Obtaining ABET Student Outcome Satisfaction from Course Learning Outcome Data Using Fuzzy Logic

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ABSTRACT
One of the approaches for obtaining the satisfaction data for ABET "Student Outcomes" (SOs) is to transform Course Learning Outcomes (CLOs) satisfaction data obtained through assessment of CLOs to SO satisfaction data. Considering the fuzzy nature of metrics of CLOs and SOs, a Fuzzy Logic algorithm has been proposed to extract SO satisfaction data from the CLO satisfaction data for any given course. The membership functions for the fuzzy variables namely CLOs, SOs and CLO-SO relationship have been defined with an implementable procedure to suit the problem. A set of 24 rules form the rule base of the fuzzy logic algorithm. The algorithm has been implemented and tested in MATLAB. An application example of a real-world problem has been presented.
Keywords: accreditation, ABET, course learning outcome, student outcome, continuous improvement, fuzzy logic

INTRODUCTION

ABET accredits academic programs in the disciplines of applied science, computing, engineering, and engineering technology at the associate, bachelor, and master degree levels (ABET, 2016a). ABET accreditation requirements for each of the disciplines include a set of "general criteria" and a "program criteria". One of the general criteria is referred to as "Student Outcomes" (SOs) (ABET, 2016c). SOs for a given discipline represent a general set of abilities and are not technical abilities for a particular branch in that discipline. They address the general abilities an engineer should possess irrespective of his branch of specialization. To understand this it may be noted that ABET-EAC (Engineering Accreditation Commission) that deals with all academic programs in the engineering discipline prescribes exactly the same set of SOs regardless of the field of study whether it is Civil, Mechanical, Electrical, Computer, Petroleum or any other branch of engineering (ABET, 2016c). ABET gives the flexibility for an

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academic program to restate the SOs, modify them or add new SOs for a particular program as long as the modified SOs encompass the SOs prescribed by ABET. Thus, an academic program seeking accreditation must ensure that the abilities represented by the SOs are being attained by the students and must show documented proof of the attainment level of each SO. If the attainment level of any of the SOs is not assessed, it may be considered a "deficiency" and the program may not be accredited (ABET, 2016b). Therefore, an assessment and evaluation system for the SOs is necessary and quantitative data must be obtained that shows SOs attainment level and its improvement over previous years.

In an academic program, students enroll in a set of courses prescribed by the curriculum. The abilities attained by the students are achieved mainly through these courses. Therefore, the curriculum design must include courses with proper Course Learning Outcomes (CLOs) that relate to the required SOs in a way that when students attain the abilities related to the CLOs of various courses they also attain the abilities related to the prescribed SOs. Once this is ensured, teaching and assessment can be focused on the CLOs because SOs will be attained automatically through the abilities represented by the CLOs.

Since, teaching and learning in academic programs is traditionally focused on CLOs, assessment of the attainment of CLOs is easier for the learners and the instructors. This approach of assessing students' abilities has been used as a routine for centuries and therefore is much more reliable. In this approach the instructor is free to focus on the subject matter of the course without worrying about the SOs and will be required to design assessments in a conventional manner that address CLOs. Another advantage of this approach is that the relevant SOs are addressed more realistically because CLOs are closer to actual contents of a

course than are SOs. As a result, scores obtained by students in such assessments are more representative of their abilities in relevant SOs. Several academic programs seeking ABET accreditation have used this approach explicitly (Oregon State University, 2007; Umm Al-Qura University, 2013; Wayne State University, 2012). However most academic programs do the same but implicitly i.e., they just relate certain courses to a given SO without giving any explicit relationship between the CLOs and the SOs.

Since continuous improvement can only be evaluated through quantitative data for SO satisfaction, the data obtained for CLO satisfaction in various courses are to be transformed to SO satisfaction data. The idea of this type of transformation was introduced first time in (Citation removed to maintain integrity of the review process). For such transformation, the relationship between CLOs and SOs must be meaningful. This relationship will be referred to as CLO-SO map in this paper. Two types of CLO-SO maps have been used in this context as follows:

1) Just using a 0/1 relation i.e., either a CLO is related to an SO or not related (New Jersey Institute of Technology, 2016; Oregon State University, 2016).

2) N/M/H relation i.e., CLO is related to an SO and the relationship strength of None, Moderate or High is specified (Rensselaer Polytechnic Institute, 2016) or, strong emphasis (1), emphasis (2) or no emphasis (3) is specified (Michigan State University, 2016).

The software package called CLOSO produces CLO and SO satisfaction analyses and generates course folders and reports required for ABET SSR (Smart-Accredit, 2016). This software is based on the approach of collecting CLO satisfaction data and then transforming them to SO satisfaction data using 0/1 type relation between CLOs and SOs. No other software was found that produces quantitative CLO and SO satisfaction data through CLO to SO transformation.

It is obvious that the 0/1 relation used in CLOSO software and the published SSRs (Computer, 2013; Oregon State University, 2007; Umm Al-Qura University, 2013; Wayne State University, 2012) is not always accurate or realistic (not always a true representation of relation) because it implies that either a CLO is 100% related to an SO or not related at all. The N/M/H relation can be useful only if fuzzy logic is used because none, moderate or high specifications are always fuzzy. There is no evidence in the published literature that a fuzzy logic has been applied to extract SO satisfaction considering the fuzzy CLO-SO relationship. This paper fills this gap and investigates the transformation of CLO satisfaction data to SO satisfaction data considering the fuzzy nature of the CLO-SO relationships. Thus it is an advancement over the idea presented in (Citation removed to maintain integrity of the review process).

Fuzzy Logic is a well-established soft computing technique. Here, a brief review of the applications of Fuzzy Logic relevant to education is presented. (Bigdeli, Boys, & Coghill, 2002) have developed a web based tutorial and examination system called Online Assessment and

Information System (OASIS) used in the department of Electrical and Electronic Engineering at the University of Auckland. This system uses fuzzy marking scheme to mark students' answers to allow marking of softer subject material where crisp numerical answers are inappropriate. Another application of fuzzy logic in assessments has been proposed in (Hwang, 2003). In this work, an algorithm to generate a test-sheet consisting of a set of questions uses fuzzy logic for specifying the difficulty level of the questions. The algorithm generates test-sheets based upon multiple criteria. The application presented in the paper includes only high school level science course. In (Ma & Zhou, 2000), authors use fuzzy logic to assess the outcomes of student-centered learning at university level. In (Rudinskiy, 2007), a fuzzy knowledge evaluation model has been proposed. This model is used for evaluating the trainee learners in humanities, social and economic sciences.

There are many applications of fuzzy logic in the published literature but none of them addresses the issue being resolved in this paper i.e. the issue of transformation of CLOs to SOs considering fuzzy nature of the CLO-SO relationships. This paper presents the idea of introducing fuzzy logic to extract realistic SO satisfaction data from the CLO satisfaction data of all courses in an academic program. This paper also presents an example application of the developed technique through a real-world case. The next section (Section II) of this paper describes the formulation, algorithm, the variables and the equations involved. Section III discusses the results of the example application that follows a brief conclusion in Section IV.

FORMULATION AND ALGORITHM

Variables

Let ζ_A be the percentage score in the assessments of a learning outcome (CLO or SO) and λ_A be the percentage of students attaining ζ_A or higher score. The subscript "A" used here indicates that it is the level attained by the students.

Let ζ_T be a certain target level of ability specified by an academic program as the acceptable level of satisfaction. Let λ_T be the percentage of students attaining the target level ζ_T. The subscript T used here indicates that it is a target prescribed by the academic program.

For the Fuzzy Logic to be applied, the following additional variables are defined:

1) $\beta_{i,j}^k$: It is an input parameter that represents the relation strength between CLO_i and SO_j for course k based on expert opinion.

2) γ_i^k: It is an input parameter that represents the value of λ_A for CLO_i of course k based on the performance of students in assessments.

3) ψ_j^k: It is an output parameter that represents the value of λ_A for SO_j based on assessments in course k.

These variables with their upper and lower bounds are shown in **Table 1**.

Table 1. Input and output variables with ranges

ID	Name	Symbol	Lower Limit	Upper Limit
1	CLO-SO connectivity strength	$\beta_{i,j}^k$	0	1
2	CLO satisfaction (%)	γ_i^k	0	100
3	SO Satisfaction (%)	ψ_j^k	0	100

Transformation Algorithm Schematic

The CLO to SO transformation algorithm schematic is shown in **Figure 1**. The crisp input parameters $\beta_{i,j}^k$ and γ_i^k are converted to fuzzy sets by the fuzzifier. These fuzzy sets are described in Section II-C. The rule base consists of "if-then" rules that are defined for different ranges of input variables to produce corresponding outputs. For the presented algorithm the rule-base is described in Section II-E. The inference engine gets the input from the fuzzifier and uses the rule base to produce fuzzy output values for SO satisfaction. The defuzzifier converts the fuzzy output into a crisp value of the output parameter ψ_j^k.

Fuzzification of Input Variables

The input parameter $\beta_{i,j}^k$ is represented by four lexical parameters namely very weak (VW), weak (W), strong (S) and very strong (VS) as shown in **Figure 2**. The choice of the lexical parameters is intuitive and suits the nature of the problem. For example, CLO-SO relationship between 0.8 and 1.0 (80 to 100%) has been described by the linguistic variable of VS (very strong) which is quite natural and most instructors will agree with this. Similarly, 0.0 to 0.3 has been described as VW (Very weak). Other possibilities exist like using fewer or more than four lexical parameters and varying the ranges for the parameters. For the presented work, the effect of such variations was not explored. The expressions for the membership functions of this parameter are represented by the following equations for applying the fuzzy logic through a software implementation:

$$\mu_{VW}(\beta) = \begin{cases} 1; & \beta_{i,j}^k < 0.1 \\ -5\beta_{i,j}^k + 1.5; & 0.1 < \beta_{i,j}^k < 0.3 \\ 0; & elsewhere \end{cases}$$

$$\mu_W(\beta) = \begin{cases} 4\beta_{i,j}^k - 0.8; & 0.2 < \beta_{i,j}^k < 0.45 \\ -4\beta_{i,j}^k + 2.8; & 0.45 < \beta_{i,j}^k < 0.7 \\ 0 & elsewhere \end{cases} \qquad (1)$$

$$\mu_S(\beta) = \begin{cases} 6.67\beta_{i,j}^k - 4; & 0.6 < \beta_{i,j}^k < 0.75 \\ -6.67\beta_{i,j}^k + 6; & 0.75 < \beta_{i,j}^k < 0.9 \\ 0 & elsewhere \end{cases}$$

$$\mu_{VS}(\beta) = \begin{cases} 6.67\beta_{i,j}^k - 5.34; & 0.8 < \beta_{i,j}^k < 0.9 \\ 1; & \beta_{i,j}^k > 0.9 \\ 0 & elsewhere \end{cases}$$

The other input variable, i.e., CLO satisfaction (γ_i^k) was divided into six lexical parameters of unsatisfactory (U), progressing (P), satisfactory (S), very good (VG), excellent (Et) and exemplary (Ey) as shown in **Figure 3**. The expressions for the membership functions are defined as follows:
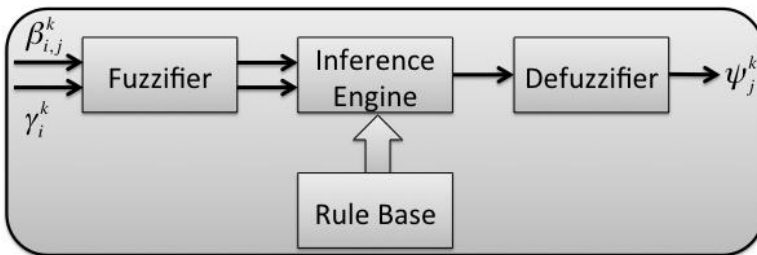

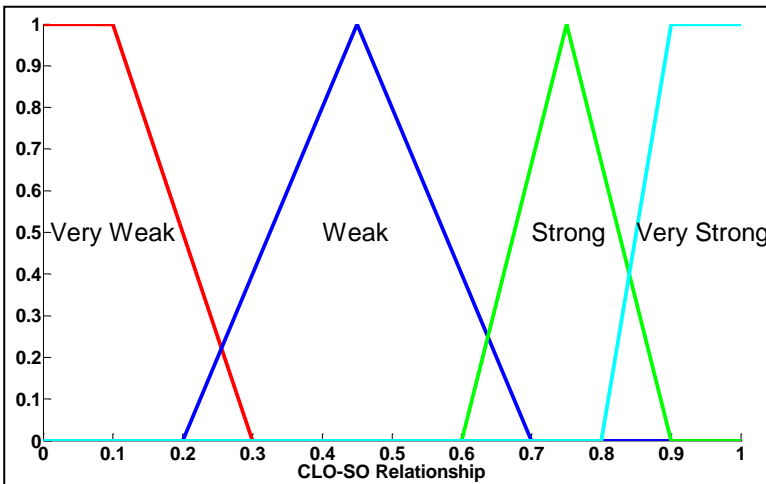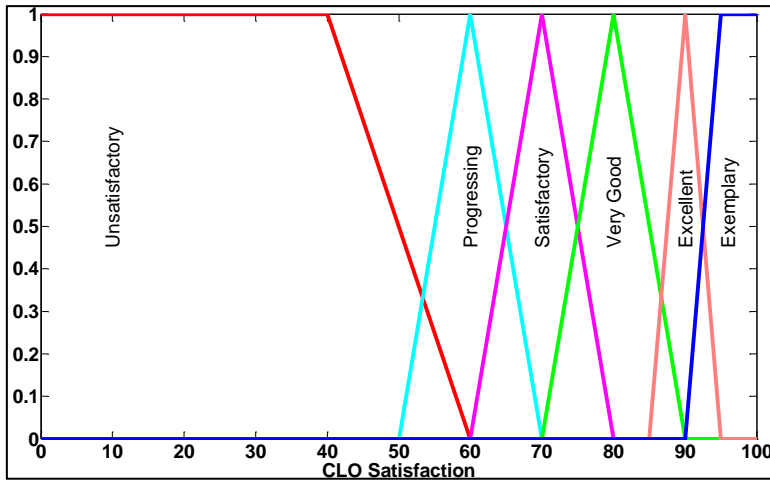**Figure 1.** Proposed fuzzy model for extracting SO satisfaction

Figure 2. Membership functions for CLO-SO relationship

Figure 3. Membership functions for CLO satisfaction

$$\mu_U(\gamma) = \begin{cases} 1; & \gamma_i^k < 40 \\ -0.05\gamma_i^k + 3; & 40 < \gamma_i^k < 60 \\ 0; & elsewhere \end{cases}$$

$$\mu_P(\gamma) = \begin{cases} 0.1\gamma_i^k - 5; & 40 < \gamma_i^k \\ -0.1\gamma_i^k + 7; & 50 < \gamma_i^k < 70 \\ 0 & elsewhere \end{cases}$$

$$\mu_S(\gamma) = \begin{cases} 0.05\gamma_i^k - 3; & 60 < \gamma_i^k < 70 \\ -0.05\gamma_i^k + 4; & 70 < \gamma_i^k < 80; \\ 0 & elsewhere \end{cases}$$

$$\mu_{VG}(\gamma) = \begin{cases} 0.1\gamma_i^k - 7; & 70 < \gamma_i^k < 80 \\ -0.1\gamma_i^k + 9; & 80 < \gamma_i^k < 90 \\ 0 & elsewhere \end{cases}$$

$$\mu_{Et}(\gamma) = \begin{cases} 0.2\gamma_i^k - 17; & 85 < \gamma_i^k < 90 \\ -0.2\gamma_i^k + 19; & 90 < \gamma_i^k < 95 \\ 0 & elsewhere \end{cases}$$

$$\mu_{Ey}(\gamma) = \begin{cases} 0.2\gamma_i^k - 18; & 90 < \gamma_i^k < 95 \\ 1; & 95 < \gamma_i^k \\ 0 & elsewhere \end{cases}$$

(2)

Again, there are various possibilities concerning the number of these parameters to be used and their ranges. The choice here is intuitive considering the nature of the problem. The justification behind designing such membership functions is as follows. In academia, a score of 60% is considered to be bare minimum level of learning. That is why the "progressing"

membership function peaks at 60%. Moreover, scores below 60% should be considered unsatisfactory. Since a score of 70% is usually considered a "C", the membership function "satisfactory" peaks at 70. Similarly, a score of 80% is usually considered a "B"; hence, the "very good" membership function peaks at 80. Using similar arguments, 90% is excellent and a score beyond 95% is considered exemplary by any standards.

Fuzzification of the Output Variable

The output variable SO satisfaction (ψ_j^k) is divided into seven lexical parameters of negligible (N), insignificant (I), very low (VL), low (L), medium (M), high (H) and very high (VH) as shown in **Figure 4**. Again, the choice is rather intuitive to suit the nature of the problem. Mathematically, they are defined as:

$$\mu_N(\psi) = \begin{cases} 1; & 10 > \psi_j^k \\ -0.1\psi_j^k + 2; & 10 < \psi_j^k < 20 \\ 0 & elsewhere \end{cases}$$

$$\mu_I(\psi) = \begin{cases} 0.05\psi_j^k - 0.5; & 10 < \psi_j^k < 30 \\ -0.05\psi_j^k + 2.5; & 30 < \psi_j^k < 50 \\ 0 & elsewhere \end{cases}$$

$$\mu_{VL}(\psi) = \begin{cases} 0.1\psi_j^k - 4; & 40 < \psi_j^k < 50 \\ -0.1\psi_j^k + 6; & 50 < \psi_j^k < 60 \\ 0 & elsewhere \end{cases}$$

$$\mu_L(\psi) = \begin{cases} 0.2\psi_j^k - 11; & 55 < \psi_j^k < 60 \\ -0.1\psi_j^k + 7; & 60 < \psi_j^k < 70 \\ 0 & elsewhere \end{cases} \tag{3}$$

$$\mu_M(\psi) = \begin{cases} 0.2\psi_j^k - 13; & 65 < \psi_j^k < 70 \\ -0.2\psi_j^k + 15; & 70 < \psi_j^k < 75 \\ 0 & elsewhere \end{cases}$$

$$\mu_H(\psi) = \begin{cases} 0.1\psi_j^k - 7; & 70 < \psi_j^k < 80 \\ -0.1\psi_j^k + 9; & 80 < \psi_j^k < 90 \\ 0 & elsewhere \end{cases}$$
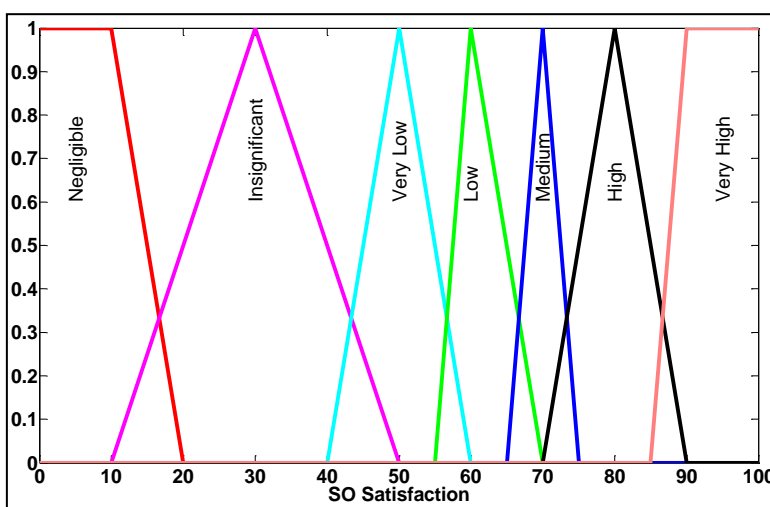
$$\mu_{VH}(\psi) = \begin{cases} 0.2\psi_j^k - 17; & 85 < \psi_j^k < 90 \\ 1; & 90 < \psi_j^k \\ 0 & elsewhere \end{cases}$$

Rule Base

The rule base encodes the knowledge of an expert into if/then rules of the form:

IF condition THEN result

Figure 4. Membership functions for SO satisfaction

Where the condition is called the antecedent or premise and the result is called the consequent. For example, two rules for the problem under consideration are as follows:

IF "CLO Satisfaction" is "Exemplary" AND "CLO-SO Relation" is "Strong", THEN "SO Satisfaction" is "High"

IF "CLO Satisfaction" is "Exemplary" AND "CLO-SO Relation" is "Weak", THEN "SO Satisfaction" is "Medium"

A total of 24 rules were generated that are summarized in **Table 2**. Bold letters in the table indicate input while the normal text in the table signifies SO satisfaction, i.e., the output variable. Mathematically, the set of 24 rules can be written as follows:

$$\mu_\psi(\psi_j^k) = \max[\min\{\mu_\beta^m(\beta_{i,j}^k), \mu_\gamma^m(\gamma_i^k)\}]; \quad m = 1,2,3,\dots,24 \tag{4}$$

where, $\mu_\psi(\psi_j^k)$ is the height of the aggregated fuzzy set for the 24 rules, and $\mu_\beta^m(\beta_{i,j}^k)$ and $\mu_\gamma^m(\gamma_i^k)$ are the values from the membership functions of the two input variables. The above set of equation are based on max-min fuzzy inference (Ross, 2009). The resulting surface plot for (4) is shown in **Figure 5**. The plot clearly shows the variation pattern of SO satisfaction as a function of CLO-SO relation and CLO satisfaction.

Defuzzification

The fuzzy subsets for the output parameter obtained after applying the inference mechanism must be converted into crisp values. This process is called defuzzification. Mathematically,

$$\psi^* = \text{Defuzzifier}\left(\mu_\psi(\psi_j^k)\right) \tag{5}$$

There are several defuzzification methods. In this work, centroid method will be used. In this method, the crisp value of the output parameter is computed by taking the centroid of the aggregate area to obtain crisp value of the output. Mathematically,

$$\psi^* = \frac{\int \mu_\psi \psi d\psi}{\int \mu_\psi d\psi} \tag{6}$$

where ψ^* is the crisp output, ψ is the fuzzified output and μ_ψ is the membership function of the fuzzified output
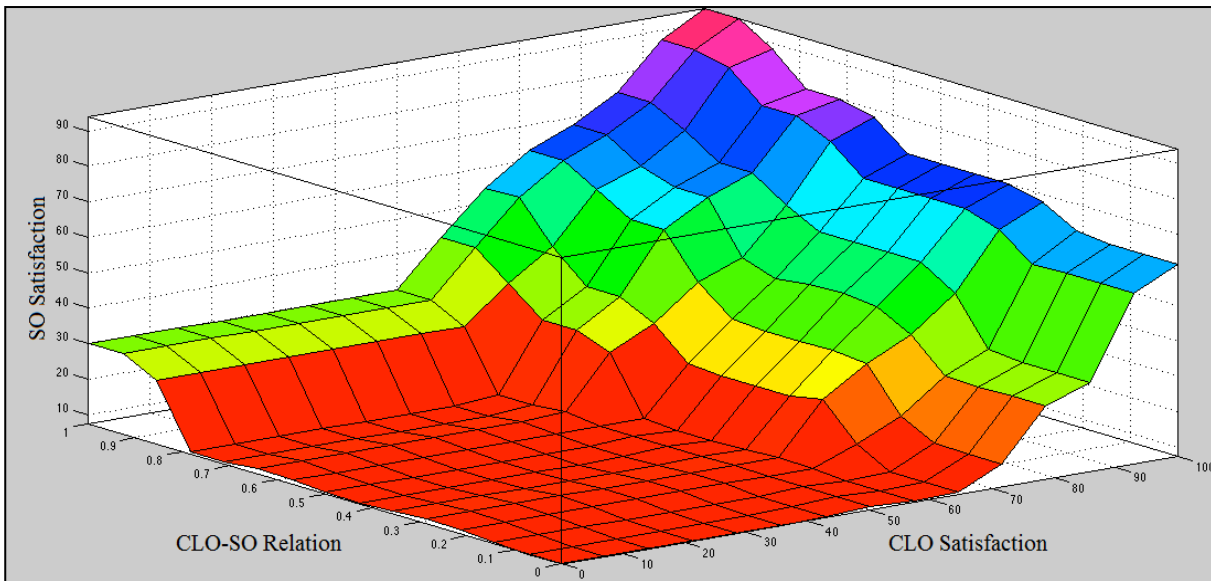
Figure 5. Surface plot of SO satisfaction as a function of CLO-SO relationship and CLO satisfaction

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Table 2. Rule base for the proposed Fuzzy System

CLO-SO Relation	CLO Satisfaction					
	Exemplary	**Excellent**	**Very Good**	**Satisfactory**	**Progressing**	**Unsatisfactory**
Very Strong	Very High	High	Medium	Low	Very Low	Insignificant
Strong	High	Medium	Low	Very Low	Insignificant	Negligible
Weak	Medium	Low	Very Low	Insignificant	Negligible	Negligible
Very Weak	Low	Very Low	Insignificant	Negligible	Negligible	Negligible

EXAMPLE APPLICATION

A real-world example application of a typical course of "Circuit Theory" is presented. The objective is to determine the satisfaction of SO "b" in this course. The input data that will be required to solve this problem is as follows:

CLOs as shown in **Table 3**.

CLO-SO map as shown in **Table 3**.

λ_A for each CLO addressing SO (b) as shown in **Table 5**.

It may be noted here that in this course only assessments 1, 5 and 6 were relevant to SO (b). To obtain the satisfaction of SO (b) the step-by-step procedure of the proposed algorithm must be applied to each of the three CLOs that address SO (b). And then the aggregate of all of them will be used to obtain the satisfaction of SO (b). The algorithm was implemented in MATLAB. The step-by-step procedure for one of the CLOs (i.e., CLO_3) is given in the following:

Step 1: From **Table 4**, the relation strength between CLO_3 and SO (b) is obtained, which is 0.8.

Step 2: From **Figure 3**, the membership function corresponding to the crisp value of 0.8 gives a value of "Strong".

Step 3: (1) is applied to obtain $\mu_S(\beta)$ yielding a value of 0.7.

Step 4: From **Table 5**, λ_A for CLO_3 is obtained as 86%.

Step 5: From **Figure 4**, for CLO satisfaction of 86%, corresponding membership functions "Excellent" and "Very Good" are obtained.

Step 6: (2) is applied to obtain: $\mu_{VG}(\gamma)$ and $\mu_{Et}(\gamma)$. The values obtained are: $\mu_{VG}(\gamma) = 0.4$, $\mu_{Et}(\gamma) = 0.2$.

Step 7: From **Table 2**, for the CLO satisfaction of "Excellent" and CLO-SO relationship of "Strong", SO satisfaction is "Medium". Similarly, for the CLO satisfaction of "Very Good" and CLO-SO relationship of "Strong", SO satisfaction is obtained as "Low".

Step 8: (4) is applied to obtain $\mu_M(\psi) = 0.2$ and $\mu_L(\psi) = 0.4$

Table 4. CLO-SO map of circuit theory

CLO	Student Outcomes										
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*
1	0.9	0.5									
2	0.9										
3	0.9	0.8			0.5						0.7
4	1	0.8			0.5						0.7
5	0.8				0.5						0.7

Table 5. Example assessment addressing specific CLOs

Assessment	Questions	CLO	λ_A
1	2 and 3	1	76%
5	1 and 2	3	86%
6	4, 5 and 6	4	72%

Step 9: De-fuzzification is done using (6). Based on the values of $\mu_M(\psi)$ for "Medium" and $\mu_L(\psi)$, for "Low", and using (6), the crisp value of satisfaction for SO "b" is obtained as 63.9%.

The above procedure is repeated for all the three relevant CLOs. For CLO_1 a value of 37.5% is obtained and for CLO_4 a value of 52.7% is obtained. The average of these three numbers, i.e., 51.4% is used as an aggregate of satisfaction of SO (b) in this course.

Table 3. Course learning outcomes of circuit theory

1. Ability to apply basic laws and do power calculations
2. Ability to analyze resistive networks and simplify complicated networks.
3. Ability to use different circuit analysis techniques and theorems
4. Ability to determine natural and step responses of first and second order circuits
5. Ability to analyze basic two port circuits.

CONCLUSION

The presented work is a new idea and a complete recipe for converting CLO satisfaction data to SO satisfaction data required for ABET accreditation. The fuzzy nature of metrics of CLOs and SOs has been considered and a Fuzzy Logic algorithm has been proposed. The membership functions for the fuzzy variables namely CLOs, SOs and CLO-SO relationship to suit the problem have been developed. An implementable procedure has also been developed. All steps of the procedure required for the application of fuzzy logic to transform the CLO satisfaction to the SO satisfaction have been described in this paper. A rule base has been developed for the fuzzy inference engine. A step-by-step procedure for converting CLO satisfaction data to SO satisfaction data has been developed and implemented in MATLAB. An application example of a real-world problem has been presented. The idea presented will help the instructors and administrators of academic programs seeking ABET

accreditation. The presented work is a unique application of fuzzy set theory not presented before in the literature. Further research is required in finding the best membership functions and the effect of variations of the lexical parameters on the output

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