IMPROVED CORRELATION COEFFICIENTS OF FERMATEAN PENTAPARTITIONED SINGLE VALUED NEUTROSOPHIC SETS AND INTERVAL FERMATEAN PENTAPARTITIONED NEUTROSOPHIC SETS FOR MULTIPLE ATTRIBUTE DECISION MAKING

Abstract

A correlation coefficient is a statistical measure that helps identify how many changes in one value signal change in another. Wang's single valued neutrosophic sets were improvised into Fermatean Pentapartitioned single valued neutrosophic sets. We investigated the attributes of the interval Fermatean pentapartitioned neutrosophic sets and Fermatean pentapartitioned single-valued neutrosophic sets. Additionally, we have used this idea in many decision-making techniques using interval and Fermatean pentapartitioned single valued neutrosophic environments. Eventually we presuming (that) an example using the problems of many attribute decision making that was previously suggested.

Keywords: The improved correlation coefficient, interval Fermatean pentapartitioned neutrosophic sets, and Fermatean pentapartitioned single-valued neutrosophic sets are related terms.

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I. INTRODUCTION

In 1965, Zadeh [21] developed fuzzy sets, a development of classical set theory that permits the membership function to be valued in the range [0, 1]. In 1986, Atanassov [1] presented theintuitionistic fuzzy set (IFS), a development oof Zadhe's fu zzy set theory that entails the degree of membership and the degree of non-membership, and the interval range is [0, 1].

IFS theory is frequently used in disciplines like logic programming, problem-solving in decision-making, and medical diagnosis, among others.

Florentin Smarandache basic neutrosphic a skill neutrosophic the deals neutrosophic of a neutrosphic set, which imparts skill of neutral thought by introducing a brand-new component known as indeterminacy to the set. The truth membership function (T), indeterminacy membership function (I), and falsity membership function (F) were therefore included in the framing of the neutrosophic set. The non- standard interval [0, 1] is dealt with by neutrosophic sets. Neutrophic set to take part of vital role in many application fields.

This is because it deals with Indeterminacy well.

Single valued neutrosophic sets (SVNS), commonly known as an extension of intuitionistic fuzzy sets, presented by Wang [12] (2010), and they have since been a very hot area of research. The notion of Fermatean Pentapartitioned Single Valued Neutrosophic Sets, which is placed on Belnap's Four Logic and Smarandache's Four Numerical Valued Logic,was proposed by Rajashi Chatterjee, et al [10]. The (FPSVNS) has five components because the indeterminacy is split into the "contradiction" (both true and false) and "unknown" (neither true nor false) functions: T_A, C_A, K_A, U_A, and F_A, all of which fall inside the non-standard unit interval [0, 1].

The correlation coefficient is a helpful statistical tool for calculating how closely two variables are related to one another. The correlation of fuzzy sets under a fuzzy environment was proposed in 1999 by D.A. In this essay, part 2 provides some fundamental ideas of Fermatean pentapartitioned neutrosophic sets, quadripartitioned single valued neutrosophic sets, and their complements. It also talk over union, intersection, interval neutrosophic sets, and the correlation coefficient of FPSVNS. In part 3, we introduced the concept of improved correlation coefficients for FPSVNSs to handle the regulation of correlation coefficients. We also enclosed some of its properties and a decision-making approach using the improved correlation coefficient of FPSVNSs. Interval Fermatean Pentapartitioned Neutrosophic sets (IFPNS) were introduced in part 4 with some basic definitions and a determined correlation coefficient. Furthermore, we have discussed some of its characteristics and a strategy for making decisions by applying an environment with an interval Fermatean pentapartitioned neutrosophic. In part 5, an illustration likewise -planned correlation method in decision-making with many criteria is provided. The paper is concluded in part 6.

II. PRELIMINARIES

2.1 Quadripartitioned single valued neutrosophic sets

Definition 2.1. [5]

The single-valued neutrosophic sets, which are defined over the standard unit interval [0, 1], are expressed across the non-standard unit range [0, 1]. It refers to the definition of a single-valued neutrosophic set A is

$A = \{\langle X, T_A(x), I_A(x), F_A(x)\rangle / x \in X\}$

Where $T_A(x), I_A(x), F_A(x) : X \to [0,1]$ like that $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

Definition 2.2. [4]

Consider a non-empty set, X. A quadripartitioned single valued neutrosophic set (QSVNS) A over X characterizes each element in X by a truth membership function $T_A(x)$, a contradiction membership function $C_A(x)$, an ignorance membership function $U_A(x)$ along with a falsity membership function $F_A(x)$ like that $x \in X$, $T_A, C_A, U_A, F_A \in [0,1]$ and $0 \leq T_A(x) + C_A(x) + U_A(x) + F_A(x) \leq 4$ whereupon X is discrete. R is act as

$R = \sum_{i=1}^{n} T_A(x), C_A(x), U_A(x), F_A(x)/x_i , x_i \in X$.

Definition 2.2. [15]

Let X represent a universe. $R = \{< x, T_A , C_A , K_A , U_A , F_A ,) >: x \in X \}$ is a Fermatean pentapartitioned neutrosophic set (FPN) on X such that $(T_A)^3 + (C_A)^3 + (K_A)^3 + (U_A)^3 + (F_A)^3 \leq 3$
Here, $T_A(x)$ is the truth membership,

$C_A(x)$ is contradiction membership,

$K_A(x)$ is ignorance membership,

$U_A(x)$ is unknown membership,

$F_A(x)$ is the false membership.

III. FERMATEAN PENTAPARTIONED SINGLE VALUED NEUTROSOPHIC SETS

3.1 Definition:

Assume that X is a non-empty set. Truth membership function $T_A(x)$, contradiction membership function $C_A(x)$, ignorance membership function $K_A(x)$, unknown membership function $U_A(x)$, and falsity membership function $F_A(x)$ such that $x \in X$, $T_A, C_A, K_A, U_A, F_A \in [0,1]$ and

$0 \leq \left(T_A(x)\right)^3 + \left(C_A(x)\right)^3 + \left(K_A(x)\right)^3 + \left(U_A(x)\right)^3 + \left(F_A(x)\right)^3 \leq 5$ When X is discrete. A is expressed as

$$A = \sum_{i=1}^{n} T_A(x), C_A(x), K_A(x), U_A(x), F_A(x)/x_i , x_i \epsilon X .$$

3.2 Definition:

The complement of an FPSVNS stands for A^C and is written as,

$$A^C = \sum_{i=1}^{n} F_A(x), U_A(x), K_A(x), C_A(x), T_A(x)/x_i , x_i \epsilon X$$

3.3 Definition:

The union of two FPSVNS A and B is stand for $A \cup B$ and it can be expressed as

$$A \cup B = \sum_{i=1}^{n} T_A(x) \vee T_B(x) , C_A(x) \vee C_B(x) , K_A(x) \wedge K_B(x) , U_A(x) \wedge U_B(x), F_A(x) \wedge F_B(x) /x_i , x_i \epsilon X$$

3.4 Definition:

The intersection of two FPSVNS A and B and it is expressed as,

$$A \cap B = \sum_{i=1}^{n} T_A(x) \wedge T_B(x) , C_A(x) \wedge C_B(x) , K_A(x) \vee K_B(x) , U_A(x) \vee U_B(x), F_A(x) \vee F_B(x) /x_i , x_i \epsilon X$$

3.5 Definition:

Let X represent a common element and be a space containing points (an object). An INS interval neutrosophic set A in X is described by the truth membership function T_A (x), falsity function F_A (x) and indeterminacy membership function I_A (x). To every point x in X, there is

$T_A(x) = [\inf T_A(x), \sup T_A(x)] \subseteq [0,1], C_A(x) = [inf\ C_A(x), sup\ C_A(x)] \subseteq [0,1]$

$K_A(x) = [\inf K_A(x), \sup K_A(x)] \subseteq [0,1], U_A(x) = [inf\ U_A(x), sup\ U_A(x)] \subseteq [0,1]$ and

$F_A(x) = [inf\ F_A(x), sup\ F_A(x)] \subseteq [0,1]$. Thus, an INS A can be described as

$A = \{\langle X, T_A(x), I_A(x), F_A(x)\rangle / x \epsilon X\}$

$= \{\langle x, [infT_A(x), supT_A(x)], [inf C_A(x), supC_A(x)], [\inf K_A(x), \sup K_A(x)] , [inf\ U_A(x), sup\ U_A(x)] , [infF_A(x), supF_A(x) \rangle / x \epsilon X\}$

Then the conditions can be met by the sum of $T_A(x), I_A(x), F_A(x)$. $0 \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3$. Generally, an INS reduces to the SVNS when the interval values of

T_A (x), I_A (x), and F_A (x) are equal upper and lower ends. However, SVNSs and INSs are the positions of neutrosophic sets.

3.6. Definition

The complement of an INS A stands for A^C, which is be expressed as

$T_{A^c}(x) = F_A(x)$, $inf\ I_{A^c}(x) = 1 - supI_A(x), supI_{A^c}(x) = 1 - infI_A(x)$, and $F_{A^c}(x) = T_A(x)$ for any x in X.

3.7. Definition

An INS A is contained in another INS B, A⊆B if and only if $infT_A(x) \leq infT_B(x), supT_A(x) \leq supT_B(x), inf\ I_A(x) \geq\ infI_B(x), supI_A(x) \geq\ supI_B(x)$ and inf $F_A(x) \geq\ infF_B(x), supF_A(x) \geq\ supF_B(x)$.

3.8. Definition

If A⊆B and B⊆ A then two INSs A and B are equal, which is represented by the symbol A = B

3.8. Definition: Correlation coefficient of QSVNSs

Based on the correlation coefficient of SVNSs, Rajashi Chatterjee [4] has provided additional the idea for the correlation coefficient of QSVNSs: K (A, B) = $\frac{C(A,B)}{[T(A).T(B)]^{1/2}}$

$$= \frac{\sum_{i=1}^{n} T_A^3(x_i).T_B^3(x_i)+C_A^3(x_i).C_B^3(x_i)+K_A^3(x_i).K_B^3(x_i)\ +U_A^3(x_i).U_B^3(x_i)+F_A^3(x_i).F_A^3(x_i)}{\sqrt[3]{\sum_{i=1}^{n} T_A^6(x_i)+C_A^6(x_i)+K_A^6(x_i)+U_A^6(x_i)+F_A^6(x_i)}\ \sqrt[3]{\sum_{i=1}^{n} T_B^6(x_i)+C_B^6(x_i)+K_B^6(x_i)+U_B^6(x_i)+F_B^6(x_i)}}$$

------ (1)

The requirements for the correlation coefficient K (A, B) are as follows:

1. K (A, B) = K(B, A);
2. 0 ≤ $K(A, B) \leq 1$;
3. K (A, B) = 1, iff A = B.

Equation (1) has a few shortcomings, which are listed below.

In the case of two QSVNSs A and B, if $T_A(x_i) = C_A(x_i) = U_A(x_i) = F_A(x_i) = 0$ and /or $T_B(x_i) = C_B(x_i) = U_B(x_i) = F_B(x_i) = 0$ at all in X (i = 1, 2, 3,…n).

Eq. (1) is either irrelevant or not defined. In this case, the formula is invalid, but Equation (1) only meets the necessary, not the sufficient, condition of Property (3). That is A≠ B. It's possible that the value of equation (1) is 1.

3.9. Example

Consider accounts A and B selected by $A = \{\langle x, 0.4,0.2,0.3,0.1\rangle\}$ as QSVNSs in X, and

$B = \{\langle x, 0.8,0.4,0.6,0.2\rangle\}$. Here, seemingly, A ≠ B.

Next K (A, B) = $\frac{0.4X0.8+0.2X0.4+0.3X0.6+0.1X0.2}{\sqrt{0.4^2+0.2^2+0.3^2+0.1^2}\,\sqrt{0.8^2+0.4^2+0.6^2+0.2^2}} = 1$ ------------(2)

Therefore, it is not practical to use real-world examples of problems in this situation. So, we will define a better correlation coefficient as address these types of drawbacks.

IV. IMPROVED TO CORRELATION COEFFICIENTS

The strengthened correlation coefficient of FPSVNSs has been defined in the next subsection using the correlation coefficient of FPSVNSs.

4.1. Definition

To determine the improved correlation among A and B, we assume that they are two FPSVNSs

X = $\{x_1, x_2, \dots\dots x_n\}$,

$$M(A,B) = \frac{1}{5N}\sum_{i=1}^{n}[\varphi_{1_i}(1-\Delta T_i) + \varphi_{2_i}(1-\Delta C_i) + \varphi_{3_i}(1-\Delta K_i) + \varphi_{4_i}(1-\Delta U_i) + \varphi_{5_i}(1-\Delta F_i)] \quad \text{---------(3)}$$

Where $\varphi_{1_i} = \frac{5-\Delta T_i - \Delta T_{max}}{5-\Delta T_{min} - \Delta T_{max}}$, $\varphi_{2_i} = \frac{5-\Delta C_i - \Delta C_{max}}{5-\Delta C_{min} - \Delta C_{max}}$,

$$\varphi_{3_i} = \frac{5-\Delta K_i - \Delta K_{max}}{5-\Delta K_{min} - \Delta K_{max}},$$

$$\varphi_{4_i} = \frac{5-\Delta U_i - \Delta U_{max}}{5-\Delta U_{min} - \Delta U_{max}}, \quad \varphi_{5_i} = \frac{5-\Delta F_i - \Delta F_{max}}{5-\Delta F_{min} - \Delta F_{max}}.$$

$\Delta T_i = \left|{T_A}^3(x_i) - {T_B}^3(x_i)\right|$, $\Delta C_i = \left|{C_A}^3(x_i) - {C_B}^3(x_i)\right|$,
$\Delta K_i = \left|{K_A}^3(x_i) - {K_B}^3(x_i)\right|$,

$\Delta U_i = \left|{U_A}^3(x_i) - {U_B}^3(x_i)\right|$, $\Delta F_i = \left|{F_A}^3(x_i) - {F_B}^3(x_i)\right|$

$\Delta T_{min} = \min_i \left|{T_A}^3(x_i) - {T_B}^3(x_i)\right|$, $\Delta C_{min} = \min_i \left|{C_A}^3(x_i) - {C_B}^3(x_i)\right|$,

$\Delta K_{min} = \min_i \left| {K_A}^3(x_i) - {K_B}^3(x_i) \right|$, $\Delta U_{min} = \min_i \left| {U_A}^3(x_i) - {U_B}^3(x_i) \right|$,

$\Delta F_{min} = \min_i \left| {F_A}^3(x_i) - {F_B}^3(x_i) \right|$,

$\Delta T_{max} = \max_i \left| {T_A}^3(x_i) - {T_B}^3(x_i) \right|$, $\Delta C_{max} = \max_i \left| {C_A}^3(x_i) - {C_B}^3(x_i) \right|$,

$\Delta K_{max} = \max_i \left| {K_A}^3(x_i) - {K_B}^3(x_i) \right|$, $\Delta U_{max} = \max_i \left| {U_A}^3(x_i) - {U_B}^3(x_i) \right|$,

$\Delta F_{max} = \max_i \left| {F_A}^3(x_i) - {F_B}^3(x_i) \right|$,

For all $x_i \epsilon\ X$ (i =1, 2, 3….n).

Theorem 4.2

The improved correlation coefficient M (A, B) meets the following criteria for each pair of FPSVNSs A and B in the discourse universe, X = $\{x_1, x_{2\ ,} \dots\dots x_n\}$.

i) M (A, B) = M(B, A);
ii) $0 \le M(A,B) \le 1$;
iii) $M(A,B) = 1\ iff\ A = B$.

Proof:

i) It is obvious and forthright.

ii) Here $0 \le \varphi_{1_i} \le 1, 0 \le \varphi_{2_i} \le 1, 0 \le \varphi_{3_i} \le 1, 0 \le \varphi_{4_i} \le 1, 0 \le \varphi_{5_i} \le 1$
$0 \le (1 - \Delta T_i) \le 1, 0 \le (1 - \Delta C_i) \le 1, 0 \le (1 - \Delta K_i) \le 1, 0 \le (1 - \Delta U_i) \le 1,$

$0 \le (1 - \Delta F_i) \le 1$. Consequently, the following in equation delight $0 \le \varphi_{1_i}(1 - \Delta T_i) + \varphi_{2_i}(1 - \Delta C_i) + \varphi_{3_i}(1 - \Delta K_i) + \varphi_{4_i}(1 - \Delta U_i) + \varphi_{5_i}(1 - \Delta F_i) \le 5.$

Therefore, we obtain $0 \le M(A,B) \le 1$.

iii) If M (A, B) = 1, then $\varphi_{1_i}(1 - \Delta T_i) + \varphi_{2_i}(1 - \Delta C_i) + \varphi_{3_i}(1 - \Delta K_i) + \varphi_{4_i}(1 - \Delta U_i) + \varphi_{5_i}(1 - \Delta F_i)$]=5. Since $0 \le (1 - \Delta T_i) \le 1, 0 \le (1 - \Delta C_i) \le 1, 0 \le (1 - \Delta K_i) \le 1,$

$0 \le (1 - \Delta U_i) \le 1$, $0 \le (1 - \Delta F_i) \le 1$, there are $\varphi_{1_i}(1 - \Delta T_i) = \varphi_{2_i}(1 - \Delta C_i) = \varphi_{3_i}(1 - \Delta K_i) = \varphi_{4_i}(1 - \Delta U_i) = \varphi_{5_i}(1 - \Delta F_i)$] =1. And also since $0 \le \varphi_{1_i} \le 1$, $0 \le \varphi_{2_i} \le 1, 0 \le \varphi_{3_i} \le 1,$

$0 \le \varphi_{4_i} \le 1$, $0 \le \varphi_{5_i} \le 1$, $0 \le (1 - \Delta T_i) \le 1$, $0 \le (1 - \Delta C_i) \le 1$, $0 \le (1 - \Delta K_i) \le 1, 0 \le (1 - \Delta U_i) \le 1, 0 \le (1 - \Delta F_i) \le 1.$

We get $\varphi_{1_i} = \varphi_{2_i} = \varphi_{3_i} = \varphi_{4_i} = \varphi_{5_i} = 1$ and $(1 - \Delta T_i) = (1 - \Delta C_i) = (1 - \Delta K_i) = (1 - \Delta U_i) = (1 - \Delta F_i) = 1$. This implies, $\Delta T_i = \Delta T_{min} = \Delta T_{max} = 0$,

$\Delta C_i = \Delta C_{min} = \Delta C_{max} = 0, \Delta K_i = \Delta K_{min} = \Delta K_{max} = 0,$

$\Delta U_i = \Delta U_{min} = \Delta U_{max} = 0, \Delta F_i = \Delta F_{min} = \Delta F_{max} = 0$

Accordingly, $T_A(x_i) = T_B(x_i)$, $C_A(x_i) = C_B(x_i)$, $K_A(x_i) = K_B(x_i)$, $U_A(x_i) = U_B(x_i)$,

$F_A(x_i) = F_B(x_i)$ for every $x_i \epsilon X$ (i = 1,2,3,….n).

So A = B. $\Delta T_i = \Delta T_{min} = \Delta T_{max} = 0$,

$\Delta C_i = \Delta C_{min} = \Delta C_{max} = 0, \Delta K_i = \Delta K_{min} = \Delta K_{max} = 0,$

$\Delta U_i = \Delta U_{min} = \Delta U_{max} = 0, \Delta F_i = \Delta F_{min} = \Delta F_{max} = 0$

Now in case that A= B, implies

$T_A(x_i) = T_B(x_i), C_A(x_i) = C_B(x_i) , K_A(x_i) = K_B(x_i) , U_A(x_i) = U_B(x_i) , F_A(x_i) = F_B(x_i)$

for all $x_i \epsilon X$ (i = 1,2,3,….n).

$\Delta T_i = \Delta T_{min} = \Delta T_{max} = 0$, $\Delta C_i = \Delta C_{min} = \Delta C_{max} = 0$, $\Delta K_i = \Delta K_{min} = \Delta K_{max} = 0,$

$\Delta U_i = \Delta U_{min} = \Delta U_{max} = 0, \Delta F_i = \Delta F_{min} = \Delta F_{max} = 0.$

So we obtain M (A, B) =1. The improved correlation coefficient formula in (3) is valid and fulfills the requirements of Theorem 3.1 when we select any constant $\lambda > 3$ in the following terms.

$\varphi_{1_i} = \frac{\lambda - \Delta T_i - \Delta T_{max}}{\lambda - \Delta T_{min} - \Delta T_{max}}$, $\varphi_{2_i} = \frac{\lambda - \Delta C_i - \Delta C_{max}}{\lambda - \Delta C_{min} - \Delta C_{max}}$, $\varphi_{3_i} = \frac{\lambda - \Delta K_i - \Delta K_{max}}{\lambda - \Delta K_{min} - \Delta K_{max}}$,

$\varphi_{4_i} = \frac{\lambda - \Delta U_i - \Delta U_{max}}{\lambda - \Delta U_{min} - \Delta U_{max}}$, $\varphi_{5_i} = \frac{\lambda - \Delta F_i - \Delta F_{max}}{\lambda - \Delta F_{min} - \Delta F_{max}}$

Let's think about the same situation in the example 2.12. when A≠B. M (A, B) = 0.912 can be found by using Equation (3).

Example 4.3

Give us two FPSVNSs in X, $A = \{\langle x, 0,0,0,0,0\rangle\}$ and $B = \{\langle x, 0.6,0.5,0.4,0.3,0.2\rangle\}$. Then it is clear that equation (1) is determined. Thus, using equation (3), we get M (A, B) = 0.912. It convention that the drawback of the correlation coefficient in [10] is appropriately by the improved correlation coefficient as exposed above.

We generated a weighted correlation coefficient among the FPSVNSs and considered the differences in the elements. By choosing w i as the weight for each element in X (i = 1, 2, 3... n), the weighted correlation coefficients among FPSVNSs A and B are calculated. Next, using the parameters $w_i \epsilon\ [0,1]$ & $\sum_{i=1}^{n} w_i = 1$, the weighted correlation coefficients between FPSVNSs A and B are computed.

$M_w(A,B) = \frac{1}{5}\sum_{i=1}^{n}\big[\varphi_{1_i}(1-\Delta T_i) + \varphi_{2_i}(1-\Delta C_i) + \varphi_{3_i}(1-\Delta K_i) + \varphi_{4_i}(1-\Delta U_i) + \varphi_{5_i}(1-\Delta F_i)\big]$....(4)

If $w = \left(\frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \dots . \frac{1}{n}\right)^T$, Equation (4) becomes equation (3) at that point. The three terms in Theorem 3.1 are also satisfied by $M_w(A,B)$.

Theorem 4.4

The weighted correlation coefficient among FPSVNSs A and B, represented by $M_w(A,B)$, is expressed as (4) and meets the following criteria. Allow w_i to be the weight for all x_i in X (i = 1, 2, 3…n), $w_i \epsilon\ [0,1]$ and $\sum_{i=1}^{n} w_i = 1$.

i) $M_w(A,B) = M_w(B,A)$;

ii) $0 \le M_w(A,B) \le 1$;

iii) $M_w(A,B) = 1\ iff\ A = B$. Theorem 3.1's attributes can be demonstrated similarly.

4.5. Decision- making method using the improved correlation coefficient of the FPSVNSs.

Multi-criteria decision making (MCDM) is difficult when making decisions in situations with numerous attributes. For example, before purchasing a vehicle, you may consider the features offered in terms of price, style, safety, and comfort. The following FPSVNS represents the features of an alternative A_i, (i =1, 2, 3… m) on an attribute

C_j, (j=1, 2, 3...n). In the context of a decision problem with multiple attributes and Feramatean pantapartitioned single-valued neutrosophic information.

$$A_i = \{\langle C_j, T_{A_i}(C_j), C_{A_i}(C_j), K_{A_i}(C_j), U_{A_i}(C_j), F_{A_i}(C_j) / C_j \epsilon C, j = 1,2,3 \dots n \rangle \qquad \text{--------(5)}$$

Where $T_{A_i}(C_j), C_{A_i}(C_j), K_{A_i}(C_j), U_{A_i}(C_j), F_{A_i}(C_j) \epsilon [0,1]$ and

$0 \le T^3_{A_i}(C_j) + (C_j) + C^3_{A_i}(C_j) + +K^3_{A_i}(C_j) + U^3_{A_i}(C_j) + F^3_{A_i}(C_j) \le 5$, for $C_j \epsilon C, j = 1,2,3 \dots n$

and i =1, 2, 3….m.

For simplicity, we discuss the following five functions $T_{A_i}(C_j), C_{A_i}(C_j), K_{A_i}(C_j), U_{A_i}(C_j), F_{A_i}(C_j)$ in terms of a fermatian pentapartitioned single valued neutrosophic value (FPSVNV):

$d_{ij} = \left(t_{ij}, c_{ij}, k_{ij}, u_{ij}, f_{ij}\right)$ $(i = 1,2, \dots . m\,; j = 1,2, \dots . n)$. The expert or decision-maker typically determines the values of d_{ij} by evaluating an alternative, A_i, in relation to a criterion, C_j.

Therefore, a fermatean pentapartitioned single-valued neutrosophic decision matrix is given as follows:

The ideal FPSVNV for the perfect alternative A* can be written as d_{ij}. In the decision-making process,

$d_j{}^* = \langle t_j{}^*,\ c_j{}^*,\ k_j{}^*,\ u_j{}^*,\ f_j{}^* \rangle = \langle 1,1,0,0,0 \rangle$ $(j = 1,2, \dots n)$.

An ideal FPSVNV can be expressed as follows for perfect alternative A*:

$d_j{}^* = \langle t_j{}^*,\ c_j{}^*,\ k_j{}^*,\ u_j{}^*,\ f_j{}^* \rangle = \langle 1,1,0,0,0 \rangle$ $(j = 1,2, \dots n)$. The weight correlation coefficient between the alternative A_i $(i = 1,2, \dots m)$ and the optimal alternative A* value is determined by:

$$M_w(A_i, A^*) = \frac{1}{5}\sum_{i=1}^{n} w_j \left[\varphi_{1_{ij}}\left(1 - \Delta t_{ij}\right) + \varphi_{2_{ij}}\left(1 - \Delta c_{ij}\right) + \varphi_{3_{ij}}\left(1 - \Delta k_{ij}\right) + \varphi_{4_{ij}}\left(1 - \Delta u_{ij}\right) + \varphi_{5_{ij}}\left(1 - \Delta f_{ij}\right)\right]. \qquad \text{--------(6)}$$

Where $\varphi_{1_{ij}} = \frac{5-\Delta t_{ij} - \Delta t_{imax}}{5-\Delta t_{imin} - \Delta t_{imax}}$, $\varphi_{2_{ij}} = \frac{5-\Delta c_{ij} - \Delta c_{imax}}{5-\Delta c_{imin} - \Delta c_{imax}}$, $\varphi_{3_{ij}} = \frac{5-\Delta k_{ij} - \Delta k_{imax}}{5-\Delta k_{imin} - \Delta k_{imax}}$,

$\varphi_{4_{ij}} = \frac{5-\Delta u_{ij} - \Delta u_{imax}}{5-\Delta u_{imin} - \Delta u_{imax}}$, $\varphi_{5_{ij}} = \frac{5-\Delta f_{ij} - \Delta f_{imax}}{5-\Delta f_{imin} - \Delta f_{imax}}$

$\Delta t_{ij} = \left|t_{ij}{}^3 - t_j{}^*\right|$, $\Delta c_{ij} = \left|c_{ij}{}^3 - c_j{}^*\right|$, $\Delta k_{ij} = \left|k_{ij}{}^3 - k_j{}^*\right|$,

$\Delta u_{ij} = \left|u_{ij}{}^3 - u_j{}^*\right|$, $\Delta f_{ij} = \left|f_{ij}{}^3 - f_j{}^*\right|$

$\Delta t_{imin} = \min_j \left|t_{ij}{}^3 - t_j{}^*\right|$, $\Delta c_{imin} = \min_j \left|c_{ij}{}^3 - c_j{}^*\right|$,

$\Delta k_{imin} = \min_j \left|k_{ij}{}^3 - k_j{}^*\right|$,

$\Delta u_{imin} = \min_j \left|u_{ij}{}^3 - u_j{}^*\right|$, $\Delta f_{imin} = \min_j \left|f_{ij}{}^3 - f_j{}^*\right|$,

$\Delta t_{imax} = \max_j \left|t_{ij}{}^3 - t_j{}^*\right|$, $\Delta c_{imax} = \max_j \left|c_{ij}{}^3 - c_j{}^*\right|$,

$\Delta k_{imax} = \max_j \left| k_{ij}{}^3 - k_j{}^* \right|,$

$\Delta u_{imax} = \max_j \left| u_{ij}{}^3 - u_j{}^* \right|,\quad \Delta f_{imax} = \max_j \left| f_{ij}{}^3 - f_j{}^* \right|$ for I = 1,2,….m and j = 1,2,…n

We can find out the order of all the alternatives and choose the best one based on the weighted correlation coefficient $M_w(A_i, A^*)$ (i=1, 2…m) mentioned above.

V. INTERVAL FERMATEAN PENTAPARTITIONED NEUTROSOPHIC SETS (IFPNS)

Definition 5.1

An IFPNS A in x represents the truth membership function $T_A(x)$, a contradiction membership function $C_A(x)$, ignorance membership function $K_A(x)$, unknown membership function $U_A(x)$ and falsity membership function$F_A(x)$. For all x in X, there are

$T_A(x) = [\inf T_A(x), \sup T_A(x)] \subseteq [0,1], C_A(x) = [inf\ C_A(x), sup\ C_A(x)] \subseteq [0,1]$

$K_A(x) = [\inf K_A(x), \sup K_A(x)] \subseteq [0,1], U_A(x) = [inf\ U_A(x), sup\ U_A(x)] \subseteq [0,1]$ and

$F_A(x) = [inf\ F_A(x), sup\ F_A(x)] \subseteq [0,1]$. Consequently, an IFPNS can be defined as

A = $\{\langle x, T_A(x), C_A(x), K_A(x), U_A(x), F_A(x)\rangle /$ x ϵ X$\}$
=$\{$
$\langle x, [\inf T_A(x), \sup T_A(x)], [inf\ C_A(x), sup\ C_A(x)], [\inf K_A(x), \sup K_A(x)], [inf\ U_A(x), sup\ U_A(x)], [inf\ F_A(x), sup\ F_A(x)]\rangle /$
x ϵ X$\}$

Next the sum of $T_A(x), U_A(x), K_A(x), C_A(x), F_A(x)$ fulfill the requirements,

$$0 \leq \left(T_A(x)\right)^3 + \left(C_A(x)\right)^3 + \left(K_A(x)\right)^3 + \left(U_A(x)\right)^3 + \left(F_A(x)\right)^3 \leq 5.$$

IFPNS decreases to FPSVNS if the lower and higher interval values of $T_A(x), U_A(x), K_A(x), C_A(x), F_A(x)$ are equal. The branches of Fermatean pentapartitioned neutrosophic sets (FPNS) are IFPNS and FPSVNS.

Definition 5.2 The complement of an IFPNS A is certified as A^C and stands for

$inf\ T_{A^c}(x) = 1 - supT_A(x), supT_{A^c}(x) = 1 - infT_A(x),$

$inf\ C_{A^c}(x) = 1 - supC_A(x), supC_{A^c}(x) = 1 - infC_A(x),$

$inf\ K_{A^c}(x) = 1 - supK_A(x), supK_{A^c}(x) = 1 - infK_A(x),$

$inf\ U_{A^c}(x) = 1 - supU_A(x), supU_{A^c}(x) = 1 - infU_A(x),$

$inf\ F_{A^c}(x) = 1 - supF_A(x), supF_{A^c}(x) = 1 - infF_A(x)$ For every x in X.

Definition 5.3. The other IFPNS B contains an IFPNS A, $A \subseteq B$ iff.

$infT_A^3(x) \le infT_B^3(x), supT_A^3(x) \le supT_B^3(x),$
$infC_A^3(x) \le infC_B^3(x), supC_A^3(x) \le supC_B^3(x),$
$infK_A^3(x) \ge infK_B^3(x), supK_A^3(x) \ge supK_B^3(x),$
$infU_A^3(x) \ge infU_B^3(x), supU_A^3(x) \ge supU_B^3(x),$
$infF_A^3(x) \ge infF_B^3(x), supF_A^3(x) \ge supF_B^3(x),$
for each x in X.

Definition 5.4

If $A \subseteq B$ and $B \subseteq A$, then two IFPNS A and B are equivalent, or A = B**.**

5.5 Correlation coefficient between IFPNSs.

In this section, we have developed an IFPNS-to-IPFNS correlation coefficient as an observation of the improved correlation coefficient of FPSVNSs.

Definition 5.6 In the discourse universe $X = \{x_1, x_2, \dots . x_n\}$,, the correlation coefficient between two IFPNS A and B is represented as follows:

N (A, B) = $\{ \frac{1}{10N} \sum_{i=1}^{n} [\varphi_{1_i}{}^L(1 - \Delta T_i{}^L) + \varphi_{2_i}{}^L(1 - \Delta C_i{}^L) + \varphi_{3_i}{}^L(1 - \Delta K_i{}^L) + \varphi_{4_i}{}^L(1 - \Delta U_i{}^L) + \varphi_{5_i}{}^L(1 - \Delta F_i{}^L) + \varphi_{1_i}{}^U(1 - \Delta T_i{}^U) + \varphi_{2_i}{}^U(1 - \Delta C_i{}^U) + \varphi_{3_i}{}^U(1 - \Delta K_i{}^U) + \varphi_{4_i}{}^U(1 - \Delta U_i{}^U) + \varphi_{5_i}{}^U(1 - \Delta F_i{}^U)]\} \dots ..$ (7)

Where $\varphi_{1_i}^L = \frac{5-\Delta T_i^L - \Delta T_{max}^L}{5-\Delta T_{min}^L - \Delta T_{max}^L}$, $\varphi_{1_i}^U = \frac{5-\Delta T_i^U - \Delta T_{max}^U}{5-\Delta T_{min}^U - \Delta T_{max}^U}$,

, $\varphi_{2_i}^L = \frac{5-\Delta C_i^L - \Delta C_{max}^L}{5-\Delta C_{min}^L - \Delta C_{max}^L}$, $\varphi_{2_i}^U = \frac{5-\Delta C_i^U - \Delta C_{max}^U}{5-\Delta C_{min}^U - \Delta C_{max}^U}$,

$\varphi_{3_i}^L = \frac{5-\Delta K_i^L - \Delta K_{max}^L}{5-\Delta T_{min}^L - \Delta T_{max}^L}$, $\varphi_{3_i}^U = \frac{5-\Delta K_i^U - \Delta K_{max}^U}{5-\Delta T_{min}^U - \Delta T_{max}^U}$,

$\varphi_{4_i}^L = \frac{5-\Delta U_i^L - \Delta U_{max}^L}{5-\Delta U_{min}^L - \Delta U_{max}^L}$, $\varphi_{4_i}^U = \frac{5-\Delta U_i^U - \Delta U_{max}^U}{5-\Delta U_{min}^U - \Delta U_{max}^U}$,,
$\varphi_{5_i}^L = \frac{5-\Delta F_i^L - \Delta F_{max}^L}{5-\Delta F_{min}^L - \Delta F_{max}^L}$, $\varphi_{5_i}^U = \frac{5-\Delta F_i^U - \Delta F_{max}^U}{5-\Delta F_{min}^U - \Delta F_{max}^U}$,

$$\Delta {T_i}^L = |\inf T_A^3\,(x_i) - \inf T_B^3\,(x_i)|, \quad \Delta {T_i}^U = |\sup T_A^3\,(x_i) - \sup T_B^3\,(x_i)|,$$

$$\Delta {C_i}^L = |\inf C_A^3\,(x_i) - \inf C_B^3\,(x_i)|, \quad \Delta {C_i}^U = |\sup C_A^3\,(x_i) - \sup C_B^3\,(x_i)|$$

$$\Delta {K_i}^L = |\inf K_A^3\,(x_i) - \inf K_B^3\,(x_i)|, \quad \Delta {K_i}^U = |\sup K_A^3\,(x_i) - \sup K_B^3\,(x_i)|$$

$$\Delta {U_i}^L = |\inf U_A^3\,(x_i) - \inf U_B^3\,(x_i)|, \quad \Delta {U_i}^U = |\sup U_A^3\,(x_i) - \sup U_B^3\,(x_i)|$$

$$\Delta {F_i}^L = |\inf F_A^3\,(x_i) - \inf F_B^3\,(x_i)|, \quad \Delta {F_i}^U = |\sup F_A^3\,(x_i) - \sup F_B^3\,(x_i)|,$$

$$\Delta T_{min}^L = \min_i |\inf T_A^3\,(x_i) - \inf T_B^3\,(x_i)|,$$

$$\Delta T_{min}^U = \min_i |\sup T_A^3\,(x_i) - \sup T_B^3\,(x_i)|,$$

$$\Delta C_{min}^L = \min_i |\inf C_A^3\,(x_i) - \inf C_B^3\,(x_i)|,$$

$$\Delta C_{min}^U = \min_i |\sup C_A^3\,(x_i) - \sup C_B^3\,(x_i)|,$$

$$\Delta K_{min}^L = \min_i |\inf K_A^3\,(x_i) - \inf K_B^3\,(x_i)|,$$

$$\Delta K_{min}^U = \min_i |\sup K_A^3\,(x_i) - \sup K_B^3\,(x_i)|$$

$$\Delta U_{min}^L = \min_i |\inf U_A^3\,(x_i) - \inf U_B^3\,(x_i)|,$$

$$\Delta U_{min}^U = \min_i |\sup U_A^3\,(x_i) - \sup U_B^3\,(x_i)|$$

$$\Delta F_{min}^L = \min_i |\inf F_A^3\,(x_i) - \inf F_B^3\,(x_i)|,$$

$$\Delta F_{min}^U = \min_i |\sup F_A^3\,(x_i) - \sup F_B^3\,(x_i)|$$

$$\Delta T_{max}^L = \max_i |\inf T_A^3\,(x_i) - \inf T_B^3\,(x_i)|$$

$$\Delta T_{max}^U = \max_i |\sup T_A^3\,(x_i) - \sup T_B^3\,(x_i)|$$

$$\Delta C_{max}^L = \max_i |\inf C_A^3\,(x_i) - \inf C_B^3\,(x_i)|,$$

$$\Delta C_{max}^U = \max_i |\sup C_A^3\,(x_i) - \sup C_B^3\,(x_i)|$$

$$\Delta K_{max}^L = \max_i |\inf K_A^3\,(x_i) - \inf K_B^3\,(x_i)|,$$

$$\Delta K_{max}^U = \max_i |\sup K_A^3\,(x_i) - \sup K_B^3\,(x_i)|,$$

$$\Delta U_{max}^L = \max_i |\inf U_A^3\,(x_i) - \inf U_B^3\,(x_i)|,$$

$$\Delta U_{max}^U = \max_i |\sup U_A^3\,(x_i) - \sup U_B^3\,(x_i)|$$

$$\Delta F_{max}^{L} = \max_i |\inf F_A^3\,(x_i) - \inf F_B^3\,(x_i)|,$$

$$\Delta F_{max}^{U} = \max_i |\sup F_A^3\,(x_i) - \sup F_B^3\,(x_i)|$$

Here, we suggest a weighted correlation coefficient between IFPNSs A and B by accounting for the weight of each element x_i (i = 1,2,…n) for each $x_i \,\epsilon X$ and i = 1, 2,…n.

Let w_i be the weight for each element of x_i (i=1, 2…n), $w_i \epsilon [0,1]$ and $\sum_{i=1}^{n} w_i = 1$, then the weighted correlation coefficient between the IFPNSs A and B, which stands for $N_w(A,B)$, is represented by the following equation (8).

$$N_w(A,B) = \{ \tfrac{1}{10} \textstyle\sum_{i=1}^{n} w_i [{\varphi_{1_i}}^L(1 - \Delta {T_i}^L) + {\varphi_{2_i}}^L(1 - \Delta {C_i}^L) + {\varphi_{3_i}}^L(1 - \Delta {K_i}^L) + {\varphi_{4_i}}^L(1 - \Delta {U_i}^L) + {\varphi_{5_i}}^L(1 - \Delta {F_i}^L) + {\varphi_{1_i}}^U(1 - \Delta {T_i}^U) + {\varphi_{2_i}}^U(1 - \Delta {C_i}^U) + {\varphi_{3_i}}^U(1 - \Delta {K_i}^U) + {\varphi_{4_i}}^U(1 - \Delta {U_i}^U) + {\varphi_{5_i}}^U(1 - \Delta {F_i}^U)]\} \;\ldots\ldots \quad (8)$$

If $w = \left(\frac{1}{n}, \frac{1}{n}, \ldots.\frac{1}{n}\right)^T$, then equation (8) becomes like to equation (7). When $T_A^3(x_i) = infT_A^3(x_i) = supT_A^3(x_i)$, $C_A^3(x_i) = infC_A^3(x_i) = supC_A^3(x_i)$, $K_A^3(x_i) = infK_A^3(x_i) = supK_A^3(x_i)$, $U_A^3(x_i) = infU_A^3(x_i) = supU_A^3(x_i)$, $F_A^3(x_i) = infF_A^3(x_i) = supF_A^3(x_i)$ in the IFPNS A and $T_B^3(x_i) = infT_B^3(x_i) = supT_B^3(x_i)$,

$C_B^3(x_i) = infC_B^3(x_i) = supC_B^3(x_i)$, $K_B^3(x_i) = infK_B^3(x_i) = supK_B^3(x_i)$, $U_B^3(x_i) = infU_B^3(x_i) = supU_B^3(x_i)$, $F_B^3(x_i) = infF_B^3(x_i) = supF_B^3(x_i)$ in the IFPNS B for any x_i in X

The IFPNS A and B then become the FPSVNSs A and B, respectively, and equations (7) and (8) become equations (3) and (4) when i = 1, 2... n. In addition, N (A, B) and $N_w(A,B)$ both meet the three requirements of theorems 3.1 and 3.2.

Theorem 5.7 The correlation coefficient N (A, B) for any two IFPNSs A and B in the discourse universe

$X = \{x_1, x_2, \ldots\ldots x_n\}$, fits the requirements given below.

i) N(A,B) = N(B,A);

ii) $0 \leq N(A,B) \leq 1$;

iii) $N(A,B) = 1 \; iff \; A = B$.

Theorem 3.1's characteristics may also be demonstrated.

Theorem 5.8

The weighted correlation coefficient between the IFPNSs A and B, which is stand for $N_w(A,B)$, and is expressed in equation (8) also satisfies the criteria specified below. Let w_i represent the weight for each of the following elements: x_i $(i = 1,2 \ldots .n), w_i \epsilon [0,1]$ and $\sum_{i=1}^{n} w_i = 1$.

i) $N_w(A,B) = N_w(B,A)$;

ii) $0 \leq N_w(A,B) \leq 1$;

iii) $N_w(A,B) = 1 \; iff \; A = B$

Theorem 3.1's attributes can be demonstrated in a similar way

5.9 Decision making method using the improved correlation coefficient of the IFPNSs.

In this instance, the following IFPNS represents the characteristic of an option-making issue using interval Fermatean pentapartitioned neutrosophic information $C_j(j = 1,2, \ldots \ldots n)$ on a multiple choice $A_i(i = 1,2, \ldots \ldots m)$ on an imbute C

$$A = \{\langle C_j, T_{A_i}(C_j), C_{A_i}(C_j), K_{A_i}(C_j), U_{A_i}(C_j), F_{A_i}(C_j)\rangle / C_j \epsilon C, j = 1,2 \ldots . . n\}$$
$$= \left\{ \frac{\langle C_j, [infT_{A_i}(C_j), supT_{A_i}(C_j)], [infC_{A_i}(C_j), supC_{A_i}(C_j)], [\inf K_{A_i}(C_j), supK_{A_i}(C_j)], [\inf U_{A_i}(C_j), supU_{A_i}(C_j)], [infF_{A_i}(C_j), supF_{A_i}(C_j)\rangle}{C_j \epsilon C}, j = 1,2 \ldots . . n \right\}$$

Where $T_{A_i}(C_j), C_{A_i}(C_j), K_{A_i}(C_j), U_{A_i}(C_j), F_{A_i}(C_j) \epsilon [0,1]$ and

$$0 \leq \sup T_{A_i}^3(C_j) + \sup C_{A_i}^3(C_j) + \sup K_{A_i}^3(C_j) + \sup U_{A_i}^3(C_j) + \sup F_{A_i}^3(C_j) \leq 5$$

for $C_j \epsilon C$, $j = 1,2 \ldots . . n$ and I = 1,2,….m.

Let's examine the following five functions for the sake of convenience.

$T_{A_i}(C_j) = [infT_{A_i}^3(C_j), supT_{A_i}^3(C_j)]$, $C_{A_i}(C_j) = [infC_{A_i}^3(C_j), supC_{A_i}^3(C_j)]$,

$K_{A_i}(C_j) = [infK_{A_i}^3(C_j), supK_{A_i}^3(C_j)]$, $U_{A_i}(C_j) = [infU_{A_i}^3(C_j), supU_{A_i}^3(C_j)]$,

$F_{A_i}(C_j) = [infF_{A_i}^3(C_j), supF_{A_i}^3(C_j)]$, based on an interval fermatean pentapartitioned neutrosophic value (IFPNV)

$$r_{ij} = \langle [t_{ij}^{L^3}, t_{ij}^{U^3}], [c_{ij}^{L^3}, c_{ij}^{U^3}], [k_{ij}^{L^3}, k_{ij}^{U^3}], [u_{ij}^{L^3}, u_{ij}^{U^3}][f_{ij}^{L^3}, f_{ij}^{U^3}]\rangle \; (i = 1,2, \ldots . m: j = 1,2,3, \ldots . n)$$

In this case, the decision maker or wizard normally determines the values of r_{ij} by evaluating an alternative A_i in light of the criterion C_j. As a result, $R = {r_{ij}}_{mxn}$ is an interval Fermatean pentapartitioned neutrosophic decision
maker. Here, an ideal IFPNV is one that:

$$r_j{}^* = \langle [t_j^{L^*}, t_j^{U^*}], [c_j^{L^*}, c_j^{U^*}], [k_j^{L^*}, k_j^{U^*}], [u_j^{L^*}, u_j^{U^*}][f_j^{L^*}, f_j^{U^*}] \rangle$$
$$= \langle [1,1], [1,1], [0,0], [0,0], [0,0] \rangle \; j = 1,2,3, \dots . n)$$

Equation (8) yields the weighted correlation coefficient between option A_i $(i = 1,2, \dots . m)$ and the ideal option A*.

$$N_w(A_i, A^*) = \frac{1}{10}\sum_{i=1}^{n} w_j[\varphi_{1_{ij}}{}^L(1 - \Delta T_{ij}{}^L) + \varphi_{2_{ij}}{}^L(1 - \Delta C_{ij}{}^L) + \varphi_{3_{ij}}{}^L(1 - \Delta K_{ij}{}^L) + \varphi_{4_{ij}}{}^L(1 - \Delta U_{ij}{}^L) + \varphi_{5_{ij}}{}^L(1 - \Delta F_{ij}{}^L) + \varphi_{1_{ij}}{}^U(1 - \Delta T_{ij}{}^U) + \varphi_{2_{ij}}{}^U(1 - \Delta C_{ij}{}^U) + \varphi_{3_{ij}}{}^U(1 - \Delta K_{ij}{}^U) + \varphi_{4_{ij}}{}^U(1 - \Delta U_{ij}{}^U) + \varphi_{5_{ij}}{}^U(1 - \Delta F_{ij}{}^U)] \; \dots . (9)$$

Where $\varphi_{1_{ij}}^L = \frac{5 - \Delta t_{ij}^L - \Delta T_{imax}^L}{5 - \Delta t_{imin}^L - \Delta t_{imax}^L}$, $\varphi_{1_{ij}}^U = \frac{5 - \Delta t_{ij_i}^{L^U} - \Delta T_{imax}^U}{5 - \Delta t_{imin}^U - \Delta t_{imax}^U}$,

$\varphi_{2_{ij}}^L = \frac{5 - \Delta c_{ij}^L - \Delta c_{imax}^L}{5 - \Delta c_{imin}^L - \Delta c_{imax}^L}$, $\varphi_{2_{ij}}^U = \frac{5 - \Delta c_{ij}^U - \Delta c_{imax}^U}{5 - \Delta c_{imin}^U - \Delta c_{imax}^U}$,

$\varphi_{3_{ij}}^L = \frac{5 - \Delta k_{ij}^L - \Delta k_{max}^L}{5 - \Delta k_{imin}^L - \Delta k_{imax}^L}$, $\varphi_{3_{ij}}^U = \frac{5 - \Delta k_{ij}^U - \Delta k_{imax}^U}{5 - \Delta k_{imin}^U - \Delta k_{imax}^U}$,

$\varphi_{4_{ij}}^L = \frac{5 - \Delta u_{ij}^L - \Delta u_{imax}^L}{5 - \Delta u_{imin}^L - \Delta u_{imax}^L}$, $\varphi_{4_{ij}}^U = \frac{5 - \Delta u_{ij}^U - \Delta u_{imax}^U}{5 - \Delta u_{imin}^U - \Delta u_{imax}^U}$,

$\varphi_{5_{ij}}^L = \frac{5 - \Delta f_{ij}^L - \Delta f_{imax}^L}{5 - \Delta f_{imin}^L - \Delta f_{imax}^L}$, $\varphi_{5_{ij}}^U = \frac{5 - \Delta f_{ij}^U - \Delta f_{imax}^U}{5 - \Delta f_{imin}^U - \Delta f_{imax}^U}$,

$\Delta t_{ij}{}^L = |t_{ij}^{L^3} - t_j^{L^*}|$, $\Delta t_{ij}{}^U = |t_{ij}^{U^3} - t_j^{U^*}|$,

$\Delta c_{ij}{}^L = |c_{ij}^{L^3} - c_j^{L^*}|$, $\Delta c_{ij}{}^U = |c_{ij}^{U^3} - c_j^{U^*}|$

$\Delta k_{ij}{}^L = |k_{ij}^{L^3} - k_j^{L^*}|$, $\Delta k_{ij}{}^U = |k_{ij}^{U^3} - k_j^{U^*}|$

$\Delta u_{ij}{}^L = |u_{ij}^{L^3} - u_j^{L^*}|$, $\Delta u_{ij}{}^U = |u_{ij}^{U^3} - u_j^{U^*}|$

$\Delta f_{ij}{}^L = |f_{ij}^{L^3} - f_j^{L^*}|$ $\Delta f_{ij}{}^U = |f_{ij}^{U^3} - f_j^{U^*}|$,

$\Delta t_{imin}^L = \min_j |t_{ij}^{L^3} - t_j^{L^*}|$, $\Delta t_{imin}^U = \min_j |t_{ij}^{U^3} - t_j^{U^*}|$,

$\Delta c_{imin}^L = \min_j |c_{ij}^{L^3} - c_j^{L^*}|$, $\Delta c_{imin}^U = \min_j |c_{ij}^{U^3} - c_j^{U^*}|$,

$\Delta k_{imin}^L = \min_j |k_{ij}^{L^3} - k_j^{L^*}|$, $\Delta k_{imin}^U = \min_j |k_{ij}^{U^3} - k_j^{U^*}|$

$$\Delta u_{imin}^{L} = \min_j \left| u_{ij}^{L^3} - u_j^{L^*} \right|, \qquad \Delta u_{imin}^{U} = \min_j \left| u_{ij}^{U^3} - u_j^{U^*} \right|$$

$$\Delta f_{imin}^{L} = \min_j \left| f_{ij}^{L^3} - f_j^{L^*} \right|, \qquad \Delta f_{imin}^{U} = \min_j \left| f_{ij}^{U^3} - f_j^{U^*} \right|$$

$$\Delta t_{imax}^{L} = \max_j \left| t_{ij}^{L^3} - t_j^{L^*} \right| \qquad \Delta t_{imax}^{U} = \max_j \left| t_{ij}^{U^3} - t_j^{U^*} \right|$$

$$\Delta c_{imax}^{L} = \max_j \left| c_{ij}^{L^3} - c_j^{L^*} \right|, \qquad \Delta c_{imax}^{U} = \max_j \left| c_{ij}^{U^3} - c_j^{U^*} \right|$$

$$\Delta k_{imax}^{L} = \max_j \left| k_{ij}^{L^3} - k_j^{L^*} \right|, \qquad \Delta k_{imax}^{U} = \max_j \left| k_{ij}^{U^3} - k_j^{U^*} \right|,$$

$$\Delta u_{imax}^{L} = \max_j \left| u_{ij}^{L^3} - u_j^{L^*} \right|, \qquad \Delta u_{imax}^{U} = \max_j \left| u_{ij}^{U^3} - u_j^{U^*} \right|$$

$$\Delta f_{imax}^{L} = \max_j \left| f_{ij}^{L^3} - f_j^{L^*} \right|, \qquad \Delta f_{imax}^{U} = \max_j \left| f_{ij}^{U^3} - f_j^{U^*} \right|$$

For i =1, 2…m and j = 1, 2, 3….n.

The options have been ranked using the weighted correlation coefficient $N_w(A_i, A^*)$ $(i = 1,2, \dots . m)$, and the best choice can be selected.

VI. ILLUSTRATIVE EXAMPLE

In this section, a multiple attribute decision-making dilemma is illustrated using an alternative that complies with the rules set forth in the fermatean pentapartitioned single valued neutrosophic environment and the interval fermatean pentapartitioned neutrosophic environment.

6.1 Decision making under feramatean pentapartitioned single valued neutrosophic environment

The high-phone example that will be discussed in this location is about quality mobile devices with all applicable options set up various testing. The mobile1, mobile2, and mobile3 are each independently designated by the options A_1, A_2, A_3 . The consumer must make a choice on the basis of the following four factors: (1) C_1 (cost), (2) C_2 (average scope), (1) C_4 (look), and (3) C_3 (characteristics of the camera). Based on these characteristics, we conclude that the client chooses the best candidate according to the stable order of all choices.

The weight vector for the aforementioned characteristics is probably given by $w = (0.35, 0.25, 0.20, 0.10, 0.15)^T$. Here, the chances for evaluation will be evaluated in accordance with the five FPSVNS qualities listed above.

For each question, a rule expert will often evaluate an alternative Ai in relation to an attribute

C_j, (i = 1,2,3; j = 1,2,3,4,5) To be more precise, when asking someone their opinion on an alternative A_1 in relation to an attribute C_1, the probability that a proposition is true is 0.5, that it is both true and false is 0.4, that it is not true or false is 0.3, and that it is false is 0.2.

It may have been intended to read $d_{11}=\langle 0.5, 0.4, 0.3, 0.2\rangle$ in the neutrosophic documentation. The following fermatean pentapartitioned single valued neutrosophic decision model will be obtained by repeating this approach for all three alternate about four characteristics.

A_i /C_j	C_1	C_2	C_3	C_4
A_1	[0.5,0.4,0.5,0.3,0.2]	[0.6,0.7,0.5,0.3,0.1]	[0.3,0.8,0.7,0.4,0.2]	[0.2,0.4,0.3,0.1,0.5]
A_2	[0.4,0.6,0.2,0.5,0.3]	[0.4,0.3,0.2,0.1,0.5]	[0.5,0.1,0.3,0.4,0.9]	[0.1,0.2,0.7,0.4,0.6]
A_3	[0.6,0.7,0.2,0.5,0.4]	[0.2,0.5,0.4,0.8,0.6]	[0.8,0.5,0.6,0.4,0.3]	[0.2,0.1,0.4,0.6,0.8]

Next, we will get the cutest alternative by applying the suggested strategy. Equation (6) can be used to determine the correlation coefficient $M_w(A_i, A^*)$ $(i = 1,2,3)$.
$M_w(A_1, A^*) = 0.94155255, M_w(A_2, A^*) = 0.6708769359, M_w(A_3, A^*) = 0.527372876$

As a result, the ranking is $A_1 > A_2 > A_3$. The most advantageous option out of the three is alternative A_1(Mobile 1).

6.3 Decision making under interval Fermatean pentapartitioned nuetrosophic environment.

Consider the current similar model, where the four qualities are to be evaluated using IFPNSs to rank the three attainable options. Each fermatean pentapartitioned of a rule expert will complete the assessment of an alternative Ai regarding an attribute C_j (i=1,2,3;j=1,2,3,4) . The resulting interval fermatean pentapartitioned nuetrosophic decision matrix M is thus captured.

$$M = \begin{pmatrix} \langle 0.3,0.5\rangle & \langle 0.1,0.2\rangle & \langle 0.3,0.6\rangle & \langle 0.4,0.7\rangle & \langle 0.2,0.5\rangle \\ \langle 0.1,0.2\rangle & \langle 0.3,0.4\rangle & \langle 0.7,0.8\rangle & \langle 0.4,0.6\rangle & \langle 0.3,0.6\rangle \\ \langle 0.6,0.8\rangle & \langle 0.6,0.7\rangle & \langle 0.4,0.6\rangle & \langle 0.3,0.6\rangle & \langle 0.4,0.7\rangle, \\ \langle 0.3,0.5\rangle & \langle 0.1,0.6\rangle & \langle 0.4,0.7\rangle & \langle 0.3,0.7\rangle & \langle 0.2,0.6\rangle \\ \langle 0.1,0.5\rangle & \langle 0.2,0.3\rangle & \langle 0.5,0.6\rangle & \langle 0.4,0.6\rangle & \langle 0.3,0.5\rangle \\ \langle 0.4,0.5\rangle & \langle 0.6,0.7\rangle & \langle 0.4,0.6\rangle & \langle 0.2,0.8\rangle & \langle 0.5,0.7\rangle \\ \langle 0.3,0.6\rangle & \langle 0.2,0.6\rangle & \langle 0.1,0.3\rangle & \langle 0.4,0.7\rangle & \langle 0.1,0.6\rangle \\ \langle 0.4,0.5\rangle & \langle 0.2,0.3\rangle & \langle 0.4,0.7\rangle & \langle 0.2,0.5\rangle & \langle 0.2,0.4\rangle \\ \langle 0.1,0.3\rangle & \langle 0.5,0.7\rangle & \langle 0.2,0.3\rangle & \langle 0.7,0.8\rangle & \langle 0.3,0.7\rangle \\ \langle 0.3,0.5\rangle & \langle 0.1,0.6\rangle & \langle 0.4,0.7\rangle & \langle 0.3,0.7\rangle & \langle 06,0.7\rangle \\ \langle 0.4,0.7\rangle & \langle 0.1,0.5\rangle & \langle 0.2,0.8\rangle & \langle 0.1,0.8\rangle & \langle 0.3,06\rangle \\ \langle 0.2,0.7\rangle & \langle 0.1,0.6\rangle & \langle 0.2,0.4\rangle & \langle 0.2,0.8\rangle & \langle 0.4,0.7\rangle \end{pmatrix}$$

The best option can then be obtained by applying the proposed procedure. Equation (9) gives the values of the correlation coefficient $N_w(A_i, A^*)(i = 1,2,3)$.

Hence $N_w(A_1, A^*) = 0.4597629$, $N_w(A_2, A^*) = 0.4775710$, $N_w(A_3, A^*) = 0.4684819$.

As a result, A2 > A3 > A1 is obtained. In accordance with the specified requirements in the interval fermatean pentapartitioning environment, alternative A_2 (Mobile 2) is the best option.

VII. CONCLUSION

The improved correlation coefficient of FPSVNSs, or IFPNSs, has been defined, and we have also examined parts where the correlation coefficient of FPSVNSs defined in [] is unclear or illogical. Decision-making is a process necessary to deal with problems in daily life. The two main steps in the decision-making process are the identification of the problem (or opportunity) and the adoption of action. In particular, multiple attribute-choice issues with several possibilities based on various criteria are an informative example. In this study, we investigated decision-making patterns using elevated correlations between FPSVNSs and IFPNSs. Therefore, our anticipated increased correlation coefficient of FPSVNs and IFPNSs aids in labeling the most appropriate alternative to the client.

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