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Evaluation of student performance in laboratory applications using fuzzy logic

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Abstract

Educational systems typically employ classical methods of performance evaluation. In this system, student performance depends on exam results and is evaluated only as success or failure. Alternative, non-classical performance evaluation methods may be used, such as fuzzy logic, a mathematical technique of set-theory that can be applied to many forms of decision-making including research on engineering and artificial intelligence.
This study proposes a new performance evaluation method based on fuzzy logic systems. Student performance of Control Technique Laboratory in Marmara University Technical Education Faculty, Electricity Education Department, was carried out with fuzzy logic and it was compared with classical evaluating method. Study samples are notes which twenty students took the control technique laboratory course.
Evaluation of the results showed variations between the classical and fuzzy logic methods. Although performance evaluation using fuzzy logic is complicated and requires additional software, it provides some evaluation advantages. Fuzzy logic evaluation is flexible and provides many evaluation options, while the classical method adheres to constant mathematical calculation. At the application stage, the teacher responsible for the laboratory application can edit the ranges of membership functions and rules, permitting non-homogenous but flexible and objective performance evaluation.

Keywords: Performance; evaluation; exam; fuzzy logic; laboratory application.

1. Introduction

Measurement of educational performance is usually expressed numerically, based on examination results. Classical evaluation therefore consists of a judgment based on the comparison of student results against established performance-criteria. Measurement and evaluating are inspirable and important parts of the educational process. Evaluating student exam scores is performed using various methods.

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Using current, classical evaluation systems, educational success or failure is therefore based on separation via certain scoring thresholds. For instance, in laboratory applications, a student scoring above 50 is evaluated as successful, but is otherwise unsuccessful. However, in laboratory applications, evaluation of student performance based on rigid scoring criteria may not be appropriate.

Fuzzy logic theory emerged during the twentieth century and, by the beginning of the twenty-first century, was predicted to be applied extensively in many fields (Altrock, 1995). One of the applications of the fuzzy logic theory is the measurement and evaluation in education. In this context, the aim of this paper is to define the "impact of the fuzzy logic theory on the measurement of student's performance" (Semerci, 2004). The use of fuzzy logic models permits more flexible forms of evaluation. Electrical control laboratory is one of the courses given in departments of Electrical, Electronics and Computer Education. Electrical control laboratory is one of the most important courses because it has a practical focus and is closely-related to industry.

2. Methods

2.1. Study Group

The study group comprised sixth term students of Electrical Education at the Technical Education Faculty of Marmara University, Turkey. The study used exam scores which twenty students took the control technique laboratory course.

2.2. The Aim of the Study

The aim of the study is to determine students' performance using a fuzzy logic model in place of classical assessment methods. The study aimed to address the following research questions:

1. Is there any difference between classical and fuzzy logic evaluation methods?
2. Is there any difference in assessment results between classical and fuzzy logic evaluation methods?
3. What are the comments of academics about these two methods?

2.2.1.Fuzzy Logic

The fuzzy logic set was introduced in 1965 as a mathematical way to represent linguistic vagueness (Zadeh, 1965). According to the fuzzy logic concept, factors and criteria can be classified without certain limits. Fuzzy logic is very useful for addressing real-world problems, which usually involve a degree of uncertainty. The modeling of many systems involves the consideration of some uncertain variables. The statistical uncertainties associated with these variables are handled through probability theory. There also exists non-statistical uncertainty (in the form of 'vagueness' or 'imprecision') associated with many variables. These variables and their influences on the system are defined in linguistic terms. This form of uncertainty can be handled in a rational framework of 'fuzzy set theory'. It can be said that probability deals with statistical uncertainty, whereas fuzziness has been introduced as a means of representing and manipulating non-statistical uncertainty (Bezdek, 1994). It is not always meaningful to relate uncertainty to frequency (Dubois & Prade, 1993). Fuzzy logic uses variables like "low", "normal", "high" in place of "yes/no" or "true/false" variables. Fuzzy sets are determined by membership functions. The membership function of a fuzzy set is expressed as $\mu A(x)$ and membership degree of its fuzzy set is determined as a number between 0 and 1. If factor x definitely belongs to set A, $\mu A(x)$ is 1 and if it definitely does not belong to set A, $\mu A(x)$ is 0. A higher membership function value (up to a value of 1) shows that factor x has a stronger degree of membership to set A (Mathworks, 2009; Timothy, 2004; Zimmermann, 2001). Boundary conditions of the membership function can be expressed with flexible structure in fuzzy sets. The most significant difference between traditional sets and fuzzy sets is the membership function. While traditional sets can be characterized by only one membership function, fuzzy sets can be characterized by numerous membership functions (Şen & Cenkçi, 2009)

3. Performance Evaluation with Fuzzy Logic

The application of a fuzzy model comprised three stages:

1. Fuzzification of input exams results and output performance value

2. Determination of application rules and inference method
3. Defuzzification of performance value

Students sit two exams, so there are two input variables. The output variable is the performance value, which is determined by fuzzy logic (Figure 1).

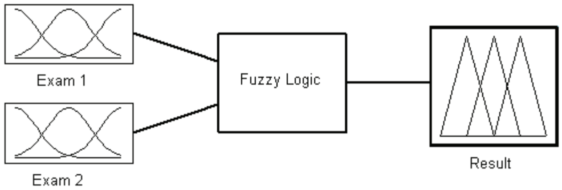

Figure 1. Determination of students' performance using fuzzy logic

3.1. Fuzzification of Exam Results and Performance Value

Fuzzification of exam results was carried out using input variables and their membership functions of fuzzy sets. Each student has two exam results, both of which form input variables of the fuzzy logic system. Each input variable has five triangle membership functions.

Initially, membership functions have the same interval, so both exams have same weighted average. The fuzzy set of input variables is shown Table 1.

Table 1. Fuzzy set of input variables

Linguistic Expression	Symbol	Interval
Very Low	VL	(0, 0, 25)
Low	L	(0, 25, 50)
Average	A	(25, 50, 75)
High	H	(50, 75, 100)
Very High	VH	(75, 100, 100)

It is seen that exam notes can belong to one or two membership functions but their membership weighting of each membership function can be different (Figure 2).

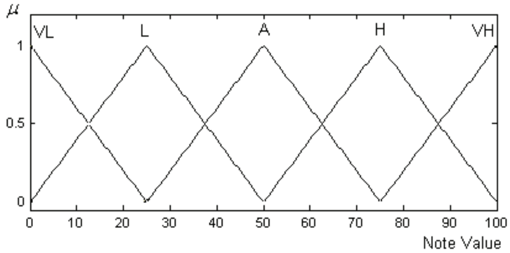

Figure 2. Membership functions of Exam 1 and Exam 2

For instance, while a score of 25 only belongs to the "Low" membership function, a score of 30 belongs to both "Low" and "Average" membership functions, but is weighted more heavily within the "Low" membership functions than the "Average" membership function.

The output variable, which is the performance value, is entitled "Result" and has five membership functions. For reasons of convenience within the application, a value range between 0 and 1 was chosen (Table 2 and Figure 3).

Table 2. Fuzzy set of output variable

Linguistic Expression	Symbol	Interval
Very Unsuccessful	VU	(0, 0, 0.25)
Unsuccessful	U	(0, 0.25, 0.5)

Average	A	(0.25, 0.5, 0.75)
Successful	S	(0.5, 0.75, 1)
Very Successful	VS	(0.75, 1, 1)

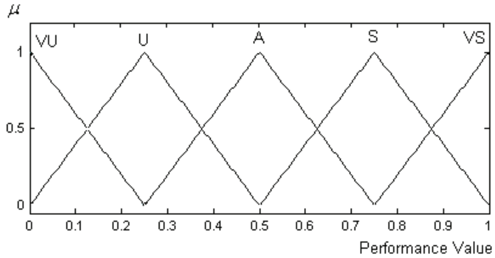

Figure 3. Membership functions of performance value

3.2. Rules and Inference

The rules determine input and output membership functions that will be used in inference process. These rules are linguistic and also are entitled "*If-Then*" rules (Altrock, 1995; Semerci, 2004).

1. If Exam1 is VL and Exam2 is VL then Result is VU
2. If Exam1 is VL and Exam2 is L then Result is VU
3. If Exam1 is VL and Exam2 is A then Result is U
4. If Exam1 is VL and Exam2 is H then Result is U
5. If Exam1 is VL and Exam2 is VH then Result is A
6. If Exam1 is L and Exam2 is VL then Result is VU
7. If Exam1 is L and Exam2 is L then Result is U
8. If Exam1 is L and Exam2 is A then Result is U
9. If Exam1 is L and Exam2 is H then Result is A
10. If Exam1 is L and Exam2 is VH then Result is A
11. If Exam1 is A and Exam2 is VL then Result is U
12. If Exam1 is A and Exam2 is L then Result is U
13. If Exam1 is A and Exam2 is A then Result is A
14. If Exam1 is A and Exam2 is H then Result is S
15. If Exam1 is A and Exam2 is VH then Result is S
16. If Exam1 is H and Exam2 is VL then Result is U
17. If Exam1 is H and Exam2 is L then Result is A
18. If Exam1 is H and Exam2 is A then Result is S
19. If Exam1 is H and Exam2 is H then Result is S
20. If Exam1 is H and Exam2 is VH then Result is VS
21. If Exam1 is VH and Exam2 is VL then Result is A
22. If Exam1 is VH and Exam2 is L then Result is S
23. If Exam1 is VH and Exam2 is A then Result is S
24. If Exam1 is VH and Exam2 is H then Result is VS
25. If Exam1 is VH and Exam2 is VH then Result is VS

In case of several rules are active for the same output membership function, it is necessary that only one membership value is chosen. This process is entitled "fuzzy decision" or "fuzzy inference". Several authors, including Mamdami, Takagi-Surgeno and Zadeh have developed a range of techniques for fuzzy decision-making and fuzzy inference. The present study uses the method proposed by Mamdami, shown in Equation (1) (Semerci, 2004; Zadeh, 1965; Rutkowski, 2004).

$$\mu_C(y) = \max_k \left[\min \left[\mu_{A_1}(input(i)).\mu_{B_1}(input(j)) \right] \right] \quad k=1,2........r \qquad (1)$$

This expression determines an output membership function value for each active rule. When one rule is active, an AND operation is applied between inputs. The smaller input value is chosen and its membership value is determined as membership value of the output for that rule. This method is repeated, so that output membership functions are determined for each rule. To sum up, graphically AND (min) operations are applied between inputs and OR (max) operations are between outputs.

3.3. Determination of Performance Value

After completing the fuzzy decision process, the fuzzy number obtained must be converted to a crisp value. This process is entitled defuzzification. Many methods have been developed for defuzzification. In this study, a "Centroid" (Center of Area) technique was applied, which is one of the most common methods. After defuzzification process, obtained fuzzy number is geometrical figure. The crisp value is calculated as below (Figure 4, Equation 2) (Semerci, 2004).

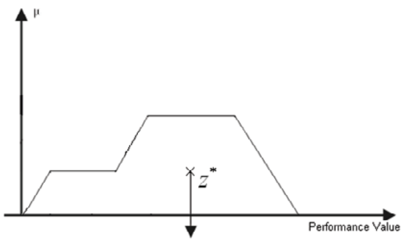

Figure 4. Defuzzification with Centroid method

$$z^* = \frac{\int \mu_C(z) \times z \times dz}{\int \mu_C(z) \times dz} \qquad (2)$$

3.4. Application Of Fuzzy Logic

Table 3 shows the scores achieved by 20 students in Exam 1 and Exam 2. For each student, both exam scores were fuzzified by means of the membership functions previously described in section 3.2 (*Rules and Inference*). Active membership functions were determined according to rule table, using the Mamdami fuzzy decision technique. The output (performance value) was then defuzzified by calculating the center (centroid) of the resulting geometrical shape. This sequence was repeated using the exam scores for each student.

Table 3. Exam scores and calculated performance values

No	Exam 1	Exam 2	Performance Value	No	Exam 1	Exam 2	Performance Value
1	40	65	0.53	11	65	45	0.576
2	20	35	0.243	12	89	100	0.908
3	50	65	0.645	13	100	100	0.92
4	10	20	0.203	14	65	35	0.5
5	45	65	0.576	15	48	50	0.473
6	34	60	0.462	16	45	55	0.5
7	48	55	0.533	17	55	25	0.31
8	56	90	0.759	18	84	80	0.765
9	74	70	0.735	19	63	65	0.639
10	45	50	0.44	20	28	30	0.31

Both inputs had same triangle membership functions. Therefore, replacing Exam 1 with Exam 2 would not change the calculated performance value (e.g. (45 & 65) and (65 & 45)). If the symmetry or the value range of the membership functions is not equal, one of the exams has a greater influence on the output performance value than the other. For example, let's change the membership functions and value range of Exam 2 (Figure 5), while retaining the original criteria for Exam 1. With this arrangement, the value range of Average membership function shrinks; the top value of L membership function is moved to 20; the top value of H membership function is moved to 80; and value ranges of VL and VH membership functions are moved to 40 and 60, respectively.

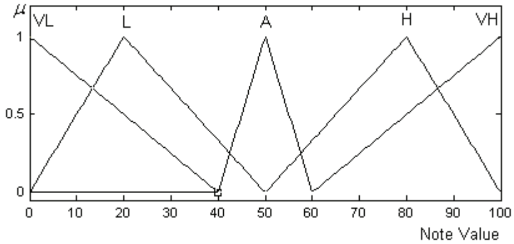

Figure 5. Arrangement membership functions for Exam 2

Aim of this arrangement in Exam 2 is to penalize scores below 50 and to reward scores above 50. This situation can be seen in Table 4. For exam scores below 50, performance values decreased and for exam scores above 50, performance values increased. There is no change for scores of 50, because this is the boundary of the limit value. Figure 6 shows the active rules and performance value obtained for exam scores of 45 and 65.

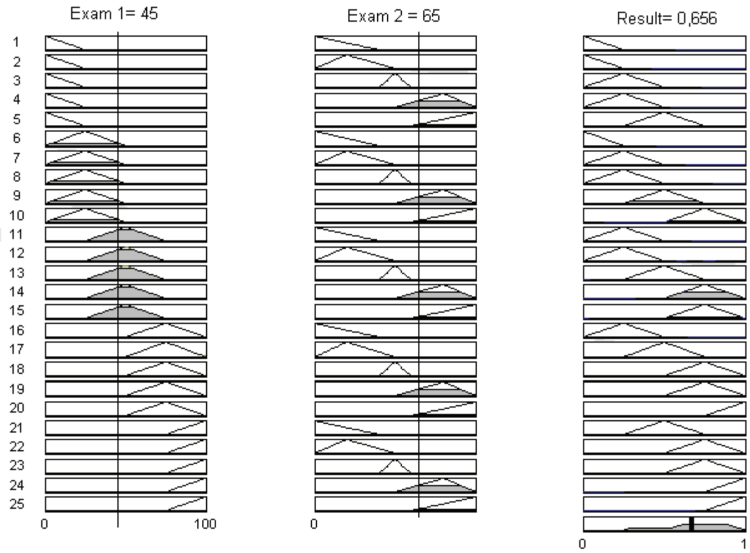

Figure 6. Active rules and performance value for exam scores of 45and 65

In this scenario, rules 9,10,14 and 15 are active and at the end of defuzzification, a performance value of 0.656 is obtained.

Table 4. Variations in performance value according to Exam 2 criteria

No	Exam 1	Exam 2	Performance Value	No	Exam 1	Exam 2	Performance Value
1	40	65	0.637	11	65	45	0.551
2	20	35	0.242	12	89	100	0.908
3	50	65	0.75	13	100	100	0.92
4	10	20	0.202	14	65	35	0.384
5	45	65	0.676	15	48	50	0.473
6	34	60	0.625	16	45	55	0.505
7	48	55	0.54	17	55	25	0.3
8	56	90	0.76	18	84	80	0.778
9	74	70	0.761	19	63	65	0.753

10	45	50	0.44	20	28	30	0.238

4. Conclusion

When the results are evaluated, a difference in outcomes is seen between the classical method and the proposed fuzzy logic method. While the classical method adheres to a constant mathematical rule, evaluation with fuzzy logic has great flexibility. At the application stage, course-conveners can edit rules and membership functions to obtain various performance values but it is important that the same rules and membership functions are used for all students taking the same lesson. It is also important for the students to understand the assessment criteria before taking exams.

For this reason, members of the educational board should communicate with each other and come to an agreement on rules, membership functions and any other criteria.

Performance values using the classical method and fuzzy logic method are given in Table 5. For comparison, average scores with classical method is divided to 100 and the success limit is accepted as 0.5.

In the Fuzzy 1 scenario, all membership functions are the same for both exams, whereas in the Fuzzy 2 scenario, membership functions of Exam 2 are modified. From Table 5, a linear relationship can be seen between the classical method and Fuzzy 1. If a student is successful in the classical assessment method, they will also be successful in the Fuzzy 1 scenario. Comparison of the classical method with the Fuzzy 2 scenario reveals differences in the performance values. For scores blow 50, the performance value of Fuzzy 2 is smaller than the classical method; however, for scores above 50, the performance value is larger than the classical method. For example, a student scoring 34 in exam 1 and 60 in exam 2 is unsuccessful in the classical method, but is successful in the Fuzzy 2 scenario.

We interviewed Electrical Education board in Marmara University and asked 20 academics about evaluation of student performance fuzzy logic. The views of academics varied on the use of the two assessment methods. Some valued the potential flexibility of the fuzzy logic method, but others pointed out drawbacks in that the calculation of performance values may be difficult to explain to students. The use of an automated computer system to perform calculations should address these issues. In conclusion, performance evaluation using fuzzy logic is suitable not only for laboratory application, but can also be used for performance evaluation of theoretical lessons.

Table 5. Comparison of Performance Evaluation Methods

No	Exam 1	Exam 2	Classical Method	Fuzzy 1	Fuzzy 2
1	40	65	0.525	0.53	0.637
2	20	35	0.275	0.243	0.242
3	50	65	0.575	0.645	0.75
4	10	20	0.15	0.203	0.202
5	45	65	0.55	0.576	0.676
6	34	60	0.47	0.462	0.625
7	48	55	0.515	0.533	0.54
8	56	90	0.73	0.759	0.76
9	74	70	0.72	0.735	0.761
10	45	50	0.475	0.44	0.44
11	65	45	0.55	0.576	0.551
12	89	100	0.945	0.908	0.908
13	100	100	1	0.92	0.92
14	65	35	0.5	0.5	0.384
15	48	50	0.49	0.473	0.473
16	45	55	0.5	0.5	0.505
17	55	25	0.4	0.31	0.3
18	84	80	0.82	0.765	0.778
19	63	65	0.64	0.639	0.753
20	28	30	29	0.31	0.238

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