) Doss(V_1)

The user-item ratings data are usually represented by an *m x n* matrix, where *m* represents the number of users, *n* denotes the number of items. An element R_{ij} in the matrix represents the multicriteria rating given by user *i* on item *j*. Assume that there are five users $u_1,...,u_5$ and four items $i_1,...,i_4$. A typical multicriteria user-item ratings matrix for a Music Recommender system contains the ratings in multiple aspects (*music, lyric and voice*) at a moment of time with a scale of *1* to *5* is shown in table I.

The overall rating may be calculated by simply taking average of multicriteria rating. It is clear that the user u_3 has different multicriteria preferences when compared with the user u_2 even though their overall rating for every music items matches perfectly. The users u_4 and u_5 have close similarity in this example because not only their overall ratings are similar but also their individual criteria preferences are closely similar.

The single criteria ratings are unable to show the details of user preference and lead to inaccurate recommendations. The multicriteria ratings provide some insights regarding why the users like an item. Most of the recommendation methods provide recommendations based on limited understanding of users and items [1]. For this reason, an additional row is maintained in this proposal, in addition to the regular user-item ratings matrix as given in table I. This last row of the matrix contains content features of the items. These content features are used to identify the reason behind the user's likes and dislikes. For example, the user may give higher rating when he likes a particular music director's music, lyric of a particular writer, or the voice of a particular singer. These item features are used to form different categories on items based on each criterion. For example, M_1 and M_2 are Music categories. Each category contains many items. L_1 and L_2 are Lyric categories. V_1 and V_2 are Voice categories. These categories based on content features are used to solve the *New item* problem [1] in this work. When the user enters a new item into the database, that new item is also considered for recommendation based on the content features. The new item's category is first identified and the users having similar preference categories can get this new item as recommendation immediately.

III. Fuzzy Linguistic Modeling

Fuzzy logic enables us to use descriptive and qualitative form for vague concepts. A *fuzzy set* is a set in which the degree of membership in a set is expressed by a number between *0* and *1*. A fuzzy set is defined by a function, called *membership function*, which maps objects in a domain of concern to their membership value in the set. The membership function of a fuzzy set *A* is defined as $\boldsymbol{\mu}_A$ and the membership value of *x* is denoted as $\boldsymbol{\mu}_A(x)$. A linguistic variable holds a qualitative value using linguistic term or a quantitative value using a corresponding membership function. A fuzzy set A in X is characterized by its membership function, which is defined as $\boldsymbol{\mu}_A(x) : x \in X \rightarrow [0, 1]$, where *X* is a domain space. According to the context in which *x* is used, the fuzzy membership function $\boldsymbol{\mu}_A(x)$ can have different interpretations. For example, the membership value of a movie *x* in the fuzzy set of *user preference* can be estimated by the user's degree of preference in that movie. The membership function defines the intensity of user's preference in favour of item *x*. Fuzzy set theory allows a continuous value for $\boldsymbol{\mu}_A(x)$ between *0* and *1* as given below:

$$\mu_A(x) = \begin{cases} 1 & \text{iff } x \in A \\ 0 & \text{iff } x \notin A \\ p & 0<p<1, \text{ if } x \text{ partially belongs to } A. \end{cases}$$

In fuzzy set theory, the statements are described in terms of membership functions. Given the measured value of an input parameter, the membership function gives the "degree of truth". Every element of fuzzy set represents a degree of membership determined by membership function. The degree of membership range from 0 to 1, where 0 means that the element does not belong to the fuzzy set, 1 means full membership and other value means partial membership [12].

Usually in collaborative filtering systems, the user's preference ratings are represented in terms of numerical values. Many aspects in the real world cannot be assessed in a quantitative form, but rather in a qualitative form with vague or imprecise knowledge [13], [9]. In a five-scale user rating (*1-5*), the rating is intrinsically imprecise because the user may give different ratings to the same item at different times and situations, due to the difficulty to make a distinction between ratings *3* and *4*. Similarly, the same rating *4* in a scale of (*1-5*), given by two users does not necessarily imply the same degree of interest in an item. The user's preference rating is treated as a fuzzy variable and its uncertainty is represented using fuzzy linguistic modeling. Even though the user ratings information is represented as numerical values, we have adopted the fuzzy linguistic assessment because this rating information is vague and imprecise, and will be better expressed with fuzzy linguistic approach. Human users might feel more comfortable with vague terms rather than numerical values during the submission of their preference. Due to the uncertain nature of ratings, the evaluation of different alternative items against different criteria requires assessment using fuzzy numbers. Based on these factors, fuzzy linguistic approach is used to represent the preference ratings in multicriteria collaborative recommendation context. In this proposal, the system deals with information that is related to user's tastes, preferences and opinions on qualitative features of the music items such as the quality of *music, lyric and voice*.

IV. Fuzzy Multicriteria User-Item ratings matrix

A collaborative recommender system can estimate the ranks of items for a user and provide ranked items as recommendations based on his item preferences. When the system provides recommendations, the user hears the preferred music item and gives his relevance feedback in the form of preference rating. In the proposed system, the user is prompted by the system to provide explicit rating in multiple aspects (*music, lyric and voice*) for the music heard so as to improve the user's model. The collected ratings are in the form of qualitative features of item such as *Less Preferred* or *Highly Preferred*. The system stores his relevance feedback as user behavior and it can be used for computing future recommendations. Only when the user provides more ratings, the system can provide accurate recommendations. Usually in a quantitative setting, the information is expressed in terms of numerical values. The ratings scale normally range from *1* to *5*, where *1* denotes the greatest dislike to the item and *5* denotes the greatest like to the item. In this work, the linguistic assessment is used instead of numerical value representation. Instead of specifying numerical scale while collecting feedback, the linguistic terms are used to collect the user's relevance feedback. The user ratings are *fuzzified* using trapezoidal membership functions, supplied to determine the degree of membership in the user preference fuzzy set. Let the fuzzy variable *degree-of-interest-in-a-music-item* based on a criteria consists of fuzzy values and are represented using five linguistic terms:

{ *Not Preferred (**NP**), Less Preferred (**LP**), Fair (**FR**), Preferred (**PR**) and Highly Preferred (**HP**)* }.

The terms of the fuzzy variable *degree-of-interest -in-a-music-item* has membership function as given in fig. 1.

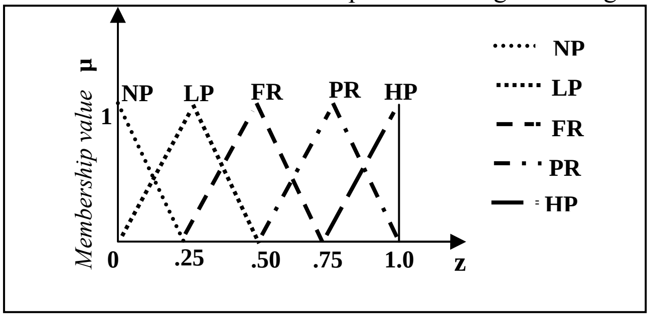

Fig. 1: The linguistic terms of fuzzy variable, *degree-of -interest-in-a-music-item* and membership functions.

The same membership function is adopted for measuring the user interest on every criteria of an item (i.e., *music, lyric and voice*) and the description of membership function is given below.

$\boldsymbol{\mu}_{\textbf{degree-of-interest-in-a-music-item}}\,\boldsymbol{(I_j)} =$

$\mu_{NP}(z)$	$= (.25 - z)\,/\,.25$	$for\ \ 0 \le z \le .25$
$\mu_{LP}(z)$	$= z\,/\,.25$	$for\ \ 0 \le z \le .25$
	$= (.50 - z)\,/\,.25$	$for\ .25 \le z \le .50$
$\mu_{FR}(z)$	$= (z - .25)\,/\,.25$	$for\ .25 \le z \le .50$
	$= (.75 - z)\,/\,.25$	$for\ .50 \le z \le .75$
$\mu_{PR}(z)$	$= (z - .50)\,/\,.25$	$for\ .50 \le z \le .75$
	$= (1.0 - z)\,/\,.25$	$for\ .75 \le z \le 1.0$
$\mu_{HP}(z)$	$= (z - .75)\,/\,.25$	$for\ .75 \le z \le 1.0$

Assume that the Recommender system maintains user-item preferences matrix with *m* users $U_1, U_2, \ldots, U_m$ in rows and with *n* items $I_1, I_2, \ldots, I_n$ in columns. The rating of a user for an item I_j is defined as multiple criteria rating $(c_1, c_2, \ldots c_k)$. The membership function to evaluate the user preference of an item I_j with respect to the criteria C_t $(t=1,\ldots,k)$ is denoted by $\boldsymbol{\mu}_A^{Ct}(I_j)$. Using this principle, in the user-item ratings matrix, the fuzzy preference ratings are denoted, for each user *i,* on every item *j and* for every criteria *t.* The rating element in the matrix is denoted as $R_{itj} = \boldsymbol{\mu}_A^{Ct}(I_j)$, where $\boldsymbol{\mu}_A^{Ct}(I_j)$ is the membership value on *preference* fuzzy set *A* of item I_j under the criteria C_t of user *i*. In this study, the multiple criteria is considered as c_k = (*music, lyric and voice*}, where $k=3$. Each matrix element contains the fuzzy representation of multicriteria rating of user *i* on item *j*. In this work, it is represented as $(\mu^{c1}(I_j),\ \mu^{c2}(I_j),\ \mu^{c3}(I_j))$. A typical fuzzy multicriteria user-item ratings matrix representation is given in table II.

Table II: Fuzzy multicriteria (*music, lyric and voice*) user-item ratings matrix

	Criteria weightage	Item 1	Item 2	Item 3	Item 4
	Criteria				
	C1, C2, C3	*C1, C2, C3*	*C1, C2, C3*	*C1, C2, C3*	*C1, C2, C3*
U_1	- - -	(.6,.7,.8), (.9,.95,1), (.7,.85,.9)	(.6,.7,.8), (.4,.5,.6), (.6,.65,.75)	- - -	(.6,.7,.8), (.4,.5,.6), (.4,.45,.55)
U_2	(.6,.65,.7), (.8,.85,.9), (.7,.8,.85)	(.55,.6,.7), (.4,.45,.5), (.75,.8,.85)	(.35,.4,.45), (.5,.55,.6), (.5,.55,.6)	(.4,.5,.55), (.35,.4,.45), (.3,.35,.4)	- - -
U_3	(.6,.7,.75), (.8,.85,.9), (.7,.75,.8)	(.4,.45,.5), (.5,.55,.65), (.5,.55,.6)	(.5,.55,.6), (.3,.35,.4), (.55,.6,.65)	(.7,.75,.8), (.6,.65,.7), (.5,.55,.6)	(.7,.75,.8), (.6,.65,.7), (.5,.55,.6)
U_4	(.6,.65,.7), (.7,.75,.8), (.7,.8,.9)	(.5,.55,.6), (.5,.6,.75), (.55,.6,.65)	(.6,.65,.75), (.4,.45,.5), (.55,.6,.65)	(.3,.35,.4), (.5,.55,.6), (.6,.65,.7)	(.3,.35,.4), (.5,.55,.6), (.6,.65,.7)
U_5	(.6,.75,.8), (.8,.85,.9), (.7,.8,.85)	(.45,.5,.55), (.7,.75,.8), (.6,.65,.7)	(.4,.45,.5), (.5,.55,.6), (.8,.9,.95)	(.7,.75,.8), (.45,.55,.6), (.7,.75,.8)	(.7,.75,.8), (.45,.55,.6), (.7,.75,.8)

I. Fuzzy MultiCriteria Decision Making (FMCDM)

The evaluation of the preference of an item in recommender systems requires fuzzy linguistic assessment. Due to the subjective, imprecise and vague user preference data, the fuzzy linguistic approach is adopted to represent the user's preferences. In addition, Fuzzy Multicriteria Decision Making (FMCDM) approach is chosen to rank items for a user based on the user-item ratings matrix in collaborative recommendation context. Reference [5] proposed a MCDM method to solve the distribution center location selection problem under fuzzy environment. Reference [4] proposed a FMCDM method for landfill site selection from different candidate sites with respect to different predetermined criteria under environmental management context. A similar type of approach is adopted here to recommend relevant items to users based on the rating decision of a set of users in a recommender system context. When the user gets recommendations from the system, he provides his relevance feedback in the form of fuzzy preference rating after seeing the interested items. The interest on the item based on the criteria cannot be clearly quantified in the decision making process, thereby requiring fuzzy description. The ratings of each item and the weight of criterion are described by linguistic variables that can be expressed in triangular fuzzy numbers (TFN). By calculating the difference of ratings between each pair of items, a fuzzy preference relation matrix is constructed to represent the intensity of the preferences of one item over another. Then a stepwise ranking procedure is proposed to determine the ranking order of all candidate items. When conducting the inference, triangular fuzzy numbers are commonly used to describe the vagueness and ambiguity in user ratings. The methods such as max, min, median, addition, multiplication and mixed operators are used to aggregate TFNs.

To evaluate the appropriateness of the items versus various criteria, the users provide their rating on different criteria of an item based on the weighting set W = { *Not Preferred, Less Preferred, Fair, Preferred, Highly Preferred* }. The membership functions of the linguistic values in the weighting set W represented by the approximate reasoning of triangular fuzzy numbers are shown in fig. 1. The different criteria that were selected for evaluating the merits of the different candidate items are *music, lyric and voice.*

The decision objective is to select the most appropriate items for a user from n different items in the database. The different alternatives are defined as I = $\{I_1, I_2, \ldots, I_n\}$ and the decision criteria are defined in this paper as C = $\{C_1, C_2, C_3\}$, where C_1=*music*, C_2=*lyric* and C_3=*voice*. Linkage between different alternatives with different criteria is shown in fig. 2.

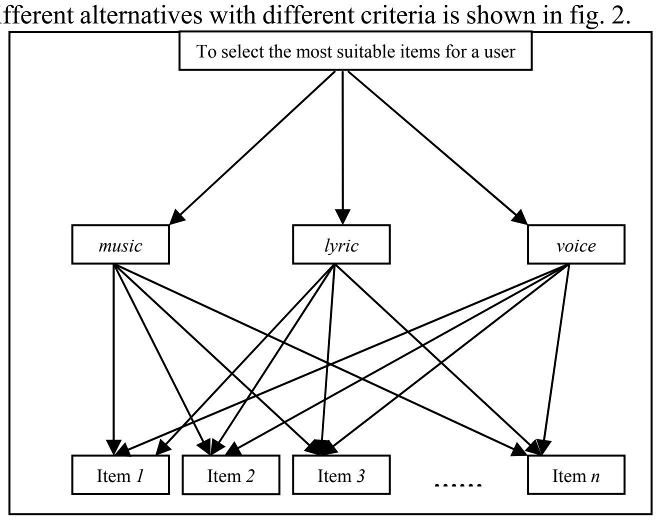

Fig. 2: Description of decision-making process (ranking) from n alternative items for a user under criteria k.

Let R_{itj} ($i=1,2,\ldots,m$; $t=1,2,\ldots,k$; $j=1,2,\ldots,n$) be the rating assigned to alternative I_i by the user U_j under criterion C_t. Let W_{tj} be the weight given to criteria C_t by user U_j. The rating R_{itj}

of n users for each alternative item vs. each criterion is aggregated. Each pooled rating is weighted by weight W_t according to the relative importance of the criteria k. Then the final score F_t, fuzzy appropriate index, of alternative item I_i is obtained by aggregating S_{itj} and W_t, which is finally ranked to obtain the most suitable items. The users give their own preference rating for different alternative items and weights for different criteria by using the triangular fuzzy numbers. Table II represents the typical fuzzy ratings given by m users to n alternative items against three criteria along with the user's weight for each criterion. The weights assigned by users to different criteria for decision-making are initially collected from every user and are represented using fuzzy representation as given in table II. This paper utilizes the mean fuzzy operator to aggregate the user's assessment. Let $\oplus$ and $\otimes$ be the fuzzy addition and fuzzy multiplication operator respectively. The aggregation of the different ratings is given by:

$$R_{itj} = (R_{it1} \oplus R_{it2} \oplus \ldots \oplus R_{itn}) \otimes (1/n).$$

$$W_t = (W_{t1} \oplus W_{t2} \oplus \ldots \oplus W_{tn}) \otimes (1/n).$$

where R_{itj} is the average fuzzy appropriateness index rating of alternative item I_i under criterion C_j, and W_t is the average importance weight of criterion C_j. Thus, the fuzzy appropriateness index F_i of the i^th alternative item can be obtained by aggregating S_{itj} and W_t, and it is expressed as:

$$F_i=[(R_{i1} \oplus W_1) \oplus (R_{i2} \oplus W_2) \oplus \ldots \oplus (R_{ik} \oplus W_k)] \otimes (1/k).$$

Let $R_{itj}=(q_{itj}, o_{itj}, p_{itj})$ and $W_{itj}=(c_{tj},a_{tj},b_{tj})$ be triangular fuzzy numbers. Then F_i can be expressed as

$$F_i=(Y_i,Q_i,Z_i), \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where

$$Y_i = \sum_{i=1-k} (q_{it}c_t / k),\quad Q_i = \sum_{i=1-k} (o_{it}a_t / k),\quad Z_i = \sum_{i=1-k} (p_{it}b_t / k),$$

$$o_{it} = \sum_{j=1-n} (o_{itj} / n),$$

$$p_{it} = \sum_{j=1-n} (p_{itj} / n),\qquad q_{it} = \sum_{j=1-n} (q_{itj} / n),$$

$$c_t = \sum_{j=1-n} (c_{tj} / n),\qquad p_t = \sum_{j=1-n} (p_{tj} / n),$$

$$a_t = \sum_{j=1-n} (a_{tj} / n)$$

for $i=1,2,...,m$; $t=1,2,...,k$; and $j=1,2,...,n$.

Based on the aggregation functions, the typical fuzzy appropriate indices are obtained as given in table III. This information may help justify the final ranking among the candidate items for a user. Therefore, the ranking values of fuzzy appropriate indices for the alternative items were computed based on the method used in (Chang and Chen, 1994).

Let F_i ($i=1,2,...,m$) be the fuzzy appropriate indices of m alternative items. The maximizing set $M = \{(x, f_m(x)) \mid x \in R\}$ with

$$f_m(x) = \begin{cases} (x - x_1) / (x_2 - x_1), & x_1 \prec x \le x_2, \\ 0 & otherwise \end{cases}$$

and minimizing set $G = \{(x, f_g(x)) \mid x \in R\}$ with

$$f_g(x) = \begin{cases} (x - x_2) / (x_1 - x_2), & x_1 \prec x \le x_2, \\ 0 & otherwise \end{cases}$$

where $x_1 = \inf S$, $x_2 = \sup S$, $S = U_{t=1,m} F_i$, $F_i = \{x \mid f_{Fi}(x) > 0\}$, for $i=1,2,...,m$.

Table III: Fuzzy appropriateness index

Alternatives	Fuzzy appropriateness index
Item 1	(0.34232,0.40213,0.45236)
Item 2	(0.41638,0.45952,0.50214)
Item 3	(0.45564,0.55988,0.61242)
Item 4	(0.53152,0.59568,0.65202)

Defining the optimistic utility $U_M(F_i)$ and pessimistic utility $U_G(F_i)$ for each appropriate index F_i as

$$U_M(F_i) = \sup(f_{Fi}(x) \wedge f_M(x)) \text{ and}$$

$$U_G(F_i) = 1 - \sup(f_{Fi}(x) \wedge f_G(x)) \ \ldots\ldots (2)$$

for $i = 1,2,...,m$ and $\wedge$ means *min.*

Ranking value $U_T(F_i)$ of fuzzy appropriate indices is defined as:

$$U_T(F_i) = \alpha\, U_M(F_i) + (1\text{-}\alpha)\, U_G(F_i),\ 0 \le \alpha \le 1.$$

The value α is an index of rating attitude. It reflects the user's risk-bearing attitude. Let $B= (c,a,b)$ be a normal triangular fuzzy number. The index of rating attitude of an individual user is defined as $Y=(a-c)/(b-c)$ (Chang and Chen, 1994). If $Y > 0.5$, it implies that the user is a risk lover. If $Y < 0.5$, it implies that the user is a risk averter. If $Y = 0.5$, the attitude of expert is neutral to the risk. Thus, the total index of rating attitude, R, with the evaluation data of individuals is given below:

$$RA = \left\{ \sum_{i=1}^{k} \sum_{j=1}^{n} (a_{tj} - c_{tj}) / (b_{tj} - c_{tj}) + \sum_{i=1}^{m} \sum_{t=1}^{k} \sum_{j=1}^{n} (o_{itj} - q_{itj}) / (p_{itj} - q_{itj}) \right\} / (kn + mkn). \qquad \ldots\ldots\ldots\ldots (3)$$

From equations (1), (2) and (3), the ranking values $U_t(F_i)$ can be approximately expressed as:

$$U_T(F_i) \approx RA[(Z_i - x_1) / (x_2 - x_1 - Q_i + Z_i)] + (1\text{-}RA)[1 - (x_2 - Y_i)/(x_2 - x_1 + Q_i + Y_i)].$$

The typical ranking values of the fuzzy appropriateness indices for alternative items are presented in table IV. Item 4 exhibits the highest potential for the active user (user 3) in this selection process. These ranked items are treated as recommendations for the active user.

Table IV: Ranking values of different alternatives

Alternatives	Ranking values
Item 4	0.82148
Item 2	0.76628
Item 3	0.68426
Item 1	0.62462

II. Experimental Design

The objective of the experiment is to evaluate the performance of the proposed recommendation approach using a Music Recommender system developed in this work. The proposed approach is compared with the traditional user-based and item-based recommendation algorithms and the performance of the algorithms is evaluated. The dataset details, experimental setup and evaluation metrics are presented below.

A. Data set and setup

In order to evaluate the proposed approach, a set of user submitted ratings are collected from the Music Recommender System developed for this experiment. During the user relevance feedback collection, the user is asked to provide their rating on the heard music item in three aspects (quality of music, lyric and voice) in a scale of 1 to 5. The developed system's database contains 9,628 user ratings, provided by 132 users for 375 music items. The sparsity level in the database is defined as 132 x 375 – 9,628 / 132 x 375 ≈ 0.81. The recommendation algorithms are evaluated over 2000 ratings set, taken at randomly from a set of 9,628 actual ratings. Each user has rated 107 music items on average and the number of common music items between the two users is 12.5 on average. Each music item has been rated by 32.3 users on average. The average number of common users between two music items is 18.4. The average rating on each criterion is 3 approximately. Since we have a small amount of data and to achieve reliable results, we have used 10-fold cross-validation technique. In this method, for each user, we have randomly divided the data set into 10 disjoint subsets. Using different random selection of the music items, 10 different runs are executed to avoid the sensitivity of sampling bias and the results are reported. In each subset, 8/10 (80%) of the data are used for training and 2/10 (20%) of data are used for testing recommendation. This process is repeated 10 times with different test dataset. For each user, using the music items in the testing set, it generates Top-N recommendations and computes the precision, recall and F1-measure. Moreover, 3,5,10,20 and 30 are used as values of variable number of items to be recommended (recommendation size).

B. Metrics

The main aim of evaluating the system is to determine whether it fulfills the objectives that the recommended information is useful to the users. A number of metrics are available to evaluate the Recommender system performance [6]. These include statistical accuracy metrics (such as mean absolute error and root mean squared error) that determine the prediction accuracy of the algorithms, and recommendation accuracy metrics that determine how well the recommendation algorithm can predict items the user would rate highly. Statistical accuracy measures are found to be less appropriate when the user task is to find good items and when the granularity of true value is small because predicting the rating 4 as 5 or the rating 3 as 2 makes no difference to the user. Instead, the recommendation metrics (Precision, Recall and F1-measure) are more appropriate [13]. For the evaluation of recommender systems precision, recall and F1-measure are the widely used metrics to evaluate the quality of the recommendations [3].

Table V: Contingency table

Music items	**Selecte d**	**Not selected**	**Total**
Relevant	*Nrs*	*Nrn*	*Nr*
Irrelevant	*Nis*	*Nin*	*Ni*
Total	*Ns*	*Nn*	*N*

To calculate these metrics, we need a contingency table to categorize the items with respect to the information needs as given in table V. The items in the database are classified either as relevant or irrelevant and selected for recommendation or not selected. *Precision P* is defined as the ratio of the selected relevant items to the selected items, that is, it measures the probability of a selected item be relevant (correct recommendations) (i.e., *P = Nrs / Ns*). *Recall R* is calculated as the ratio of the elected relevant items to the relevant items, that is, it represents the probability of relevant items is selected (coverage or hit rate) (*R=Nrs / Nr*).

F1-measure is a combination metric that gives equal weight to both precision and recall (F1=2 x R x P/ (R+P)). The precision and recall are computed using the music items for which ratings are provided and held for testing and the music items with ratings 4 and 5 are considered as liked music items.

III. RESULTS AND DISCUSSION

The results of experimental evaluation of traditional user-based and item-based algorithms along with the proposed fuzzy multicriteria decision making approach are presented. The performance of traditional user-based and item-based recommendation algorithms are compared with proposed approach using the precision, recall and F1-measure.The average precision, recall and F1-measure of the users during recommendations are shown in table VI.

Table VI: Experimental result – Average percentage of precision, recall and F1-measure

Recommendation Approaches	*Precision %*	*Recall %*	*F1-Measure %*
User_based	55.68	59.32	57.46
Item_based	56.22	52.64	58.86
Fuzzy multi-criteria DM	63.82	71.46	65.24

The average precision, recall and F1-metrics of the proposed approach are 63.82%, 71.46% and 65.24% respectively. Fig. 3 shows a graph representation of the average precision, recall and F1-measure values of the recommendations of users. These values reveal a good performance of the proposed approach.

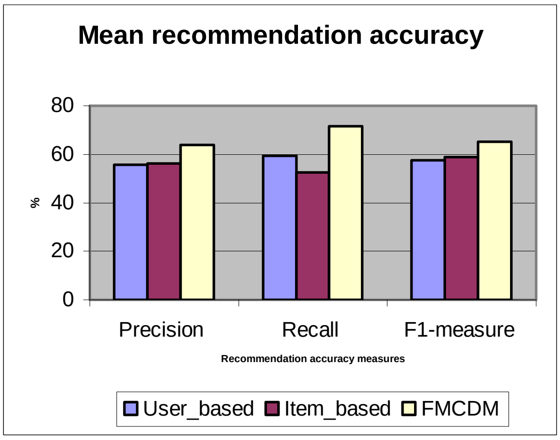

Fig. 3: Recommendation Accuracy

IV. Conclusion and Future Direction

In this paper, we have adopted fuzzy multicriteria decision making approach in collaborative recommendation context and tested the accuracy in recommendation. The performance of traditional user-based and item-based recommendation approaches are compared with the proposed approach against different sparsity levels, training/test data ratios, and neighborhood sizes. The experimental results show that the proposed approach gives better performance when compared with user-based and item-based recommendation approaches in all the sensitive parameters. Our experimental results on a real-world data set confirm that the fuzzy multicriteria decision making approach has great potential in collaborative recommender systems and they can be successfully used to build accurate and flexible Recommender systems. In future, this work can be extended by incorporating fuzzy hybrid approaches in recommendation to achieve more the prediction accuracy.

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