Career Determination using Information Theoretical Measure and It's Comparison with Distances in IFS and PFS

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***Abstract*—** In this paper, we have proposed a method to help students of High School to choose a career having multiple options available after High School. It is based on the student's marks and their Teacher's perception of their own marks using generalized intuitionistic fuzzy divergence measure. The method is also compared with distance measure using intuitionistic fuzzy sets (IFS) and pythagorean fuzzy sets (PFS). Tables are drawn using the results based on the feedback collected from the student's perception and their teacher's perception about their High School result and compared with the table of membership and non-membership values required in each subject versus career written arbitrarily.

***Keywords*—** Aggregator operator; Intuitionistic Fuzzy sets; Career determination; Distance in Pythagorean Fuzzy sets.

I. Introduction

THE classical theory of sets is based on the concept that the elements either are included or excluded from the set, i.e., based upon whether they follow the rule or they do not. But in day-to-day life that is not the case; elements may belong to a set to a certain degree. There may also be vagueness in the definition of the rule. Zadeh, in 1965 [1], extended the concept of crisp set theory to that of fuzzy set theory wherein elements have a degree of membership or inclusiveness and non-membership, i.e. non-inclusiveness, whose sum is equal to 1. This degree of inclusiveness and non-inclusiveness ranges from 0 to 1. Fuzzy sets with membership value 1 or 0 can be considered as crisp sets. Thus, fuzzy set is a generalization of classical sets. There is a wide range of applications of fuzzy set theory such as multi-criteria decision making, image processing, pattern recognition, traffic monitoring system, etc.

This concept was extended by Atanassov in 1986 [2] to intuitionistic fuzzy sets (IFS) to overcome the difficulties faced by Zadeh's fuzzy set theory. It takes into account hesitancy which is missing in fuzzy set theory. He demonstrated with an example where it is shown that in some situations IFS can be applied and fuzzy sets concept cannot be applied [3]. In A-IFS (Atanassov-Intuitionistic fuzzy sets), there are membership and non-membership values assigned to each element of the set. Hesitancy value is given by subtracting the sum of membership and non-membership values from 1. As the name suggests, membership value represents the degree of inclusiveness, non-membership value represents the degree of exclusiveness and hesitancy value represents the uncertainty of inclusiveness or exclusiveness. As crisp sets are a part of fuzzy sets, fuzzy sets are a part of intuitionistic fuzzy sets. A-IFS is applied wherever FS can be applied and, in some situations, it improves the results due to the introduction of hesitancy value such as multi-criteria decision making, medical decision support system, psychological analysis, etc.[4-8]. The concept of distances in intuitionistic fuzzy sets was defined by Szmidt et al. [9-10]. The new definitions of distances introduced in the early 20th century are compared with already available distances in fuzzy sets. In fuzzy sets, distances are defined using membership and non-membership values, whereas, in A-IFS, the hesitancy values are also included. A distance measure between two Intuitionistic fuzzy sets was defined by Hatzimichailidis et al. [11] in 2012. It is a generalization of the previous distances proposed and the author has shown an application of it in pattern recognition. The results obtained are accurate from the already known distances and has shown a high degree of confidence.

Aggregation operators were developed to conjugate two sets, as the use of max and min operators caused the loss of data, hence filled the gap in real data and aggregated data. It was first introduced in 1985 by Dubois and Prade [12] where they have defined arithmetic mean and geometric mean for fuzzy sets. Zu [13] in 2007 has extended the concept of aggregation operator and defined Intuitionistic Fuzzy Hybrid Averaging (IFHA) Operator. Yager [14] extended the concept of weighted aggregation operators to ordered weighted operators (OWA), where the membership values of the elements of the fuzzy set are ordered in descending order. Since then many more aggregation operators have been developed. These operators are widely used in the field of data mining, multi-criteria decision making, sensor fusion etc. Verma et al. [15] have proposed a new divergence measure which provides flexibility in multi-criteria decision

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making.

In fuzzy and intuitionistic fuzzy sets, the sum of the membership and non-membership should be less than or equal to one. Yager et al. [16] introduced an extension of IFS, i.e. Pythagorean fuzzy set, where the membership values and the non-membership values are pythagorean complement of each other with respect to the strength of commitment. The sum of the squares of the membership values and the non-membership values are less than the square of the strength of commitment. This squaring causes the domain of the fuzzy sets to increase. Various applications were shown by researchers and a lot of papers were published [17-22]. Some results were proposed on Pythagorean fuzzy sets by Peng et al. [23] in 2017. The aggregation operator [24] and distances [25] on PFS were defined and it has been used to combine the data in the form of PFS.

In this paper, IFS and PFS concept is used to draw the conclusion of the career based on the students and teachers perception of the subjects chosen by the students. A questionnaire response from the candidate and teacher's is used to convert the data into intuitionistic fuzzy values. The aggregator operator and generalized intuitionistic fuzzy divergence measure are used to analyze the result obtained. The results of the IFS and PFS are compared and shown in the form of a table.

II. Basic Definitions

In this section, we will define some basic definitions related to fuzzy, intuitionistic fuzzy and pythagorean fuzzy sets. We will list the distances and aggregation operators for fuzzy, intuitionistic fuzzy and pythagorean fuzzy sets. Further, the generalized intuitionistic fuzzy divergence measure will be used in this research paper for calculating divergence between two intuitionistic fuzzy set matrices. Its results will be compared with the distance measure in intuitionistic fuzzy sets and pythagorean fuzzy sets.

Definition 1 (Fuzzy Sets) [1]: Let us consider a non-empty set *X*. A fuzzy set *A* defined on the elements of the set *X* having the membership value $\mu_A(x)$, defined as $A = \{< x, \mu_A(x) >: x \in X, \mu_A(x) \in [0,1]\}$.

Definition 2 (Intuitionistic Fuzzy Sets) [2]: Let us consider a non-empty set *X*. An intuitionistic fuzzy set *A* defined on the elements of the set *X* having the membership value $\mu_A(x)$ and non-membership value $v_A(x)$, defined as $A = \{ < x, \mu_A(x), v_A(x) >: x \in X\}$, where $\mu_A(x) + v_A(x)$ lies in the interval [0,1].

Furthermore, we have $\pi_A(x) = 1 - (\mu_A(x) + v_A(x))$ called the hesitancy margin of x in *A*.

Definition 3 (Pythagorean Fuzzy Sets) [23]:

Let X be a universe of discourse, a pythagorean fuzzy set is given by

$$P = \{< x, \mu_p(x), v_p(x) >: x \in X\}$$

where $\mu_p : X \to [0,1]$ denotes the degree of membership of an element x and $v_p : X \to [0,1]$ denotes the degree of non-membership of the element x, where the element $x \in X$ to the set P, respectively with condition that $0 \leq \mu_p(x)^2 + v_p(x)^2 \leq 1$. The degree of hesitancy $\pi_p(x) = \sqrt{1 - (\mu_p(x)^2 + v_p(x)^2)}$.

Definition 4 (Distances for FS) [9]: The most widely used distance measures for fuzzy sets *A*, *B* in $X = \{x_1, x_2, ..., x_n\}$ are

- The Hamming distance, $d(A,B)$

$$d(A,B) = \sum_{i=1}^{n} |\mu_A(x_i) - \mu_B(x_i)|$$

- The normalized Hamming distance, $l(A,B)$

$$l(A,B) = \frac{1}{n}\sum_{i=1}^{n} |\mu_A(x_i) - \mu_B(x_i)|$$

- The Euclidian Distance,

$$e(A,B) = \sqrt{\sum_{i=1}^{n} (\mu_A(x_i) - \mu_B(x_i))^2}$$

- The normalized Euclidian distance, $q(A,B)$

$$q(A,B) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\mu_A(x_i) - \mu_B(x_i))^2}$$

Szmidt and Kacprzyk [9] extended the concept of distances defined in fuzzy sets to intuitionistic fuzzy sets, in which the hesitancy factor is also considered which is missing in the distances defined for fuzzy sets.

Definition 5 (Distances for IFS) [9]: Szmidt and Kacprzyk defined the widely used distances for two intuitionistic fuzzy sets, A and B, for all elements x of a non-empty set X as per following:

- Hamming distance

$$d_{IFS}(A,B) = \frac{1}{2}\sum_{i=1}^{n} \begin{pmatrix} |\mu_A(x) - \mu_B(x)| \\ + |v_A(x) - v_B(x)| + |\pi_A(x) - \pi_B(x)| \end{pmatrix}$$

- Normalized Hamming distance

$$q_{IFS}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}\begin{pmatrix}|\mu_A(x)-\mu_B(x)|+|\nu_A(x)-\nu_B(x)|\\+|\pi_A(x)-\pi_B(x)|\end{pmatrix}$$

- Euclidian distance

$$e_{IFS}(A,B)=\sqrt{\frac{1}{2}\sum_{i=1}^{n}\begin{pmatrix}(\mu_A(x)-\mu_B(x))^2\\+(\nu_A(x)-\nu_B(x))^2\\+(\pi_A(x)-\pi_B(x))^2\end{pmatrix}}$$

- Normalized Euclidian distance

$$l_{IFS}(A,B)=\sqrt{\frac{1}{2n}\sum_{i=1}^{n}\begin{pmatrix}(\mu_A(x)-\mu_B(x))^2\\+(\nu_A(x)-\nu_B(x))^2\\+(\pi_A(x)-\pi_B(x))^2\end{pmatrix}}$$

Definition 6 (Distances in Pythagorean Fuzzy Sets) [21]:

The following distance measure defined by Zhang and Xu between two PFS p_1 and p_2 is:

The distance between p_1 and p_2 is as follows:

$$D(p_1,p_2)=\frac{1}{2}\begin{pmatrix}\left|(\mu_{p_1})^2-(\mu_{p_{21}})^2\right|\\+\left|(\nu_{p_1})^2-(\nu_{p_2})^2\right|\\+\left|((\pi_{p_1})^2-(\pi_{p_2})^2\right|\end{pmatrix}$$

In this paper, we have also used aggregation operator to combine results obtained from the student point of view and of their Teacher's perception. Aggregation operators are defined for both fuzzy sets and Intuitionistic fuzzy sets.

Definition 7 (Intuitionistic Fuzzy Aggregation Operator [IFWA]) [13]:

Let $a_j=\left[t_{a_j},1-f_{a_j}\right],(j=1,2,...,n)$, be a collection of intuitionistic fuzzy values; then their aggregated value by using the IFWA is defined as

$$IFWA_w(a_1,a_2,...,a_n)=\left[1-\prod_{j=1}^{n}\left(1-t_{a_j}\right)^{w_j},1-\prod_{j=1}^{n}\left(f_{a_j}\right)^{w_j}\right]$$

, where $w=(w_1,w_2,...,w_n)^T$ is the weight vector of $a_j,(j=1,2,...,n)$, with $w_j\in[0,1]$ and $\sum_{j=1}^{n}w_j=1$.

Definition 8 (Generalized Intuitionistic Fuzzy Divergence) [15]:

Let A and B are two intuitionistic fuzzy sets defined on $X=\{x_1,x_2,...,x_n\}$ having the membership values $\mu_A(x_i)$ and $\mu_B(x_i), i=1,2,...,n$, and non-membership values $\nu_A(x_i)$, $\nu_B(x_i), i=1,2,...,n$ respectively. The measure of generalized intuitionistic fuzzy divergence denoted by $D_\lambda(A|B)$ and defined between two IFS A and B as

$$D_\lambda(A|B)=\frac{1}{n}\sum_{i=1}^{n}\begin{bmatrix}\mu_A(x_i)log\frac{\mu_A(x_i)}{\lambda\mu_A(x_i)+(1-\lambda)\mu_B(x_i)}\\+\upsilon_A(x_i)log\frac{\upsilon_A(x_i)}{\lambda\upsilon_A(x_i)+(1-\lambda)\upsilon_B(x_i)}\\+\pi_A(x_i)log\frac{\pi_A(x_i)}{\lambda\pi_A(x_i)+(1-\lambda)\pi_B(x_i)}\end{bmatrix}$$

where $0\le\lambda\le1$.

Definition 9 (Symmetric Generalized Intuitionistic Fuzzy Divergence) [15]: The symmetric generalized Intuitionistic Fuzzy divergence measure between two IFS A and B is defined as

$$D_\lambda(A;B)=D_\lambda(A|B)+D_\lambda(B|A).$$

In our paper, we have used Generalized Intuitionistic Fuzzy divergence measure as it's a generalization of all the previous known measures and its simplicity and applicability in multi-criteria decision making that was shown in the paper.

Definition 10 (Pythagorean Fuzzy Weighted Geometric Aggregator) [24]:

Let a collection of Pythagorean Fuzzy Sets, denoted by p_i, be of the form $p_i=(\mu_i,\nu_i)$ having a weight vector $w=(w_1,w_2,...,w_n)^T$ with $\sum_{I=1}^{n}w_i=1$, then a Pythagorean fuzzy weighted geometric (PFWG) aggregation operator is a mapping PFWPA: $P^n\to P$, where

$$\text{PFWPA}(p_1,p_2,...,p_n)=\left(\sum_{I=1}^{n}w_i\mu_i^{\,2}\right)^{1/2}\left(\sum_{I=1}^{n}w_i\nu_i^{\,2}\right)^{1/2}$$

III. Career Determination After High School Using Fuzzy Divergence Measure

Many research scientists have used the concept of distances in fuzzy sets and Intuitionistic fuzzy sets in various fields such as in research questionnaire, career determination, selection of best student, student evaluation, etc. In this paper, we have formed a questionnaire and given to six different High School Students and their Teachers of different subjects. The response of the questionnaire is converted into Intuitionistic fuzzy values in a normalized way and is depicted in Tables I and II. The membership (μ) and non-membership (v) values are shown in Table I and II, whereas hesitancy index is calculated as $1-(\mu+v)$. Table III is formed by taking the aggregation values of both students and teachers perception. The hypothetical Table IV is created from the intuitionistic fuzzy values required in each subject versus career. Using the definitions 8 and 9, the generalized intuitionistic fuzzy divergence measure between students and careers are depicted in Table V. The least divergency measure in columns of Table V for careers against the students will give choice to the students to choose a proper career.

TABLE I
STUDENT PERCEPTION ABOUT HIGH SCHOOL RESULT

		Students											
		S1		**S2**		**S3**		**S4**		**S5**		**S6**	
		μ_1	ν_1	μ_2	ν_2	μ_3	ν_3	μ_4	ν_4	μ_5	ν_5	μ_6	ν_6
Subjects	**Maths**	.8	.1	.9	.05	.6	.3	.55	.3	.7	.2	.75	.15
	Physics	.8	.15	.8	.1	.6	.3	.5	.2	.7	.2	.8	.1
	Chemistry	.6	.2	.7	.2	.7	.1	.7	.2	.6	.2	.6	.3
	Biology	.5	.3	.6	.3	.8	.1	.7	.1	.5	.3	.5	.3
	Computer	.8	.1	.7	.2	.6	.2	.5	.2	.9	.05	.85	.1
	English	.7	.2	.6	.2	.7	.2	.8	.1	.7	.2	.7	.2

Table I is depicting the student's perception of his / her high school result. Here S1, S2, S3, S4, S5, and S6 are used for six different students. The membership and non-membership values are shown for all students. The hesitancy is calculated using $\pi_i(x)=1-(\mu_i(x)+v_i(x))$. Similarly Table II is drawn taking the perception of the teacher's for students of various subjects. The response is converted into IFS values in a normalized way.

TABLE II
TEACHER'S PERCEPTION ABOUT THE STUDENTS

		Students											
		S1		**S2**		**S3**		**S4**		**S5**			**S6**
		μ_1	ν_1	μ_2	ν_2	μ_3	ν_3	μ_4	ν_4	μ_5	ν_5	μ_6	ν_6
Subjects	**Maths**	.75	.15	.8	.15	.55	.25	.5	.2	.65	.3	.8	.1
	Physics	.8	.1	.75	.15	.7	.2	.6	.2	.65	.2	.85	.1
	Chemistry	.6	.2	.7	.2	.8	.15	.7	.2	.6	.1	.7	.2
	Biology	.55	.25	.6	.3	.8	.1	.75	.2	.6	.2	.6	.2
	Computer	.8	.1	.75	.2	.7	.2	.6	.2	.75	.2	.85	.1
	English	.7	.15	.65	.25	.7	.25	.7	.2	.6	.2	.7	.2

Table III values are calculated by taking the aggregation of students and teacher's perception of IFS values from Table I and II. Here equal weights are taken for both Tables I and II, that is $w_i=0.5$. Intuitionistic Fuzzy aggregation operator is used to aggregate two Tables, i.e. I and II, of concern.

TABLE III
AGGREGATION (IFWA) OF TABLE I AND TABLE II STUDENTS

		Students											
Subjects		S1		S2		S3		S4		S5		S6	
		μ_1	ν_1	μ_2	ν_2	μ_3	ν_3	μ_4	ν_4	μ_5	ν_5	μ_6	ν_6
	Maths	.78	.13	.86	.10	.58	.28	.53	.25	.68	.25	.78	.13
	Physics	.80	.13	.78	.13	.65	.25	.55	.20	.68	.20	.83	.10
	Chemistry	.60	.20	.70	.20	.76	.13	.70	.20	.60	.15	.65	.25
	Biology	.53	.28	.60	.30	.8	.10	.73	.15	.55	.25	.55	.25
	Computer	.80	.10	.73	.20	.65	.30	.55	.20	.84	.13	.85	.10
	English	.70	.18	.63	.23	.70	.23	.76	.15	.65	.20	.70	.20

TABLE IV
IFS VALUES REQUIRED IN EACH SUBJECT VERSUS CAREER

		Subjects											
Career		Maths		Physics		Chemistry		Biology		Computer		English	
		μ_1	ν_1	μ_2	ν_2	μ_3	ν_3	μ_4	ν_4	μ_5	ν_5	μ_6	ν_6
	Engineering	.8	.1	.8	.1	.6	.2	.5	.3	.8	.1	.7	.2
	Medical	.6	.2	.7	.2	.7	.2	.7	.2	.6	.2	.6	.2
	B.Sc. Biology	.5	.3	.6	.2	.7	.2	.7	.2	.5	.3	.7	.2
	B.Sc. Maths	.8	.1	.8	.1	.7	.2	.5	.3	.8	.1	.5	.3
	BCA	.7	.2	.6	.2	.5	.3	.5	.3	.8	.1	.5	.3

Table IV is constructed of IFS values in such a manner where more membership value is given depending on the choice of careers. The career in engineering requires a good background in Mathematics, Physics, and Computers. Similarly to choose a career in Medical, one should good in Biology, Physics, and Chemistry. Similarly, for other careers, fuzzy values are given corresponding to each subject of concern. Table V is constructed using the generalized intuitionistic fuzzy divergence measure [15]. It is seen that students S1 and S6 have less value of divergence in Engineering, S2 in B.Sc. Mathematics, S3 in Medical, S4 in B.Sc. Bio, S5 in BCA. Thus, it is concluded from Table V that for students S1 and S6 it is better to choose Engineering, S2 to choose B.Sc. Mathematics, S3 to choose Medical, S4 to choose B.Sc. Biology, S5 to choose BCA. So, finally, it is concluded from the table that the lesser divergence value will be a preferable choice of the students in choosing a career.

TABLE V
CAREERS AGAINST STUDENTS USING INTUITIONISTIC FUZZY DIVERGENCE MEASURE

		Students					
Career		S1	S2	S3	S4	S5	S6
	Engineering	0.00790	0.03765	0.11746	0.13498	0.04414	0.01735
	Medical	0.22447	0.07087	0.03664	0.03784	0.09085	0.08724
	BSc. Biology	0.39908	0.12438	0.05969	0.02095	0.13003	0.16150
	BSc. Mathematics	0.06868	0.03229	0.13134	0.06725	0.06725	0.02791
	BCA	0.06567	0.07717	0.12954	0.12359	0.04296	0.07140

In table V, Hamming distance for Intuitionistic fuzzy set, proposed by Szmidt and Kacprzyk [10] is used to showcase the dissimilarity between the students' fuzzy values and the standard fuzzy set

TABLE VI
CAREERS AGAINST STUDENTS USING HAMMING DISTANCE FOR IFS

		Students					
Career		S1	S2	S3	S4	S5	S6
	Engineering	0.01683	0.07658	0.16713	0.19166	0.08226	0.04337
	Medical	0.14179	0.10206	0.08012	0.07872	0.12381	0.14201
	BSc. Biology	0.17923	0.15588	0.08911	0.04985	0.15599	0.18364
	BSc. Mathematics	0.06273	0.06853	0.18283	0.20833	0.11679	0.06777
	BCA	0.10034	0.14347	0.18850	0.19166	0.09211	0.12659

Table VII depicts the distance between the students' membership and non-membership value, as shown in Table III, and the standard fuzzy set, Table IV. The distance measure proposed by Zhang and Xu [21] for Pythagorean fuzzy sets is used to calculate distances. The ranking of a suitability of each career for every student by all the three measures is shown in table VIII.

TABLE VII
CAREERS AGAINST STUDENTS USING DISTANCE FOR PYTHAGOREAN FUZZY SET

		Students					
Career		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
	Engineering	0.00928	0.05886	0.14042	0.16039	0.05925	0.03095
	Medical	0.11817	0.08334	0.05885	0.06302	0.09124	0.12026
	BSc. Biology	0.14585	0.12876	0.06278	0.03588	0.12163	0.14693
	BSc. Mathematics	0.04827	0.05168	0.15320	0.17336	0.08541	0.05620
	BCA	0.08327	0.11408	0.15018	0.15670	0.06195	0.103451

TABLE VIII
COMPARISON TABLE USING THREE DIFFERENT DISTANCE MEASURE

Measure / Students	**Symmetric Generalized Fuzzy Divergence**	**Distance for Intuitionistic Fuzzy Sets**	**Distance for Pythagorean Fuzzy Sets**
S1	c1>c5>c4>c2>C3	c1>c4>c5>c2>c3	c1>c4>c5>c2>c3
S2	c4>c1>c2>c5>c3	c4>c1>c2>c5>c3	c4>c1>c2>c5>c3
S3	c2>c3>c1>c5>c4	c2>c3>c1>c4>c5	c2>c3>c1>c5>c4
S4	c3>c2>c4>c5>c1	c3>c2>c1>c5>c4	c3>c2>c5>c1>c4
S5	c5>c1>c4>c2>c3	c1>c5>c4>c2>c3	c1>c5>c4>c2>c3
S6	c1>c4>c5>c2>c3	c1>c4>c5>c2>c3	c1>c4>c5>c2>c3

Here, c1, c2, c3, c4, and c5 represent careers 1 to 5, i.e. Engineering, Medical, B.Sc. Biology, B.Sc. Mathematics and BCA respectively. As we observe from Table VIII, that the choice of the career changes according to the measure. In Table VIII, we see that using symmetric generalized fuzzy divergence the second and third choice for student S1 changes when we use distances in intuitionistic and Pythagorean fuzzy sets. For student S2, for all the measures the result remains the same. For student S3, generalized fuzzy divergence and Pythagorean gives the same result, but the distance measure for IFS gives different rankings. Similarly, for other students a small variation can be observed.

IV CONCLUSION

In this paper, a generalized intuitionistic fuzzy divergence measure, Hamming distance for intuitionistic fuzzy set, and distance measure for Pythagorean fuzzy set are used to find the proper choice of the career based on the students and teachers perception depicted in the form of membership and non-membership values in Table I and II. In Table VIII, the proper choice is depicted in the form of rank.

REFERENCES

[1] L.A. Zadeh, "Fuzzy Sets", *Inform. and Control*, vol. 8, 1965, pp. 338 - 353.
[2] K. T. Atanassov, "Intuitionistic Fuzzy sets", *Fuzzy Sets Syst.*, vol. 20, 1986, pp. 87 – 96 .
[3] K.T. Atanassov, "Inuitionistic Fuzzy Sets Past, Present and Future", *Proceedings of the 3rd International Conference of the European Society for Fuzzy Logic and Technology*, Zittau, Germany, September 2003, pp. 10 – 12.
[4] P. A. Ejegwa, A. J. Akubo, and O. M. Joshua, "Intuitionistic Fuzzy Set and Its Application in Career Determination via Normalized Euclidean Distance Method", *Eur. Sci. J.*, vol. 10, no. 15, 2014, pp. 529 – 536.
[5] R. R.Yager, "Some Aspects of Intuitionistic Fuzzy Sets", *Fuzzy Optim. Decis. Making*, vol. 8, 2009, pp. 67 – 90 .
[6] Z. Xu, and R. R.Yager, "Dynamic Intuitionistic Fuzzy Multi-attribute Decision Making", *Int. J. Approx. Reason*., vol. 48, 2008, pp. 246 – 262.
[7] E. Szmidt, and J. Kacprzyk, "Intuitionistic Fuzzy Sets in Some Medical Applications", *Sofia* 22- 23 Sept. 2001, NIFS 7, 4, p. 58 – 64.
[8] A. M. Kozae, A. Elshenawy, and M. Omran, "Intuitionistic Fuzzy Set and Its Application in Selecting Specialization: A Case Study for Engineering Students", *Int. J. Math. Anal. Appl.*, vol. 2, no. 6, 2015, pp. 74 – 78.
[9] E. Szmidt, and J. Kacprzyk, "Distances between Intuitionistic Fuzzy Sets", *Fuzzy Sets and Systems*, vol. 114, no. 3, 2000, pp. 505 – 518.
[10]E. Szmidt, and J. Kacprzyk, "Distances between Intuitionistic Fuzzy sets: A straight forward approaches may not work", *3rd International IEEE Conference Intelligent Systems* , 2006.
[11]A. G. .Hatzimichailidis, G. A. Papakostas, and V .G. Kaburlasos, "A Novel Distance Measure of Intuitionistic Fuzzy Sets and Its Application to Pattern Recognition Problems", *International Journal of Intelligent Systems*, vol. 27, 2012, pp. 396 – 409.
[12]D. Dubois, and H. Prade, "A Review of Fuzzy Set Aggregation Connectives", *Inf. Sci.*, vol. 36, 1985, pp. 85 – 121.
[13]Z. Xu, "Intuitionistic Fuzzy Aggregation Operators", *IEEE Transactions on Fuzzy Systems*, vol. 15, no. 6, 2007, pp. 1179 – 1187.
[14]R. R. Yager, "On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decision Making", *IEEE Transactions on Systems, Man and Cybernetics*, vol. 18, no. 1, 1988, pp. 183 – 190.
[15]R.Verma, and B. D. Sharma, "On Generalized Intuitionistic Fuzzy Divergence (Relative Information) and Their Properties", *J. Uncertain Systems*, vol. 6, no. 4, 2012, pp. 308 – 320.
[16]R. R Yager, and A. M. Abbasov, "Pythagorean Membership Grades, Complex Numbers, and Decision Making", *International Journal of Intelligent Systems*, vol. 28, no. 5, 2013, pp. 436–452.
[17]R. R. Yager, "Pythagorean Membership Grades in Multicriteria Decision Making", *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 4, 2014, pp. 958-965.
[18]H. Garg, "Linguistic Pythagorean fuzzy sets and its applications in multiattribute decision-making process", *International Journal of Intelligent Systems*, vol. 33, no. 6, 2018, pp. 1234–1263.
[19]R. R. Yager, "Pythagorean fuzzy subsets", *Joint IFSA World Congress and NAFIPS Annual Meetin*g (IFSA/NAFIPS), 2013.
[20]H. Garg, "A New Generalized Pythagorean Fuzzy Information Aggregation Using Einstein Operations and Its Application to Decision Making", *International Journal of Intelligent Systems*, vol. 31, no. 9, 2016, pp. 886–920.
[21]X. Zhang, and Z. Xu, "Extension of TOPSIS to Multiple Criteria Decision Making with Pythagorean Fuzzy Sets", *International Journal of Intelligent Systems*, vol. 29, no. 12, 2014, pp. 1061–1078.
[22]H. Garg, "A Novel Correlation Coefficients between Pythagorean Fuzzy Sets and Its Applications to Decision-Making Processes", *International Journal of Intelligent Systems*, vol. 31, no. 12, 2016, pp. 1234– 1252,.
[23]X. Peng, and Y.Yang, "Some Results for Pythagorean Fuzzy Sets", *International Journal of Intelligent Systems*, vol. 30, no. 11, 2015, pp. 1133–1160.
[24]X. Peng, and Y Yang, "Fundamental Properties of Interval-Valued Pythagorean Fuzzy Aggregation Operators", *International Journal of Intelligent Systems*, vol. 31, no. 5, 2015, pp. 444–487.
[25]D. Li, and W. Zeng, "Distance Measure of Pythagorean Fuzzy Sets", *International Journal of Intelligent Systems*, vol. 33, no. 2, 2017, pp. 348–361.

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