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A Fuzzy Soft Set-Based MADM Technique for Handling Uncertainty in Recruitment Decisions

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Abstract: *Since every organization operates smoothly and efficiently through the efforts of its employees, selecting the best person for any organization plays a crucial role in its effective functioning. However, this selection process involves many attributes that must be analyzed carefully. Making a well-informed decision based on several factors requires a multi-attribute decision-making (MADM) technique. To handle uncertainty and ambiguity in this process, a framework integrated with MADM is needed. In this regard, this article presents an advanced MADM technique based on the similarity measures of the complex Fermatean fuzzy soft set. Furthermore, the proposed model is applied to a case study for employee selection in an organization. Finally, the article concludes with remarks on the limitations of the proposed model and directions for future research.*

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

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.

1.1 Fundamental knowledge:

Before understanding the structure of Complex Fermatean Fuzzy Hypersoft Sets (CFFHSS), it is essential to grasp the concept of the following fundamental definitions.

Definition 1.1 *[7] Let G be a universal set ,then the fuzzy set on G is given as:*

$$\{(\epsilon, U^m(\epsilon)) | \epsilon \in G\}$$

Where $U^m: G \to [0,1]$ and $U^m(\epsilon)$ is known as membership of G.

Definition 1.2 *[10] Let G be a universal set ,then the Fermatean fuzzy set on G is given as:*

$$\{(\epsilon, U^m(\epsilon), U^n(\epsilon)) | \epsilon \in G\}$$

Where $U^m: G \to [0,1]$ and $U^n: G \to [0,1]$ and $U^m(\epsilon)$ is known as membership of G and

$U^n(\epsilon)$ is known as non-membership of G.

$$0 \leq (U^m(\epsilon))^3 + (U^n(\epsilon))^3 \leq 1 \quad \text{forall} \quad \epsilon \in G.$$

Definition 1.3 *[11] Let G be a universal set and P be the set of parameters, then the soft set S over universal G is defined as $\{(\eta, U^m(\eta)) : \eta \in P\}$, where $U^m: P \to P(G)$ and $P(G)$ is the power set of the universal set G.*

2- 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 2.1: *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).

2.1 Algorithm:

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

1. Design the CFrFSS based on set of alternatives $G = \{\epsilon_1, \epsilon_2, \epsilon_3, \ldots, \epsilon_n\}$ by using set of key parameters $P = \{\eta_1, \eta_2, \eta_3, \ldots, \eta_m\}$ with the help of experts opinions, e.g.

$$E(\eta_1) = \{\langle \sigma_m^1(\eta)e^{i\ell_m^1(\eta)}, \sigma_n^1(\eta)e^{i\ell_n^1(\eta)}\rangle\}, \cdots, E(\eta_m) = \{\langle \sigma_m^m(\eta)e^{i\ell_m^m(\eta)}, \sigma_n^m(\eta)e^{i\ell_n^m(\eta)}\rangle\}$$

2. Rationalize the CFrFSS decision sets for each alternative ϵ_i as given in Table 1.

CFrFSS DV	η_1	η_2	$\cdots$	η_m
ϵ_i	$\begin{pmatrix}\sigma_m^1(\eta)e^{i\ell_m^1(\eta)}\\ \sigma_n^1(\eta)e^{i\ell_n^1(\eta)}\end{pmatrix}$	$\begin{pmatrix}\sigma_m^2(\eta)e^{i\ell_m^2(\eta)}\\ \sigma_n^2(\eta)e^{i\ell_n^2(\eta)}\end{pmatrix}$	$\cdots$	$\begin{pmatrix}\sigma_m^m(\eta)e^{i\ell_m^m(\eta)}\\ \sigma_n^m(\eta)e^{i\ell_n^m(\eta)}\end{pmatrix}$

Table 1: Rationalize the CFrFSS Decision Values

3. Create the ideal CFFSS matrix by using set of key parameters $P = \{\eta_1, \eta_2, \eta_3, \dots, \eta_m\}$ from step (1) , for ideal alternative ϵ as given in Table 2.

CFrFSS DV	η_1	η_2	$\cdots$	η_m
ϵ	$\begin{pmatrix}\sigma_m^1(\eta)e^{i\ell_m^1(\eta)}\\ \sigma_n^1(\eta)e^{i\ell_n^1(\eta)}\end{pmatrix}$	$\begin{pmatrix}\sigma_m^2(\eta)e^{i\ell_m^2(\eta)}\\ \sigma_n^2(\eta)e^{i\ell_n^2(\eta)}\end{pmatrix}$	$\cdots$	$\begin{pmatrix}\sigma_m^m(\eta)e^{i\ell_m^m(\eta)}\\ \sigma_n^m(\eta)e^{i\ell_n^m(\eta)}\end{pmatrix}$

Table 2: Ideal Rationalize CFrFSS Decision Values

4. Find the similarity measures $S_1(\epsilon, \epsilon_i), S_2(\epsilon, \epsilon_i), S_3(\epsilon, \epsilon_i)$ and $S_4(\epsilon, \epsilon_i)$ by using the following formula:

$$S_2(\bar{E}_1, \bar{E}_2) =$$

$$\frac{\sum_{j=1}^{n}\left\{\min\left(\varpi^1_{m_j}(\gamma),\varpi^2_{m_j}(\gamma)\right)+\frac{1}{2\pi}\min\left(\wp^1_{n_j}(\gamma)\right),\wp^2_{n_j}(\gamma)+\min\left(\varpi^1_{n_j}(\gamma),\varpi^2_{n_j}(\gamma)\right)+\frac{1}{2\pi}\min\left(\wp^1_{m_j}(\gamma),\wp^2_{m_j}(\gamma)\right)\right\}}{\sum_{j=1}^{n}\left\{\max\left(\varpi^1_{m_j}(\gamma),\varpi^2_{m_j}(\gamma)\right)+\frac{1}{2\pi}\max\left(\wp^1_{n_j}(\gamma)\right),\wp^2_{n_j}(\gamma)+\max\left(\varpi^1_{n_j}(\gamma),\varpi^2_{n_j}(\gamma)\right)+\frac{1}{2\pi}\max\left(\wp^1_{m_j}(\gamma),\wp^2_{m_j}(\gamma)\right)\right\}}$$

and

$$S_2(\bar{E}_1, \bar{E}_2) =$$

$$\frac{\sum_{j=1}^{n}\left\{\min\left(\varpi^1_{m_j}(\gamma),\varpi^2_{m_j}(\gamma)\right)+\frac{1}{2\pi}\min\left(\wp^1_{n_j}(\gamma)\right),\wp^2_{n_j}(\gamma)+\min\left(\varpi^1_{n_j}(\gamma),\varpi^2_{n_j}(\gamma)\right)+\frac{1}{2\pi}\min\left(\wp^1_{m_j}(\gamma),\wp^2_{m_j}(\gamma)\right)\right\}}{\sum_{j=1}^{n}\left\{\max\left(\varpi^1_{m_j}(\gamma),\varpi^2_{m_j}(\gamma)\right)+\frac{1}{2\pi}\max\left(\wp^1_{n_j}(\gamma)\right),\wp^2_{n_j}(\gamma)+\max\left(\varpi^1_{n_j}(\gamma),\varpi^2_{n_j}(\gamma)\right)+\frac{1}{2\pi}\max\left(\wp^1_{m_j}(\gamma),\wp^2_{m_j}(\gamma)\right)\right\}}$$

5. Calculate the mean of similarity measures, that is, $\frac{S_1+S_2+S_3+S_4}{4}$.

6. Rank the similarity measures from least to highest.

7. Choose the alternative with highest similarity measure which give the best alternative from the given options.

2.2 Case Study:

A company $\mathcal{C}$ from the city $\mathcal{Y}$ of a country $\mathcal{H}$ wanted to hire suitable employees for a certain job position, so it organized a selection committee which consist of group of four members $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ from Human resource and technical departments. After comprehensive discussion and taking into account the demand and objectives of the company, the experts reached to the conclusion to select four candidates, i.e. $\tau_1, \tau_2, \tau_3, \tau_4$. To select the suitable candidate, the company also choose some evalution parameters that are $\gamma_1 = Qualification, \gamma_2 = Skills, \gamma_3 = Experience, \gamma_4 = Personality$. To express decision making factors, the experts chose the set $K = \{\gamma_1, \gamma_2, \gamma_3, \gamma_4\}$ which comprised of four main attributes. Also for employees they took the set of alternatives as $\chi = \{\tau_1, \tau_2, \tau_3, \tau_4\}$.

1. The CFFSS for the set of alternative τ_1,τ_2 ,τ_3, and τ_4 by using set of parametersγ_1,γ_2,γ_3, and γ_4 will be given as

$$\mho(\gamma_1) = \begin{Bmatrix} \left(\tau_1, \langle 0.52\, e^{2\mathbf{i}\pi(0.23)}, 0.44\, e^{2\mathbf{i}\pi(0.27)} \rangle\right) \\ \left(\tau_2, 0.37\, e^{2\mathbf{i}\pi(0.16)}, 0.25\, e^{2\mathbf{i}\pi(0.28)} \rangle\right) \\ \left(\tau_3, \langle 0.6\, e^{2\mathbf{i}\pi(0.23)}, 0.22\, e^{2\mathbf{i}\pi(0.42)} \rangle\right) \\ \left(\tau_4, \langle 0.25\, e^{2\mathbf{i}\pi(0.51)}, 0.5\, e^{2\mathbf{i}\pi(0.04)} \rangle\right) \end{Bmatrix}$$

$$\mho(\gamma_2) = \begin{Bmatrix} \left(\tau_1, \langle 0.44\, e^{2\mathbf{i}\pi(0.28)}, 0.35\, e^{2\mathbf{i}\pi(0.22)} \rangle\right) \\ \left(\tau_2, 0.36\, e^{2\mathbf{i}\pi(0.21)}, 0.43\, e^{2\mathbf{i}\pi(0.29)} \rangle\right) \\ \left(\tau_3, \langle 0.35\, e^{2\mathbf{i}\pi(0.13)}, 0.44\, e^{2\mathbf{i}\pi(0.67)} \rangle\right) \\ \left(\tau_4, \langle 0.43\, e^{2\mathbf{i}\pi(0.35)}, 0.36\, e^{2\mathbf{i}\pi(0.14)} \rangle\right) \end{Bmatrix}$$

$$\mho(\gamma_3) = \begin{Bmatrix} \left(\tau_1, \langle 0.24\, e^{2\mathbf{i}\pi(0.22)}, 0.35\, e^{2\mathbf{i}\pi(0.46)} \rangle\right) \\ \left(\tau_2, 0.37\, e^{2\mathbf{i}\pi(0.21)}, 0.42\, e^{2\mathbf{i}\pi(0.36)} \rangle\right) \\ \left(\tau_3, \langle 0.4\, e^{2\mathbf{i}\pi(0.26)}, 0.53\, e^{2\mathbf{i}\pi(0.25)} \rangle\right) \\ \left(\tau_4, \langle 0.6\, e^{2\mathbf{i}\pi(0.12)}, 0.23\, e^{2\mathbf{i}\pi(0.44)} \rangle\right) \end{Bmatrix}$$

$$\mho(\gamma_4) = \begin{Bmatrix} \left(\tau_1, \langle 0.34\, e^{2\mathbf{i}\pi(0.37)}, 0.24\, e^{2\mathbf{i}\pi(0.36)} \rangle\right) \\ \left(\tau_2, 0.27\, e^{2\mathbf{i}\pi(0.32)}, 0.35\, e^{2\mathbf{i}\pi(0.41)} \rangle\right) \\ \left(\tau_3, \langle 0.18\, e^{2\mathbf{i}\pi(0.24)}, 0.35\, e^{2\mathbf{i}\pi(0.39)} \rangle\right) \\ \left(\tau_4, \langle 0.22\, e^{2\mathbf{i}\pi(0.36)}, 0.28\, e^{2\mathbf{i}\pi(0.25)} \rangle\right) \end{Bmatrix}$$

2. Rationalized the CFrFSS for each alternative is given in Table 3;

CFrFSS DV	γ_1	γ_2	γ_3	γ_4
τ_1	$\begin{pmatrix}0.52^{0.23}\\0.44^{0.27}\end{pmatrix}$	$\begin{pmatrix}0.37^{0.16}\\0.25^{0.28}\end{pmatrix}$	$\begin{pmatrix}0.6^{0.23}\\0.22^{0.42}\end{pmatrix}$	$\begin{pmatrix}0.25^{0.51}\\0.5^{0.04}\end{pmatrix}$
τ_2	$\begin{pmatrix}0.44^{0.28}\\0.35^{0.22}\end{pmatrix}$	$\begin{pmatrix}0.36^{0.21}\\0.43^{0.29}\end{pmatrix}$	$\begin{pmatrix}0.35^{0.13}\\0.44^{0.67}\end{pmatrix}$	$\begin{pmatrix}0.43^{0.35}\\0.36^{0.14}\end{pmatrix}$
τ_3	$\begin{pmatrix}0.24^{0.22}\\0.35^{0.46}\end{pmatrix}$	$\begin{pmatrix}0.37^{0.21}\\0.42^{0.36}\end{pmatrix}$	$\begin{pmatrix}0.4^{0.26}\\0.53^{0.25}\end{pmatrix}$	$\begin{pmatrix}0.6^{0.12}\\0.23^{0.44}\end{pmatrix}$
τ_4	$\begin{pmatrix}0.34^{0.37}\\0.24^{0.36}\end{pmatrix}$	$\begin{pmatrix}0.27^{0.32}\\0.35^{0.41}\end{pmatrix}$	$\begin{pmatrix}0.18^{0.24}\\0.35^{0.39}\end{pmatrix}$	$\begin{pmatrix}0.22^{0.36}\\0.28^{0.25}\end{pmatrix}$

Table 3: CFrFSS Decision Matrix

3. The ideal CFrFSS matrix value, shown in Table 4.

CFrFSS DV	τ_1	τ_2	τ_3	τ_4
τ	$\begin{pmatrix}0.52^{0.23}\\0.24^{0.36}\end{pmatrix}$	$\begin{pmatrix}0.37^{0.21}\\0.25^{0.28}\end{pmatrix}$	$\begin{pmatrix}0.6^{0.23}\\0.22^{0.42}\end{pmatrix}$	$\begin{pmatrix}0.6^{0.12}\\0.23^{0.44}\end{pmatrix}$

Table 4: Ideal CFrFSS Decision Value

4. The calculated similarity measures $S_1(\tau,\tau_i), S_2(\tau,\tau_i)$ by using formulas are given in Table 5.

Similarity measures	(τ,τ_1)	(τ,τ_2)	(τ,τ_3)	(τ,τ_4)
$S_1(\tau,\tau_i)$	0.6179	0.6889	0.7349	0.6152
$S_2(\tau,\tau_i)$	0.7533	0.6788	0.7188	0.6036

Table 5: Ideal CFrFSS Decision Value

5. The mean of all the similarity measures is given in Table 6.

$S(\tau, \tau_i)$	τ_1	τ_2	τ_3	τ_4
τ	0.6856	0.6838	0.7268	0.6094

Table 6: Mean of the similarity measures

6. Rank the alternatives on the basis of obtained similarity measure is:

$$S(\tau, \tau_4) \leq S(\tau, \tau_2) \leq S(\tau, \tau_1) \leq S(\tau, \tau_3)$$

7. Since the alternative τ_3 has the highest similarity measure of the with the ideal alternative, therefore, the best alternative from available will be τ_3.

3- Conclusion

This article presented an advanced multi-attribute decision making approach based on the similarity measure of the complex fermatean fuzzy soft set. The presented MADM approach based on complex Fermatean fuzzy soft sets effectively overcomes the uncertainty and ambiguity in the selection of employee for any organization. By considering evaluation of multiple attributes and using similarity measures, the model provides a effective model for identifying the most suitable candidate. Further, the effectiveness of the proposed model is provided by applying it a case study for selection of employee. The case study demonstrated the practicality and efficiency of the model, while the findings highlight its potential for broader applications in organizational decision-making.

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