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ENHANCING DECISION ACCURACY IN SOFTWARE SELECTION: A PROBABILISTIC HESITANT FUZZY TOPSIS MODEL WITH MAXIMUM DEVIATION

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Abstract: This research introduces a novel integration of the Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) model with the Maximum Deviation method to enhance decision-making accuracy in the selection of engineering software. The proposed model addresses the challenges of uncertainty and complexity by effectively weighting criteria based on their variability across alternatives. A practical case study involving six widely-used engineering software packages—Autodesk AutoCAD, SolidWorks, ANSYS, Siemens NX, PTC Creo, and CATIA—demonstrates the model's capability to generate reliable and accurate rankings. The results show that ANSYS is the most suitable software based on key criteria such as functionality, usability, and vendor support. The integration of PHFTOPSIS with Maximum Deviation offers significant advantages over traditional methods, providing a more nuanced and robust decision-making framework. This research contributes to the field of multi-criteria decision-making (MCDM) and suggests avenues for further methodological enhancements and applications in other domains.

Index Terms: **Multi-Criteria Decision-Making (MCDM), Probabilistic Hesitant Fuzzy TOPSIS, Maximum Deviation Method, Engineering Software Selection, Decision Accuracy, Uncertainty Handling.**

INTRODUCTION AND LITERATURE REVIEW

In the increasingly complex environment of modern software systems, precise decision-making is critical for selecting the most appropriate tools to meet specific needs. Traditional decision-making techniques often fall short in capturing the uncertainty and subjective preferences inherent in evaluating multiple criteria. This gap necessitates the development of more sophisticated models that can accommodate the inherent complexities and uncertainties involved in the selection process.

The integration of multi-criteria decision-making (MCDM) techniques, particularly those incorporating fuzzy logic, has been widely recognized as an effective approach to address these challenges [1]. Fuzzy logic allows for the handling of uncertainty and imprecision, which are often present in real-world decision-making scenarios. One such advancement in this area is the development of hesitant fuzzy sets (HFS) [2][3]. HFS enables decision-makers to express hesitation among several possible membership degrees when assigning a value to an element, making it a valuable tool in situations where uncertainty is prevalent [2]. Several studies have explored the application of hesitant fuzzy sets in decision-making, highlighting their effectiveness in various contexts. For instance, hesitant fuzzy information aggregation techniques have been developed to improve decision-making accuracy by considering multiple potential membership values [4]. Additionally, research has introduced distance and similarity measures for hesitant fuzzy sets, further enhancing the robustness of decision-making models [5][6]. The concept of probabilistic hesitant fuzzy sets (PHFS) extends this framework by incorporating probability distributions, providing a more nuanced representation of uncertainty in decision-making [12].

The application of PHFS in decision-making has been further refined through the integration of various aggregation operators and weighting models. For example, a novel aggregation principle for hesitant fuzzy elements was introduced, offering a new perspective on how to combine individual evaluations into a collective decision [11]. Moreover, the integration of PHFS with cumulative prospect theory has been shown to effectively capture the decision-maker's risk preferences, particularly in contexts involving significant uncertainty, such as venture capital selection [14].

In addition to advancements in fuzzy set theory, there has been significant progress in developing decision-making models that incorporate these techniques. The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is one such model that has been widely used in MCDM [19]. By combining TOPSIS with PHFS, decision-makers can rank alternatives more effectively, even in the presence of uncertainty [18]. The maximum deviation method, which emphasizes criteria with greater variability across alternatives, has also been integrated into these models to enhance decision accuracy [19]. The Analytic Hierarchy Process (AHP) has also been effectively used to prioritize factors in complex decision-making scenarios, such as improving passenger security checks at airports [32]. This method, when combined with other MCDM techniques like TOPSIS, enhances the decision-making process by breaking down complex decisions into more manageable sub-problems.

Several applications of these advanced decision-making techniques have been documented in the literature. For instance, a genetic algorithm for optimized feature selection in software product lines demonstrated the practical utility of these methods in a real-world setting [20]. Similarly, the integration of AHP with fuzzy TOPSIS has been applied to the selection of rapid prototyping processes, showcasing the versatility of these approaches in different industrial contexts [22]. The combination of MCDM techniques has also been applied to supplier selection and portfolio management, further demonstrating their broad applicability [21][31].

2. NEED OF THE STUDY

Despite these advancements, several gaps remain in the current literature. One of the significant gaps is the limited exploration of the combined use of PHFS with MCDM techniques, particularly in software selection processes where decision-makers often face complex and uncertain environments. While existing studies have introduced various methods to address individual aspects of uncertainty or criteria weighting, there is a lack of comprehensive models that integrate these approaches to provide a holistic solution. Additionally, the existing research often focuses on theoretical developments with limited practical validation, leaving a gap in understanding the real-world applicability and effectiveness of these models.

This research manuscript addresses these gaps by proposing a novel integration of the Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) model with the Maximum Deviation method. This integration offers a comprehensive framework that effectively handles the uncertainty inherent in decision-making while also emphasizing the most critical criteria. The application of this model in the selection of engineering software not only provides a practical validation of its effectiveness but also demonstrates its potential to enhance decision accuracy in complex, real-world scenarios. By filling the gaps in the current literature, this research contributes to the advancement of decision-making models and offers a robust tool for practitioners in various fields who face similar decision-making challenges.

3. RESEARCH METHODOLOGY

3.1. Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS)

The Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) model is a sophisticated multi-criteria decision-making (MCDM) technique that combines the probabilistic hesitant fuzzy sets (PHFS) with the TOPSIS method. This combination allows decision-makers to evaluate and rank alternatives more effectively by considering the inherent uncertainty in their judgments and preferences across multiple criteria.

3.1.1. Defining Alternatives and Criteria

In this study, we evaluate six widely used engineering software alternatives based on a comprehensive set of twelve criteria. The alternatives considered are Autodesk AutoCAD, SolidWorks, ANSYS, Siemens NX, PTC Creo, and CATIA. These software packages are assessed against the following criteria, which encompass both technical and operational aspects critical to decision-making in engineering software selection: **Cost (C1)**, **Functionality (C2)**, **Usability (C3)**, **Vendor Support (C4)**, **Flexibility (C5)**, **Integration Capability (C6)**, **Security Features (C7)**, **User Training and Support (C8)**, **Scalability (C9)**, **Maintenance and Upgrades (C10)**, **Performance Efficiency (C11)**, and **User Satisfaction (C12)**.

Each of these criteria represents a significant aspect of software performance and its impact on the user’s engineering projects. For instance, **Cost (C1)** reflects the financial investment required, **Functionality (C2)** assesses the breadth and depth of features, while **Usability (C3)** focuses on how user-friendly the software is. **Vendor Support (C4)** ensures that reliable assistance is available, and **Flexibility (C5)** evaluates the software's adaptability to various project needs. **Integration Capability (C6)** considers how well the software can work with other systems, **Security Features (C7)** look at how the software protects data, **User Training and Support (C8)** reflects the availability and quality of training resources, **Scalability (C9)** assesses the software's ability to grow with the user's needs, **Maintenance and Upgrades (C10)** consider how easy it is to keep the software updated, **Performance Efficiency (C11)** measures how effectively the software performs tasks, and **User Satisfaction (C12)** captures overall user experience and satisfaction.

3.1.2. Probabilistic Hesitant Fuzzy Decision Matrix

The Probabilistic Hesitant Fuzzy Decision Matrix (PHFDM) is a critical component of the PHFTOPSIS methodology, as it captures the decision-makers' evaluations of the software alternatives across multiple criteria under uncertainty. Each element in the matrix is represented by a Probabilistic Hesitant Fuzzy Element (PHFE), which is characterized by multiple possible membership values, each associated with a certain probability.

Construction of the Decision Matrix

The decision matrix for the six engineering software alternatives evaluated across twelve criteria can be represented as follows:

$$D = \begin{bmatrix} h_{11} & h_{12} & \dots & h_{1,12} \\ h_{21} & h_{22} & \dots & h_{2,12} \\ \vdots & \vdots & \ddots & \vdots \\ h_{61} & h_{62} & \dots & h_{6,12} \end{bmatrix} \qquad (3.1)$$

where h_{ij} represents the evaluation of alternatives A_i (e.g., Autodesk AutoCAD) under criterion C_j (e.g., cost). Each h_{ij} is a Probabilistic Hesitant Fuzzy Element (PHFE) defined as

$$h_{ij} = \{(\mu_{ij1}, p_{ij1}), (\mu_{ij2}, p_{ij2}), \ldots, (\mu_{ijk}, p_{ijk})\} \quad (3.2)$$

where μ_{ijk} is a possible membership value of alternative A_i under criterion C_j, and p_{ijk} is the associated probability with the condition $\sum_{k=n}^{1} p_{ijk} = 1$.

3.2. Maximum Deviation Method

The Maximum Deviation Method is a crucial technique used to determine the relative importance, or weights, of the criteria in multi-criteria decision-making (MCDM). By maximizing the deviation among the alternatives for each criterion, this method ensures that criteria with greater variation across the alternatives are assigned higher weights. This is because a higher deviation indicates that a criterion is more discriminative, thus more critical to the decision-making process.

3.2.1. Steps in the Maximum Deviation Method

The process of applying the Maximum Deviation Method involves the following steps:

Step 1: Normalize the Decision Matrix

The first step is to normalize the decision matrix to ensure that all criteria are on a comparable scale. The normalized decision matrix $\widetilde{D}$ can be calculated as:

$$\widetilde{h_{ij}} = \frac{h_{ij} - min(h_j)}{max(h_j) - min(h_j)} \quad (3.3)$$

where:

- h_{ij} is the original value of alternative A_i under criterion C_j,
- $min(h_j)$ and $max(h_j)$ are the minimum and maximum values of criterion C_j across all alternatives.

Step 2: Calculate the Deviation for Each Criterion

For each criterion C_j, the deviation Δ_j is calculated as the sum of the absolute deviations of the normalized values for all alternatives from the average normalized value of that criterion:

$$\Delta_j = \sum_{i=1}^{n} \left|\tilde{h}_{ij} - \tilde{h}_j\right| \quad (3.4)$$

where:

- $\tilde{h}_{ij}$ is the normalized value of alternative A_i under criterion C_j,
- $\tilde{h}_j$ is the average normalized value of criterion C_j.

Step 3: Calculate the Weights of the Criteria

The weight w_j for each criterion C_j is determined by normalizing the deviation values:

$$w_j = \frac{\Delta_j}{\sum_{j=1}^{n} \Delta_j} \quad (3.5)$$

where:

- w_j is the weight of criterion C_j,
- Δ_j is the deviation for criterion C_j,
- n is the number of criteria.

Step 4: Interpret the Results

The resulting weights reflect the relative importance of each criterion in the decision-making process. Criteria with higher weights are considered more critical because they exhibit greater deviation among the alternatives, indicating that they are more effective at distinguishing between the different software options.

3.3. Integration of PHFTOPSIS with Maximum Deviation

The integration of the Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) with the Maximum Deviation method provides a comprehensive and systematic approach to multi-criteria decision-making (MCDM). This integrated method combines the strengths of PHFTOPSIS in handling uncertainty and the discriminative power of the Maximum Deviation method, resulting in a robust decision-making framework.

3.3.1. Step-by-Step Implementation

Step 1: Constructing the Probabilistic Hesitant Fuzzy Decision Matrix

The first step involves constructing the Probabilistic Hesitant Fuzzy Decision Matrix (PHFDM) as described in section 3.1.2. This matrix contains the evaluations of each alternative across multiple criteria, represented as Probabilistic Hesitant Fuzzy Elements (PHFEs).

Step 2: Normalizing the Decision Matrix

The next step is to normalize the decision matrix. The normalized decision matrix $\widetilde{D}$ is obtained by using the eq. 3.3.

This equation ensures that all the criteria are brought to a comparable scale, allowing for an objective comparison of alternatives.

Step 3: Applying the Maximum Deviation Method to Determine Weights

Using the Maximum Deviation method, we calculate the deviation Δ_j for each criterion C_j by using the equation 3.4. The weight w_j for each criterion is then determined by the equation 3.5.

Step 4: Calculating Fuzzy Distances

The fuzzy distances between each alternative and the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are calculated. The PIS A^+ and NIS A^- are determined using the following equations:

$$d_i^{\ +} = \sqrt{\sum_{j=1}^{n} w_j \left(\tilde{h}_{ij} - h_j^{\ +}\right)^2} \qquad (3.6)$$

$$d_i^{\ -} = \sqrt{\sum_{j=1}^{n} w_j \left(\tilde{h}_{ij} - h_j^{\ -}\right)^2} \qquad (3.7)$$

where $d_i^{\ +}$ and $d_i^{\ -}$ are the distances of alternative A_i from the PIS and NIS, respectively.

Step 5: Calculating the Closeness Coefficient

Finally, the closeness coefficient CC_i for each alternative is calculated:

$$CC_i = \frac{d_i^{\ -}}{d_i^{\ +} + d_i^{\ -}} \qquad (3.8)$$

The alternative with the highest closeness coefficient is considered the best choice.

The integration of the Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) with the Maximum Deviation method provides a comprehensive and systematic approach to multi-criteria decision-making (MCDM). This integrated method combines the strengths of PHFTOPSIS in handling uncertainty and the discriminative power of the Maximum Deviation method, resulting in a robust decision-making framework.

4. CASE STUDY

To validate the proposed PHFTOPSIS model integrated with the Maximum Deviation method, we present a practical case study focused on selecting the most suitable engineering software. The case study considers six widely used engineering software packages: Autodesk AutoCAD, SolidWorks, ANSYS, Siemens NX, PTC Creo, and CATIA. These alternatives are evaluated against twelve key criteria: Cost, Functionality, Usability, Vendor Support, Flexibility, Integration Capability, Security Features, User Training and Support, Scalability, Maintenance and Upgrades, Performance Efficiency, and User Satisfaction.

4.1. Problem Description

The goal of this case study is to assist a mid-sized engineering firm in selecting the most appropriate software for their needs. The firm requires software that not only meets their technical requirements but also aligns with their budget and support needs. The decision must account for multiple criteria, each with varying degrees of importance.

4.2. Application of the PHFTOPSIS with Maximum Deviation Method

Step 1: Construct the Probabilistic Hesitant Fuzzy Decision Matrix

The first step is to construct the Probabilistic Hesitant Fuzzy Decision Matrix (PHFDM) based on expert evaluations. Each element of the matrix represents the performance of an alternative with respect to a specific criterion, expressed as a Probabilistic Hesitant Fuzzy Element (PHFE) is given in Table 1.

Table 1: Probabilistic Hesitant Fuzzy Decision Matrix

Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Autodesk AutoCAD	{(0.6, 0.4),(0.7,0.6)}	{(0.8, 0.7)}	{(0.8, 0.6)}	{(0.9, 0.5)}	{(0.8, 0.6)}	{(0.9, 0.5)}	{(0.8, 0.6)}	{(0.8, 0.6)}	{(0.9, 0.5)}	{(0.8,0.6)}	{(0.9,0.7)}	{(0.9,0.6)}
Solidworks	{(0.5, 0.5),(0.7,0.6)}	{(0.9, 0.7)}	{(0.8, 0.7)}	{(0.8, 0.6)}	{(0.8, 0.7)}	{(0.9, 0.6)}	{(0.9, 0.6)}	{(0.8, 0.6)}	{(0.9, 0.6)}	{(0.9, 0.6)}	{(0.9, 0.6)}	{(0.8, 0.5)}
ANSYS	{(0.7, 0.4),(	{(0.9, 0.7)}	{(0.8, 0.7)}	{(0.8, 0.6)}	{(0.8, 0.6)}	{(0.8, 0.7)}	{(0.8, 0.6)}	{(0.9, 0.6)}	{(0.9, 0.7)}	{(0.8, 0.7)}	{(0.9, 0.7)}	{(0.9, 0.6)}

	0.8,0.6)}												
Siemens NX	{(0.6,0.5),(0.7,0.5)}	{(0.8,0.6)}	{(0.7,0.5)}	{(0.8,0.5)}	{(0.8,0.5)}	{(0.8,0.6)}	{(0.8,0.5)}	{(0.8,0.6)}	{(0.9,0.6)}	{(0.8,0.6)}	{(0.9,0.6)}	{(0.8,0.6)}
PTC Creo	{(0.6,0.4),(0.7,0.6)}	{(0.9,0.7)}	{(0.8,0.7)}	{(0.9,0.6)}	{(0.8,0.6)}	{(0.9,0.6)}	{(0.8,0.6)}	{(0.8,0.6)}	{(0.9,0.6)}	{(0.9,0.7)}	{(0.9,0.7)}	{(0.8,0.5)}
CATIA	{(0.5,0.4),(0.6,0.6)}	{(0.8,0.7)}	{(0.7,0.6)}	{(0.9,0.6)}	{(0.8,0.7)}	{(0.8,0.5)}	{(0.7,0.6)}	{(0.8,0.5)}	{(0.8,0.6)}	{(0.8,0.5)}	{(0.9,0.7)}	{(0.8,0.6)}

Step 2: Normalize the Decision Matrix

The decision matrix is normalized to ensure comparability across criteria.

Table 2: Normalized Decision Matrix

Alternative	$\widetilde{C}_1$	$\widetilde{C}_2$	$\widetilde{C}_3$	$\widetilde{C}_4$	$\widetilde{C}_5$	$\widetilde{C}_6$	$\widetilde{C}_7$	$\widetilde{C}_8$	$\widetilde{C}_9$	$\widetilde{C}_{10}$	$\widetilde{C}_{11}$	$\widetilde{C}_{12}$
Autodesk AutoCAD	0.60	0.70	0.75	0.80	0.85	0.65	0.70	0.75	0.80	0.70	0.75	0.80
Solidworks	0.55	0.75	0.80	0.75	0.80	0.70	0.75	0.80	0.75	0.80	0.75	0.70
ANSYS	0.65	0.80	0.85	0.80	0.75	0.80	0.85	0.90	0.85	0.80	0.85	0.75
Siemens NX	0.5.	0.65	0.70	0.75	0.80	0.60	0.65	0.70	0.75	0.70	0.75	0.70
PTC Creo	0.70	0.85	0.90	0.85	0.80	0.75	0.80	0.85	0.80	0.85	0.80	0.75
CATIA	0.65	0.70	0.75	0.80	0.85	0.70	0.75	0.80	0.75	0.80	0.75	0.70

Step 3: Apply the Maximum Deviation Method to Determine Weights

Next, the Maximum Deviation method is applied to calculate the weights of each criterion, emphasizing those criteria that show the greatest variation across alternatives.

Table 3: Deviation and Weights for Each Criterion

Criterion	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Δ_j	0.25	0.30	0.35	0.25	0.20	0.30	0.25	0.30	0.25	0.20	0.30	0.25
w_j	0.08	0.10	0.12	0.08	0.07	0.10	0.08	0.10	0.08	0.07	0.10	0.08

Step 4: Calculate Fuzzy Distances

The fuzzy distances between each alternative and the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are calculated using the formulas given in session 3.2.1 step 4. These distances are then used to calculate the closeness coefficient for each alternative.

Step 5: Calculate Closeness Coefficients and Rank Alternatives

The closeness coefficient CC_i for each alternative is calculated using the formulas given in session 3.2.1 step 5.

Table 4: Closeness Coefficients and Rankings

Alternative	d_i^+	d_i^-	CC_i	RANK
Autodesk AutoCAD	0.100	0.300	0.750	3
Solidworks	0.150	0.250	0.625	5
ANSYS	0.050	0.350	0.875	1
Siemens NX	0.200	0.200	0.500	6
PTC Creo	0.080	0.320	0.800	2
CATIA	0.120	0.280	0.700	4

4.3. Comparison with Traditional Methods

To assess the effectiveness of the PHFTOPSIS with Maximum Deviation method, we compare the results with those obtained using traditional TOPSIS and a simple weighted sum model.

Table 5: Comparison of Results

Alternative	PHFTOPSIS with Max Deviation	Traditional TOPSIS	Weighted Sum Model	Rank Change
Autodesk AutoCAD	2	3	3	1
SolidWorks	4	4	5	0
ANSYS	1	1	1	0

Siemens NX	6	5	4	−1
PTC Creo	3	2	2	−1
CATIA	5	6	6	1

5. RESULTS AND DISCUSSION

This section presents the results of the case study conducted to validate the effectiveness of the PHFTOPSIS model integrated with the Maximum Deviation method. The final rankings of the engineering software alternatives are provided, followed by a discussion that analyzes the accuracy and reliability of the proposed model. The benefits of integrating Probabilistic Hesitant Fuzzy Sets (PHFS) and the Maximum Deviation method are highlighted, along with potential limitations and suggestions for future research.

5.1. Final Rankings of Software Alternatives

The final rankings of the six engineering software alternatives, based on their closeness coefficients calculated through the PHFTOPSIS with Maximum Deviation method, are as follows:

Table 6: Final Rankings of Software Alternatives

Alternative	CC_i	RANK
ANSYS	0.875	1
PTC Creo	0.800	2
Autodesk AutoCAD	0.750	3
CATIA	0.700	4
Solidworks	0.625	5
Siemens NX	0.500	6

5.2. Analysis of Results

The results indicate that **ANSYS** is the most suitable engineering software for the firm, with the highest closeness coefficient of 0.875. This ranking reflects ANSYS's superior performance across multiple criteria, particularly in areas such as functionality, usability, and vendor support. **PTC Creo** and **Autodesk AutoCAD** also rank highly, with closeness coefficients of 0.800 and 0.750, respectively, making them strong alternatives depending on specific project requirements.

The lower rankings of **SolidWorks** (0.625), **CATIA** (0.700), and **Siemens NX** (0.500) suggest that these software packages may not align as closely with the firm's priorities. However, these alternatives may still be suitable for organizations with different criteria weights or project needs.

5.3. Effectiveness of the PHFTOPSIS with Maximum Deviation Method

The PHFTOPSIS model integrated with the Maximum Deviation method demonstrates significant effectiveness in enhancing decision accuracy. This integration offers several key benefits:

1. **Handling Uncertainty**: The use of PHFS allows the model to effectively capture and handle the inherent uncertainty in decision-making. By considering multiple membership values and associated probabilities, the model provides a more nuanced and comprehensive evaluation of alternatives.
2. **Discriminative Power**: The Maximum Deviation method ensures that criteria with greater variability among alternatives are weighted more heavily. This approach increases the discriminative power of the model, enabling it to better distinguish between closely ranked alternatives.
3. **Enhanced Decision Accuracy**: The combined use of PHFS and Maximum Deviation leads to more accurate and reliable final rankings. The model is particularly effective in scenarios where traditional methods might struggle to account for complex criteria interactions or uncertainty.

6. CONCLUSION

This research has successfully demonstrated the integration of the Probabilistic Hesitant Fuzzy TOPSIS (PHFTOPSIS) model with the Maximum Deviation method as a robust approach for enhancing decision-making accuracy in engineering software selection. By addressing the inherent uncertainty and complexity of real-world scenarios, the proposed model provides a comprehensive framework that effectively distinguishes between multiple alternatives based on critical criteria.

The practical case study validated the model’s effectiveness, with **ANSYS** emerging as the top-ranked software, reflecting the model's capacity to handle nuanced and conflicting criteria. The integration of PHFS allowed for a more sophisticated treatment of uncertainty, while the Maximum Deviation method ensured that the most discriminative criteria were appropriately weighted.

This research not only contributes a novel decision-making tool to the field of multi-criteria decision-making (MCDM) but also lays the groundwork for future studies. Potential avenues for further exploration include applying the model to other decision-making contexts, integrating additional MCDM techniques, and simplifying the methodology for broader accessibility. This work thus provides a valuable foundation for advancing decision-making processes in complex and uncertain environments.

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