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Course Selection for Higher Education Using Distance Measures of Complex Fermatean Fuzzy Soft Sets

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Abstract: *Education plays a crucial role in the development of every country, as it not only raises awareness but also provides the ability to create new sources of employment. In this regard, selecting the most suitable course for higher education is essential, based on an individual's abilities and educational background. Although many decision-making approaches exist, each has its own limitations and drawbacks. Making a well-informed decision based on multiple factors requires a multi-attribute decision-making (MADM) technique. To address uncertainty and ambiguity in this process, a framework integrated with MADM is necessary. Accordingly, this article presents an advanced MADM technique based on distance measures of the complex Fermatean fuzzy soft set. Furthermore, the proposed model is applied to a case study on course selection for higher education. Finally, the article concludes with remarks on the limitations of the proposed model and directions for future research.*

Keywords: *Multi-Attribute Problems, Decision Methods, Distance Measures, Global Trading, Fuzzy Systems, Statistical Analysis*

1. Introduction

To take decision to choose a career for students is very complex and uncertain as it involves a careful balance of multiple factors such as student interest,job satisfaction, goal orientation, future growth,duration and cost associated with that particular career.Decision making process become more complicated by uncertainties and ambiguity resulting from unemployment due to increasing competition and saturation of students in a particular field,also innovation and advancement of emerging technologies in different fields make it difficult for the careers counselors and students to take inform decisions to choose a suitable careers.

Additionally global changes and increase of new challenges to reshape the horizon of careers path.As society grows demand of expert and skilled workers in various sectors also increased which add complexity for experts and students to choose a career that meet the demand of industry and society.While choosing a career students must take in account the range of growing feilds and opportunities to make an inform decisions that allign with their interest and skill, and also need of the growing world.

To overcome the challenges associated with decision-making regarding the best career selection, many researchers [1-4] have utilized multi-attribute decision-making (MADM) methods [5, 6]. MADM approaches are particularly useful in reducing the uncertainty and vagueness, helping decision-makers to make well informed decision for right selection of elements or objects. To further address this uncertainty, Zadeh [7] extended the classical concept of a set by allowing membership values to range within the interval [0,1] for each element. Further, Atanassov [8] introduced the idea of Intuitionistic Fuzzy Sets (I_nFS). Peng, X., and Yang, Y [9] proposed the Pythagorean Fuzzy Set (PyFS) as an extension of IFS. In PyFS, membership and non-membership functions are defined with the constraint that the sum of the squares of membership and non-membership values must lie within the interval [0,1]. Senapati and Yager [10] introduced the Fermatean Fuzzy Set (FFS), which employs a more robust condition: the sum of the cubes of membership and non-membership values must be less than or equal to 1.

After that, Molodtsov [16] proposed the concept of soft set theory. Cagman et al. [12] introduced Fuzzy Soft Sets (FSS), an extension of SS that provides improved handling of uncertainty and vagueness for decision-making problems. Jiang et al. [17] expanded the concept of FSS to Intuitionistic Fuzzy Soft Sets (IFSS) by including non-membership values along with membership in the parameterized framework. Thirunavukarasu et al. [20] extended soft set theory from the real line to the complex plane by introducing Complex Fuzzy Soft Sets (CFSS). Finally, Kumar, T., and Bajaj, R. K. [21] expanded the concepts of IFSS and SS to propose Complex Intuitionistic Fuzzy Soft Sets (CIFSS).

These all the existing framework has their own limitations, as the fuzzy set deals with only membership function without dealing the non-membership function. The intuitionistic fuzzy set handles both the membership and non-membership functions but imposes a restriction on the sum of these functions. This article leverages the advancements of both Complex

Intuitionistic Fuzzy Soft Sets (CIFSS) and Fermatean Fuzzy Soft Sets (FrFSS) to propose the Complex Fermatean Fuzzy Soft Set (CFrFSS), aiming to address complex decision-making problems more effectively. This paper introduced a Multi-Attribute Decision-Making (MADM) algorithmic model based on the mathematical structure CFrFSS, that can efficiently overcome the both data uncertainty and parametric uncertainty involved in decision-making processes.

2. Preliminaries

For the fundamental definition of the complex Fermatean fuzzy soft set (CFrFSs) and its related properties, let's recall the some basic definitions that leads to the main concept.

Definition 2.1 *[7] Let Y be a universal set ,then the fuzzy set on Y is given as* $\{(\hbar, T^{\alpha}(\hbar))|\hbar \in Y\}$, *where* $T^{\alpha}(\hbar): Y \rightarrow [0,1]$ *and* $T^{\alpha}(\hbar)$ *is known as membership of* Y.

Definition 2.2 *[8] Let Y be a universal set ,then the Intuitionistic fuzzy set on Y is given as:*

$$\{(\hbar, T^{\alpha}(\hbar), T^{\beta}(\hbar))|\hbar \in Y\}$$

Where $T^{\alpha}(\hbar): Y \rightarrow [0,1]$ and $T^{\beta}(\hbar): Y \rightarrow [0,1]$ and $T^{\alpha}(\hbar)$ is known as membership of Y and $T^{\beta}(\hbar)$ is known as non-membership of Y.

Definition 2.3 *[9] Let Y be a universal set ,then the Pythagorean fuzzy set on Y is given as:*

$$\{(\hbar, T^{\alpha}(\hbar), T^{\beta}(\hbar))|\hbar \in Y\}$$

Where $T^{\alpha}(\hbar): Y \rightarrow [0,1]$ and $T^{\beta}(\hbar): Y \rightarrow [0,1]$ and $T^{\alpha}(\hbar)$ is known as membership of Y and $T^{\beta}(\hbar)$ is known as non-membership of Y.

$$0 \leq \ (T^{\alpha}(\hbar))^2 + (T^{\beta}(\hbar))^2 \leq 1 \quad \text{forall} \quad \hbar \in Y.$$

Definition 2.4 *[10] Let Y be a universal set ,then the Fermatean fuzzy set on Y is given as:*

$$\{(\hbar, T^{\alpha}(\hbar), T^{\beta}(\hbar) | \hbar \in Y\}$$

Where $T^{\alpha}(\hbar): Y \to [0,1]$ and $T^{\beta}(\hbar): Y \to [0,1]$ and $T^{\alpha}(\hbar)$ is known as membership of Y and $T^{\beta}(\hbar)$ is known as non-membership of Y.

$$0 \leq \ (T^{\alpha}(\hbar))^3 + (T^{\beta}(\hbar))^3 \leq 1 \quad \text{forall} \quad \hbar \in Y.$$

Definition 2.5 *[11] Let Y be a universal set and K be the subset of set of parameters, then the soft set S over universal Y is defined as $\{(\hat{\lambda}, T^{\alpha}(\hat{\lambda})): \hat{\lambda} \in K\}$, where $T^{\alpha}: K \to P(Y)$ and $P(Y)$ is the power set of the universal set Y.*

Definition 2.6 *[12] Let Y be a universal set and K be the subset of set of parameters, then the fuzzy soft set F_{ss} over universal Y is defined as $F_{ss} = \{(\hat{\lambda}, T^{\alpha}(\hat{\lambda})): \hat{\lambda} \in K\}$, where $T^{\alpha}: K \to F(Y)$ and $F(Y)$ is the collection of all fuzzy subset over the universal set Y.*

Definition 2.7 *Let Y be a universal set and K be the subset of set of parameters, then the fermatean fuzzy soft set FrF_{ss} over universal Y is defined as $FrF_{ss} = \{(\hat{\lambda}, T^{\alpha}(\hat{\lambda}), T^{\beta}(\hat{\lambda})): \hat{\lambda} \in K\}$, where T^{α} , $T^{\beta}: K \to FrF(Y)$ and $FrF(Y)$ is the collection of all fermatean fuzzy subset over the universal set Y. With constraints*

$$0 \leq (T^{\alpha}(\hat{\lambda}))^3 + (T^{\beta}(\hat{\lambda}))^3 \leq 1 \quad \text{forall} \quad \hat{\lambda} \in K.$$

3. Proposed Methodology

This section provided the modified definition of the complex fermatean fuzzy soft set (CFrFSs) and then a algorithmic approach based on the complex fermatean fuzzy soft set. The modified definition of CFrFSs is given as:

Definition 3.1 *Let G be the universe of discourse and E be the subset of set of parameters P. Define the complex fuzzy mappings $U^m, U^n: E \to \Delta_{CFFs}(G)$ by $U^m(\eta) = \sigma_m(\eta)e^{i\ell_m(\eta)}$ and $U^n(\eta) = \sigma_n(\eta)e^{i\ell_n(\eta)}$, then the CFrFSs is defined as,*

$$\tilde{\Gamma} = (E, \hat{\vartheta}) = \{(\eta, \langle U^m(\eta), U^n(\eta)\rangle): \eta \in P\}$$

Where $U^m(\eta)$ and $U^n(\eta)$ are positive membership and negative membership functions respectively with constraints $0 \leq (\sigma_m(\eta))^3 + (\sigma_n(\eta))^3 \leq 1$ and $0 \leq \ell_m(\eta) + \ell_n(\eta) \leq 2\pi$.while The terms $\sigma_m(\eta)$, $\sigma_n(\eta)$ known as amplitude terms and the terms $\ell_m(\eta)$, $\ell_n(\eta)$ are called phase terms. The grade of refusal membership is defined as,

$$H_R(\eta) = [1 - ((\sigma_m(\eta))^3 + (\sigma_n(\eta))^3)]e^{i[2\pi-(\ell_m(\eta)+\ell_n(\eta))]} \in \mathbb{C}^{[0,1]}$$

where $\langle \sigma_m(\eta)e^{i\ell_m(\eta)}, \sigma_n(\eta)e^{i\ell_n(\eta)} \rangle$ represented complex fermatean fuzzy soft number (CFFSN).

The calculated proposed distance measures d_1, d_2 by using following theorem are given in Table 3.

Theorem 3.2 *Let* $(J_1, \hat{\vartheta}_1) = \left\{(\mu^1, \langle \delta^1_\alpha(\mu)e^{i\varphi^1_\alpha(\mu)}, \delta^1_\beta(\mu)e^{i\varphi^1_\beta(\mu)} \rangle : \mu \in J_1\right\}$ *and* $(J_2, \hat{\vartheta}_2) = \left\{(\mu^2, \langle \delta^2_\alpha(\mu)e^{i\varphi^2_\alpha(\mu)}, \delta^2_\beta(\mu)e^{i\varphi^2_\beta(\mu)} \rangle : \mu \in J_2\right\}$ *are two CFrFSss over the universe* Υ, *then the* ***Euclidean-based distance measures*** *between any two CFrFSS is defined as:*

$$d_1(J_1, J_2) = \sum_{j=1}^{m} \sum_{i=1}^{n} [\frac{1}{4}\left((\delta^1_{\alpha_i}(\mu_j) - \delta^2_{\alpha_i}(\mu_j))^2 + (\delta^1_{\beta_i}(\mu_j) - \delta^2_{\beta_i}(\mu_j))^2\right)$$

$$+ \frac{1}{16\pi^4}\left((\varphi^1_{\alpha_i}(\mu_j) - \varphi^2_{\alpha_i}(\mu_j))^2 + (\varphi^1_{\beta_i}\mu_j) - \varphi^2_{\beta_i}(\mu_j))^2\right)]^{\frac{1}{2}},$$

and normalized Euclidean-based distance measures is given as:

$$d_2(J_1, J_2) = \frac{1}{mn}\sum_{j=1}^{m} \sum_{i=1}^{n} [\frac{1}{4}\left((\tau^1_{\alpha_i}(\mu_j) - \delta^2_{\alpha_i}(\mu_j))^2 + (\delta^1_{\beta_i}(\mu_j) - \delta^2_{\beta_i}(\mu_j))^2\right)$$

$$+ \frac{1}{16\pi^4}\left((\varphi^1_{\alpha_i}(\mu_j) - \varphi^2_{\alpha_i}(\mu_j))^2 + (\varphi^1_{\beta_i}(\mu_j) - \varphi^2_{\beta_i}(\mu_j))^2\right)]^{\frac{1}{2}}$$

The proposed multi attribute decision making technique based on the distance measures of complex fermatean fuzzy soft set has the following steps:

3.3. Algorithm

[1] Universe of alternatives $\Upsilon = \{\hbar_1, \hbar_2, \ldots, \hbar_n\}$; set of attributes $\rho = \{\hat{\lambda}_1, \hat{\lambda}_2, \ldots, \hat{\lambda}_m\}$ Optimal alternative based on distance measures

Construct the CFrFSS matrix using Υ and ρ Construct the ideal CFrFSS matrix from Step 1 each pair (K_1, K_2) of CFrFSS matrices Compute the following distance measures:

- $d_1(K_1, K_2)$ using the Euclidean-based formula

• $d_2(K_1, K_2)$ using the normalized Euclidean-based formula

Compute the average distances for d_1 and d_2 Rank all alternatives based on their distance values in ascending order Select the alternative with the smallest distance as the optimal choice.

4. Case Study

A person $\overline{H}$ from the country W wanted to select a suitable programe for higher study so he met with group of experts for counseling. After detail discusion and taking into account the student's interest and financial back groung the experts reached to the conclusion and decided to select four different programes i.e. $\phi_1 = ArtificialIntelligence, \phi_2 = DataScience, \phi_3 = SoftwareEngineering, \phi_4 = GraphicDesigning$.The experts also choose some attributes to show the alignment of already mentined programes that are $\mu_1 = Studentgoal, \mu_2 = durationofprograme, \mu_3 = scope, \mu_4 = skills$. To express above decision making factors, we define the set $A = \{\mu_1, \mu_2, \mu_3, \mu_4\}$ which consist of four main parameters. Also we take the set of programes that are $\Upsilon = \{\phi_1, \phi_2, \phi_3, \phi_4\}$.

1. The CFFSS for the set of alternative ϕ_1,ϕ_2 ,ϕ_3, and ϕ_4 by using set of parametersμ_1,μ_2,μ_3, and μ_4 will be given as

$$\hat{\vartheta}(\mu_1) = \begin{Bmatrix} \left(\phi_1, \langle 0.44\, e^{2i\pi(0.26)}, 0.27\, e^{2i\pi(0.37)} \rangle\right) \\ \left(\phi_2, 0.37\, e^{2i\pi(0.46)}, 0.33\, e^{2i\pi(0.29)} \rangle\right) \\ \left(\phi_3, \langle 0.51\, e^{2i\pi(0.53)}, 0.22\, e^{2i\pi(0.27)} \rangle\right) \\ \left(\phi_4, \langle 0.55\, e^{2i\pi(0.24)}, 0.32\, e^{2i\pi(0.11)} \rangle\right) \end{Bmatrix}$$

$$\hat{\vartheta}(\mu_2) = \begin{Bmatrix} \left(\phi_1, \langle 0.34\, e^{2i\pi(0.23)}, 0.14\, e^{2i\pi(0.32)} \rangle\right) \\ \left(\phi_2, 0.29\, e^{2i\pi(0.12)}, 0.23\, e^{2i\pi(0.19)} \rangle\right) \\ \left(\phi_3, \langle 0.54\, e^{2i\pi(0.26)}, 0.24\, e^{2i\pi(0.34)} \rangle\right) \\ \left(\phi_4, \langle 0.45\, e^{2i\pi(0.15)}, 0.19\, e^{2i\pi(0.24)} \rangle\right) \end{Bmatrix}$$

$$\hat{\vartheta}(\mu_3) = \begin{Bmatrix} \left(\phi_1, \langle 0.24\, e^{2i\pi(0.22)}, 0.24\, e^{2i\pi(0.42)} \rangle\right) \\ \left(\phi_2, 0.25\, e^{2i\pi(0.22)}, 0.62\, e^{2i\pi(0.35)} \rangle\right) \\ \left(\phi_3, \langle 0.23\, e^{2i\pi(0.19)}, 0.41\, e^{2i\pi(0.15)} \rangle\right) \\ \left(\phi_4, \langle 0.56\, e^{2i\pi(0.21)}, 0.28\, e^{2i\pi(0.24)} \rangle\right) \end{Bmatrix}$$

$$\hat{\vartheta}(\mu_4) = \begin{Bmatrix} (\phi_1, \langle 0.34\, e^{2i\pi(0.42)}, 0.24\, e^{2i\pi(0.34)} \rangle) \\ (\phi_2, 0.17\, e^{2i\pi(0.14)}, 0.35\, e^{2i\pi(0.38)} \rangle) \\ (\phi_3, \langle 0.48\, e^{2i\pi(0.23)}, 0.32\, e^{2i\pi(0.16)} \rangle) \\ (\phi_4, \langle 0.62\, e^{2i\pi(0.16)}, 0.12\, e^{2i\pi(0.18)} \rangle) \end{Bmatrix}$$

The Rationalized data of CFrFSS matrix is given in Table 1.

CFrFSS DV	μ_1	μ_2	μ_3	μ_4
ϕ_1	$\begin{pmatrix} 0.44^{0.26} \\ 0.27^{0.37} \end{pmatrix}$	$\begin{pmatrix} 0.37^{0.46} \\ 0.33^{0.29} \end{pmatrix}$	$\begin{pmatrix} 0.51^{0.53} \\ 0.22^{0.27} \end{pmatrix}$	$\begin{pmatrix} 0.55^{0.24} \\ 0.32^{0.11} \end{pmatrix}$
ϕ_2	$\begin{pmatrix} 0.34^{0.23} \\ 0.14^{0.32} \end{pmatrix}$	$\begin{pmatrix} 0.29^{0.12} \\ 0.23^{0.19} \end{pmatrix}$	$\begin{pmatrix} 0.54^{0.26} \\ 0.24^{0.34} \end{pmatrix}$	$\begin{pmatrix} 0.45^{0.15} \\ 0.19^{0.24} \end{pmatrix}$
ϕ_3	$\begin{pmatrix} 0.24^{0.22} \\ 0.24^{0.42} \end{pmatrix}$	$\begin{pmatrix} 0.25^{0.22} \\ 0.62^{0.35} \end{pmatrix}$	$\begin{pmatrix} 0.23^{0.19} \\ 0.41^{0.15} \end{pmatrix}$	$\begin{pmatrix} 0.56^{0.21} \\ 0.28^{0.24} \end{pmatrix}$
ϕ_4	$\begin{pmatrix} 0.34^{0.42} \\ 0.24^{0.34} \end{pmatrix}$	$\begin{pmatrix} 0.17^{0.14} \\ 0.35^{0.38} \end{pmatrix}$	$\begin{pmatrix} 0.48^{0.23} \\ 0.32^{0.16} \end{pmatrix}$	$\begin{pmatrix} 0.62^{0.16} \\ 0.12^{0.18} \end{pmatrix}$

Table 1: CFrFSS Decision Matrix

The ideal CFrFSS matrix value, shown in Table 2.

CFrFSS DV	μ_1	μ_2	μ_3	μ_4
ϕ	$\begin{pmatrix} 0.44^{0.26} \\ 0.14^{0.32} \end{pmatrix}$	$\begin{pmatrix} 0.37^{0.46} \\ 0.23^{0.19} \end{pmatrix}$	$\begin{pmatrix} 0.54^{0.26} \\ 0.22^{0.27} \end{pmatrix}$	$\begin{pmatrix} 0.62^{0.16} \\ 0.12^{0.18} \end{pmatrix}$

Table 2: Ideal CFrFSS Decision Value

Distance Measure	ϕ_1	ϕ_2	ϕ_3	ϕ_4
$d_1(\phi, \phi_i)$	0.2999	0.4121	0.2669	0.2834
$d_2(\phi, \phi_i)$	0.0187	0.0258	0.0167	0.0177

Table 3: Distance measures between ideal ϕ and available alternatives ϕ_i

The mean of all the distance measures is given in Table 4.

Average value	ϕ_1	ϕ_2	ϕ_3	ϕ_4
$d(\phi,\phi_i)$	0.1593	0.2190	0.1418	0.1506

Table 4: Mean of all the distance measures

Note from Table 4, the ranking of the distance meausres is $d(\phi,\phi_2) \succ d(\phi,\phi_1) \succ d(\phi,\phi_4) \succ d(\phi,\phi_3)$. Thus the best alternative is ϕ_2, which means the Data Science is the suitable programe for higher study.

5. Conclusion

In conclusion, the proposed multi-attribute decision-making approach based on the distance measures of the complex Fermatean fuzzy soft set effectively handles uncertainty and ambiguity in employee selection processes. The case study validates the practicality and efficiency of the model, demonstrating its capability to identify the most suitable candidate among multiple alternatives. Overall, the findings suggest that the proposed model can serve as a reliable decision-support tool with potential applications in various organizational decision-making scenarios.

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