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A Fuzzy Logic Model for Students' Scholarship Selection

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Abstract

Fuzzy logic has been successfully applied in many fields such as in engineering, computer science and management sciences. One of its useful applications is in decision-making where, in "real world" problems, factors involved are normally vague. Formulation of the problems using common approaches would be difficult due to the situation that have an inherent lack of precision. In this paper a fuzzy logic model has been developed for the selection process of students applying for scholarship. The selection is based on certain criteria determined by the sponsor. An example is given at the end of the paper to illustrate the model. The MATLAB fuzzy logic tool box is used to calculate the output.

Keywords: Fuzzy logic model, selection process, fuzzy logic toolbox.

1. Introduction

Classical logic assigns the truth value of a proposition to be either 0 or 1. This two-valued logic is particularly important in describing the existence of an event, object or condition. In reality, many situations are too complex to be defined precisely by the classical logic. This is especially so, for example when describing performances of candidates in an interview for student scholarship selection. Though two or more candidates may fall under the same category of 'good', their degrees of being 'good' tend to vary from one to another. In other words, the truth value for the proposition 'performance is good' cannot be precisely determined as either 0 or 1 but could also take any value between 0 and 1. Thus, the concept of fuzzy logic is of great importance in explaining this sort of problem.

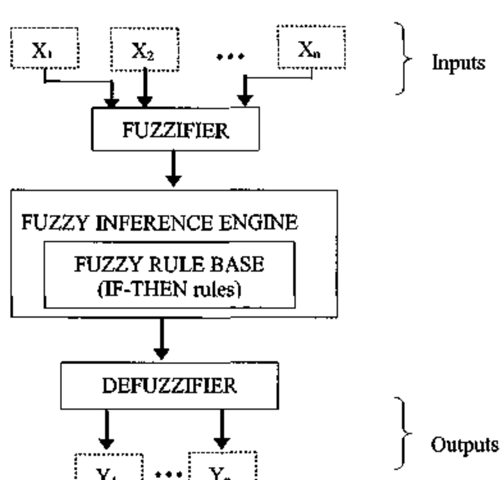
The idea of fuzzy logic was first conceived by Lotfi Zadeh as early as 1960s. Fuzzy logic extends the concept of two-valued logic by allowing the truth value of a proposition to take any number in the interval [0,1]. The emergence of the fuzzy logic in general provides a platform for approximate reasoning to take place especially when dealing with linguistic expressions and descriptions in human thinking (Wang, 1997). Fuzzy logic expressed in the form of IF-THEN rules is very much in resemblance with the structure of human logical thinking. In fact, most decisions made by human being are indirectly performed based on IF-THEN statements.

Fuzzy logic has been successfully applied in many fields such as in engineering, computer sciences and management sciences particularly in areas where solving multi-criteria problems are of main concerns. Formulations of a multi-criteria decision making (MCDM) problem using common approaches would be insufficient as the input data may be more appropriately described in linguistic terms instead of precise numerical values. The 'real world' problems normally involve factors that are vague and very subjective in nature. Fuzzy logic has the capabilities of dealing with these types of factors. Due to this, many researchers have started to incorporate the theory of fuzzy logic in some of decision-making techniques. Costa et al (2004) used a fuzzy linguistic model based on fuzzy logic to measure varying levels of functional disability in accordance to an individual's definition of social and physical activities and mobility. Craiger et. al (2003) on the other hand developed a fuzzy associative memory (FAM), a rule-based system that utilizes fuzzy sets and logic in predicting job performance for four US air force job families. The results showed that FAM provided a better job classification as compared to the linear mathematical models.

2. Fuzzy Logic Decision Model (FLDM)

A fuzzy logic decision model (FLDM) is a fuzzy system that provides a simple and an effective way of getting definite conclusions or outputs from imprecise and ambiguous inputs (Klir & Folger, 1988). An FLDM basically consists of four main components namely the fuzzifier, fuzzy inference engine, fuzzy rule base and defuzzifier. Figure 1 shows an overview of an FLDM.

Figure 1. Overview of a fuzzy logic decision model



The role of the fuzzifier is to transform crisp inputs (numerical values) into fuzzy values or fuzzy sets via triangular, trapezoidal or Gaussian fuzzifier. In the fuzzy inference engine, with fuzzy values as new inputs, a series of fuzzy IF-THEN rules in the fuzzy rule base will be executed. The rules are of the form

$$\begin{array}{ll} \textbf{Rule 1}: & \text{IF } A \text{ is } A_1 \text{ and } B \text{ is } B_1 \text{ and } \ldots \text{ THEN } C \text{ is } C_1 \\ \vdots & \vdots \\ \textbf{Rule } n: & \text{IF } A \text{ is } A_k \text{ and } B \text{ is } B_r \text{ and } \ldots \text{ THEN } C \text{ is } C_m \end{array}$$

where A, B and C are fuzzy representation of linguistic variables, and, Ak , Br and Cm are the corresponding linguistic values with respect to the n-th rule. The above IF-THEN statements could also be written in terms of the following mathematical expression where the intersection ($\cap$) and implication ($\Rightarrow$) are used to represent the operators 'and' and 'IF-THEN' respectively.

$$\begin{array}{ll} \textbf{Rule 1}: & (A_1 \cap B_1 \cap \ldots) \Rightarrow C_1 \\ \vdots & \vdots \\ \textbf{Rule } n: & (A_k \cap B_r \cap \ldots) \Rightarrow C_m \end{array}$$

The fuzzy rule base is the heart of a fuzzy system (Wang, 1997). The decision process carried out by the fuzzy inference engine has to strictly follow this set of rules and expert knowledge is highly required in creating these fuzzy rules. The output of the fuzzy inference engine will be a fuzzy region (fuzzy output). This fuzzy region needs to undergo a defuzzification process so that it can be translated back into a crisp value. One of the most commonly used defuzzification methods is the centroid method given by the equation

$$K = \sum_{i=1}^{n} x_i \mu(x_i) \Big/ \sum_{i=1}^{n} \mu(x_i)$$

3. Case Study : The Student's Scholarship Selection Problem

Selecting student's scholarship is not easy as many criteria have to be put into consideration and be evaluated simultaneously to ensure that scholarships are awarded to most qualified candidates. Yeh (2003) presented what were claimed to be suitable compensatory multi-attribute decision making methods for solving the scholarship student selection problem namely, the total sum (TS), simple additive weighting (SAW), weighted product (WP) and finally the TOPSIS method or the technique for order preference by similarity to ideal solution. However, subjectivities and uncertainties in some of the selection criteria and ways of handling these factors were not being addressed in his paper. Undeniably, neglecting what seem to be 'fuzzy' factors may result in losing some information on candidate(s) actual performances. According to Klir et. al (1997), uncertainties and ambiguities involved in the decision making process can be handled by the fuzzy logic. In this paper, we propose a decision model based on fuzzy logic as an alternative method to assist decision makers in the selection process.

3.1 Application of the Fuzzy Logic Decision Model

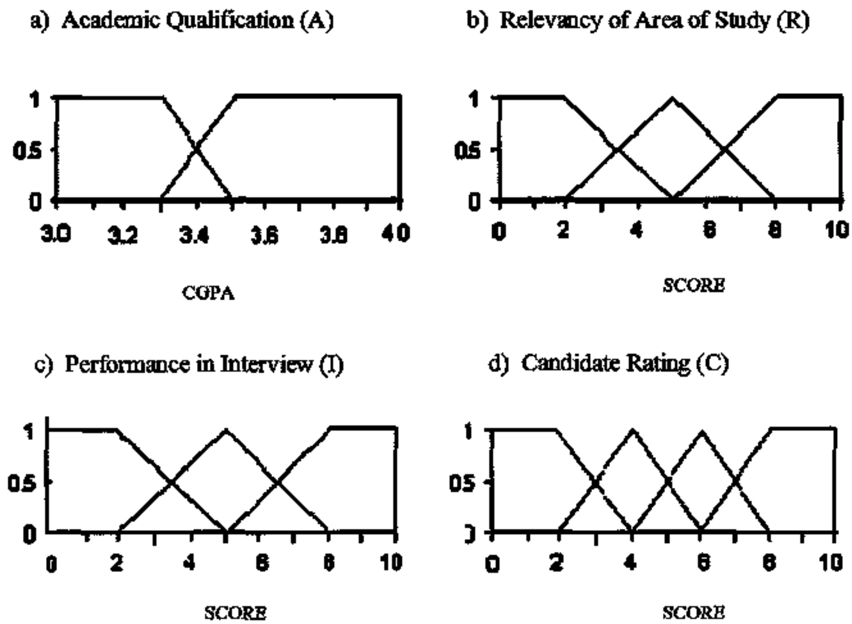
For the application of the FLDM with regards to the scholarship student selection problem under the FTMSK Young Lecturer Scheme, three criteria were identified as the selection criteria namely the academic qualification (A), relevancy of area of study (R) and performance in the interview (I). The academic qualification is based on the CGPA obtained by the candidate. The relevancy of area of study on the other hand depends on how relevant the area of study that the candidate intends to pursue as compared to the areas offered by the scholarship. Meanwhile, the performance in interview is evaluated based on the personality, communication skills, maturity and interests in taking up the scholarship. These criteria will be used as input variables. The rating of the candidate (C) is set as the output variable. Table 1 displays the linguistic variables and respective fuzzy numbers associated with each linguistic value. Each linguistic value is represented by a trapezoidal fuzzy number, which is generally expressed by the membership function

$$\mu_A(x) = \mu_A(x: a, b, c, d) = \begin{cases} \dfrac{x-a}{b-a} & \text{if} \quad a \le x \le b \\ 1 & \text{if} \quad b \le x \le c \\ \dfrac{d-x}{d-c} & \text{if} \quad c \le x \le d \\ 0 & \text{if} \quad x \le a \text{ or } x \ge d \end{cases} .$$

Table 1. Linguistic variables and respective fuzzy numbers.

Linguistic Variables		Linguistic Values	Fuzzy Numbers , (*a, b, c, d*)	Range
Inputs	Academic Qualification (A)	High, A_1	(3.0, 3.0, 3.3, 3.5)	[3.0, 4.0]
		Very High, A_3	(3.3, 3.5, 4.0, 4.0)	
	Relevancy of area of study (R)	Low, R_1	(0, 0, 3, 5)	[0, 10]
		Medium, R_2	(3, 5, 5, 7)	
		High, R_3	(5, 7, 10, 10)	
	Performance in Interview (I)	Low, I_1	(0, 0, 3, 5)	[0, 10]
		Medium, I_2	(3, 5, 5, 7)	
		High, I_3	(5, 7, 10, 10)	
Output	Candidate Rating (C)	Least preferred, C_1	(0, 0, 2, 4)	[0, 10]
		Less preferred, C_2	(2, 4, 4, 6)	
		Preferred, C_3	(4, 6, 6, 8)	
		Most preferred, C_4	(6, 8, 10, 10)	

The corresponding membership function for each linguistic value with respect to each variable involved are shown in Figure 2 (a)-(d).



Based on the requirement set by the faculty and the sponsor, eighteen rules are generated for this scholarship student selection. Table 2 shows the fuzzy associative memories (FAMs) representing all the rules. The following are some of decision rules that are used to determine the rating for each candidate.

$$\text{Rule 1}: (A_1 \cap R_1 \cap I_1) \Rightarrow C_1$$
$$\text{Rule 2}: (A_1 \cap R_1 \cap I_2) \Rightarrow C_1$$
$$\text{Rule 3}: (A_1 \cap R_1 \cap I_3) \Rightarrow C_2$$

The implementation of the inference process is made easy with the use of MATLAB® Fuzzy Logic Toolbox.

Table 2. The FAMs representing the decision rules

A_1		Interviews, I		
		I_1	I_2	I_3
Relevancy (R)	R_1	C_1	C_1	C_2
	R_2	C_1	C_2	C_3
	R_3	C_2	C_3	C_3

A_2		Interviews, I		
		I_1	I_2	I_3
Relevancy (R)	R_1	C_2	C_2	C_3
	R_2	C_2	C_3	C_4
	R_3	C_3	C_4	C_4

Numerical Example

As an illustration, inputs for four candidates are fed into the model presented in Section 2, and the respective outputs are shown in Table 3.

Table 3. Inputs and outputs for candidates

CANDIDATE	INPUTS			OUTPUT (Candidate Rating)
	Academic Qualification (A)	Relevancy (R)	Interview (I)	
Candidate1	3.30	7	4	5.13
Candidate2	3.60	4	4	5.00
Candidate3	3.51	8	7	8.47
Candidate4	3.10	8	9	6.00

The inference process of obtaining the final output (rating) for *Candidate1* is presented in Figure 3. It can be interpreted that considering all the 18 rules, with CGPA 3.50, a score of 7 out of 10 in terms of the relevancy of the area that this candidate intends to pursue as compared to the area offered for scholarship and a score of 4 out of 10 for performance in the interview, *Candidate1* managed to get 5.13 in terms of candidate rating. The same process applies to the rest of candidates. From the outputs displayed in Table 3, obviously, *Candidate3* received the highest rating. Overall, the ranking order for the four candidates is *Candidate3*, *Candidate4*, *Candidate1* followed by *Candidate2*.

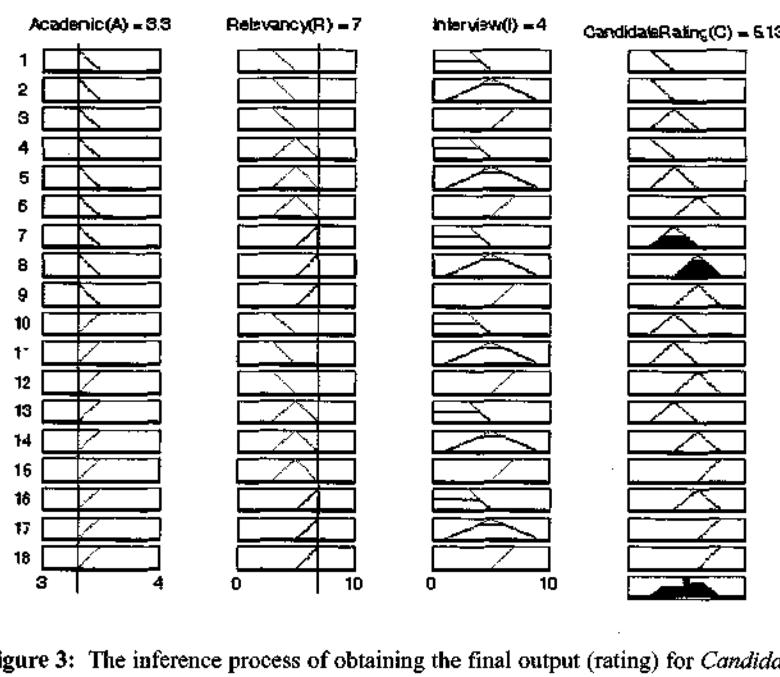


Figure 3: The inference process of obtaining the final output (rating) for *Candidate1*

4. Discussions

In this paper we have successfully implemented FLDM in a student scholarship selection problem that involves assessment process based on multiple selection criteria. We consider three criteria namely academic qualification, relevancy of area of study and performance in interview. All criteria evaluations are transformed to linguistic variables as inputs to FLDM. These criteria however are not exhaustive as they depend on the requirements of the faculty and/or the university. The membership functions representing linguistic values of each variable are also changeable for the same reason. The result of this model would be an output that ranks the students overall performance that can be used by the authority to make the selection easily. This model can be explored further by investigating the validity of the results and the stability of the model for a large-scale selection problem as been investigated by Yeh (2003) for other MADM methods.

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