Development of a Fuzzy Mamdani Inference System for the Assessment of the Academic Standing/Continuation Requirements in Higher Educational Institutions

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ABSTRACT *- We developed a Fuzzy Mamdani Inference System (FMIS) for the assessment of the Academic Standing and Continuation Requirements in Higher Educational Institutions with the objective of identifying early, students who are at risk of failing out. The developed model has three inputs: Cumulative Grade Point Average (CGPA), Failed Units and Repetition Status and two outputs: Academic Standing and Semester Report. Results show that the model can be used to easily identify and advice students whose performance is going below expectation, to avoid failure and dropout.*

Keywords -Fuzzy logic, Student Performance Evaluation, Academic Standing, CGPA, Continuation Requirement,

I. INTRODUCTION

Students in Higher Educational Institutions (HEIs) have their academic performance evaluated at the end of each of two semesters that makeup an academic session. These evaluations are necessary in order to access the students progress and also, for early identification of students whose poor performance my lead to failure. Academic advisers appointed by the institutions provide guidance to the students with the hope that all their students will succeed. This is not always so, as some students still fall below their Continuation Requirements (CR) which is based on their Cumulative Grade Point Average (CGPA), Number of Credit Units failed (CF) and whether or not they have repeated previously. These students often labeled Students At Risk are then asked to go on probation, repeat or withdraw from the academic program.

As noted in [1], “A high quality evaluation system which is able to provide grounds for individual improvement and ensures that all students receive fair evaluation so as not to limit students’ present and future opportunities is required and very important”. The conditions for assessment of academic standing and continuation requirements may vary for different institutions but the dataset for analysis is usually quantitative in nature and therefore fits into the domain of Fuzzy logic[1]. The data also has imprecision and uncertainty which Fuzzy logic is known to handle well [2][3][4].

Cortez, *et. al.* noted in [5] that “Modeling of student’s achievement is a useful tool for both educators and students, as this can help to have better understanding of student’s weakness and bring about enhancement”. Atkins *et. al.* had also noted in [6] that “Evaluation of student performance is one of the most important parts in educational systems. Assessment is important for the purpose of making academic decisions about the students now, or in the future. Assessment is also important to indicate the level of performance for graduation purposes, and this usually has a permanent effect on the future career of students”.

In this paper, we build a Fuzzy Mamdani Inference System (FMIS) for the evaluation of students’ Continuation requirement and Academic standing using fuzzy membership functions.

II. RELATED WORK

Ikuomola and Arowolo used Adaptive Neuro-Fuzzy approach to produce crisp values for the evaluation of students’ academic performance[7]. Oladipupo *et. al.* applied Fuzzy Association Rule Mining for Analyzing Students Academic Performance. Their system determines students’ performance ratings against their pre-admission academic profile [8]. Marquez-Vera et. al. Used data mining to predict school failure. They conducted several experiments in an attempt to improve the accuracy in the prediction of students’ final performance and to identify which students might fail.[9] Odii *et. al.* Developed a fuzzy rule based application that can “efficiently schedule jobs so as to reduce time of delivery” in a Job Scheduling

System [10]. Sirigiri *et. al.* experimented on the use of two different Fuzzy Membership Functions (triangular and trapezoidal) on the same set of data for Teacher Performance Evaluation and compared their performance. Their results showed similarity in performance for both membership functions.[11]

III. METHODOLOGY

A typical Fuzzy Inference System consist of three main steps: Fuzzification, Fuzzy Reasoning, and Defuzzyfication, as shown in Figure 1

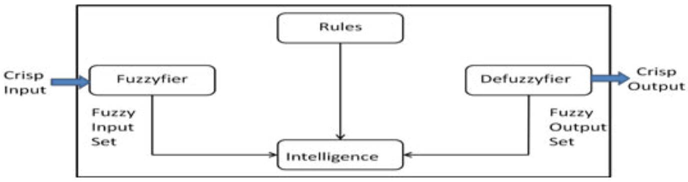

Figure 1: Architecture of a Fuzzy Logic System.

In Fuzzification, we convert the crisp input values into fuzzy values. We do this by using one of several membership functions of fuzzy logic. These membership functions may be triangular, Gaussian, trapezoidal, piecewise linear, singleton etc. Next step is Fuzzy reasoning, when the degree of membership of the input to the fuzzy output is computed from fuzzy rules using an inference mechanism. And finally Defuzzyfication when we convert the fuzzy values into crisp values

A. Membership Function

As noted in [12] "Fuzzy Membership functions allow us to quantify linguistic term and represent a fuzzy set graphically".

For a fuzzy set P on the universe of discourse X, its membership function is defined as

$\mu P: X \rightarrow [0,1]$.

This means that each element of X is mapped to a membership value between 0 and 1. It also shows the degree of membership of the element in X to the fuzzy set P in quantitative terms.
Figure 3 shows an example of a membership function chart where:

- the x axis represents the universe of discourse (X) and
- the y axis represents the degrees of membership in the interval [0, 1].

There can be multiple membership functions applicable to fuzzify a numerical value". Some are simple while others are complex. Results from [11] and others shows that using a complex functions does not add more precision in the output when compared to using a simple function. For this research work, we adopted the Triangular and Gaussian membership functions for fuzzification.

B. The Data Set.

For the construction of Fuzzy Inference Rules, Fuzzy logic requires the identification and specification of the input and output variables. In the following sections we describe the input and output variables and their linguistic terms as used for this work.

Different institutions apply varying rules for the evaluation of students for continuation, probation or withdrawal from programs. Sometimes the same institution may apply different rules for different courses of study. The input and output variables for this work were obtained from the 2017 Student Handbook of a private university in South-West, Nigeria. They are as follows:

INPUTS: 1 CGPA:- The Cumulative Grade Point Average of the student.
2 FAILED UNITS:- The total number credits failed (the sum of all the credit units of failed courses.
3 REPETITION STATUS:- If the student has repeated before.

OUTPUTS: 1 STANDING:- A student is either in good standing or not in good standing based on the input variables
2 REPORT:- A student can have one of four verdicts at the end of each academic year as shown in table 2

The fuzzy profile for the input and output variables are as shown in Table 1 and 2 respectively. Fuzzy membership functions were generated using the linguistics shown on the tables for ease of identification by human experts for the assessment of the students.

Table 1: Fuzzy Profile for the Input Variables

INPUT NAME	LINGUISTIC	ACTUAL VALUES
CGPA	Excellent	1.5 to 5.0
	Fair	1.0 to 1.49
	Bad	0.0 to 0.99
FAILED UNITS	Excellent	0
	Fair	1 to 15
	Poor	16 to 24
	Bad	25 to 150
REPETITION STATUS	Good	No previous repetition
	Bad	Already repeated

Table 2: Fuzzy Profile for the Output Variables

OUTPUT NAME	LINGUISTIC	ACTUAL VALUES
ACADEMIC STANDING	Good	In Good Standing
	Bad	Not in Good Standing
REPORT	Excellent	Clean Bill
	Fair	Proceed with Carryover (PWC)
	Poor	Proceed on Probation (PonP)
	Very Poor	Repeat
	Bad	Advised to Withdraw

IV. IMPLEMENTATION AND RESULT

The proposed model was implemented in MATLAB (R2013a) using the Fuzzy Logic Design Toolbox version 2.2.17. For this model we developed a three input, two output Fuzzy Mamdani model as shown in figure 2. The graphical representation of the input and output variables are shown in figures 3-7.

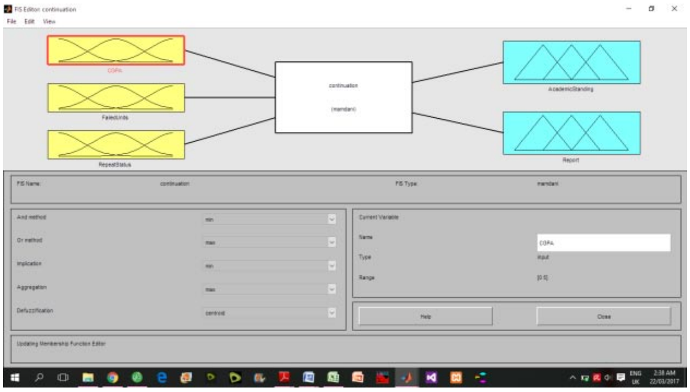

Figure 2: Input and Output Variables

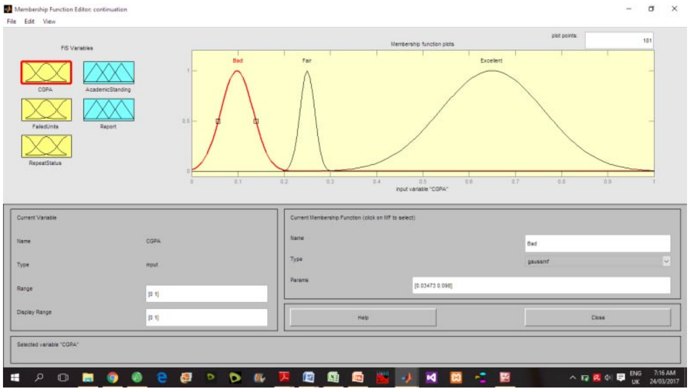

Figure 3: Input Variable CGPA

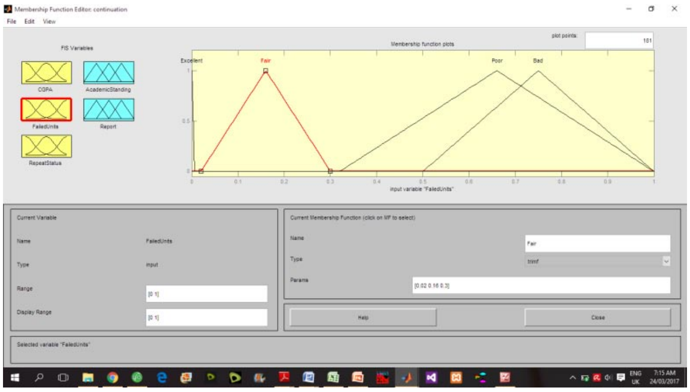

Figure 4: Input Variable Failed Units

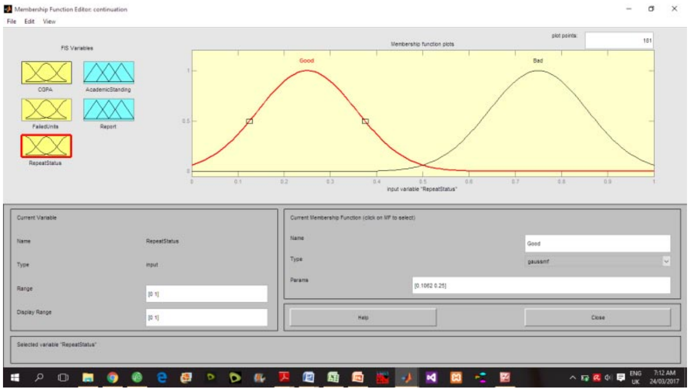

Figure 5: Input Variable Repeat Status

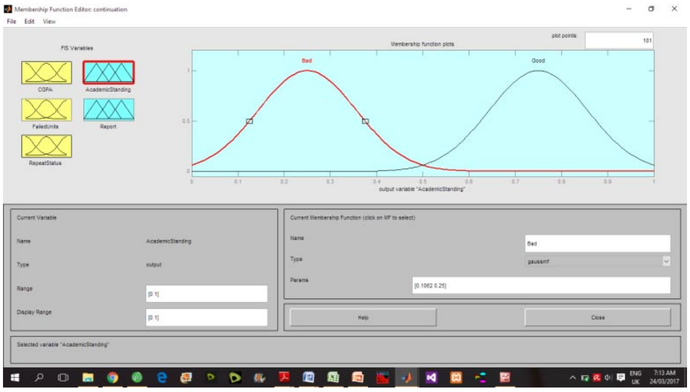

Figure 6: Output Variable Academic Standing

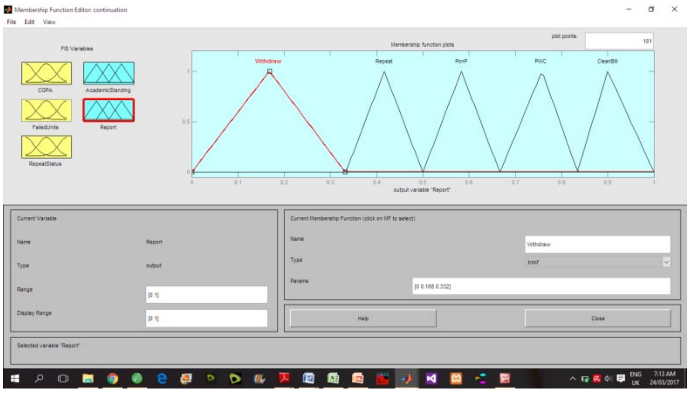

Figure 7: Output Variable Report

A. Rule Construction

Fuzzy Mamdani inference rules were constructed based on the defined input and output variables. Some of the rules that make up the rule base for the proposed three inputs and one output model is shown below.

1. If (CGPA is Excellent) and (Failed Units is Excellent) and (Repeat Status is Good) then (Academic Standard is Good) and (Report is CleanBill)
2. If (CGPA is Excellent) and (Failed Units is Fair) and (Repeat Status is Good) then (Academic Standard is Good) and (Report is PWC)
3. If (CGPA is Excellent) and (Failed Units is Poor) and (Repeat Status is Good) then (Academic Standard is Good) and (Report is PonP)
4. If (CGPA is Fair) and (Failed Units is Bad) and (Repeat Status is Good) then (Academic Standard is Bad) and (Report is Repeat)
5. If (CGPA is Fair) and (Failed Units is Bad) and (Repeat Status is Bad) then (Academic Standard is Bad) and (Report is Withdraw)
6. If (CGPA is Bad) then (Academic Standard is Bad) and (Report is Withdraw)

V. RESULT AND DISCUSSION

The micro view of the detailed fuzzy inference system is shown in figure 8. CGPA, Failed Unit and Repeat Status data of 35 students from a higher educational institution in South-South, Nigeria was used to test the model's accuracy. It was found that the Academic Standing and Report from the model is accurate. Furthermore, Figures 9 to 14 show entire surface plots of 2 inputs against 1 output of the proposed model.

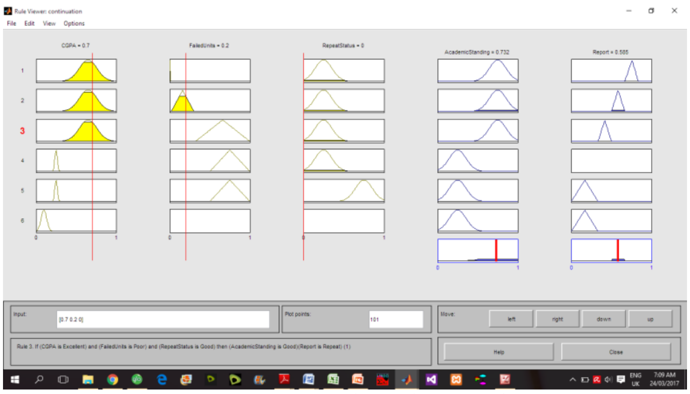

Figure 8: Micro view of the fuzzy Inference system for an input of 0.7, 0.2 and 0.0 for CGPA, Failed Units and Repeat Status respectively.

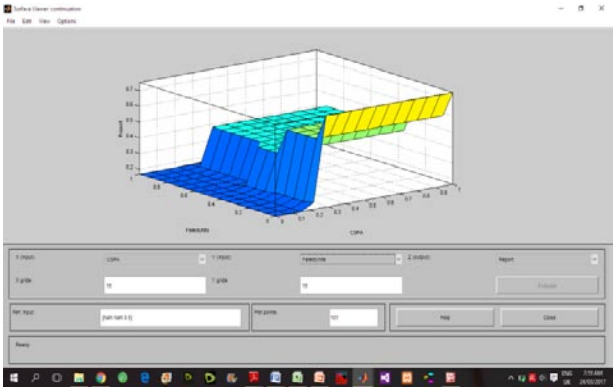

Figure 9: Surface plot for the inputs CGPA and Failed Units against the output Report.

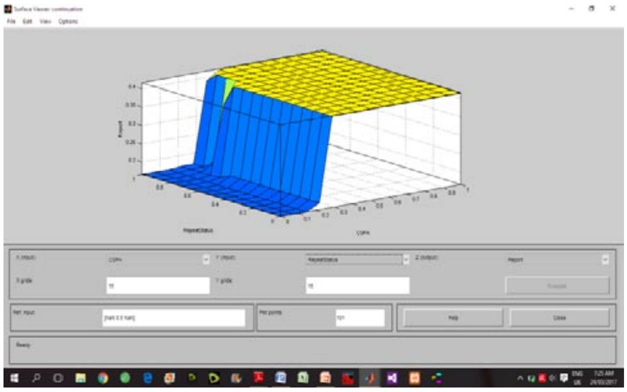

Figure 10 : Surface plot for the inputs CGPA and Repeat Status against the output Report.

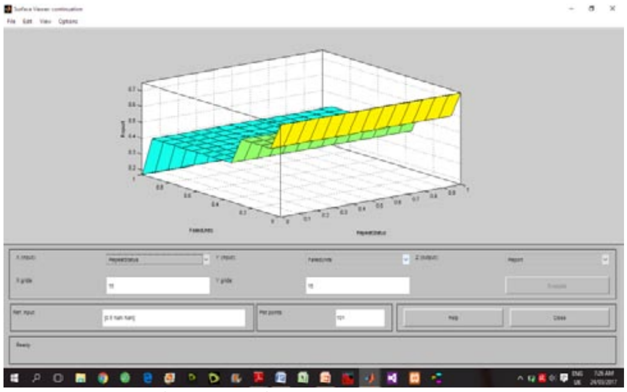

Figure 11: Surface plot for the inputs Repeat Status and Failed Units against the output Report.

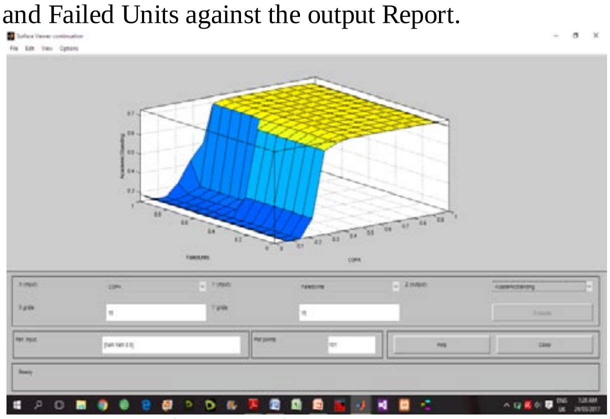

Figure 12: Surface plot for the inputs CGPA and Failed Units against the output Academic Standing.

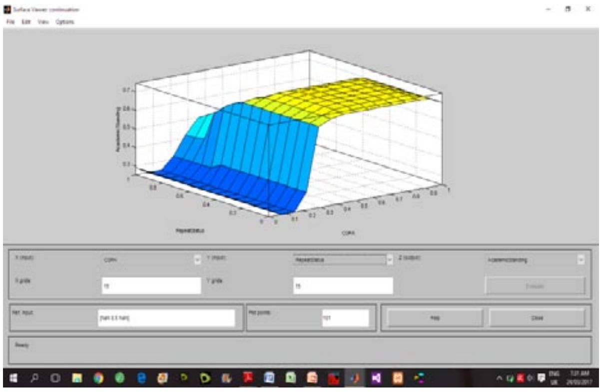

Figure 13: Surface plot for the inputs CGPA and Repeat Status against the output Academic Standing.

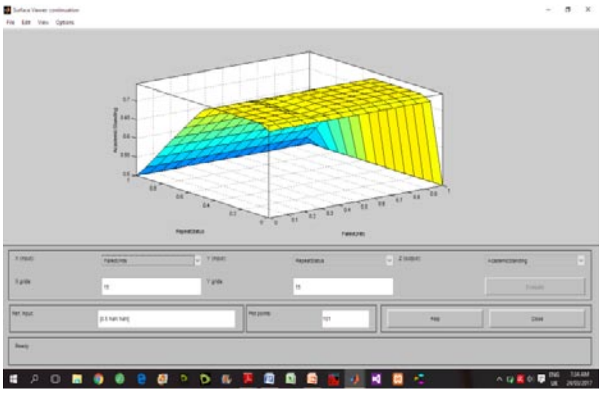

Figure 14: Surface plot for the inputs Failed Units and Repeat Status against the output Academic Standing.

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VII. LIMITATIONS OF THE STUDY

Different Higher educational Institutions may use different criteria for the computation of Academic Standing and Continuation Requirement. Some institutions even apply multiple criteria depending on the course of study. This study assumes that all students in the institution are evaluation on the same criteria

VIII. CONCLUSION AND FUTURE WORK

In this research work, we developed a Fuzzy Mamdani Inference System for the modeling of the Academic Standing and Continuation Requirements of students in Higher Educational Institutions using their CGPA, Failed Units and Repeat Status as input. Results show that the model can be used to easily identify and advice students whose performance is going below expectation, to avoid failure and dropout.

In the future, we hope to model the scenario where the criteria for evaluation may differ based on the course of study. This will bring in more variables into the model and introduce a new set of rules.

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