HYBRID SUBJECTIVE EVALUATION METHOD USING WEIGHTED SUBSETHOOD – BASED (WSBA) RULE GENERATION ALGORITHM

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ABSTRACT

Fuzzy rules are important elements that should take into account in any fuzzy expert system. This paper proposes the framework of subjective performance evaluation using fuzzy technique for ranking the attributes of different types of datasets under a multi-criteria environment. The techniques such as fuzzy similarity function, fuzzy synthetic decision and satisfaction function have been adopted in these fuzzy evaluation methods. The framework is based on fuzzy multi-criteria decision-making that consists of fuzzy rules. The use of fuzzy rules, which were extracted directly from input data through Weighted Subsethood-based (WSBA) Rule Generation Algorithm. WSBA rule generation use the subsethood values to generate the weights which finally produced the fuzzy general rules. The rules generated through the data provided knowledge in developed fuzzy rule The fuzzy rules embedded in the framework of subjective evaluation method showed advantages in generalizing the evaluation of the performance achievement, where the evaluation process can be conducted consistently in producing good evaluation results with the use of the membership set score. . The results from the numerical examples are comparable to other fuzzy evaluation methods, even with the use of small rule size.

Keywords:fuzzy technique; weighted subsethood based; rule generations, subjective evaluation

INTRODUCTION:

Decision making environment involves a lot of important information which help to generate fuzzy rule generation. With more data collection, the increasing on knowledge involve that will help in order to generate the fuzzy rules. To be more realistic, in evaluation problems there involve many subjectivity, vagueness and imprecise information. Therefore, the use of fuzzy set theory which focuses on the rule generation will help to improve the result on evaluation. Most of the rule generation derive from the data collection as the input that have been discussed in Hong(1996), Yager(1991) and Wang (1992). They stated on how the fuzzy rules was generated from the membership functions which adapted from the input data. This method helped to reduce the time and effort other than by developing the fuzzy expert system.

In order to generates rules, there involves all the possible combinations of the fuzzy partitions of the input variables. Basically, if there are only two input variables and three fuzzy partitions for each variable, 9 rules will be generated. The outcome result will be produce by working on with the rule generated together with the defuzzification of the output.

Most subjective evaluation represents the human knowledge. The model can be represented in form of IF-THEN rules. A simple fuzzy IF-THEN rules is written in form of IF x is A THEN y is B where A and B are fuzzy sets. The fuzzy IF-THEN rules involve the antecedents and consequences which explain the fuzzy condition. A more complex fuzzy application system consisted of many fuzzy IF-THEN rules. According to Mendel (2001), there are six different types of fuzzy rules which are Incomplete rules, Mixed Rules, Fuzzy Statement Rules, Comparative Rules, Unless Rules and Quantifiers Rules. There are two type of linguistic fuzzy model that broadly used are Mamdani –type FRBS and Takagi-Sugeno-Kang (TSK).

According to Rasmani (2002), the WSBA was used for rules generation is because the subsethood values is used as weights over the significance for different conditions available which results in the conclusion. He modified Subsethood- Based techniques which ease the rule- learning process. The weight was obtained from the subsethood values then generated the rules for each possible conclusion.

In classical theories, the statement used to define a certain set usually involves two mantic values. That is, a particular statement must have a clear truth value of either true or false, yes or no, but not both of them. The truth value is usually represented by numerical value zero or one. On the contrary, in fuzzy set theory approach, a statement can have values in the range of [0, 1]. In this paper the proposed framework subjective evaluation method evaluate the student performance in linguistic terms Good, Average and Poor. This approach gives more space to measure subjective criteria to improve the expressions and assessments under the fuzzy environment.

The paper is organized as follows: In section 2, the fuzzy rule generation method is described and section 3 presents algorithm of the proposed subjective evaluation method. Section 4 will presents the numerical results and concluding remarks are given in section 5.

CASE STUDY:

This study has adopted the data on Student Performance used in Rasmani (2002). The data used is on the Student Academic Performance (SAP) data that involves three attributes which are the Assignment, Test and Final Exam. The outcomes involve the final grades that are Poor, Average and Good. All the attributes measured in percentage such as assignment, test and final exam which are 50%, 20%, 30% and 50% respectively. The dataset is divided into two subsets, each dataset contained 15 instances: SAP-1 is used for training, and SAP-2, is used for testing. Table 1 depicted the training dataset and Table 2 shows the testing dataset.

Table 1: Training dataset (SAP-1)

Case	Assigment (20%)	Test (30%)	Final Exam (50%)	Final Mark (100%)	Grade
1	2	12	10	24	Poor
2	16	24	45	85	Poor
3	9	11	30	50	Poor
4	5	17	17	39	Good
5	10	20	15	45	Good
6	18	28	48	94	Average
7	15	20	23	58	Poor

8	5	5	10	20	Poor
9	7	23	35	65	Good
10	15	17	40	75	Average
11	2	6	15	23	Average
12	17	23	48	88	Good
13	15	25	50	90	Average
14	7	11	11	28	Average
15	11	15	15	41	Good

Table 2: Testing dataset (SAP-1)

Case	Assigment(20%)	Test (30%)	Final Exam (50%)	Final Mark (100%)	Grade
1	2	7	9	18	Poor
2	8	11	20	39	Poor
3	6	10	14	30	Poor
4	7	14	16	37	Poor
5	3	6	19	28	Poor
6	11	10	21	42	Average
7	9	15	31	55	Average
8	8	22	27	57	Average
9	10	21	31	62	Average
10	17	25	24	66	Average
11	17	20	38	75	Good
12	15	24	41	80	Good
13	18	22	44	84	Good
14	16	26	48	90	Good
15	19	27	50	96	Good

Table 3 shows the labels used to represent the linguistic terms employed within the whole SAP dataset.

Table 3: Labels used for each linguistic term in SAP dataset

Label	Linguistic Term
A1	Assignment is Poor
A2	Assignment is Average
A3	Assignment is Good
B1	Test is Poor
B2	Test is Average
B3	Test is Good
C1	Final Exam is Poor
C2	Final Exam is Average
C3	Final Exam is Good
X	Final Grade is Poor
Y	Final Grade is Average
Z	Final Grade is Good

THE PROPOSED HYBRID SUBJECTIVE EVALUATION METHOD:

The proposed method is based on the work done by Rasmani (2002) and Othman et al.(2008) on the use of similarity function and synthetic decision-making. However, this method focuses on extracting rules and membership set score from data which is different from the works of Rasmani (2002) and Othman et al.(2008). The proposed method uses the fuzzy rules which are determined by the rule generation. The rule generation is the enhancement of the Rasmani (2002) fuzzy rule generation method which based on Weight Subsethood algorithm is embedded in the subjective evaluation method are discussed in Section 3.5. The use of fuzzy rules, which are extracted from the data input in making evaluation, contributes a better decision in selecting the best choice.

The proposed method consisted of two phase, the initial phase consisted of three steps of fuzzy rules generation method. The second phase involved integrating the fuzzy rules into nine steps of the proposed subjective evaluation method. The first step of the initial phase is to classify the training data into subgroups according to the underlying classification outcomes, poor, average and good. Next step is to calculate fuzzy subsethood values to obtain for every variable in each subgroup and

The Fuzzy Subsethood values can be defined as follow. Let A and B be two fuzzy set defined on the universe U. The fuzzy subsethood value of A with regard to B, S(B,A) represents the degree to which A is subsethood of B.

$$S(B,A) = \frac{M(B \wedge A)}{M(B)} = \frac{\sum_{x \in U} \nabla(\mu_B(x), \mu_A(x))}{\sum_{x \in U} \mu_B(x)} \tag{1}$$

where $S(B, A) \in [0, 1]$ and ∇ is the t-norm operator.

The related weight for the linguistic terms A_i with regard to classification X is calculated using Equation 2.

$$w(X,A_i) = \frac{S(X, A_i)}{\max_{i=1,2,\ldots l} S(X, A_j)} \tag{2}$$

Let $w(X,A_i) \in [0,1]$ and $i = 1,2\ldots.,l$

The linguistic terms are attached with the weight generated which associates with the attributes. The Equation 3 is used to calculated weight conjunction of linguistic terms

$$T(A) = \left(\frac{w_1}{w}(A_1)\nabla\ldots\nabla\frac{w_m}{w}(A_m) \right) \tag{3}$$

where A is the conditional attribute $T(A)$ is the compound weight and ∇ is the t-norm, A_i , i= 1,2,… , m, are the linguistic terms of variable A which are conjunctively combined and w is the largest amongst the m associated weights.

For the compound weight $T(B)$ of the weighted disjunction of linguistic terms associated with variables B is calculated as in Equation 4.

$$T(B) = \left(\frac{w_1}{w}(B_1)\Delta\ldots\Delta\frac{w_m}{w}(B_m) \right) \tag{4}$$

Where Δ is the t- conorm and B_i, i=1,2,…, n are the linguistic terms B, which are disjunctively combined.

There are five steps in the proposed method for evaluating the student performance. The first step is to calculate the normalized synthetic score value. The next three steps in this proposed method deal with the evaluation of the attribute rule value and the appraisal product value followed by the calculation of the satisfaction value. Lastly, the ranking of the students' performance based on the satisfaction value were done, where the biggest value would indicate the best student quality performance. Results of the transformation of the Normalized Synthetic Score Value for quality attribute F_i of each cases are shown in Table 4.

Table 4: Normalized Synthetic Score Value

Case	**Factor**			
	F_1	F_2	F_3	F_4
1	0.10	0.23	0.18	0.18
2	0.40	0.37	0.40	0.39
3	0.35	0.47	0.32	0.37
4	0.3	0.33	0.28	0.30
5	0.15	0.20	0.38	0.28
6	0.55	0.33	0.42	0.42
7	0.45	0.50	0.62	0.55
8	0.40	0.73	0.54	0.57

9	0.50	0.70	0.62	0.62
10	0.85	0.83	0.48	0.66
11	0.85	0.67	0.76	0.75
12	0.75	0.80	0.82	0.80
13	0.90	0.73	0.88	0.84
14	0.84	0.87	0.96	0.90
15	0.95	0.90	1.00	0.96

The decision criteria DC_i (for i = 1, 2, 3, …, m) is the intersection or combination of factor rules which is in the form of antecedent of the rule. The precedent of the rule indicates the conclusion in terms of linguistic variable A_k (k = 1, 2, …, K). The linguistic variables are described by satisfactory, very satisfactory, very very satisfactory, perfect and unsatisfactory respectively. The appraisal set is defined as $A = \{A_k\}$, k = 1, 2, ..., 5, where $v \in V$, the unit appraisal space $V = \{v_l\} = \{0, 0.1, 0.2, \ldots, 1\}$ and l = 1, 2, ..., 11. The rule value in Table 6 is obtained by processing the normalized synthetic score value according to the multi-criteria decision of Table 5.

Table 5: Multicriteria Rules Combination

Decision Criteria	Factor Rule	Description	Grade	Appraisal Set
DC_1	$F_1 \cap F_3$	Satisfactory	*Poor*	v
DC_2	$F_1{*}F_1 \cap F_2{*}F_2 \cap F_3{*}F_3$	Very satisfactory	*Average*	$v^{3/2}$
DC_3	F_3	Very very satisfactory	*Good*	v^2

The combination of multi-criteria rule from Table 5 can be written as in Equation (5) also known as fuzzy rule and the approximate reasoning is used to calculate the factor rule value.

$$\text{IF } (C_i = \bigcap_{j=1}^{4} \cup F_j) \text{ THEN } A_k \qquad (5)$$

where, C_i is the decision criteria, F_j represents the factor rules (j = 1, 2, 3, 4), A_k uistic variable and k stands for grade. The symbols $\bigcup$, $\bigcap$ stand for the union and the intersection respectively. The factor rule value in Table 6 is obtained by processing the normalized synthetic score value according to the multi-criteria decision of Table 5.

Table 6: Factor rule value

	C_1	C_2	C_3
1	0.1000	0.0100	0.1800
2	0.4000	0.1344	0.4000
3	0.3200	0.1024	0.3200
4	0.2800	0.0784	0.2800
5	0.1500	0.0225	0.3800
6	0.4200	0.1111	0.4200
7	0.4500	0.2025	0.6200
8	0.4000	0.1600	0.5400
9	0.5000	0.2500	0.6200
10	0.4800	0.2304	0.4800
11	0.7600	0.4445	0.7600
12	0.7500	0.5625	0.8200
13	0.8800	0.5377	0.8800
14	0.8400	0.7056	0.9600
15	0.9500	0.8100	1.0000

The appraisal product value is computed through the identification of the appraisal fuzzy value for n decision criteria. Each entry of appraisal fuzzy value D_j for every decision criteria is computed as follows :

$$d_j(m,l) = 1 \wedge (1 - \tilde{c}(u_m) + A_k(v_l)) \qquad (6)$$

where $j = 1, 2, 3, \ldots, m$, $l = 1, 2, \ldots, 11$ and $\tilde{c}(u_m)$ is the factor rule value. The appraisal fuzzy value of for the decision criteria is shown in Table 7.

Table 7: Appraisal Fuzzy Value For Decision Criteria C_1

Case	Appraisal Set									
1	0.9900	1	1	1	1	1	1	1	1	1	1
2	0.8656	0.8972	0.9550	1	1	1	1	1	1	1	1
3	0.8976	0.9292	0.9870	1	1	1	1	1	1	1	1
4	0.9216	0.9532	1	1	1	1	1	1	1	1	1
5	0.9775	1	1	1	1	1	1	1	1	1	1
6	0.8889	0.9205	0.9784	1	1	1	1	1	1	1	1
7	0.7975	0.8291	0.8869	0.9618	1	1	1	1	1	1	1
8	0.8400	0.8716	0.9294	1	1	1	1	1	1	1	1
9	0.7500	0.7816	0.8394	0.9143	1	1	1	1	1	1	1
10	0.7696	0.8012	0.8590	0.9339	1	1	1	1	1	1	1
11	0.5555	0.5871	0.6450	0.7198	0.8085	0.8333	0.9091	1	1	1	1
12	0.4375	0.4691	0.5269	0.6018	0.6905	0.7911	0.9023	1	1	1	1
13	0.4623	0.4939	0.5517	0.6266	0.7153	0.8153	0.9270	1	1	1	1
14	0.2944	0.3260	0.3838	0.4587	0.5474	0.6480	0.7592	0.8801	1	1	1
15	0.1900	0.2216	0.2794	0.3543	0.4430	0.5436	0.6548	0.7757	0.9055	1	1

Therefore, the appraisal product value D is calculated by multiplying all elements of the appraisal fuzzy value obtained earlier, with D_j following the formula given in Equation (7).

$$D = \left(\prod_{j=1}^{J} d_j(m,l) \right) = \left(\tilde{E}_1, \tilde{E}_2, \ldots, \tilde{E}_F, \ldots, \tilde{E}_L \right) \in M_{L \times 1} \qquad (7)$$

The appraisal product value for the student performance is shown in Table 8.

Table 8: Appraisal Product Value

Case	Appraisal Set									
1	0.7306	0.8300	0.8600	0.9100	0.9800	1	1	1	1	1	1
2	0.3116	0.3831	0.4890	0.6210	0.7600	0.8500	0.9600	1	1	1	1
3	0.4151	0.5001	0.6254	0.7546	0.8400	0.9300	1	1	1	1	1
4	0.4778	0.5706	0.6992	0.8100	0.8800	0.9700	1	1	1	1	1
5	0.5151	0.5985	0.6600	0.7100	0.7800	0.8700	0.9800	1	1	1	1
6	0.2990	0.3693	0.4731	0.5896	0.7252	0.8300	0.9400	1	1	1	1
7	0.1667	0.2102	0.2794	0.3842	0.5130	0.6300	0.7400	0.8700	1	1	1
8	0.2318	0.2868	0.3718	0.4950	0.6200	0.7100	0.8200	0.9500	1	1	1
9	0.1425	0.1829	0.2468	0.3438	0.4860	0.6300	0.7400	0.8700	1	1	1
10	0.2081	0.2633	0.3464	0.4671	0.6256	0.7700	0.8800	1	1	1	1
11	0.0320	0.0499	0.0795	0.1283	0.2070	0.3296	0.5040	0.6862	0.8800	1	1
12	0.0197	0.0312	0.0522	0.0894	0.1526	0.2551	0.4141	0.6365	0.8200	0.9900	1
13	0.0067	0.0141	0.0282	0.0553	0.1041	0.1872	0.3204	0.5002	0.6992	0.9300	1
14	0.0019	0.0042	0.0111	0.0274	0.0613	0.1240	0.2308	0.4011	0.6528	0.8500	1
15	0.0000	0.0003	0.0028	0.0112	0.0319	0.0747	0.1532	0.2851	0.4926	0.7695	1

Finally, the students' performance can be ranked using the satisfaction value, *SV(m)*, as given below:

$$SV(m) = \frac{1}{\alpha_{maks}} \sum_{l=1}^{L} H_l(E_{m\alpha}) \Delta\alpha_l \qquad (8)$$

where α = degree of appraisal product value D; $\Delta\alpha_l = \alpha_l - \alpha_{l-1}$; $\alpha_0 = 0$; $H_l(E_{m\alpha})$= mid-point of V_l (l = 1, 2, 3,…, L); and α_{max} = maximum degree of appraisal product value. The calculated values of the range of appraisal product value (α), the difference of range of appraisal product value ($\Delta\alpha_l = \alpha_l - \alpha_{l-1}$), and mean value of $E_{m\alpha}$, ($H_l(E_{m\alpha})$) are tabulated in Table 9.

Table 9: Calculated Range Of α, $\Delta\alpha_l$, and $H_l(E_{n\alpha})$

l	Range α	$E_{m\alpha}$	$H_l(E_{n\alpha})$	$\Delta\alpha_l$
1.	0.0000 < α ≤ 0.7306	{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.50	0.7306
2.	0.6506 < α ≤ 0.8300	{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.55	0.0994
3.	0.7630 < α ≤ 0.8600	{0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.60	0.0300
4.	0.8600 < α ≤ 0.9100	{0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.65	0.0500
5.	0.9100 < α ≤ 0.9800	{0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.70	0.0700
6.	0.9800 < α ≤ 1.0000	{0.5, 0.6, 0.7, 0.8, 0.9, 1}	0.75	0.0200
7.	1.0000 < α ≤ 1.0000	{0.6, 0.7, 0.8, 0.9, 1}	0.80	0.0000
8.	1.0000 < α ≤ 1.0000	{0.7, 0.8, 0.9, 1}	0.85	0.0000
9.	1.0000 < α ≤ 1.0000	{0.8, 0.9, 1}	0.90	0.0000
10.	1.0000 < α ≤ 1.0000	{ 0.9, 1}	0.95	0.0000
11.	1.0000< α ≤ 1.0000	{1}	1	0.0000

The highest satisfaction value is considered as the best performance which implies that the lecturer are much more satisfied with the students score as discussed in Lee et al. (1994).

NUMERICAL RESULT:

Comparison of results between the statistical method, Rasmani (2002) and the proposed method are exhibited in Table 10 the students performance are ranked based on the satisfaction values. The experimental results show that the proposed method is comparable to Rasmani (2002). The model is in fact better because of the use of fuzzy rules in making a good ranking in accordance with human decision making (Ku Mahamud,2010). The method has shown good consistency in accuracy in ranking with shorter rule properties where there are only three (3) rules with a minimum length of one (1) and the maximum length of three (3). In addition, the most important feature is that the developed rules have extracted the knowledge from the data input and hence are more understandable to humans. The experiment on data normalization in the model was seen as significant to stabilize the input data since there are extreme values in the input data. Noise or bias in the data distribution can be diminished through data normalization which is one of the objectives of the model. The use of rules is demonstrated to be reliable as it works like human thinking and meets the goals of the assessment. The quality of a method depends on the properties of the method and the functions for which the method is designed .The model had exhibited a good method where it had fulfiled three major properties: (1) formal consistency; (2) usefulness; (3) efficiency in the desired function at minimum effort, time and cost.

Table 10 : Comparison of the Result

Case	Statistical Average Method				Rasmani Method				Proposed Fuzzy Method			
	Performance			Grade	Performance			Grade	Performance			New Grade
1	2	7	7	Poor	1	0.28	0	Poor	10	23.33	18	Poor
2	8	11	11	Poor	0.5	0.28	0	Poor	40	36.67	40	Poor
3	6	10	10	Poor	0.83	0.33	0	Poor	35	46.67	32	Poor
4	7	14	14	Poor	0.36	0.29	0	Poor	30	33.33	28	Poor
5	3	6	6	Poor	0.6	0.28	0	Poor	15	20	38	Poor

6	11	10	10	Average	0.06	0.23	0	Average	55	33.33	42	Average
7	9	15	15	Average	0.04	0.75	0.08	Average	45	50	62	Average
8	8	22	22	Average	0.04	0.4	0	Average	40	73.33	54	Average
9	10	21	21	Average	0.04	0.5	0.1	Average	50	70	62	Average
10	17	25	25	Average	0	0.29	0	Average	85	83.33	48	Average
11	17	20	20	Good	0	0.2	0.33	Good	85	66.67	76	Good
12	15	24	24	Good	0	0.22	0.75	Good	75	80	82	Good
13	18	22	22	Good	0	0.22	0.67	Good	90	73.33	88	Good
14	16	26	26	Good	0	0.22	1	Good	84	86.7	96	Good
15	19	27	27	Good	0	0.22	1	Good	95	90	100	Good

In this research, the determination method is adopted from Khairul Anwar Rasmani (2002) integrated with subjective evaluation method Othman(2004). The experimental result in Table 6, show that the proposed new range according to the fuzzy approach is comparable to the conventional range with accuracy is 100%. Therefore, the proposed method can be used as an alternative way in order to evaluate the student's performance. The factor rule produce from the WSBA rule generation also automatically can be used based on the comparable result produced for the range between the conventional and the proposed.

By adopting this proposed method into the proposed fuzzy rule generation method, we able to create the fuzzy rule through a simple generating process. The results of the experiments showed remarkable ranking performance even with the use of small sized rule properties.

CONCLUSION:

This research proposed the new rule generation method based on WSBA rule generation adapted from Khairul Anwar Rasmani (2002). This paper also produces the new range which can also be used in student's performance evaluation. The result gain shows that the new range on the students evaluation can be used as an alternative way with the new rule generation method which is more easy to understand and implement in the fuzzy evaluation approach in subjective way. This rule generation method on WSBA rule generation which employs the linguistic fuzzy model in the generation process will reflects how human make evaluation and judgements in the real world. This evaluation can reduce the problems that involve uncertainty which is very subjective. In this research, the main advantages and contribution is where we propose one new platform in order to generate rules which involves the simplicity with reducing in number of rules used and can be apply in different level of evaluation. Meanwhile, rules which are directly extracted from input data can contribute the better decision with less reliable from the input data (Ku-Mahamud et al, 2010).

The model has been implemented using the C++ programming language and it was design for many type of fuzzy evaluation data. In many problems that involve uncertainty and subjectivity, this method can act as an alternative approach to solve problems with uncertainty such as performance evaluation.

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