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IMPLEMENTING FUZZY LOGIC REASONING APPROACH TO EVALUATE STUDENTS PERFORMANCE

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Abstract

This paper presents a report for analyzing students' performance using fuzzy logic. The performance evaluation of students in private schools. The characteristics considered for evaluation over academic performance of the students by using a fuzzy reasoning approach.
Key Words and Phrases: Fuzzy logic, fuzzy reasoning approach.

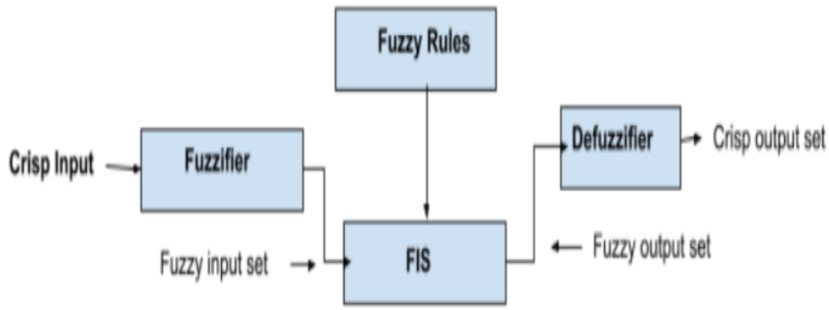
1. INTRODUCTION

Fuzzy inference techniques are used in performance evaluation of students and proposed an approach which is a combination of two membership functions [4]. A fuzzy expert system for evaluation of studentsâĂŹ academic performance and also proposed many approaches using fuzzy logic techniques to provide practical methods for evaluating students with existing statistical methods[5]. Fuzzy expert system proposed for evaluating teachers overall performance based on fuzzy logic techniques. In this paper we are going to use fuzzy logic reasoning that has been proposed for performance evaluation of students.

2. FUZZY LOGIC REASONING APPROACH

Fuzzy logic theory was introduced by L.A. Zadeh in 1965. Fuzzy logic comes in when conventional logic fails. It is a computational paradigm which is based on human thinking. An important concept in fuzzy logic is the application of linguistic variables i.e. variables whose values are words or sentences in natural language (Zadeh, 1975). The fuzzy reasoning approach has found a wide application in designing of certain complex industrial and management systems which cannot be modeled precisely under various assumptions and approximations. One of the famous applications of fuzzy logic and fuzzy set theory is the Fuzzy inference system (FIS) (Guillaume, 2001). FIS are knowledge-based or rule-based systems that contain descriptive if-then rules created from human knowledge and experience (Kharola and Gupta, 2014). A basic fuzzy architecture consists of three components: fuzzifier, FIS and defuzzifier. Fuzzifier maps crisp numbers into fuzzy sets whereas the defuzzifier maps output sets into crisp numbers. The FIS represents the core of fuzzy logic controllers (FLC's). It is built of rule-base and data-base, which constitute the knowledge base and inference engine. A view of the basic architecture of the fuzzy system is shown in figure 1.

Figure 1. Basic architecture of fuzzy system



2.1. FUZZY LOGIC CONTROLLERS FOR DESIGNING. In this study step by step fuzzy logic reasoning approach [7] has been used for designing an inference system for the controllers. A View of step by step approach is shown in figure 2. It can be observed from the figure in step 1 academics with attendance gives the knowledge performance. And in step 2 knowledge and extra curriculum gives the overall performance.

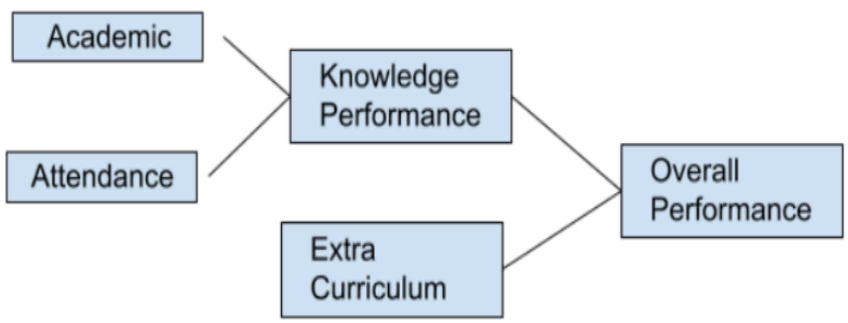


Figure 2. Step by step fuzzy logic reasoning

Fuzzy Inference system for knowledge controller is shown in figure 3. In this study we have used input and output attributes that are fuzzified with linguistic variables are very poor, poor, average, good, very good and given a universe of discover of [0 1]. A view of input Membership functions for input attributes i.e. academic and attendance are shown in figure 5 and 6 respectively.

3. FUZZY RULE BASED SYSTEM

Fuzzy linguistic descriptions are formal representations of systems made through fuzzy IF-THEN rules. They encode knowledge about a system in statements of the form IF(a set of conditions) are satisfied THEN(a set of consequences) can be inferred. Fuzzy IF-THEN rules are coded in the form

If (x_1 is A_1, x_2 is $A_2, \ldots x_n$ is A_n) THEN (y_1 is B_1, y_2 is $B_2, \ldots y_n$ is B_n)

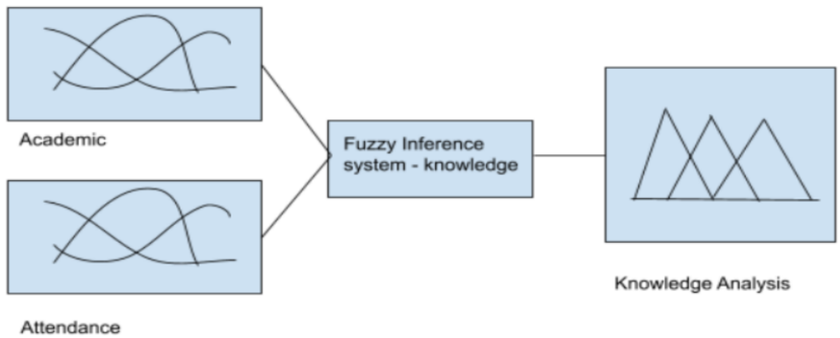


Figure 3. Fuzzy inference systems for knowledge controller

Where linguistic variables x_i, y_j take the values of fuzzy sets A_i and B_j respectively.
A collection of rules referring to a particular system is known as a fuzzy rule base. If the conclusion C to be drawn from a rule base R is the conjunction of all the individual consequents Ci of each rule, then

$$C = C_1 \cap C_2 \cap \ldots C_n$$

where

$$\mu_c(y) = min(\mu_{c_1}(y), \mu_{c_2}(y), \ldots, \mu_{c_n}(y)) \ \forall y \in Y$$

Where Y is the universe of discourse.

On the other hand, if the conclusion C to be drawn from a rule base R is the disjunction of the individual consequences of each rule , then

$$C = C_1 \cup C_2 \cup \ldots c_n$$

where

$$\mu_c(y) = max(\mu_{c_1}(y), \mu_{C_2}(y), \ldots, \mu_{c_n}(y)) \ \forall y \in Y$$

Where Y is the universe of discourse.

3.1. Application. Evaluating the performance of the students using a Fuzzy rule based system. The rules are framed under Academics and Attendance
Rule 1: If academic is V.P and attendance is V.P then performance isV.P
Rule 2: If academic is V.P and attendance is P then performance is V.P
Rule 3: If academic is V.P and attendance is A then performance is V.P
Rule 4: If academic is V.P and attendance is G then performance is V.P
Rule 5: If academic is V.P and attendance is V.G then performance is V.P
Rule 6: If academic is P and attendance is V.P then performance is P
Rule 7: If academic is P and attendance is P then performance is P
Rule 8: If academic is P and attendance is A then performance is P
Rule 9: If academic is P and attendance is G then performance is P
Rule 10: If academic is P and attendance is V.G then performance is P
Rule 11: If academic is A and attendance is V.P then performance is P
Rule 12: If academic is A and attendance is P then performance is P

Rule 13: If academic is A and attendance is A then performance is A
Rule 14: If academic is A and attendance is G then performance is A
Rule 15: If academic is A and attendance is V.G then performance is G
Rule 16: If academic is G and attendance is V.P then performance is A
Rule 17: If academic is G and attendance is P then performance is A
Rule 18: If academic is G and attendance is A then performance is G
Rule 19: If academic is G and attendance is G then performance is G
Rule 20: If academic is G and attendance is V.G then performance is V.G
Rule 21: If academic is V.G and attendance is V.P then performance is A
Rule 22: If academic is V.G and attendance is P then performance is G
Rule 23: If academic is V.G and attendance is A then performance is G
Rule 24: If academic is V.G and attendance is G then performance is V.G
Rule 25: If academic is V.G and attendance is V.G then performance is V.G
Key:
V.P -Very Poor
P - Poor
A - Average
G - Good
V.G - Very Good
Computation of fuzzy membership value
For the fuzzification of inputs, that is , to compute the membership for the antecedents, the formula is illustrated as

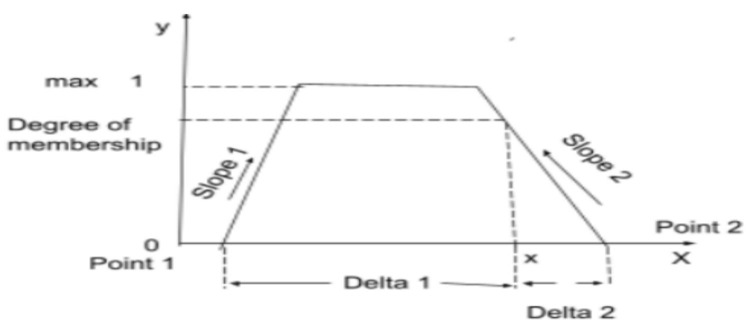


Figure 4. Computation of fuzzy membership value

Delta 1 = x-point 1
Delta 2 = point 2-x
If (Delta 1 ≤ 0) or (Delta 2 ≤ 0) then degree of membership = 0
Else degree of membership = min{Delta 1 * slope 1, Delta 2 * slope 2, max }
Here , x which is the system input has its membership function values computed for all fuzzy sets. For example, the system input academics of the students deals with three fuzzy sets, namely V.G - Very Good , G - Good, A - Average , P - Poor and V.P - Very Poor. The other input attendance of the students deals with three fuzzy sets, namely V.G - Very Good , G - Good, A - Average , P - Poor and V.P - Very Poor.

The computation of the fuzzy membership values for the academics of the students (x = 95), the qualifying fuzzy sets are shown in the fig 5.

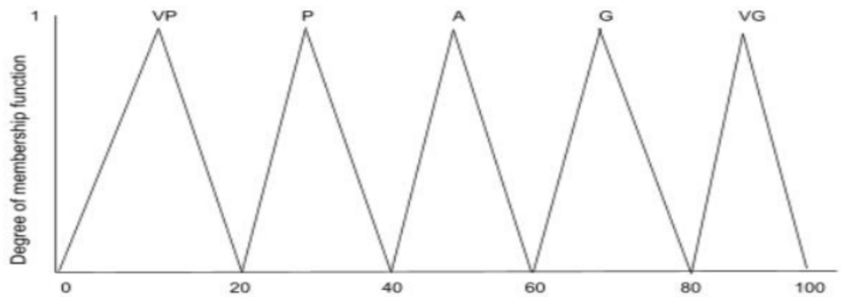


Figure 5. Membership function for input Academic

Fuzzy membership functions of x = 95 for the fuzzy set V.G-Very Good.
Delta 1 = 95 - 80 = 15
Delta 2 = 100 - 95 = 5
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_{V,G}(x) = min(15 * 0.05, 5 * 0.05, 1)$

$= min(15 * 0.05, 5 * 0.05, 1) = 0.25$

Fuzzy membership functions of x = 95 for the fuzzy set G - Good.
Delta 1 = 95 - 60 = 35
Delta 2 = 80 - 95 = -15
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_G(x) = 0$

Fuzzy membership functions of x = 95 for the fuzzy set A - Average.
Delta 1 = 95 - 40 = 55
Delta 2 = 60 - 95 = -15
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_A(x) = 0$

Fuzzy membership functions of x = 95 for the fuzzy set P - Poor.
Delta 1 = 95 - 20 = 75
Delta 2 = 40 - 95 = -55
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_P(x) = 0$

Fuzzy membership functions of x = 95 for the fuzzy set V.P-Very Poor.
Delta 1 = 95 - 0 = 95
Delta 2 = 20 - 95 = -75
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_{V,P}(x) = 0$

The computation of the fuzzy membership values for the attendance of the students (x = 75), the qualifying fuzzy sets are shown in the fig 6.

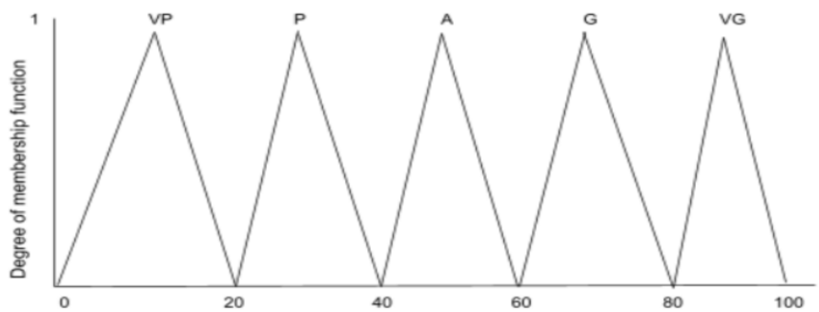


Figure 6. Membership function for input Attendance

Fuzzy membership functions of x = 75 for the fuzzy set V.G-Very Good.
Delta 1 = 75 - 80 = -5
Delta 2 = 100 - 75 = 25
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_{V.G}(x) = 0$

Fuzzy membership functions of x = 75 for the fuzzy set G-Good.
Delta 1 = 75 - 60 = 15
Delta 2 = 80 - 75 = 5
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_G(x) = min(15 * 0.05, 5 * 0.05, 1)$
= min(0.75,0.25,1)
= 0.25

Fuzzy membership functions of x = 75 for the fuzzy set A - Average.
Delta 1 = 75 - 40 = 35
Delta 2 = 60 - 75 = -15
Slope 1 = 1/20 = 0.05

Slope 2 = 1/20 = 0.05
$\mu_A(x) = 0$

Fuzzy membership functions of x = 75 for the fuzzy set P - Poor.
Delta 1 = 75 - 20 = 55
Delta 2 = 40 - 75 = -35
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_P(x) = 0$

Fuzzy membership functions of x = 75 for the fuzzy set V.P-Very Poor. Delta 1 = 75 - 0 = 75 Delta 2 = 20 - 75 = -55 Slope 1 = 1/20 = 0.05 Slope 2 = 1/20 = 0.05 $\mu_{V,P}(x) = 0$

For the Fuzzy rule base, the fuzzy membership values satisfies the rule 24
Rule 24 : min(0.25, 0.25) = 0.25
The fuzzy outputs of rules 24with strengths of 0.25
That is, Academic is V.G and attendance is G then performance is V.G
The computation of the fuzzy membership values for the Extra curriculum of the students (x = 85), the qualifying fuzzy sets are shown in the fig 7.

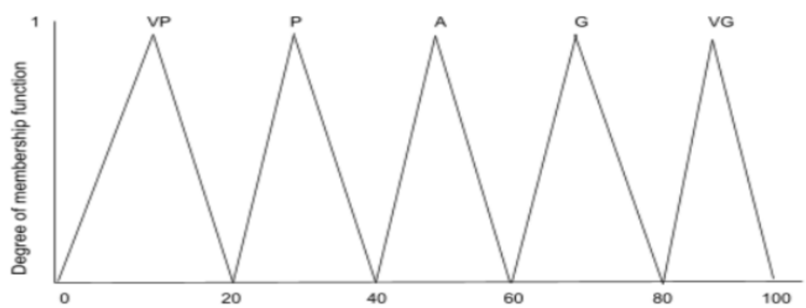


Figure 7. Membership function for input Extra curriculum

Fuzzy membership functions of x = 85 for the fuzzy set V.G-Very Good.
Delta 1 = 85 - 80 = 5
Delta 2 = 100 - 85 = 15
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_{V,G}(x) = min(5 * 0.05, 15 * 0.05, 1) = 0.25$

Fuzzy membership functions of x =85 for the fuzzy set G-Good.
Delta 1 = 85 - 60 = 25
Delta 2 = 80 - 85 = -5
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_G = 0$

Fuzzy membership functions of x = 85 for the fuzzy set A - Average.
Delta 1 =85 - 40 = 45
Delta 2 = 60 - 85 = -25
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_A(x) = 0$

Fuzzy membership functions of x = 85 for the fuzzy set P - Poor.
Delta 1 = 85 - 20 = 65
Delta 2 = 40 - 85 = -45
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_P = 0$

Fuzzy membership functions of x = 85 for the fuzzy set V.P-Very Poor.
Delta 1 = 85 - 0 = 85
Delta 2 = 20 - 85 = -65
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05
$\mu_{V,P}(x) = 0$

The fuzzy output for extra curriculum is V.G(Very Good).
If the membership function of x = 50 for extra curriculum then the output will be A(Average).

4. CONCLUSION

In this paper the general description and requirements for designing and creating a decision support system based on fuzzy logic are presented. Fuzzy inference systems can be applied in a vast number of meteorological application areas. An important advantage of the fuzzy expert system is that the knowledge is expressed in the form of an easy to understand linguistic fuzzy model, while maintaining the approximation accuracy at a reasonable level. This goal is achieved by modifying the rule antecedents to produce a flexible and interpretable output space. This model demonstrated that decision making on this method provides a better evaluation. Results indicate that fuzzy rule- based modeling in fuzzy reasoning is a promising alternative to the traditional approach. The result is based on the overall studentsâĂŹ performance, which is 0.25 by comparing knowledge and extra curriculum.

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