Timeliness of Materials on Reading Recommendation System

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Abstract— **An improved fuzzy logic recommendation method named TFLRS is presented in this paper. The timeliness of reading materials is focused. The upload time of reading materials is attached as an important input parameter, and the numeric weights of input factors are further revised. The experiment result demonstrates that the recommendation ranking order of the latest and the out-of-date reading materials has obviously improved in comparison to the previous FLRS method. It solves the problem that the new reading materials cannot be timely discovered but the out-of-date reading materials always in the front of the recommendation ranking. The timeliness of reading materials effectively guarantees the user preferred newer materials are always at the higher level than the older materials in the recommendation ranking result and the accuracy of reading recommendation system has significantly improved.**

Keywords— **timeliness; recommendation method; fuzzy logic; fuzzy set; membership function**

I. INTRODUCTION

As the increase of the reading materials for online learning, people feel more difficult to locate the content of their interest. Reading recommendation system for online learning is to timely, accurately and efficiently recommend different reading materials to relevant users based on different user preference [1]. A lot of methods were used in the previous study of recommendation system [2]. The most common methods are Collaborative Filtering algorithm, Content-Based algorithm and Hybrid algorithm [3]–[5]. These methods are successful in the practice of recommendation system, but they still remain some problems, such as cold start problem, data-sparse and some important factors of reading materials are not be effectively applied [6].

The author proposed a fuzzy logic method named FLRS on the reading recommendation system in previous research [7]. In this method, a fuzzy logic with numeric weight was proposed. Three input variables that user group preference, grade of reading materials and a click-through rate of reading materials was considered. Different numeric weights are attached to the input factors which affect recommendation ranking result of reading materials in FLRS. The experiment result demonstrated that FLRS method significantly improves the recommendation accuracy with 6.89% in comparison with the previous method. However, FLRS method does not consider the timeliness of reading materials. Some new reading materials that user preferred cannot be displayed in the front of the recommendation ranking result whereas some out-of-date reading materials in the front due to their high-grade feedback and high click-through rate. The reading materials residing in the front of the recommendation ranking result has higher click-through rate than those in the back. If the reading materials comments are good, the recommendation ranking order will be gradually stepping up to the front of the ranking. With the time going on, this results in some new reading materials may not have a chance to be clicked and read almost. As the result of being pushed down in the ranking order due to low exposure to users, these reading materials may disappear forever in the recommendation result.

This paper is an extended version of work published in [7]. In this study, an improved TFLRS method is proposed in which upload time factor of reading the material as a critical input parameter is considered in the design. The experimental results showed that the recommendation ranking order of the new and the old reading materials had improved significantly compared with the previous FLRS method.

Fuzzy logic method and timeliness of data are discussed in this research related works.

A. Fuzzy Logic Method

Fuzzy Logic is widely applied in vague and uncertain systems for it is more convenient to describe the input data,

simulate human reasoning and interpret the output consequence [8]. Sinhal and Verma [9] proposed a fuzzy approach in the constructive cost model for the more precise effort estimation of the software development. It describes the detailed definition of each cost driver fuzzy set. The result proves that this method is better than the traditional methods. In another study, fuzzy logic was applied to automatic mining in cognitive metadata [10]. It introduced a metadata extraction framework based on the fuzzy inference. The documents were divided into semantic granules which were associated with fuzzy attributes and then inferred the possible metadata values. The results of the experiment showed that the application of fuzzy logic in this method had improved the precision, perceived quality and the performance on the metadata field. Wan et al. [11] presented an intelligent decision system for stock managers based on the fuzzy inference which can assist in deciding that people buy, sell or hold their stock. Fuzzy-based clustering was introduced in another study [12]. It categorized the web service's quality using a Fuzzy C-Means algorithm which assigned the data into different clusters with membership degree. Kumar et al. [13] compared the effectiveness of Linear Regression and five machine learning methods on soft testing time assessment model by training two failure data sets of real projects. Fuzzy inference system and adaptive neuro-fuzzy inference system are more beneficial in the assessment of software testing time. The adaptive neuro-fuzzy also was applied in web pages retrieval [14]. In this study, content page, page content of neighbours and link analysis were calculated, and the fuzzy system was applied to obtain the output.

There are some other studies introducing the application of fuzzy logic in the recommendation system [15], [16]. A fuzzy similarity matching model computed various similarity measures and translated it into fuzzy measurement scales to solve the problems of recommendation [17]. In addition, a numerical case study was demonstrated in this paper to prove the effectiveness and availability of the recommendation system. There is another recommendation framework with multi-agent based on fuzzy logic for e-learning [18]. In the study, two fuzzy sets of input that user performance and user feedback were first defined, then it inferences the recommended study materials. It attempted to provide a personalized study environment based on learners' requirements, study goals and level. Chaudhari et al. [8] discussed a multilayer fuzzy inference system. The data weighted average was used in the first fuzzy layer, and the fuzzy output was applied in the second fuzzy layer. It provided a view in overcoming both types of the fuzzy system separately used. Muyeba et al. [19] proposed a fuzzy classification algorithm using fuzzy quantifiers in web mining. In the study, numeric weights were used in each traversed path based on the level of importance. The numeric weights can be calculated and translated into the fuzzy linguistic quantifiers attached to the fuzzy rules. From what has been discussed above, fuzzy logic is one of the advantage methods that can make the system behaving more intelligent and easier to describe the data used in linguistic variables like humans. It is more suitable to apply fuzzy logic to the situation in which the data is imprecise, uncertain and vague.

B. Timeliness of Data

The timeliness of data plays an important role in the network learning environment. The new data is more advanced and effective than older data for user [20]. So, more and more researchers begin to focus on the timeliness of data in their application. Luo et al. [20] proposed an algorithm that called timeliness online regularized extreme learning machine to improve the learning performance. In the study, a regularization technique for the timeliness scheme was added through applying a weight factor to achieve better generalization performance. The simulation results showed that this method achieved higher learning accuracy and better stability than other previous machine learning methods. Similarly, another machine learning algorithm which improves online sequential extreme learning based on timeliness management scheme was presented by Gu et al. [21]. The experimental result of the proposed method also outperformed other methods in higher learning accuracy and faster convergence. Han et al. [22] incorporated influence decay function, opportunistic selection and broader maximization accommodating to timeliness, acceptance ratio and breadth in their research titled an exploration of broader influence maximization in timeliness networks with the opportunistic selection. Kong et al. [23] also applied timeliness as an important factor to measure the efficiency of information acquisition in their research of optimizing social connections for efficient information acquisition. The characteristics that affect timeliness based on information seeking and organizational behaviour was identified by Ranganath et al. [24] to facilitate time-critical information seeking in social media. In another study, Shamsul and Dublin [25] focused the data quality changing with timeliness in information manufacturing system. Another timeliness optimization model based on information flow was established by Zhang et al. [26]. In the study, the timeliness optimization objectives and constraint condition were analysed, sub-structure bottleneck was iteratively optimized until the effect of optimization converge. Zhang et al. [27] focused a timeliness factor on improving the recommendation algorithms. In the result of the experiment, the obsolete items were suppressed strongly, and the recommendation accuracy was enhanced substantially. It can be summed up that all the research above mentioned are more beneficial in system performance after applied timeliness.

In this paper, the mean of timeliness is that the recommended trend and the distribution of the reading materials change with time passing by in reading recommendation system. The rest of this paper is organized as follows. Section 2 introduces fuzzy logic method design applied timeliness factor on reading materials system. In section 3, the experiment and results are analysed. Finally, a conclusion of this research will be pointed out in Section 4.

II. MATERIAL AND METHOD

A. Fuzzy Set and Membership Function

The fuzzy set can be defined with fuzzy boundaries. If X is the reference super set discussed and FS is a subset of X, then FS is a fuzzy subset of X, the definition of FS can be expressed by the following equation:

$$FS = \{(x, \mu_{FS}(x)\} \quad x \in X, \quad \mu_{FS}(x): X \to [0,1] \quad (1)$$

where $\mu_{FS}(x)$ is the membership function of x.

The equation above can be extended to all the fuzzy subset FS limited reference super set X can be expressed as:

$$FS = \{(x_1, \mu_{FS}(x_1)\}, \{(x_2, \mu_{FS}(x_2)\}, \dots, \{(x_n, \mu_{FS}(x_n)\} \quad (2)$$

In this study, four influence factors of reading material recommendation as input variables. They are user group preference (UGP), grade of reading materials (GRM), a click-through rate of reading materials (CTR), upload time of reading materials(ULT). One output variable that recommendation degree (RM) is defined. The fuzzy set of this method can be expressed as follows:

$$FS_{input} = \{(x_{UGP}, \mu_{UGP}(x_{UGP})\}, \{(x_{GRM}, \mu_{GRM}(x_{GRM})\},$$
$$\{(x_{CTR}, \mu_{CTR}(x_{CTR})\}, \{(x_{ULT}, \mu_{UTL}(x_{ULT})\} \quad (3)$$

$$FS_{output} = \{(x_{RM}, \mu_{RM}(x_{RM})\} \quad (4)$$

All linguistic variables, linguistic values and their ranges are set up based on the domain expert. The fuzzy linguistic variables description of TFLRS method are shown in Table 1 to Table 5, and the relevant membership functions of these fuzzy sets are represented by Fig. 1 to Fig. 5.

TABLE I
UGP INPUT VARIABLE DETAILS

Abbr.	VL	L	M	H	VH
Describe	Very low	Low	Medium	High	Very high
Range	0-20	10-40	30-60	50-80	70-100

TABLE II
GRM INPUT VARIABLE DETAILS

Abbr.	VB	B	F	G	VG
Describe	Very bad	Bad	Fair	Good	Very good
Range	0-20	10-40	30-60	50-80	70-100

TABLE III
CTR INPUT VARIABLE DETAILS

Abbr.	VL	L	M	H	VH
Describe	Very low	Low	Medium	High	Very high
Range	0-20	10-40	30-60	50-80	70-100

TABLE IV
ULT INPUT VARIABLE DETAILS

Abbr.	VL	L	G	N	VN
Describe	Very low	Low	General	New	Very new
Range	0-20	10-40	30-70	60-90	80-100

TABLE V
RM OUTPUT VARIABLE DETAILS

Abbr.	NR	LR	R	HR
Describe	No recommend	Low recommend	recommend	High recommend
Range	0-30	10-50	40-80	70-100
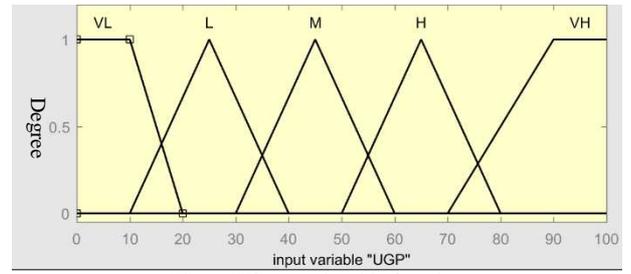
Fig. 1 UGP membership function
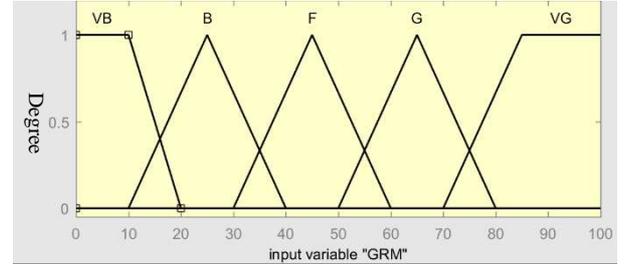
Fig. 2 GRM membership function
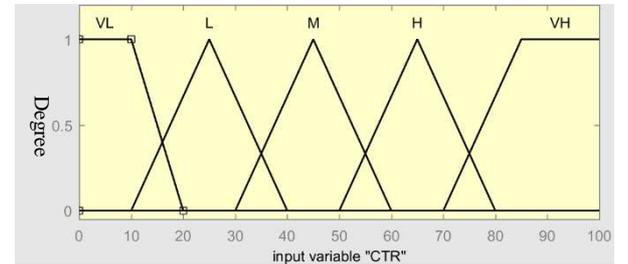
Fig. 3 CTR membership function
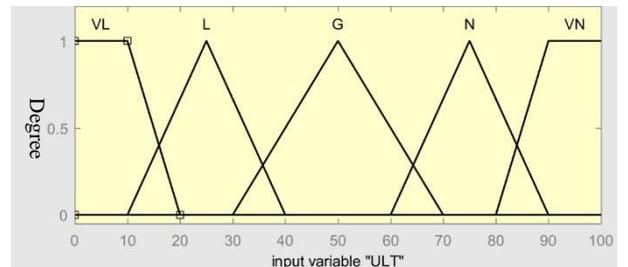
Fig. 4 ULT membership function
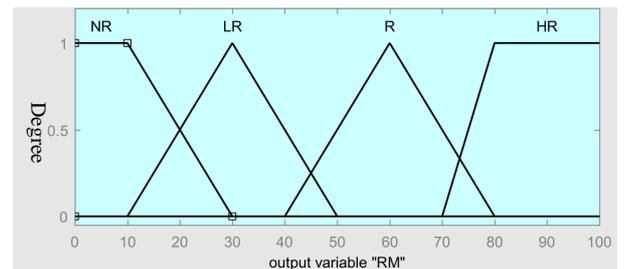
Fig. 5 RM membership function

Because the important degree of input variables is different based on the real practice, in this study, a set of weight is used in the input parameters.

$$W= \{w_1, w2, \dots, w_i, \dots, w_n\} \ w_i \in [0,1] \text{ and } \sum_1^n w_i = 1 \quad (5)$$

The new membership degree is calculated as:

$$y_i = w_i * \mu_{FS}(x_i) \qquad (6)$$

where $\mu_{FS}(x_i)$ is the membership function of x_i, w_i is the weight of the membership function and y_i is the ultimate membership degree result.

B. Fuzzy Rules

The general form of fuzzy rules that multiple inputs and one output variables are expressed as follows:

If (x_1 is FS$_1$ | not FS$_1$ [and x_2 is FS$_2$ | not FS2 and… and x_n is FS$_n$ | not FS$_n$]) then (y is FR).

If (x_1 is FS$_1$ | not FS$_1$ [or x_2 is FS$_2$ | not FS2 or… or x_n is FS$_n$ | not FS$_n$]) then (y is FR).

where x_n is the value of input parameters, FS$_n$ is the fuzzy set of input parameters, and FR is the fuzzy set of the output parameter. The fuzzy rules of TFLRS method are represented in Fig. 6 and the rule viewer in the system shown in Fig. 7.

1. If (UPG is VL) then (RM is NR) (1)
2. If (UPG is L) and (ULT is VL) then (RM is NR) (1)
3. If (UPG is L) and (ULT is L) then (RM is NR) (1)
4. If (UPG is L) and (ULT is G) then (RM is NR) (1)
5. If (UPG is L) and (GRM is VB) and (ULT is N) then (RM is NR) (1)
6. If (UPG is L) and (GRM is B) and (ULT is N) then (RM is NR) (1)
7. If (UPG is L) and (GRM is F) and (ULT is N) then (RM is LR) (1)
8. If (UPG is L) and (GRM is G) and (ULT is N) then (RM is LR) (1)
9. If (UPG is L) and (GRM is VG) and (ULT is N) then (RM is LR) (1)
10. If (UPG is L) and (GRM is VB) and (CTR is VL) and (ULT is VN) then (RM is LR) (1)
11. If (UPG is L) and (GRM is VB) and (CTR is L) and (ULT is VN) then (RM is LR) (1)
12. If (UPG is L) and (GRM is VB) and (CTR is M) and (ULT is VN) then (RM is LR) (1)
13. If (UPG is L) and (GRM is VB) and (CTR is H) and (ULT is VN) then (RM is NR) (1)
14. If (UPG is L) and (GRM is VB) and (CTR is VH) and (ULT is VN) then (RM is NR) (1)
15. If (UPG is M) and (ULT is VL) then (RM is NR) (1)
16. If (UPG is M) and (ULT is L) then (RM is NR) (1)
17. If (UPG is M) and (GRM is VB) and (ULT is G) then (RM is NR) (1)
18. If (UPG is M) and (GRM is not VB) and (ULT is G) then (RM is LR) (1)
19. If (UPG is M) and (GRM is VB) and (CTR is VL) and (ULT is N) then (RM is LR) (1)
20. If (UPG is M) and (GRM is VB) and (CTR is L) and (ULT is N) then (RM is LR) (1)
21. If (UPG is M) and (GRM is VB) and (CTR is M) and (ULT is N) then (RM is LR) (1)
22. If (UPG is M) and (GRM is VB) and (CTR is H) and (ULT is N) then (RM is NR) (1)
23. If (UPG is M) and (GRM is VB) and (CTR is VH) and (ULT is N) then (RM is NR) (1)
24. If (UPG is M) and (GRM is B) and (CTR is VL) and (ULT is N) then (RM is LR) (1)
25. If (UPG is M) and (GRM is B) and (CTR is L) and (ULT is N) then (RM is LR) (1)
26. If (UPG is M) and (GRM is B) and (CTR is M) and (ULT is N) then (RM is R) (1)
27. If (UPG is M) and (GRM is B) and (CTR is H) and (ULT is N) then (RM is R) (1)
28. If (UPG is M) and (GRM is B) and (CTR is VH) and (ULT is N) then (RM is R) (1)
29. If (UPG is M) and (GRM is F) and (ULT is N) then (RM is R) (1)
30. If (UPG is M) and (GRM is G) and (ULT is N) then (RM is R) (1)
31. If (UPG is M) and (GRM is VG) and (ULT is N) then (RM is R) (1)
32. If (UPG is M) and (GRM is VB) and (ULT is VN) then (RM is LR) (1)
33. If (UPG is M) and (GRM is not VB) and (ULT is VN) then (RM is R) (1)
34. If (UPG is H) and (GRM is VB) and (CTR is VL) and (ULT is VL) then (RM is LR) (1)
35. If (UPG is H) and (GRM is VB) and (CTR is L) and (ULT is VL) then (RM is LR) (1)
36. If (UPG is H) and (GRM is VB) and (CTR is M) and (ULT is VL) then (RM is NR) (1)
37. If (UPG is H) and (GRM is VB) and (CTR is H) and (ULT is VL) then (RM is NR) (1)
38. If (UPG is H) and (GRM is VB) and (CTR is VH) and (ULT is VL) then (RM is NR) (1)
39. If (UPG is H) and (GRM is not VB) and (ULT is VL) then (RM is LR) (1)
40. If (UPG is H) and (GRM is VB) and (CTR is VL) and (ULT is L) then (RM is LR) (1)
41. If (UPG is H) and (GRM is VB) and (CTR is L) and (ULT is L) then (RM is LR) (1)
42. If (UPG is H) and (GRM is VB) and (CTR is M) and (ULT is L) then (RM is LR) (1)
43. If (UPG is H) and (GRM is VB) and (CTR is H) and (ULT is L) then (RM is NR) (1)
44. If (UPG is H) and (GRM is VB) and (CTR is VH) and (ULT is L) then (RM is NR) (1)
45. If (UPG is H) and (GRM is not VB) and (ULT is L) then (RM is LR) (1)
46. If (UPG is H) and (GRM is VB) and (CTR is VL) and (ULT is G) then (RM is R) (1)
47. If (UPG is H) and (GRM is VB) and (CTR is L) and (ULT is G) then (RM is R) (1)
48. If (UPG is H) and (GRM is VB) and (CTR is M) and (ULT is G) then (RM is LR) (1)
49. If (UPG is H) and (GRM is VB) and (CTR is H) and (ULT is G) then (RM is LR) (1)
50. If (UPG is H) and (GRM is VB) and (CTR is VH) and (ULT is G) then (RM is LR) (1)
51. If (UPG is H) and (GRM is not VB) and (CTR is VH) and (ULT is G) then (RM is R) (1)
52. If (UPG is H) and (GRM is VB) and (CTR is VL) and (ULT is N) then (RM is HR) (1)
53. If (UPG is H) and (GRM is VB) and (CTR is L) and (ULT is N) then (RM is HR) (1)
54. If (UPG is H) and (GRM is VB) and (CTR is M) and (ULT is N) then (RM is R) (1)
55. If (UPG is H) and (GRM is VB) and (CTR is H) and (ULT is N) then (RM is LR) (1)
56. If (UPG is H) and (GRM is VB) and (CTR is VH) and (ULT is N) then (RM is LR) (1)
57. If (UPG is H) and (GRM is not VB) and (ULT is N) then (RM is HR) (1)
58. If (UPG is H) and (GRM is VB) and (CTR is VL) and (ULT is VN) then (RM is HR) (1)
59. If (UPG is H) and (GRM is VB) and (CTR is L) and (ULT is VN) then (RM is HR) (1)
60. If (UPG is H) and (GRM is VB) and (CTR is M) and (ULT is VN) then (RM is R) (1)
61. If (UPG is H) and (GRM is VB) and (CTR is H) and (ULT is VN) then (RM is R) (1)
62. If (UPG is H) and (GRM is VB) and (CTR is VH) and (ULT is VN) then (RM is R) (1)
63. If (UPG is H) and (GRM is not VB) and (ULT is VN) then (RM is HR) (1)
64. If (UPG is VH) and (GRM is VB) and (CTR is VL) and (ULT is VL) then (RM is LR) (1)
65. If (UPG is VH) and (GRM is VB) and (CTR is L) and (ULT is VL) then (RM is LR) (1)
66. If (UPG is VH) and (GRM is VB) and (CTR is M) and (ULT is VL) then (RM is NR) (1)
67. If (UPG is VH) and (GRM is VB) and (CTR is H) and (ULT is VL) then (RM is NR) (1)
68. If (UPG is VH) and (GRM is VB) and (CTR is VH) and (ULT is VL) then (RM is NR) (1)
69. If (UPG is VH) and (GRM is not VB) and (ULT is VL) then (RM is LR) (1)
70. If (UPG is VH) and (GRM is VB) and (CTR is VL) and (ULT is L) then (RM is LR) (1)
71. If (UPG is VH) and (GRM is VB) and (CTR is L) and (ULT is L) then (RM is LR) (1)
72. If (UPG is VH) and (GRM is VB) and (CTR is M) and (ULT is L) then (RM is LR) (1)
73. If (UPG is VH) and (GRM is VB) and (CTR is H) and (ULT is L) then (RM is NR) (1)
74. If (UPG is VH) and (GRM is VB) and (CTR is VH) and (ULT is L) then (RM is NR) (1)
75. If (UPG is VH) and (GRM is not VB) and (ULT is L) then (RM is LR) (1)
76. If (UPG is VH) and (GRM is VB) and (CTR is VL) and (ULT is G) then (RM is R) (1)
77. If (UPG is VH) and (GRM is VB) and (CTR is L) and (ULT is G) then (RM is R) (1)
78. If (UPG is VH) and (GRM is VB) and (CTR is M) and (ULT is G) then (RM is LR) (1)
79. If (UPG is VH) and (GRM is VB) and (CTR is H) and (ULT is G) then (RM is LR) (1)
80. If (UPG is VH) and (GRM is VB) and (CTR is VH) and (ULT is G) then (RM is LR) (1)
81. If (UPG is VH) and (GRM is not VB) and (ULT is G) then (RM is R) (1)
82. If (UPG is VH) and (GRM is VB) and (CTR is VL) and (ULT is N) then (RM is HR) (1)
83. If (UPG is VH) and (GRM is VB) and (CTR is L) and (ULT is N) then (RM is HR) (1)
84. If (UPG is VH) and (GRM is VB) and (CTR is M) and (ULT is N) then (RM is R) (1)
85. If (UPG is VH) and (GRM is VB) and (CTR is H) and (ULT is N) then (RM is LR) (1)
86. If (UPG is VH) and (GRM is VB) and (CTR is VH) and (ULT is N) then (RM is LR) (1)
87. If (UPG is VH) and (GRM is not VB) and (ULT is N) then (RM is HR) (1)
88. If (UPG is VH) and (GRM is VB) and (CTR is VL) and (ULT is VN) then (RM is HR) (1)
89. If (UPG is VH) and (GRM is VB) and (CTR is L) and (ULT is VN) then (RM is HR) (1)
90. If (UPG is VH) and (GRM is VB) and (CTR is M) and (ULT is VN) then (RM is R) (1)
91. If (UPG is VH) and (GRM is VB) and (CTR is H) and (ULT is VN) then (RM is R) (1)
92. If (UPG is VH) and (GRM is VB) and (CTR is VH) and (ULT is VN) then (RM is R) (1)
93. If (UPG is VH) and (GRM is not VB) and (ULT is VN) then (RM is HR) (1)

Fig. 6 Fuzzy rules
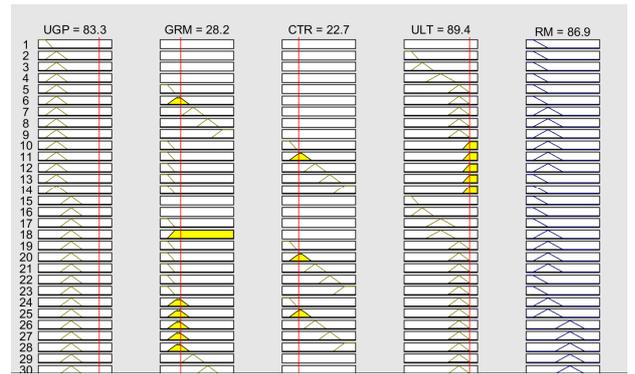
Fig. 7 Rule viewer TFLRS

C. Defuzzification

Defuzzification is to translate the fuzzy output into a crisp number. There are a lot of methods for defuzzification, such as Centroid, Bisector and the Mean of Maximum (MOM). In this study, a centroid method is applied for defuzzification. The mathematical equation of centroid can be expressed as following.

$$C = \frac{\sum_{x=a}^{b} y_i x_i}{\sum_{x=a}^{b} y_i} \qquad (7)$$

where y_i is the membership degree of x_i, a, b is the interval values of output fuzzy set. C is the crisp output value of defuzzification. The 3D surface of defuzzification with ULT and other parameters shown in Fig. 8 -Fig. 10:
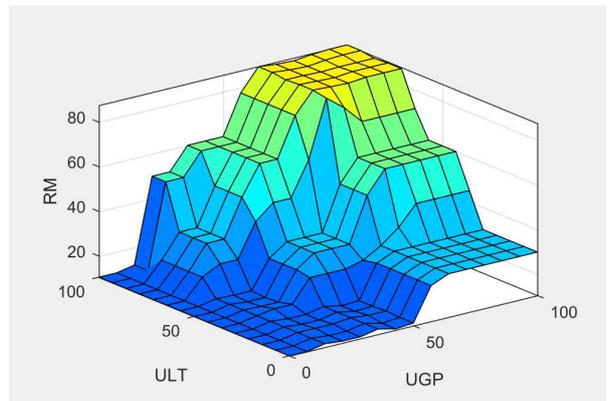
Fig. 8 3D defuzzification surface with ULT and UGP
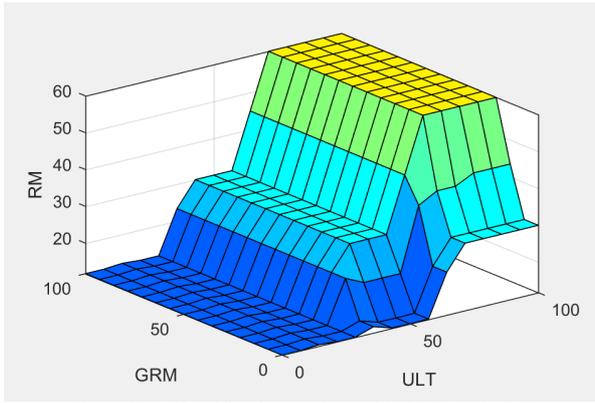
Fig. 9 3D defuzzification surface with GRM and ULT
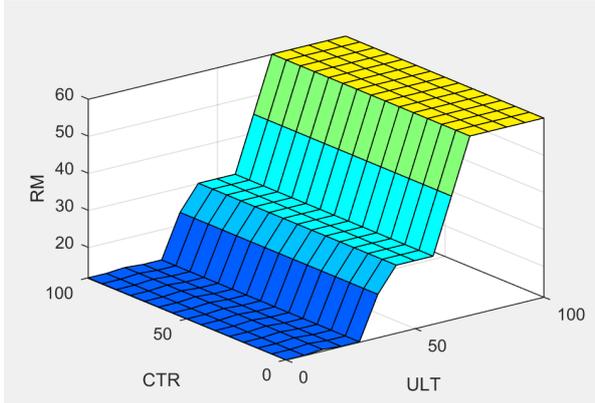
Fig. 10 3D defuzzification surface with CTR and ULT

TABLE VI
FLRS INPUT VALUES

Input Number	UGP	GRM	CTR
1	99.66212	83.12475	91.32184
2	94.04104	13.74342	16.36572
3	91.28758	26.10445	38.45479
4	88.13761	95.96448	77.67326
5	85.92308	30.03728	21.12382
6	83.41861	72.72388	86.83671
7	79.44624	90.95055	84.92698
8	74.72919	29.3384	33.22551
9	82.52748	29.50114	12.06081
10	87.15758	98.09146	71.34621
11	86.80514	11.15762	5.736578
12	83.34611	88.33933	75.31729
13	76.76616	90.01953	98.47112
14	83.27332	21.50748	28.24741
15	81.24802	34.50693	22.59507

III. RESULTS AND DISCUSSION

In the experiment, 100 reading materials was selected to recommend to users. Among the 100 reading materials, 15 special reading materials of user preference was observed: 8 reading materials upload time are new but the comment grade and click-through rate are lower, the other 7 reading materials upload time are long while the comment grade and click-through rate are higher.

A. FLRS Method

There are three input variables in FLRS: UGP, GRM and CTR. The input values of 15 reading materials as following Table 6.

The numerical weights of input variables are set as following:

$$w_i = \begin{cases} 0.4 & UGP \\ 0.4 & GRM \\ 0.2 & CTR \end{cases} \quad i = 1,2,3 \qquad (8)$$

The defuzzification output value RM and the ranking order show in Table 7.

B. TFLRS Method

ULT parameter was added in this method. Because the comment grade is null for the new materials, the weight of GRM was reduced. This study suggests that it is more accurate to enhance the important degree of ULT and reduces the important degree of GRM in real situation.

TABLE VII
FLRS OUTPUT RESULTS

Number	RM	Ranking
1	85.4954	1
2	14.3444	87
3	47.0161	46
4	85.3889	11
5	59.9855	39
6	85.4954	2
7	85.4925	6
8	43.5939	47
9	58.0247	44
10	85.37	12
11	14.0225	97
12	85.4826	8
13	85.4313	10
14	29.5296	64
15	59.9639	40

The numerical weights of input variables are revised as following:

$$w_i = \begin{cases} 0.3 & UGP \\ 0.2 & GRM \\ 0.2 & CTR \\ 0.3 & ULT \end{cases} \quad i = 1,2,3,4 \qquad (9)$$

The ULT input value, RM output value and ranking order show in Table 8.

TABLE VIII
TFLRS ULT INPUT VALUES AND RESULTS

Number	ULT	RM	Ranking
1	3.4746	30.0256	52
2	96.7342	85.3441	5
3	85.2437	85.1697	13
4	23.6148	30.0093	59
5	88.9438	85.2053	11
6	18.5693	30.0176	56
7	24.6543	30.0149	58
8	88.4672	85.2678	9
9	76.8759	85.3242	6
10	12.6418	30.0025	62
11	88.4352	85.459	2

12	24.5324	30.0081	60
13	36.2547	46.8021	39
14	93.2459	85.1875	12
15	82.5631	85.1274	15

C. Discussion

The experiment results of recommendation ranking order in TFLRS method are compared with FLRS method in Fig. 11. In fig, 'o' is devote the ranking order result of FLRS method and '*' is devote the ranking order result of TFLRS method. The ranking order and difference value is show in Table 9.

The experiment results showed that all the 15 reading materials recommendation ranking order have greater change. The greatest ranking change is the 11th reading material. This reading material has very bad user comment and very low click-through rate, but because the materials upload time is very new, the recommendation ranking order up from the 97th to the 2nd place. Meanwhile, the 6th reading material has good user comment and very high click-through rate, but the upload time is very long, so the ranking order down from the 2nd to the 56th. In additional, the least change of recommendation ranking order is the 15th reading material, it also adjust 25 ranking orders.
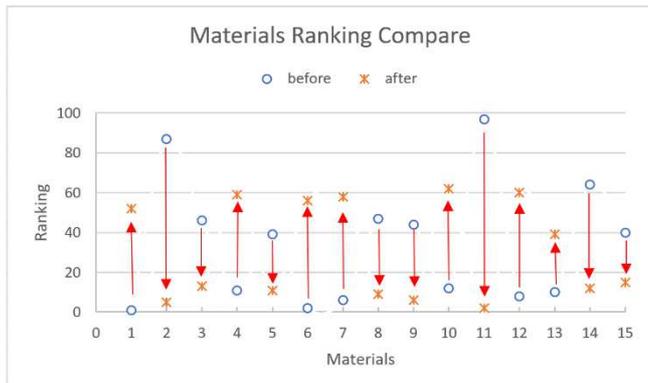
Fig. 11 Ranking order in TFLRS and FLRS

TABLE IX
RANKING ORDER AND DIFFERENCE VALUE

Number	FLRS	TFLRS	Deference value
1	1	52	51
2	87	5	82
3	46	13	33
4	11	59	48
5	39	11	28
6	2	56	54
7	6	58	52
8	47	9	38
9	44	6	38
10	12	62	50
11	97	2	95
12	8	60	52
13	10	39	29
14	64	12	52
15	40	15	25

To verify the consistency of the experiment, another two groups reading materials were selected and repeated this experiment. The results of experiment also showed that the latest reading materials can display at the further front of the recommendation ranking order and the out-of-date reading materials were at the further back orders. The comparison of ranking order between TFLRS method and FLRS method for the three times experiments is illustrated by the Fig. 12.
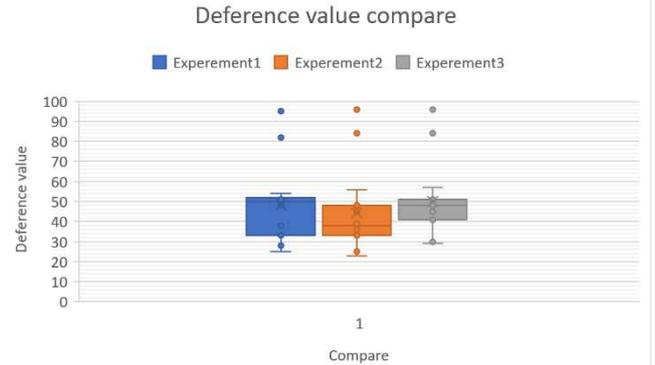
Fig. 12 The deference values between TFLRS and FLLRS in three times experiments

The experiment results show that the ranking order have improved with 48.47%, 44.4% and 50.07% in three times experiments respectively and the average ranking order has been improved with 47.64%. The outcome shows that it is obviously revise the order of recommendation materials after applied ULT parameter in TFLRS method. It is better than FLRS method in the timeliness of reading materials.

IV. CONCLUSION

In this study, an improved fuzzy logic method that focuses on timeliness of reading materials was introduced. The ULT parameter as an important input variable is attached and the numeric weight of input parameters based on their important degree has been revised in practicing reading recommendation system. The experiment result demonstrates that the proposed method successful adjusts the recommendation ranking order of the latest and out-of-date reading materials. It enables the new reading materials of user preference are always at the further front of the recommendation sequence. The accuracy of recommendation results obviously outdistances FLRS method. Future research includes but is not limited to the following topics: how to dynamically adjust the weights associated with the parameters and a Neuro Network approach will be used in the system.

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