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Analysis of Fuzzy Logic Modification for Student Assessment in e-Learning

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***Abstract*—The phenomenon of the rapid transfer of learning to online systems, such as e-Learning, has occurred massively. Institutions must ensure that student assessments run well. The characteristics of learning in e-Learning require an appropriate assessment method. The fuzzy logic method can be an option. Research shows that fuzzy logic is capable of providing flexible and objective performance evaluation. Fuzzy logic is a method that can overcome the uncertainty of transparency and objectivity of student assessments. In general, fuzzy logic applications are carried out by standards. Modification is an attempt to reveal the flexibility and to optimize the use of fuzzy logic. This study presents an analysis of fuzzy logic modification for the assessment of Algorithm and Data Structures courses held in e-Learning. These modifications include (i) modification of the parameter score with score compatibility, (ii) consequent modification of the fuzzy rules and (iii) modification of the implication process. The study results show that although the use of fuzzy logic requires more complicated procedures and tools, it can present various kinds of assessment as an option for educators to assess students in e-Learning.**

Keywords*—*student assessment; e-Learning; fuzzy logic; compatibility; fuzzy rule; implication

1 INTRODUCTION

The coronavirus pandemic in 2020 has led to the phenomenon of a rapid and unplanned move towards online learning [1]. e-Learning is a form of online learning system [2]. The institution should keep the quality of learning guaranteed. One of them is by ensuring that the student assessment in e-Learning is going well.

In general, assessment in learning uses a classical approach quantitatively and assertively. Classical assessment is deemed inappropriate if applied to assessment in e-Learning. This is because the characteristics of the online environment are different from the offline environment. Besides, various aspects of assessment in an online environment are often related to behavior that cannot possibly be assessed strictly and only quantitatively. The fuzzy logic method can be an option.

Fuzzy logic proposes the basis for modeling, evaluating, and optimization of a task for various areas including teaching and learning [3]. Reference [4] mentions the fuzzy logic theory as one of the best methods in reducing uncertainty over the need for transparency and objectivity in student assessments. Fuzzy logic uses the fuzzy set as a classic set development. The classic set states explicitly where a small change in value causes a significant difference in the status of the value in the set so that it looks unwise and fair [5]. Not so with fuzzy logic. Fuzzy logic states that something is no longer right or wrong but is always right if it has a degree of membership in the range [0,1]. Fuzzy logic uses the term to overcome differences in perceptions in opinion. Fuzzy logic overcomes something that cannot, is not easy or impossible to measure due to the absence of measuring instruments [6]. Reference [7] state that fuzzy logic is flexible but still objective.

However, the assessment generally applies the standard fuzzy logic method [8][9][7][10]. Modification is an attempt to reveal the flexibility and to optimize the use of fuzzy. Several studies have modified fuzzy logic for student assessment. Reference [7] analyzes the modification of membership function on parameters. The results show that the modification of the membership function in the parameters produces different assessment results from the classic assessment. However, the study [7] did not discuss the difference in score ranges on the assessment parameters, as suggested [11]. Besides, the application of fuzzy logic by [7] is not implemented in the assessment in an online learning environment but in laboratory learning. Reference [12] modified the fuzzy rule base where several $Rules_5^7$ rules should be used, only 58 rules are chosen based on recommendations. Reference [12] applies the fuzzy rules based on the recommendations but does not discuss what if there are differences of opinion in the consequent formulation for the same antecedent. Other studies related to the application of fuzzy logic in the assessment are [8][9][10]. The three references apply the fuzzy inference system with the Mamdani approach as an implication interpretation approach and do not compare with other interpretation approaches.

This study proposes several modifications to reveal the flexibility of fuzzy logic to optimize student assessment. Modifications include score compatibility on input parameters, modification of consequent fuzzy rules, and modification of interpretation of implication processes. The results of this study are expected to provide various options for educators in conducting student assessments in e-Learning.

2 METHOD

2.1 Dataset and tools

This research was conducted in lectures on Data Structure and Algorithms in the Even Semester 2019/2020, February to May 2020. Learning is implemented through e-Learning into LMS Moodle with a total of 52 students. This study uses 20 students as simulation instances referring to [8][9][13]. Simulation using scripts and fuzzy logic toolbox in Matlab.

2.2 Learning Design

Learning is carried out weekly for 14 weeks. The various activities in each meeting are material, discussion in forums, assignments, and exams in the last week of learning. Students must participate in the forum by posting an opinion at least 5 times from the entire available forum. Attendance is calculated from the total activity time of students in online classes at least equivalent to 150 minutes per week or 2100 minutes.

2.3 Input Variables, Output Variable and Preprocessing

Input variables are assessment parameters, i.e., knowledge, forum_participation, and attendance. The output variable is student_performance. The score for the knowledge variable is the result of the test stated in the range of 0-100. The forum_participation variable score is the number of opinions posted in the range 0-10. The attendance variable score is the total time of student activities in the system, expressed in minutes in the range 0-4000. The student_performance variable score is the student's performance expressed in a score range of 0-100.

The data source is the e-Learning database. Attributes, tables, and data extraction methods for input variables are shown in Table 1. Data for knowledge variables were extracted from mdl_quiz and mdl_quiz_grades tables, forum_participation variable data from the mdl_forum_posts, and mdl_forum_discussion tables, and attendance variable data from the mdl_logstore_standart_log table. Preprocessing is done to obtain clean data before the data is processed further [14]. Attendance data preprocessing resulted in 18.488 student activity instances, which became the basis for calculating the total attendance time.

2.4 Fuzzy Inference System for assessing student

A fuzzy inference system is built based on rules or knowledge that manages crisp input to crisp output using a fuzzifier, fuzzy rule base, fuzzy inference engine, and defuzzifier [15]. Fig. 1 depicts a diagram of the fuzzy inference system. The fuzzifier maps input variables: knowledge, forum_participation, and attendance, in a fuzzy set with a membership function approach.

Table 1 Data and Extraction Methods

Input Variables	Attribute	Extraction Method
Knowledge	grade	calculating quiz score
Forum_ Participation	message	counting the number of posting opinions in the forum
Attendace	timecreated, eventname, component, action, target	calculating the time range for the action: accepted, created, deleted, ended, graded, reviewed, searched, shown, started, submitted, updated, uploaded, and viewed during the learning process

The fuzzy input value from the fuzzifier with the fuzzy rule base is processed by the fuzzy inference engine to become the fuzzy output value [15][16]. Defuzzifier converts the fuzzy output value into a crisp value as a student performance score.

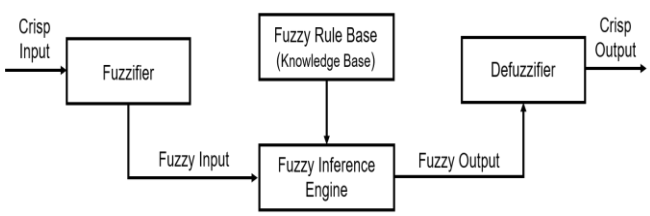

Figure 1. The diagram of a Fuzzy Inference System

3 RESULT AND DISCUSSION

3.1 Fuzzification

3.1.1 *Knowledge Fuzzification:* The linguistic variable Knowledge is a representation of the test score with the domain [0, 100]. The linguistic variable Knowledge has 5 sets of linguistic terms, i.e., Very Low, Low, Average, High, and Very High [7]. Table 2 shows the linguistic terms, symbols, and intervals for the linguistic variable knowledge [13]. For example, the linguistic term Average has an interval [25, 75] where the lower limit of the test score is 25 and the upper limit is 75.

Table 2 The Fuzzy Set of Knowledge Input Variable

Linguistics Term	Symbol	Support
Very Low	VL	[0, 25]
Low	L	[5, 50]
Average	A	[25, 75]
High	H	[50, 95]
Very High	VH	[75, 100]

3.1.2 *Forum_Participation Fuzzification:* The linguistic variable forum_participation is a representation of the number of student opinion posts in a forum with a domain [0, 10]. The linguistic variable forum _participation has 3 sets of linguistic terms, i.e., Less, Medium, and High [12]. Table 3 shows the linguistic terms, symbols, and intervals for the linguistic variable forum_participation. For example, the linguistic term Medium is in the interval [4, 8] where the lower limit of the number of opinion posts is 4 and the upper limit is 8.

Table 3 The Fuzzy Set of Forum_Participation Input Variable

Linguistics Term	Symbol	Support
Less	L	[0, 6]
Medium	M	[4, 8]
High	H	[6, 10]

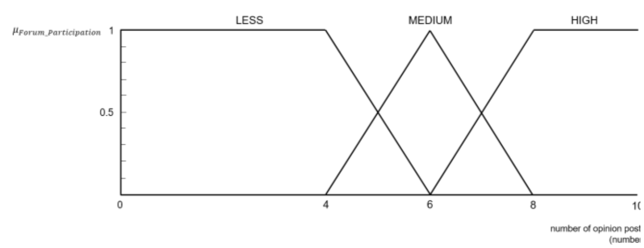

Figure 2. The Membership Function of Forum Participation Variable

Equation (1) shows the membership function for each fuzzy set on the Forum_Participation variable based on Fig. 2.

$$\mu_{Forum\_Less}(x) = \begin{cases} 1, & x \le 4 \\ \dfrac{6-x}{6-4}, & 4 \le x \le 6 \\ 0, & x \ge 6 \end{cases} \tag{1}$$

$$\mu_{Forum\_Medium}(x) = \begin{cases} 0, & x \le 4 \; atau \; x \ge 8 \\ \frac{x-4}{6-4}, & 4 \le x \le 6 \\ \frac{8-x}{8-6}, & 6 \le x \le 8 \end{cases}$$

$$\mu_{Forum\_High}(x) = \begin{cases} 1, & x \ge 8 \\ \frac{x-6}{8-6} & 6 \le x \le 8 \\ 0, & x \le 6 \end{cases}$$

3.1.3 *Attendance Fuzzification:* The linguistic variable attendance is a representation of the total student activity time in the system with the domain [0, 4000] in minutes. The linguistic variable attendance has 5 sets of linguistic terms, i.e., Very Less, Less, Medium, High, and Very High [12]. Table 4 shows the linguistic terms, symbols, and intervals for linguistic variable attendance. For example, the term linguistic Medium is in the interval [1000, 3000] where the lower limit for the total activity time is 1000 minutes and the upper limit is 3000 minutes.

Table 4 The Fuzzy Set of Attendance Input Variable

Linguistics Term	Symbol	Support
Very Less	VL	[0, 1000]
Less	L	[250, 2000]
Medium	M	[1000, 3000]
High	H	[2000, 3750]
Very High	VH	[3000, 4000]

3.1.4 *Student Performance Fuzzification:* The linguistic variable student_performance is a representation of student performance scores with domain [0, 100]. The linguistic variable student_performance has 5 sets of linguistic terms, i.e., Unacceptable, Poor, Satisfactory, Good, and Excellent [17].

Table 5 The Fuzzy Set of Student_Performance Output Variable

Linguistics Term	Symbol	Support
Unacceptable	U	[0, 40]
Poor	P	[20, 60]
Satisfactory	S	[40, 80]
Good	G	[60, 95]
Excellent	E	[80, 100]

Table 5 shows the linguistic terms, symbols, and intervals for the linguistic variable student_performance. For example, the linguistic term Satisfactory has an interval [40, 80] where the lower limit of the performance score is 40 and the upper limit is 80.

3.2 *Fuzzy Rule Base*

Rules are knowledge in a fuzzy system that is formed by fulfilling complete and consistent requirements [5][6][12]. In fuzzy inference system, every fuzzy rule has two parts: antecedent part (premise) expressed by IF, and consequent part expressed by THEN. The general IF-THEN structure of the Mamdani algorithm as shown (2).

$$R_i: if \; x \; is \; A_i \; and \; \ldots \; then \; y \; is \; B_i \; (for \; i = 1, 2, \ldots, k) \qquad (2)$$

where k is the number of rules, R_i is the rule number, A_i and B_i are the fuzzy sets, x is the antecedent variable representing the input in the fuzzy system, and y is the consequent variable related to the output of the fuzzy system [16]. To fulfill the complete and consistent requirements, 75 fuzzy rules were formulated [12][5]. Here are some of the rules:

[Rule1]. IF (Knowlegde is Very Low) AND (Forum_Participation is Less) AND (Attendance is Very Less) THEN (Student_Performance is Unacceptable)

[Rule2]. IF (Knowlegde is Very Low) AND (Forum_Participation is Less) AND (Attendance is Less) THEN (Student_Performance is Poor)

[Rule3]. IF (Knowlegde is Very Low) AND (Forum_Participation is Less) AND (Attendance is Medium) THEN (Student_Performance is Poor)

[Rule4]. IF (Knowlegde is Very Low) AND (Forum_Participation is Less) AND (Attendance is High) THEN (Student_Performance is Poor)

[Rule5]. IF (Knowlegde is Very Low) AND (Forum_Participation is Less) AND (Attendance is Very High) THEN (Student_Performance is Satisfactory)

[Rule6]. IF (Knowlegde is Very Low) AND (Forum_Participation is Medium) AND (Attendance is Very Less) THEN (Student_Performance is Poor)

[Rule7]. IF (Knowlegde is Very Low) AND (Forum_Participation is Medium) AND (Attendance is Less) THEN (Student_Performance is Poor)

[Rule8]. IF (Knowlegde is Very Low) AND (Forum_Participation is Medium) AND (Attendance is Medium) THEN (Student_Performance is Poor)

[Rule9]. IF (Knowlegde is Very Low) AND (Forum_Participation is Medium) AND (Attendance is High) THEN (Student_Performance is Satisfactory)

[Rule10]. IF (Knowlegde is Very Low) AND (Forum_Participation is Medium) AND (Attendance is Very High) THEN (Student_Performance is Satisfactory).

3.3 Determine Performance

Based on the fuzzy inference system diagram Fig. 1, after the fuzzification process, the next process is to convert the fuzzy input into the fuzzy output. The inference system handles how the rules are combined. The Max-Min and Max-Product methods are the most commonly used techniques for the composition of fuzzy relations [16]. Equation (3) shows the Max-Min composition used in the fuzzy inference system.

$$\mu_{C_k}(Z) = \max[min[\mu_{A_k}(input(x)), \mu_{B_k}(input(y))]] \quad (3)$$

where μ_{C_k} , μ_{A_k} and μ_{B_k} are the membership functions of output z for rule k, input x and input y, respectively. The minimum value is calculated in each rule then aggregation to produce the composition of the operation of each rule.

Graphical methods are commonly used to aggregate the minimum values for each rule. The result of aggregation is a fuzzy value that must be converted to a crisp by defuzzification. Defuzzification transform the fuzzy output into a final crisp output.

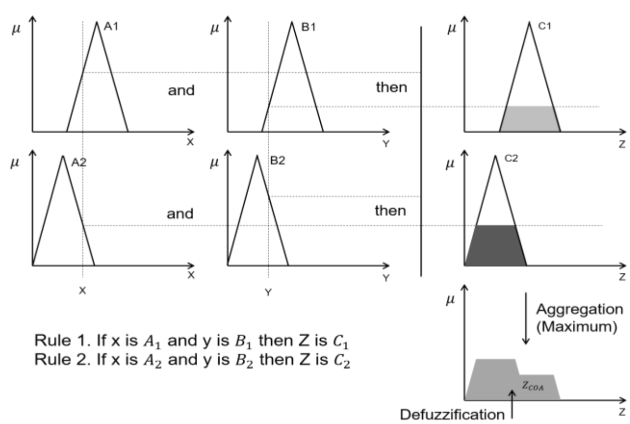

Figure 3. A Mamdani Two-Rule Fuzzy Inference System with 2 Inputs

Fig. 3 illustrates the process of obtaining z output from a Mamdani two-rule fuzzy inference system with 2 inputs, x and y [18][16]. There are several defuzzification methods, including center of area (COA) or centroid, center average, maximum membership principle, and min-max membership (middle of maxima) [6]. This study uses the centroid method for defuzzification based on the following equation:

$$Z_{COA} = \frac{\int_z \mu_A(z)zdz}{\int_z \mu_A(z)dz} \quad (4)$$

where Z_{COA} is the crisp value for the z output and $\mu_A(z)$ is the aggregated output membership function.

Fig. 4 shows the calculation of student performance with the Matlab toolbox. The results of the performance assessment of 20 instances with the Mamdani fuzzy inference system are shown in

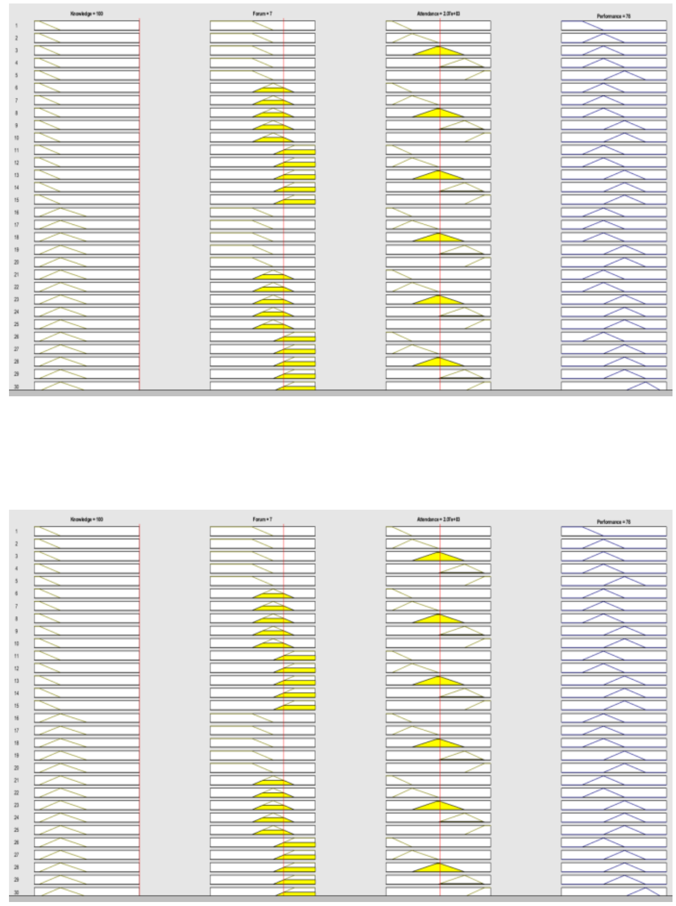

Figure 4. The Result of Student Performance with Matlab Toolbox

Table 6 The Student Performance Scores

Student	Knowledge (0-100)	Forum_ Participation (frequency, 0-10)	Attendance (minute, 0-4000)	Student_ Performance (0-100)
1	93.3	10	2461	78.1
2	93.3	8	3657	89.4
3	100.0	5	227	60.0
4	93.3	5	826	57.0
5	100.0	7	2072	78.0
6	100.0	8	3088	79.1
7	40.0	5	1071	50.0
8	100.0	6	3120	78.3
9	93.3	9	1836	75.8
10	100.0	5	1820	68.1
11	80.0	5	2475	67.9
12	100.0	7	7911	82.6
13	100.0	8	4018	93.3

Student	Knowledge (0-100)	Forum_ Participation (frequency, 0-10)	Attendance (minute, 0-4000)	Student_ Performance (0-100)
14	100.0	6	1904	75.6
15	100.0	6	255	60.0
16	100.0	6	1400	66.8
17	93.3	5	2553	68.5
18	100.0	5	227	60.0
19	66.7	6	1199	60.0
20	100.0	5	481	60.0

3.4 Modification of Fuzzification with Parameter Score Compatibility

Based on the explanation of point 3.3, the use of fuzzy logic can provide objective assessment results even though the input parameters have different score ranges. In general, in the implementation of educational evaluation, according to [11][19], score compatibility can be done to overcome different score conditions so that the scores are easier to understand and meaningful. Score compatibility is done by changing the initial score into a new score with the absolute value reference approach [19] at an ideal maximum score of 100 as shown by (5):

$$Score = \frac{Real\ Score}{Ideal\ Maximum\ Score} \times 100 \qquad (5)$$

where Score is a new score, Real Score is an initial score, and Ideal Maximum Score is an absolute value reference i.e. 100. Compatibility is performed on the Forum_Participation and Attendance variables. The new domain for the Forum_Participation and Attendance variables is [0, 100].

Table 7 The Fuzzy Set of Forum_Participation Input Variable after Score Compatibility

Linguistics Term	Symbol	Support
Less	L	[0, 60]
Medium	M	[40, 80]
High	H	[80, 100]

Table 7 is the new fuzzy set of Forum_participation input variable. For example, the new values for the first instance are 93.3, 100, and 62 as Table 8 shows.

Table 8 Student Performance Scores with Score Compatibility

Student	Knowledge (0-100)	Forum_ Participation (0-100)	Attendance (0-100)	Y1 (0-100)	Y2 (0-100)
1	93.3	100	62	84.9	80.0
2	93.3	80	91	88.3	87.5
3	100.0	50	6	51.9	60.0
4	93.3	50	21	54.7	57.0
5	100.0	70	52	73.9	80.0
6	100.0	80	77	85.7	80.1
7	40.0	50	27	38.9	50.0
8	100.0	60	78	79.3	80.0
9	93.3	90	46	76.4	77.7
10	100.0	50	45	65.2	70.0
11	80.0	50	62	64.0	69.8
12	100.0	70	100	90.0	82.6
13	100.0	80	100	93.3	93.3
14	100.0	60	48	69.2	77.8
15	100.0	60	6	55.5	60.0
16	100.0	60	35	65.0	68.4
17	93.3	50	64	69.1	70.5
18	100.0	50	6	51.9	60.0
19	66.7	60	30	52.2	60.0
20	100.0	50	12	54.0	60.0

Y1. Student Performance Score by Classical Assessment, Y2. Student Performance Score after Compatibility and with Logika Fuzzy

Table 8 shows the results of the assessment with score compatibility between classical assessment and fuzzy logic. The classical assessment results were obtained from the mean of the three scores of the input variables [7]. The mean difference between the results of the assessment of fuzzy logic compared to classical assessment is 4.56. The mean difference between the results of the fuzzy logic assessment with and without the compatibility score is 1.3. The mean difference from the assessment results using the compatibility score between classical assessment and fuzzy logic is 5.24.

3.5 Modification of Fuzzy Rule Base

A fuzzy rule is the knowledge base in a fuzzy system. Reference [12] uses 58 rules of all possible probabilities from 78.125 combinations. The rules are determined based on recommendations [12]. Differences of opinion in formulating the consequences of the same antecedents are very likely to be found [6].

Modifications were made to the consequences of the 15 antecedent combinations of previous rules by changing the consequences to higher linguistic values, namely Poor to Satisfactory for rules 4, 18, 32, and 46, Satisfactory to Good for rules 25, 35, 39, 49, 53, 63, 67, and Good to Excellent for rules 60, 65, 70 and 74. Based on modified rules, the student performance assessment results are obtained as shown in Table 9.

Table 9 Student Performance Scores after Modification to Consequent Rules

Student	Knowledge (0-100)	Forum_ Participation (frequency, 0-10)	Attendance (minute, 0-4000)	Student_ Performance (0-100)
1	93.3	10	2461	82.2
2	93.3	8	3657	90.3

3	100.0	5	227	60.0
4	93.3	5	826	68.1
5	100.0	7	2072	78.7
6	100.0	8	3088	93.0
7	40.0	5	1071	51.0
8	100.0	6	3120	79.4
9	93.3	9	1836	75.8
10	100.0	5	1820	72.4
11	80.0	5	2475	68.1
12	100.0	7	7911	92.0
13	100.0	8	4018	93.3
14	100.0	6	1904	78.3
15	100.0	6	255	60.1
16	100.0	6	1400	78.1
17	93.3	5	2553	74.9
18	100.0	5	227	60.0
19	66.7	6	1199	63.8
20	100.0	5	481	66.0

Based on the assessment results in Table 9, the modification of the consequent fuzzy rules to a higher linguistic value gives an average difference between before and after modification is 3.85. The assessment results of 75% of students tended to increase.

Fig. 5 shows the difference in the results of the assessment before and after the consequent modification of the rules. In general, the graphics pattern did not change but increased in several student scores.

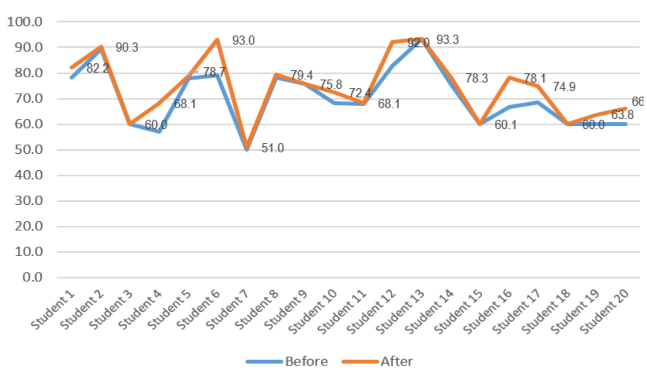

Figure 5. The Comparison of Assessment Results Before and After Modification of The Rules

3.6 *Modification of Implications*

Referring to Fig. 1, the combination of fuzzification results and fuzzy rules will lead to the next process, namely implications. The inference process with Mamdani uses the implications of min and combined composition (max) [20]. According to [6], three alternative interpretations can be applied in fuzzy $P \implies Q$ implications as follows:

Interpretation 1: $\bar{P} \vee Q$,

Interpretation 2: $\bar{P} \vee (P \& Q)$

Interpretation 3: $P \& Q$ (Mamdani)

Modifications apply interpretation 1 instead of interpretation 3 using the following (6).

$$\mu_{FP}(\underset{\sim}{x}, \underset{\sim}{y}) = s\left(c\left(\mu_{\underset{\sim}{A}}(\underset{\sim}{x}), \mu_{\underset{\sim}{B}}(\underset{\sim}{y})\right)\right) \quad (6)$$

where P and Q are propositions, $\underset{\sim}{x}$ is a variable vector, $\underset{\sim}{y}$ is a value vector, s is a s_norm relation, c is a complement relation, $\mu_{\underset{\sim}{A}}(\underset{\sim}{x})$ is a membership function x on A, and $\mu_{\underset{\sim}{B}}(\underset{\sim}{y})$ is a membership function y on B. Based on interpretation 1 in the implication process, the results of student performance assessment are obtained as shown in Table 10.

Table 10 The Student Performance Score after The Modification of Implications

Student	Knowledge (0-100)	Forum_ Participation (frequency, 0-10)	Attendance (minute, 0-4000)	Student_ Performance (0-100)
1	93.3	10	2461	69.2
2	93.3	8	3657	89.8
3	100.0	5	227	27.4
4	93.3	5	826	38.1
5	100.0	7	2072	61.4
6	100.0	8	3088	80.9
7	40.0	5	1071	41.4
8	100.0	6	3120	81.3
9	93.3	9	1836	56.7
10	100.0	5	1820	56.4
11	80.0	5	2475	69.5
12	100.0	7	7911	100.0
13	100.0	8	4018	100.0
14	100.0	6	1904	58.1
15	100.0	6	255	28.1
16	100.0	6	1400	48.0
17	93.3	5	2553	71.1
18	100.0	5	227	27.4
19	66.7	6	1199	44.0
20	100.0	5	481	33.0

As can be seen in Table 10, the implication modification was carried out using the $\bar{P} \vee Q$ interpretation approach to replace $P \& Q$ (Mamdani) and provide an average difference in the assessment results before and after the modification of 14.93.

4 CONCLUSION

This study describes the analysis of fuzzy logic modification as a way to reveal flexibility and to optimize the use of fuzzy logic for student assessment in e-Learning. The results of this study indicate that the fuzzy logic modification gives different assessment results from classical assessment as the real value. The mean difference between the assessment results with fuzzy logic compared to the classical assessments is 4.56. The use of fuzzy logic with score compatibility and no score compatibility gives a mean difference of 1.3. The mean difference between classical assessment and fuzzy logic with score compatibility was 5.24. The consequent modification of some fuzzy rules to a higher linguistic value gives the assessment results that tend to increase. Implication modification on the fuzzy inference system also provides differences in the assessment results. The use of fuzzy logic for student assessment requires more complicated procedures and tools. However, fuzzy logic modification can present various kinds of assessments that can be an option for educators in assessing student in e-Learning.

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