A Fuzzy Inference based Decision Support System for Solving the University-Course Admission Choice Problem

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ABSTRACT
The university admission choice problem is that of selecting a combination of a course of study and a university, either as first or second choice, given a candidate's academic ability and interest with the goal of maximizing the candidate's chance of securing university admission in a competitive process. This study was aimed at developing a decision support system for university admission seekers, who are faced with the admission choice problem, using the concept of fuzzy logic. Through literature search, interviews, and expert knowledge mining, relevant factors characterizing the Nigerian University admission system were determined and the dynamics of their interactions appropriately modelled. The equivalent Fuzzy Inference System of the decision process was developed. Model parameterization was carried out using information from the Nigerian University Admission System. A two state variable model incorporating student ability and interest was adopted. The resulting fuzzy inference model generates very reasonable decisions on sample test combinations. It is concluded that fuzzy inference system is a veritable tool for building practical decision support systems for the University course admission choice problem.

General Terms
Education, Soft computing, Fuzzy, Decision support system

Keyword
Fuzzy inference, Soft computing, Decision support system, University admission, Education management

1. INTRODUCTION
1.1 General Background
One of the most important choices of young school leavers, and their parents, is the university-course admission choice. The university-course admission choice problem is that of selecting a combination of a course of study and a university, either as first or second choice, given a candidate's academic ability and interest while maximizing the candidate's chance of securing university admission in a competitive process. Apart from a candidate's academic ability the University-Course combination is a major determinant of a candidate's chance. Unfortunately many students are disadvantaged right from the point of filling the admission examination forms because of the poor matching of university-course choices with their academic strengths [1]. This has resulted into many good candidates becoming frustrated and desperate, especially in a country like Nigeria where there is a serious gap between the number of students seeking university admission and the total available university admission slots. Recent information on the Nigerian situation shows that less than 15 percent of qualified applicants are eventually admitted into universities [2] [1]. The aim of this study therefore is to develop decision support systems for the university admission choice problem using the concept of fuzzy logic. The specific objectives are 1) to study and identify the various critical elements and structure of the Nigerian University admission system and 2) to develop a decision support system based on fuzzy logic model of the Nigeria university admission system.

Fuzzy Logic's approach adopts linguistic and intuitive models, like in human reasoning and communication, to describe systems rather than closed form-mathematical expressions. Fuzzy reasoning therefore provides a way to model the behaviour of complex real world decision process using imprecise, vague and uncertain information based on the concept of fuzzy set. According to [3] fuzzy logic allows the decision makers to express their preferences and opinions in linguistic terms; these preferences expressed in linguistic terms are then converted into fuzzy numbers by using Fuzzy membership functions. Fuzzy logic presents a framework for incorporating human knowledge into engineering systems in a systematic and efficient manner [4] [5] and it provides a basis for dealing with uncertainties in the system's parameters and does not require building the analytical model of the system. In recent years, these Fuzzy Logic based models have shown remarkable effectivness in building decision support tools for many real-world complex problems. Several Fuzzy logic applications involving human judgment such as suppliers and contractors selections in supply chain management, portfolio management etc [6] [7] [8] [9] [10] [11] abound in the literature.

1.1 Fuzzy Inference Systems
Fuzzy Inference Systems, also referred to as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modelling, fuzzy associative memory, or fuzzy logic controllers, have been successfully applied in various classification, control, and selections tasks [12] [8] [13] [6]. Fuzzy logic or fuzzy set theory which provides a mathematical tool for modelling uncertain, imprecise and vague data encountered in most real life problems is the basis for building fuzzy inference systems [14] [15] [7] [16]. Fuzzy inference provides the methodologies for building intelligent decision support systems through fuzzy logic based processes. The two most popular methodologies for building these elements into fuzzy inference systems are those based on the Mamdani and Sugeno approaches [16] [8] [11] [17] [18]. The fuzzy inference process is made up of Membership Functions, Fuzzy Logical Operations and Fuzzy If-Then Rules. The fuzzy inference process essentially involves mapping from a given input to an output so that the mapping can provide a basis for decision making.

We observe that the decision process associated with the admission choice problem is laced with a lot of subjectivity. The choice makers normally adopt linguistic terms and intuitive process rather than numerical terms in expressing their preferences. It is, intuitively, a process of inferring from certain factors (inputs) the most appropriate combination of course and university advisable for a student's first or second choice based on his/her ability. We are adopting the Mamdani approach, which is the more general method for building Inference systems, for the proposed fuzzy inference systems. The elements of the proposed Fuzzy Inference based decision system include a Fuzzifier module, the Fuzzy inference engine, the knowledge base, and a defuzification module, see figure 1.

1.2 The Nigerian University Admission Scenario

Presently there are about 120 accredited universities offering different courses ranging from engineering, social sciences, sciences, law, medicine, agricultural sciences [19]. These universities can be grouped into Federal, State, and Private universities. Each category offers different level of competiveness based on perceived level of quality and fee regimes. The first generation universities are generally most sought after because of low tuition fees, superior learning and accommodation facilities and perceived high employers' rating of their graduates. In terms of admission cut off marks, the first generation federal universities are the most competitive while the state universities are moderately competitive. While the cut off points in many private universities are comparatively low their fees regimes are relatively on the high side.

Another characteristic of the Nigerian university admission system is that professional courses like medicine, law, accounting, economics, engineering, computer science are generally more competitive than the non professional courses. Ironically while thousands high school graduates are left frustrated due to several failed attempts at securing university admissions, several courses in many of the universities remain undersubscribed. Meanwhile there has been a corresponding increased pressure on the process which has lead to rampant cases of admission fraud and related problems [2]. One way to reduce this pressure is to provide applicants with some intelligent decision support system for making the tradeoffs, based on a candidate's ability and preferences, involved in the course-university choices.

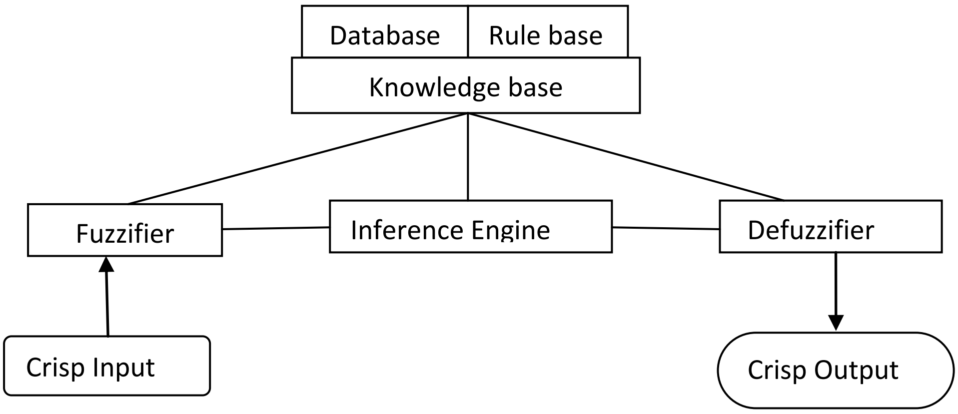

Fig 1 Fuzzy Inference System Structure

2. MODEL DEVELOPMENT

2.1 Model Description

The university course choice decision system seeks to match a candidate's ability with course-university combinations of viable levels of competition or difficulty indices. Student ability can be measured by an IQ test and or past student academic records. While difficulty index or competiveness is influenced by the competiveness of both the course and university of interest as shown in Fig2: for instance, quadrants C1 and C4 are the least and most competitive respectively. A typical advisory matching template is shown in Table 1 with the added effect of the choice type (first or second choice).

It is obvious however that the boundary between competiveness and non competiveness may not be as distinct as depicted in the figure above because competiveness, the resulting difficulty index and even student ability are really fuzzy variables: they are indeed linguistic variables. We now present a fuzzy logic framework for implementing a Decision Support System.

The proposed fuzzy system is essentially a simulation of a humanoid career counsellor model. The linguistic variables and their term sets, the membership functions adopted for fuzification/de-fuzification and the fuzzy rules form the core of the FIS.

2.2 Linguistic Variables and Membership Functions

The linguistic variables that most suitably describe and capture the essential logic of the course choice system were identified and characterized (see Tables 2 and 3). Since there are several MFs available to model a given linguistic term, the trial and error approach was used to compare possible functions and selection made based on our understanding of the course choice making process. The Gaussian membership functions (GaussMf) were adopted for range of values that exhibit symmetry while the DsigMf (difference between two sigmoidal functions) and polynomial based Pi curve (PiMf) were adopted for asymmetric range values. Also the polynomial based curves Z shaped and S shaped membership functions were adopted for the open-left linguistic terms and open-right linguistic terms respectively.

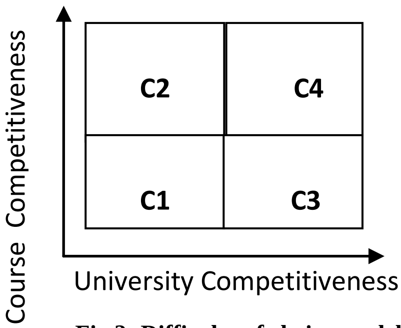

Fig 2: Difficulty of choice model

Table 1 Choice Competition and Ability matching Adapted from [1]

Quadrants	Choice Type	Minimum Student Ability
C1	1st Choice	All candidates
C2	1st Choice	All candidates
C3	1st Choice	All candidates
C4	1st Choice	Bright candidates
C1	2nd Choice	All candidates
C2	2nd Choice	Bright candidates
C3	2nd Choice	Bright candidates
C4	2nd Choice	Very bright candidates

2.1.1 Student ability (A):

The ability of candidate is obtained from the mean of a test score and or the average of past's academic scores of the student. This score is fuzzified using the MFs as shown in figure3

2.1.2 Course competitiveness (CC):

For practical purpose the competiveness score CC of a course is calculated as the average cut off points (of a reference university) over the last 3 years on the scale of 0- 10. This score is fuzzified using the MFs as shown in Fig. 4

2.1.3 University competitiveness (UC):

Competiveness score UC_k of a university k is calculated based on the number of first choice applicants (A_k) seeking admission to the university relative to the number of available slots (S_k): This is shown in equation 1. This expression is equivalent to the probability of a candidate not missing admission. The average value of UC_k for the three most recent years is used for modelling.

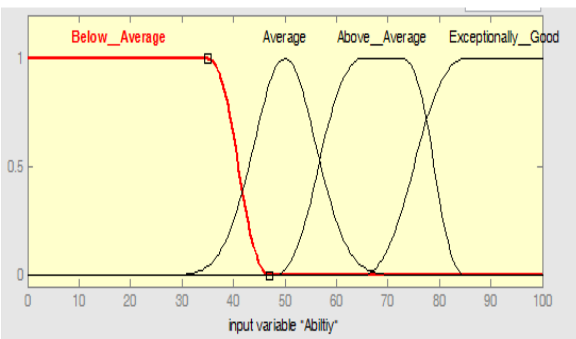

Fig 3 Membership functions Plots for Linguistics Variable Ability

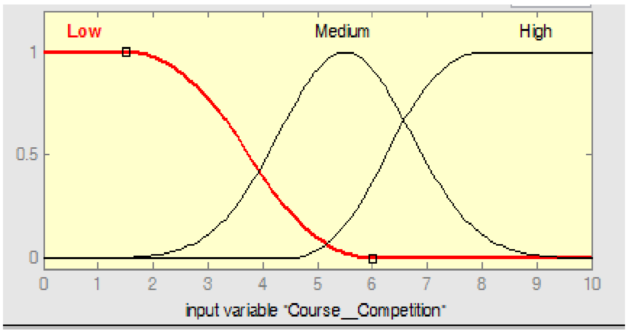

Fig 4 Membership functions for Linguistics Variable Course Competiveness

$$UC_k = \begin{cases} (1-\frac{S_k}{A_k})\times 10 & \text{if } S_k \geq A_k \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where S_k is the number of available admission slots and A_k number of university first choice applicants

2.1.4. Choice preference (CP):

The usual choice categories or preferences are the First Choice and Second Choice assigned values 0 and 1 respectively. This scoring is fuzzified as shown in figure 6

2.1.5 Choice Viability (CV)

The output variable, Choice viability, with four possible variable values or term sets is fuzzified as shown in figure 7.

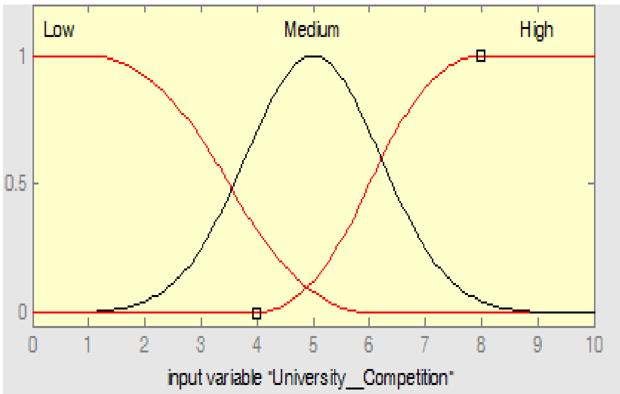

Fig. 5 Membership functions for Linguistics Variable University Competiveness

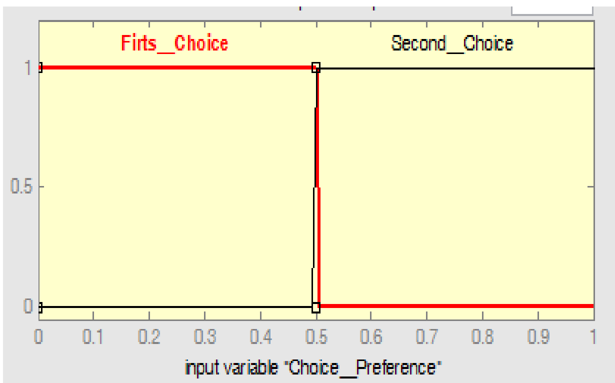

Fig 6 Membership functions plots for Linguistics Variable Choice Preference

Table2: Input Linguistic Variables Description

Linguistic Variables	Notation	Linguistics Values (Terms)	Notation	Index	Membership function
Ability	A	Below Average	Ba	1	ZMf
		Average	Av	2	GaussMf
		Above Average	Abv	3	PiMf
		Exceptionally Good	Exg	4	SMf
Course Competitiveness	CC	Low	L	1	ZMf
		Medium	M	2	GaussMf
		High	H	3	SMf
University Competitiveness	UC	Low	L	1	ZMf
		Medium	M	2	GaussMf
		High	H	3	SMf
Choice Preference	CP	First Choice	Fc	1	TrapMf
		Second Choice	Sc	2	TrapMf

Table3: Output Linguistic Variables Description

Linguistic Variables	Notation	Linguistics Values (Terms)	Notation	Index	Membership function
Choice Viability	CV	Not Viable	Nv	1	ZMf
		Marginally Viable	Mv	2	GaussMf
		Viable	V	3	DsigMf
		Highly Viable	Hv	4	SMf

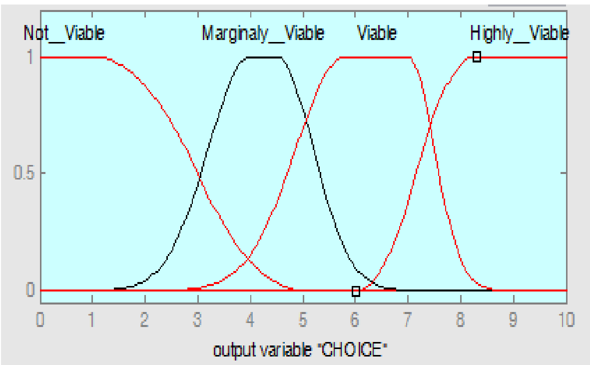

Fig 7 Membership functions plots for the Output Linguistics Variable Choice Viability

2.2 Knowledge Base Development

The proposed FIS is built to simulate a human career counselling expert. Knowledge base of the system therefore consists of the information and data bank as well as the set of rules that guide the judgement of the experts.

2.2.1 The Fuzzy Inference Rule base

The first component of the fuzzy system knowledge base is the fuzzy rules defined to simulate the judgment of a human career counselling expert. The rules set the basis for deriving the values of the output variable, Choice Viability, from the four input variables: Ability (A), Course Competeveness (CC), University Competeveness (UC), and Choice Preference (CP). The rules model how a career counselling expert will advise a candidate by comparing the candidate's academic ability with the perceived competition associated with his or her choice.

Table 4 is a summary of the rules defining the choice difficulty level based on the various combinations of course and university competeveness. The choice viability rating based on candidate's ability and level choice difficulty is defined as shown in table 5. From tables 4 and 5 it clear that a total of seventy two (72) fuzzy rules are explicitly implied for the rules base if all factors are given equal weight. By eliminating redundancy due to overlapping of rules we observe that some fifty 52 fuzzy rules adequately capture the rule base.

Table 4: First and second Choice Difficulty Rating

Course competitiveness / University Competitiveness	Low	Medium	High		Low	Medium	High
	First Choice				Second Choice		
Low	Very Easy	Very Easy	Easy		Easy	Easy	Difficult
Medium	Very Easy	Easy	Easy		Easy	Difficult	Very Difficult
High	Easy	Easy	Difficult		Difficult	Very Difficult	Very Difficult

Table 5 Output Variable Choice Viability

Student Ability / Choice Difficulty Rating	Bellow Average	Average	Above Average	Exceptionally Good
Very Easy (VE)	Viable	Viable	Highly Viable	Highly Viable
Easy (E)	Marginally Viable	Viable	Viable	Highly Viable
Difficult (D)	Not Viable	Not Viable	Viable	Highly Viable
Very Difficult (VD)	Not Viable	Not Viable	Marginally Viable	Viable

3. APPLICATION AND RESULTS

Using data from past admission exercise of a leading Nigerian university; the model was used to do a post-mortem analysis of some real-life admission decisions of candidates. Sample choice decisions are shown in Table 6.

Some snapshots of the 3-D plots mapping from input variables to choice viability are shown in Figures 8. Figures 9a and b show the graphics of the rules combinations for two choice combinations (nos 1 and 2) of table 6.

Table 6. Model's Post-mortem analysis of some typical candidate's choices

s/n	Input Variables				Output Variable: CHOICE	
	Ability Score	UC score	CC	CP	Score	Linguistically (degree of Membership μ)
1	50	8.5	6.5	2nd choice	1.77	Not viable (μ =1)
2	50	4.1	6.5	1st choice	6.09	Viable (μ =1)
3	80	8.4	8.2	2nd Choice	5.56	Viable(μ=0.8)
4	80	8.4	8.2	1st choice	7.48	Highly Viable (μ=0.8)

5	60	8.4	8.6	2nd choice	3.5	Marginally Viable (μ=0.7)
6	60	8.4	4.6	1st choice	6.04	Viable (μ=1)
7	45	8.4	8.6	1st choice	1.86	Not Viable (μ=1)
8	45	8.4	5.0	1st choice	5.78	Viable (μ=0.8)
9	45	2.6	5.0	1st choice	5.93	Viable (μ=0.9)
10	70	5.0	5.0	2nd choice	5.87	Viable (μ=0.9)

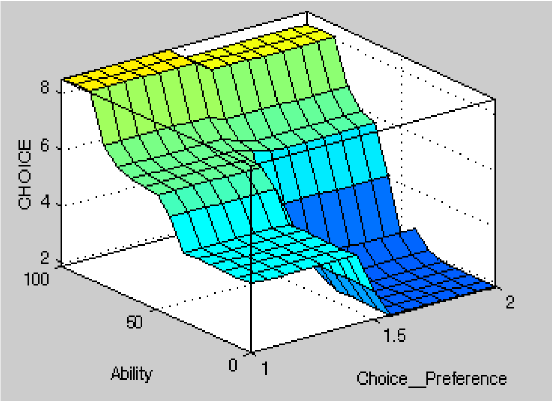

Fig 8a Choice, Ability and Preference 3D plots

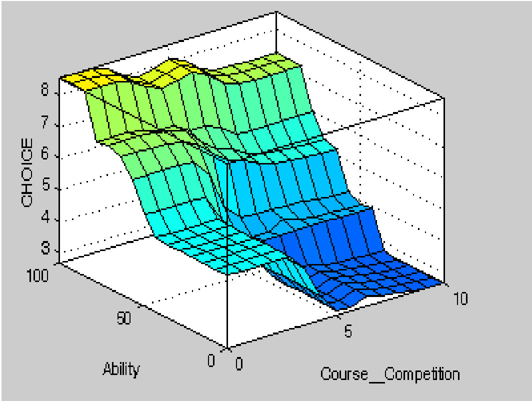

Fig 8b Choice, Ability and Course competitiveness 3D plots

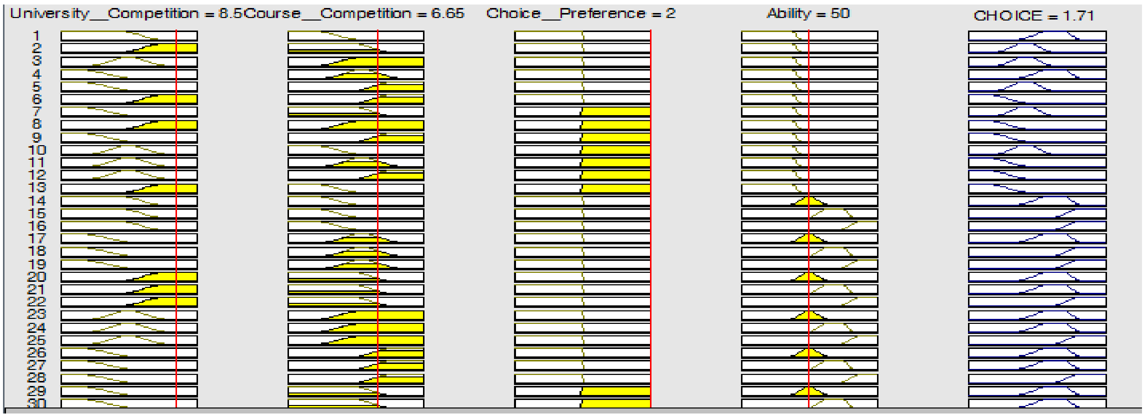

Fig 9a. Competitive course in a highly competitive university as 2nd choice by an average student

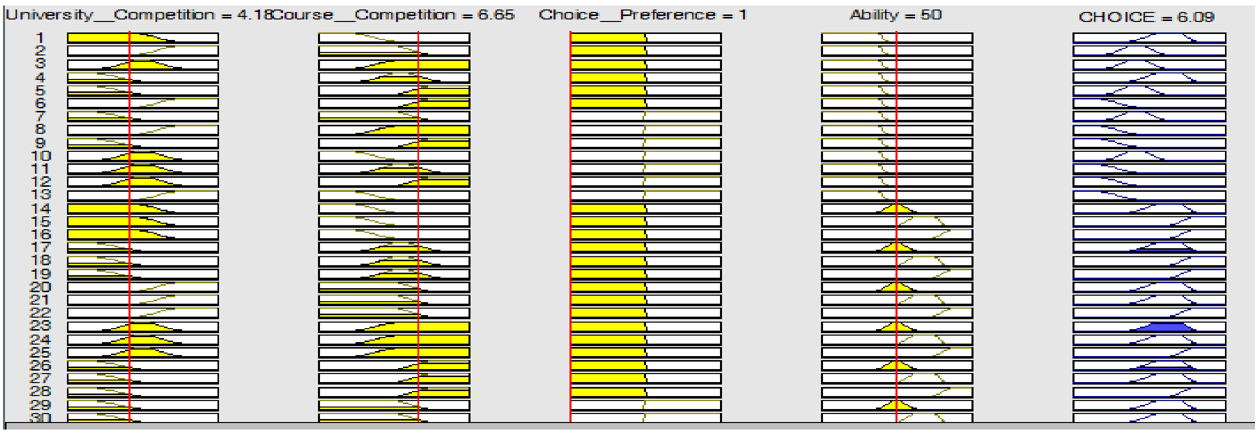

Fig 9b Competitive course in a non competitive university as 1st choice by an average student

4. CONCLUSION

The model result conforms to the expectations and intuitions that characterises the course choice system. The chance of a candidate improves with decreasing degree of competition especially at course competition and choice preference levels. It is also seen that 2nd choice preference is only advisable and viable for universities and courses with low competition. That the ability of the student is the dominant factor is seen from the surface plots and sample results. The model thus provides an easy to use tool for assessing the viability of a choice or advising on the level of efforts required to meet the competition associated with a choice. It is concluded that the Mamdani based Fuzzy Inference System will be a veritable tool for the university admission choice problem.

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