ANNALS OF COMMUNICATIONS IN MATHEMATICS
Volume 1, Number 1 (2018), 38-47
ISSN: 2582-0818

AN OBJECT ORIENTED APPROACH TO THE APPLICATION OF INTUITIONISTIC FUZZY SETS IN COMPETENCY BASED TEST EVALUATION

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ABSTRACT. The theory of intuitionistic fuzzy sets (IFS) is a viable tool in decision science, robotics and control, medical imaging, among others. From the applications of IFS, it is proven that the concept of IFS is useful in providing a reliable and efficient framework or model to tackle uncertainty and vagueness embedded in decision making. In this paper, we explore the resourcefulness of IFS in competency based test evaluation (CBTE) for course selection into higher institution. We employ distance and similarity measures for IFS to achieve the test through a BESPOKE program developed using an object oriented programming language, JAVA to be specific. Using the output of the program in terms of distance and similarity between applicants and courses in intuitionistic fuzzy sense, we determine applicants suitable courses.

1. INTRODUCTION

The notion of intuitionistic fuzzy sets (IFS) proposed and studied in [1, 2, 3, 4, 6, 7] is a generalization of fuzzy sets with an additional degree of freedom called non-membership degree, when compared to fuzzy sets [26], which are fully described by the degree of membership only. In an IFS, the value of membership plus the value of non-membership for an element does not necessarily make one because of the possibility of hesitation. The additional degree of freedom means inherent possibility to model and process more adequately and more human consistently imprecise information, and makes the concept of IFS a useful tool in decision making [24].

The ability of expressing imprecise information leads to a construction of more reliable models. The use of these models is connected with processing of imprecise information via different measures. The measures of distance and similarity are the basic tools in applying IFS to decision making. See [16, 18, 23, 24] for details on distance measures and similarity measures, respectively.

The concept of IFS seems to be a comprehensive tool for handling many aspects of imprecise information and as such, attracts much attention due to its significant in tackling

2010 *Mathematics Subject Classification.* 20N20, 03E72, 47S40.
Key words and phrases. Competency based test evaluation; Distance measure; Fuzzy sets; Intuitionistic fuzzy sets; Object oriented programming language; Similarity measure.
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vagueness or the representation of imperfect knowledge in decision making. Many applications of IFS have been proposed and researched since inception in areas of medical diagnosis, medical imaging, career determination, appointment procedure, pattern recognition, supplier evaluation, etc. as seen in [5, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 21, 22, 25].

In this paper, we explicate an application of IFS in CBTE for the purpose of course selection in a situation where the number of applicants is more than the available slots using the most accurate measure of the measures discussed in [23, 24] through a BESPOKE program developed using an object oriented programming language (JAVA). The output of the program in terms of distance and similarity between applicants and courses, determines a suitable course selections.

The paper is organized thus. In Section 2, we recall some basic concepts of IFS while Section 3 discusses some selected distance and similarity measures between IFS together with a reliability analysis of the measures. In Section 4, we explore the advantage of IFS in CBTE using a JAVA programming language that utilizes the most accurate distance and similarity measures for the sake of efficiency.

2. PRELIMINARIES

We recall some basic notions of IFS (cf. [1, 2, 3, 4, 6, 26]).

Definition 2.1. Let X be a nonempty set. A fuzzy set A of X is characterized by a membership function

$$\mu_A : X \to [0, 1].$$

That is,

$$\mu_A(x) = \begin{cases} 1, & \text{if } x \in X \\ 0, & \text{if } x \notin X \\ (0,1) & \text{if } x \text{ is partly in } X \end{cases}$$

Alternatively, a fuzzy set A of X is an object having the form

$$A = \{\langle x, \mu_A(x)\rangle \mid x \in X\}$$

or

$$A = \{\langle \frac{\mu_A(x)}{x} \rangle \mid x \in X\},$$

where the function

$$\mu_A(x) : X \to [0, 1]$$

defines the degree of membership of the element $x \in X$.

Definition 2.2. Let a nonempty set X be fixed. An IFS A of X is an object having the form

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle \mid x \in X\}$$

or

$$A = \{\langle \frac{\mu_A(x), \nu_A(x)}{x} \rangle \mid x \in X\},$$

where the functions

$$\mu_A(x) : X \to [0, 1] \text{ and } \nu_A(x) : X \to [0, 1]$$

define the degree of membership and the degree of non-membership, respectively of the element $x \in X$ to A, which is a subset of X, and for every $x \in X$,

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1.$$

For each A in X,

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$$

is the intuitionistic fuzzy set index or hesitation margin of x in X. The hesitation margin $\pi_A(x)$ is the degree of non-determinacy of $x \in X$, to the set A and $\pi_A(x) \in [0,1]$. The hesitation margin is the function that expresses lack of knowledge of whether $x \in X$ or $x \notin X$. Thus,

$$\mu_A(x) + \nu_A(x) + \pi_A(x) = 1.$$

We denote the set of all intuitionistic fuzzy sets over X as $IFS(X)$.

Example 2.3. Let $X = \{1, 2, 3\}$ be a fixed universe of discourse and

$$A = \{\langle 1, 0.6, 0.1\rangle, \langle 2, 0.8, 0.1\rangle, \langle 3, 0.5, 0.3\rangle\}$$

be the intuitionistic fuzzy set of X.

The hesitation margins of the elements $1, 2, 3$ to A are

$$\pi_A(1) = 0.3,\ \pi_A(2) = 0.1 \text{ and } \pi_A(3) = 0.2$$

Definition 2.4. Let $A, B \in IFS(X)$. Then, the following operations hold.

(i) Inclusion

$$A \subseteq B \Leftrightarrow \mu_A(x) \leq \mu_B(x) \text{ and } \nu_A(x) \geq \nu_B(x) \forall x \in X.$$

(ii) Equality

$$A = B \Leftrightarrow \mu_A(x) = \mu_B(x) \text{ and } \nu_A(x) = \nu_B(x) \forall x \in X.$$

(iii) Complement

$$A^c = \{\langle x, \nu_A(x), \mu_A(x)\rangle \mid x \in X\}$$

(iv) Union

$$A \cup B = \{\langle x, max[\mu_A(x), \mu_B(x)], min[\nu_A(x), \nu_B(x)]\rangle \mid x \in X\}$$

(v) Intersection

$$A \cap B = \{\langle x, min[\mu_A(x), \mu_B(x)], max[\nu_A(x), \nu_B(x)]\rangle \mid x \in X\}$$

(vi) Addition

$$A \oplus B = \{\langle x, \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x), \nu_A(x)\nu_B(x)\rangle \mid x \in X\}$$

(vii) Multiplication

$$A \otimes B = \{\langle x, \mu_A(x)\mu_B(x), \nu_A(x) + \nu_B(x) - \nu_A(x)\nu_B(x)\rangle \mid x \in X\}$$

Example 2.5. Let $X = \{1, 2, 3\}$ be a fixed universe of discourse. Then

$$A = \{\langle 1, 0.6, 0.1\rangle, \langle 2, 0.8, 0.1\rangle, \langle 3, 0.5, 0.3\rangle\}$$

and

$$B = \{\langle 1, 0.8, 0.1\rangle, \langle 2, 0.4, 0.3\rangle, \langle 3, 0.75, 0.1\rangle\}$$

be the intuitionistic fuzzy sets of X.

Clearly, $A \nsubseteq B$ and $B \nsubseteq A$. Also, $A \neq B$.

$$A^c = \{\langle 1, 0.1, 0.6\rangle, \langle 2, 0.1, 0.8\rangle, \langle 3, 0.3, 0.5\rangle\},$$
$$B^c = \{\langle 1, 0.1, 0.8\rangle, \langle 2, 0.3, 0.4\rangle, \langle 3, 0.1, 0.75\rangle\},$$
$$A \cup B = \{\langle 1, 0.8, 0.1\rangle, \langle 2, 0.8, 0.1\rangle, \langle 3, 0.75, 0.1\rangle\},$$
$$A \cap B = \{\langle 1, 0.6, 0.1\rangle, \langle 2, 0.4, 0.3\rangle, \langle 3, 0.5, 0.3\rangle\},$$
$$A \oplus B = \{\langle 1, 0.92, 0.01\rangle, \langle 2, 0.88, 0.03\rangle, \langle 3, 0.875, 0.03\rangle\}$$

and

$$A \otimes B = \{\langle 1, 0.48, 0.19\rangle, \langle 2, 0.32, 0.37\rangle, \langle 3, 0.375, 0.37\rangle\}$$

3. Distance and similarity measures between IFSs

In this section, we consider some distance and similarity measures between IFSs studied in [19, 20, 23, 24]. Distance measure is a term that describes the difference between intuitionistic fuzzy sets and can be considered as a dual concept of similarity measure.

Definition 3.1. Let X be nonempty set and $A, B, C \in IFS(X)$. The distance measure d between A and B is a function

$$d : IFS \times IFS \to [0, 1]$$

satisfies

(i) $0 \leq d(A, B) \leq 1$ (boundedness)
(ii) $d(A, B) = 0$ iff $A = B$ (separability)
(iii) $d(A, B) = d(B, A)$ (symmetric)
(iv) $d(A, C) + d(B, C) \geq d(A, B)$ (triangle inequality)
(v) if $A \subseteq B \subseteq C$, then $d(A, C) \geq d(A, B)$ and $d(A, C) \geq d(B, C)$.

Definition 3.2. Let X be nonempty set and $A, B, C \in IFS(X)$. The similarity measure s between A and B is a function

$$s : IFS \times IFS \to [0, 1]$$

satisfies

(i) $0 \leq s(A, B) \leq 1$ (boundedness)
(ii) $s(A, B) = 1$ iff $A = B$ (separability)
(iii) $s(A, B) = s(B, A)$ (symmetric)
(iv) $s(A, C) + s(B, C) \geq s(A, B)$ (triangle inequality)
(v) if $A \subseteq B \subseteq C$, then $s(A, C) \leq s(A, B)$ and $s(A, C) \leq s(B, C)$.

Remark. It follows that

(i) $d = 1 - s$
(ii) $d(A, B) = d(A^c, B^c)$
(iii) $s(A, B) = s(A^c, B^c)$.

We make use of some measures proposed in [20, 23, 24] between IFSs, which were partly based on the geometric interpretation of IFS, and have some good geometric properties.

Let

$$A = \{\langle x, \mu_A(x_i), \nu_A(x_i), \pi_A(x_i)\rangle \mid x \in X\}$$

and

$$B = \{\langle x, \mu_B(x_i), \nu_B(x_i), \pi_B(x_i)\rangle \mid x \in X\}$$

be two IFS in $X = \{x_1, ..., x_n\}$, for $i = 1, ..., n$. Then, the distance measures are:

Hamming distance;

$$\begin{aligned} d_H(A, B) &= \frac{1}{2}\Sigma_{i=1}^{n}(\mid \mu_A(x_i) - \mu_B(x_i) \mid + \mid \nu_A(x_i) - \nu_B(x_i) \mid \\ &+ \mid \pi_A(x_i) - \pi_B(x_i) \mid) \end{aligned}$$

Euclidean distance;

$$\begin{aligned} d_E(A, B) &= (\frac{1}{2}\Sigma_{i=1}^{n}[(\mu_A(x_i) - \mu_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2 \\ &+ (\pi_A(x_i) - \pi_B(x_i))^2])^{\frac{1}{2}} \end{aligned}$$

normalized Hamming distance;

$$d_{n-H}(A,B) = \frac{d_H(A,B)}{n} \Rightarrow$$

$$\begin{aligned} d_{n-H}(A,B) &= \frac{1}{2n}\Sigma_{i=1}^{n}(\mid \mu_A(x_i) - \mu_B(x_i) \mid + \mid \nu_A(x_i) - \nu_B(x_i) \mid \\ &+ \mid \pi_A(x_i) - \pi_B(x_i) \mid) \end{aligned}$$

normalized Euclidean distance;

$$d_{n-E}(A,B) = \frac{d_E(A,B)}{\sqrt{n}} \Rightarrow$$

$$\begin{aligned} d_{n-E}(A,B) &= (\frac{1}{2n}\Sigma_{i=1}^{n}[(\mu_A(x_i) - \mu_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2 \\ &+ (\pi_A(x_i) - \pi_B(x_i))^2])^{\frac{1}{2}} \end{aligned}$$

Similarly, the following are the similarity measures of the aforementioned distance measures:

Hamming similarity;

$$\begin{aligned} s_H(A,B) &= 1 - \frac{1}{2}\Sigma_{i=1}^{n}(\mid \mu_A(x_i) - \mu_B(x_i) \mid + \mid \nu_A(x_i) - \nu_B(x_i) \mid \\ &+ \mid \pi_A(x_i) - \pi_B(x_i) \mid) \end{aligned}$$

Euclidean similarity;

$$\begin{aligned} s_E(A,B) &= 1 - (\frac{1}{2}\Sigma_{i=1}^{n}[(\mu_A(x_i) - \mu_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2 \\ &+ (\pi_A(x_i) - \pi_B(x_i))^2])^{\frac{1}{2}} \end{aligned}$$

normalized Hamming similarity;

$$\begin{aligned} s_{n-H}(A,B) &= 1 - \frac{1}{2n}\Sigma_{i=1}^{n}(\mid \mu_A(x_i) - \mu_B(x_i) \mid + \mid \nu_A(x_i) - \nu_B(x_i) \mid \\ &+ \mid \pi_A(x_i) - \pi_B(x_i) \mid) \end{aligned}$$

normalized Euclidean similarity;

$$\begin{aligned} s_{n-E}(A,B) &= 1 - (\frac{1}{2n}\Sigma_{i=1}^{n}[(\mu_A(x_i) - \mu_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2 \\ &+ (\pi_A(x_i) - \pi_B(x_i))^2])^{\frac{1}{2}} \end{aligned}$$

Now, we verify each of the distance and similarity measures with the aid of an example to ascertain the most accurate. The distance measure with the smallest value shows an accurate distance. Also, the greatest value of the similarity measure indicates the most reliable similarity.

Example 3.3. Let $X = \{x, y, z\}$ be a fixed universe of discourse. Then

$$A = \{\langle x, 0.6, 0.2, 0.2\rangle, \langle y, 0.8, 0.1, 0.1\rangle, \langle z, 0.5, 0.3, 0.2\rangle\}$$

and

$$B = \{\langle x, 0.8, 0.2, 0.0\rangle, \langle y, 0.7, 0.2, 0.1\rangle, \langle z, 0.9, 0.1, 0.0\rangle\}$$

be the intuitionistic fuzzy sets of X.

Now, using the distance measures above for $i = 1, 2, 3$, we have

$$\begin{aligned} d_H(A,B) &= \frac{1}{2}(|0.6-0.8| + |0.2-0.2| + |0.2-0.0| + |0.8-0.7| \\ &+ |0.1-0.2| + |0.1-0.1| + |0.5-0.9| + |0.3-0.1| + |0.2-0.0|) \\ &= \frac{1}{2}(1.4) \\ &= 0.7000 \end{aligned}$$

$$\begin{aligned} d_E(A,B) &= (\frac{1}{2}[(0.6-0.8)^2 + (0.2-0.2)^2 + (0.2-0.0)^2 + (0.8-0.7)^2 \\ &+ (0.1-0.2)^2 + (0.1-0.1)^2 + (0.5-0.9)^2 + (0.3-0.1)^2 + (0.2-0.0)^2])^{1/2} \\ &= \sqrt{\frac{1}{2}(0.34)} \\ &= 0.4123 \end{aligned}$$

$$\begin{aligned} d_{n-H}(A,B) &= \frac{1}{6}(1.4) \\ &= 0.2333 \end{aligned}$$

$$\begin{aligned} d_{n-E}(A,B) &= \sqrt{\frac{1}{6}(0.34)} \\ &= 0.2380 \end{aligned}$$

The normalized Hamming distance yields the smallest distance between A and B. Hence, the most accurate.

Similarly, from the similarity measures above, we get

$$s_H(A,B) = 0.3000,\ s_E(A,B) = 0.5877,\ s_{n-H}(A,B) = 0.7667,\ s_{n-E}(A,B) = 0.7620$$

The normalized Hamming similarity gives the greatest similarity between A and B. Thus, the most reliable. Since both normalized Hamming distance and normalized Hamming similarity are the most reliable and accurate, we use both as the computational measures embedded to the program owing to their accuracy.

4. Intuitionistic fuzzy sets in CBTE using JAVA programming language

Competency based test evaluation (CBTE) is a viable tool in course selection into higher institutions. This is essential because many applicants are vying to study some courses with a limited slots. Placing an applicant with a requisite academic qualification to study a course enhances academic success. Many factors such as academic qualification, interest, personality make-up, etc. are indispensable in course selection. However, academic qualification is the only measureable factor as seem across the globe.

In this section, we propose the application of IFS in CBTE via object oriented approach to curb the embedded imprecisions in course selection. In carry out the application, we assume that a set of applicants sit for a competency based test free from malpratice to ascertain how suitable they are to study their proposed courses. We use IFS as tool since it incorporates the membership degree (i.e. the applicant score), the non-membership degree (i.e. the marks of the questions the student failed) and the hesitation degree (which is the mark allocated to the questions the student do not attempt).

4.1. **Case study.** Let $A = \{A_1, A_2, A_3, A_4, A_5\}$ be the set of applicants for course selections,

$$C = \{\text{medicine, pharmacy, surgery, anatomy, physiology}\}$$

be the set of courses the applicants are vying for, and

$$S = \{\text{English Language, Mathematics, Biology, Physics, Chemistry, Health Science}\}$$

be the set of subjects related to the set of courses.

Table 1 is a quasi-real database for courses and the related subjects' require performance for course selections over 100%.

	English	Maths	Biology	Physics	Chemistry	Health Sci
medicine	(0.8,0.1,0.1)	(0.7,0.2,0.1)	(0.9,0.1,0.0)	(0.6,0.3,0.1)	(0.8,0.2,0.0)	(0.8, 0.1,0.1)
pharmacy	(0.9,0.1,0.0)	(0.8,0.1,0.1)	(0.8,0.2,0.0)	(0.5,0.2,0.3)	(0.7,0.2,0.1)	(0.8, 0.2,0.0)
surgery	(0.5,0.3,0.2)	(0.5,0.2,0.3)	(0.9,0.1,0.0)	(0.5,0.4,0.1)	(0.7,0.1,0.2)	(0.8, 0.1,0.1)
anatomy	(0.7,0.2,0.1)	(0.5,0.4,0.1)	(0.8,0.1,0.1)	(0.6,0.3,0.1)	(0.8,0.2,0.0)	(0.9, 0.1,0.0)
physiology	(0.8,0.1,0.1)	(0.5,0.3,0.2)	(0.9,0.1,0.0)	(0.6,0.2,0.2)	(0.7,0.2,0.1)	(0.8, 0.1,0.1)

Table 1

Each score is described by three entries comprise of membership value, non-membership value and hesitation margin value.

The applicants $A = \{A_1, A_2, A_3, A_4, A_5\}$ sat for a competency based test in the aforesaid subjects and obtained the following marks over 100% as shown in Table 2.

	English	Maths	Biology	Physics	Chemistry	Health Sci
A_1	(0.6,0.3,0.1)	(0.5,0.4,0.1)	(0.6,0.2,0.2)	(0.5,0.3,0.2)	(0.5,0.5,0.0)	(0.6,0.2,0.2)
A_2	(0.5,0.3,0.2)	(0.6,0.2,0.2)	(0.5,0.3,0.2)	(0.4,0.5,0.1)	(0.7,0.2,0.1)	(0.7,0.1,0.2)
A_3	(0.7,0.1,0.2)	(0.6,0.3,0.1)	(0.7,0.1,0.2)	(0.5,0.4,0.1)	(0.4,0.5,0.1)	(0.6,0.3,0.1)
A_4	(0.6,0.4,0.0)	(0.8,0.1,0.1)	(0.6,0.1,0.3)	(0.6,0.3,0.1)	(0.5,0.3,0.2)	(0.7,0.2,0.1)
A_5	(0.8,0.1,0.1)	(0.7,0.1,0.2)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.6,0.1,0.3)	(0.8, 0.1,0.1)

Table 2

The scores in both Table 1 and Table 2 are marks obtained out of 100% in intuitionistic fuzzy values of the set

$$S = \{\text{English Language, Mathematics, Biology, Physics, Chemistry, Health Science}\}.$$

4.2. **Algorithm for calculating distance and similarity measures between applicants and courses.** We present algorithm of normalized Hamming distance and normalized Hamming similarity.

$$S = \{\text{English Language, Mathematics, Biology, Physics, Chemistry, Health Science}\}$$

is the set of subjects under consideration. Recall

$$d_{n-H}(A, C) = \frac{1}{2n}\Sigma_{i=1}^{n}(\mid \mu_A(s_i) - \mu_C(s_i) \mid + \mid \nu_A(s_i) - \nu_C(s_i) \mid + \mid \pi_A(s_i) - \pi_C(s_i) \mid)$$

and

$$s_{n-H}(A, C) = \frac{2n - \Sigma_{i=1}^{n}(\mid \mu_A(s_i) - \mu_C(s_i) \mid + \mid \nu_A(s_i) - \nu_C(s_i) \mid + \mid \pi_A(s_i) - \pi_C(s_i) \mid)}{2n}$$

are the normalized Hamming distance and normalized Hamming similarity measures between

$$A = \{A_1, A_2, A_3, A_4, A_5\}$$

and

$$C = \{\text{medicine, pharmacy, surgery, anatomy, physiology}\},$$

where $i = 1, ..., 6$.

4.2.1. *Algorithm for calculating normalized Hamming distance and normalized Hamming similarity between applicants and courses.* Precondition: ac, cs, as are object references to a collection of applicant course, course subject and applicant subject entities.

Postcondition: the algorithm on steps 1-13 compute the normalized Hamming distance and normalized Hamming similarity, respectively.

1: retrieve a collection of applicant course record as ac and course subject record as cs
2: repeat steps 3-6 while (as! =null and as.isEmpty())
3: repeat steps 4 and 5 while (cs! =null && !cs.isEmpty())
4: for each as and cs compute normalized Hamming distance as
$$\frac{1}{2n}\Sigma_{i=1}^{n}(\mid \mu_A(s_i)-\mu_C(s_i)\mid + \mid \nu_A(s_i)-\nu_C(s_i)\mid + \mid \pi_A(s_i)-\pi_C(s_i)\mid)$$
5: persist applicant courses database with computed normalized Hamming distance
6: end while
7: end while
8: repeat steps 9-12 while (as! =null and as.isEmpty())
9: repeat steps 10 and 11 while (cs! =null && !cs.isEmpty())
10: for each as and cs compute normalized Hamming similarity as
$$\frac{2n-\Sigma_{i=1}^{n}(\mid \mu_A(s_i)-\mu_C(s_i)\mid + \mid \nu_A(s_i)-\nu_C(s_i)\mid + \mid \pi_A(s_i)-\pi_C(s_i)\mid)}{2n}$$
11: persist applicant courses database with computed normalized Hamming similarity
12: end while
13: end while
14: exit

4.3. **Results and decision.** Using the algorithm above via JAVA programming language, the following results are obtained. The choice of JAVA is because of its portability, architecture neurality, robustness, security raptness and multi-threaded nature.

	medicine	pharmacy	surgery	anatomy	physiology
A_1	0.2167	0.2333	0.2167	0.1667	0.2000
A_2	0.2000	0.2333	0.1333	0.2000	0.2000
A_3	0.1833	0.2167	0.2000	0.1833	0.1833
A_4	0.1833	0.1833	0.2000	0.2000	0.2167
A_5	0.1333	0.1500	0.1667	0.2000	0.1333

Table 3

	medicine	pharmacy	surgery	anatomy	physiology
A_1	0.7833	0.7667	0.7833	0.8333	0.8000
A_2	0.8000	0.7667	0.8667	0.8000	0.8000
A_3	0.8167	0.7833	0.8000	0.8167	0.8167
A_4	0.8167	0.8167	0.8000	0.8000	0.7833
A_5	0.8667	0.8500	0.8333	0.8000	0.8667

Table 4

Table 3 is gotten using steps 1-7 while Table 4 is gotten using steps 1, 8-13. In Table 3, the smallest value gives the CBTE of the applicants. Also, the greatest value provides the CBTE of the applicants in Table 4.

From both Table 3 and Table 4, A_1 is suitable for anatomy, A_2 is suitable for surgery, A_3 is suitable for medicine, anatomy and physiology, A_4 is suitable for both medicine and pharmacy, and A_5 is suitable for both medicine and physiology.

We observe that A_3, A_4 and A_5 have the leeway to choice based on their personal interest from the courses they are suitable for.

5. Conclusions

We have proposed an application of IFS in CBTE via object oriented approach embedded with normalized Hamming distance and normalized Hamming similarity. We conclude that IFS theory is a decisive tool use in critical decision making problems like this. It is observed that without IFS, this exercise would have been compromised with a consequent effect on the applicants. The object oriented approach disscussed in the work could be extended to other measures for easily application to multi-criteria decision making problems in future research.

6. Acknowledgements

The authors are thankful to the Editor-in-Chief, Prof. G. Muhiuddin for the technical comments and to the anonymous reviewers for their relevant suggestions.

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