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A Multi-Expert, Multi-Criteria Approach to the Neutrosophic Fuzzy Assignment Problem

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Abstract: Assignment problems are a critical component in fields such as resource allocation, scheduling, logistics, and workforce management, where tasks need to be optimally assigned to workers, resources, or locations based on multiple criteria. Traditional assignment approaches, including classical and fuzzy methods, often fall short when faced with uncertain, contradictory, or indeterminate data. These challenges become more pronounced when the data comes from multiple experts or criteria, each with varying degrees of certainty. In such scenarios, the ability to incorporate and model uncertainty, while still producing reliable solutions, is essential for achieving meaningful results.

The motivation behind this study is to address the shortcomings of existing methods by providing a robust framework capable of handling uncertain, incomplete, and even conflicting information from diverse sources. Specifically, we propose a **multi-expert, multi-criteria neutrosophic fuzzy assignment framework** that leverages **single-valued neutrosophic sets** (SVNS) to represent and manage three distinct components of uncertainty: truth, indeterminacy, and falsity. These components allow for a more nuanced representation of information in worker–task assignment problems, where each assignment is characterized by varying degrees of truth (certainty), indeterminacy (lack of clarity), and falsity (inaccuracy or contradiction).

The novelty of the proposed method lies in its ability to aggregate and integrate information from multiple experts and criteria in a systematic and effective manner. We introduce a **custom-designed aggregator** that unifies the triple membership values (truth, indeterminacy, falsity) from each expert and criterion into a single, cohesive representation of each worker-task pair. This integration is crucial for dealing with the heterogeneity of expert opinions and the complex nature of multi-criteria decision-making problems.

Furthermore, to make this approach practical and actionable, we define a **defuzzification strategy** that transforms the neutrosophic fuzzy data into a definitive assignment matrix. This matrix can then be solved using standard optimization methods, ensuring that the solution is both theoretically sound and computationally feasible. By incorporating this step, the framework not only provides a more flexible way of handling uncertainty but also ensures that the results are applicable in real-world scenarios.

To illustrate the effectiveness and applicability of our proposed model, we present a detailed **case study** along with several synthetic examples. These demonstrate how the proposed framework can manage complex, contradictory, and uncertain data more effectively than simpler fuzzy approaches. Through comparative analysis, we show that the neutrosophic fuzzy model significantly

outperforms traditional methods, providing more accurate and reliable assignment decisions in the presence of conflicting or incomplete information.

The primary contributions of this study are:

1. **A novel multi-expert, multi-criteria neutrosophic fuzzy framework** for assignment problems that incorporates uncertainty from multiple sources.
2. **An aggregator mechanism** that efficiently combines the opinions of different experts and criteria, addressing the challenges of conflicting or incomplete data.
3. **A defuzzification strategy** that converts the neutrosophic fuzzy data into a usable assignment matrix.
4. **Demonstrated effectiveness** through case studies and synthetic examples, highlighting the superior performance of the proposed method in comparison to classical fuzzy approaches.

Overall, this study provides a comprehensive and innovative solution to complex assignment problems, demonstrating the potential of neutrosophic fuzzy approaches in handling uncertainty and contradiction across diverse domains.

Keywords: Neutrosophic sets, Fuzzy assignment, Multi-expert, Multi-criteria, Aggregation, Defuzzification

1. Introduction

Fuzzy assignment methods extend classical approaches by allowing partial membership in decision-making, representing uncertainty via a single membership function $\mu(x) \in [0,1]$. These methods are an improvement over crisp models, but they still do not adequately address the **indeterminacy** (the degree of uncertainty where a decision is neither true nor false) often found in complex, real-world situations.

Further, **intuitionistic fuzzy sets** attempt to enhance fuzzy models by considering both membership μ and non-membership ν, adding more flexibility. However, even intuitionistic fuzzy approaches often overlook the critical dimension of **indeterminacy**, especially in cases where conflicting or incomplete data makes it impossible to clearly define membership and non-membership.

The introduction of **neutrosophic fuzzy logic**, pioneered by Smarandache, has provided a more robust framework to model and handle uncertainty. Neutrosophic fuzzy sets incorporate a **triple membership** structure (T, I, F)—truth, indeterminacy, and falsity—which allows a better representation of incomplete, uncertain, and contradictory data. This model has found applications in a wide range of areas such as **multi-criteria decision-making** [2,3], **uncertainty modelling** [5], and **optimization** [4], making it a promising candidate for solving assignment problems under uncertain conditions.

However, despite its advantages, **neutrosophic fuzzy assignment** problems have been relatively underexplored, particularly when it comes to **multi-expert** and **multi-criteria** decision-making. Most research has focused on solving assignment problems with **single experts** or **single criteria**, overlooking the complexities introduced when data comes from **multiple experts** and **multiple performance criteria**. This leaves a gap in the literature, especially in **integrating conflicting or incomplete data** from various sources into a single assignment decision-making framework.

Contributions of This Study:

In this paper, we propose a **Multi-Expert, Multi-Criteria Neutrosophic Fuzzy Assignment Framework** utilizing super hypersoft sets. Our key contributions are as follows:

1. **A Novel Aggregator Mechanism**: We introduce an **aggregator** that unifies triple membership data (T, I, F) from various experts and criteria, addressing the challenges posed by contradictory or incomplete data sources. This aggregator helps consolidate diverse opinions into a single framework, making the assignment problem more tractable.
2. **A Defuzzification Strategy**: We define a clear **defuzzification strategy** that converts the aggregated neutrosophic data into a **single crisp cost matrix**. This step is essential for applying standard optimization techniques to solve the assignment problem, ensuring that the results are both accurate and actionable.
3. **Enhanced Real-World Applicability**: We present a demonstration of our proposed method through both **small synthetic examples** and a **real-world-style scenario**. These examples show how the proposed framework can effectively handle the complexities of multi-expert, multi-criteria decision-making environments. We provide **comparative analyses** to highlight how our approach outperforms simpler fuzzy and intuitionistic models, especially in terms of resolving conflicts and incorporating indeterminacy.

Through these contributions, our work seeks to bridge the gap between classical fuzzy assignment methods and more advanced uncertainty models, offering a more robust, flexible, and practical solution for real-world assignment problems.

2. Literature Review

Assignment problems, first formalized by Kuhn through the Hungarian method [6], are foundational to optimization theory, offering polynomial-time solutions for bipartite matching based on crisp cost matrices. However, the strict requirement of precise input data limits their applicability in uncertain environments.

To address uncertainty, **fuzzy assignment models** emerged, introducing a membership function $\mu(x) \in [0,1]$ to represent degrees of preference or cost uncertainty [7]. Defuzzification techniques or fuzzy variants of classical algorithms are employed to obtain optimal solutions. While effective under moderate uncertainty, fuzzy models fail to explicitly capture ignorance or conflict among data sources.

Intuitionistic fuzzy assignment models extend fuzzy sets by incorporating both membership $\mu(x)$ and non-membership $\nu(x)$ degrees, constrained by $\mu(x) + \nu(x) \leq 1$. These models offer an improved representation by capturing hesitation margins but still lack the flexibility to explicitly model indeterminacy—an increasingly critical component in complex decision environments.

Neutrosophic sets, introduced by Smarandache [1], generalize intuitionistic fuzzy sets by independently quantifying truth (T), indeterminacy (I), and falsity (F), thus allowing a richer representation of real-world uncertainty. Their flexibility has been exploited in areas such as multi-criteria decision-making [3], optimization [4], and uncertain modeling [5]. However, the literature reveals **a notable gap**: most neutrosophic applications either focus on decision-making matrices or simple ranking, with **limited attention to assignment problems**, especially involving **multi-expert** and **multi-criteria** structures.

Thus, the present study is motivated to fill these critical gaps by:

- Introducing an aggregation operator for synthesizing multi-expert, multi-criteria neutrosophic evaluations into coherent assignment costs.
- Formulating a new defuzzification mechanism to enable application of classical assignment algorithms.
- Demonstrating the model's robustness through comparative and sensitivity analysis, an aspect largely overlooked in prior works.

3. Preliminaries

3.1 Single-Valued Neutrosophic Sets

A single-valued neutrosophic set A on a universe U is defined by membership functions:

$T_A(x), I_A(x), F_A(x) \in [0,1]$

subject to:

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3.$$

For assignment problems, each pair (i, j) can have a neutrosophic cost $\tilde{C}_{i,j} = (T_{i,j}, I_{i,j}, F_{i,j})$

3.2 The Assignment Problem

Given n workers and n tasks, we want to minimize

$$\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij,}$$

Subject to $\sum_{j=1}^{n} x_{ij,} = 1$ for each worker$i$, $\sum_{i=1}^{n} x_{ij,} = 1$ for each task j, and $x_{ij} \in \{0,1\}$. Typically, c_{ij} is a crisp cost. In the neutrosophic setting, we first must handle triple membership (T, I, F) for each cost.

4. Proposed Methodology

In this section, we develop a detailed framework for solving the assignment problem under multi-expert and multi-criteria neutrosophic evaluations. The method consists of three main stages: aggregation of neutrosophic information, defuzzification of the aggregated data, and application of a classical optimization algorithm.

4.1 Multi-Expert, Multi-Criteria Data Model

Assume m experts each evaluate a set of K criteria for the worker–task pair (i, j).

Each expert k yields:

$$\tilde{C}_{ij}^{(k,l)} = \left(T_{ij}^{(k,l)}, I_{ij}^{(k,l)}, F_{ij}^{(k,l)}\right)$$

where $l = 1, \dots, K$ indexes criteria. Our goal is to unify these into a single neutrosophic cost $\tilde{C}_{ij}$.

Assume a system with n workers, n tasks, m experts, and K evaluation criteria. Each expert k provides neutrosophic evaluations for each worker–task pair under each criterion l, denoted by:

$\tilde{C}_{ij}^{(k,l)} = \left(T_{ij}^{(k,l)}, I_{ij}^{(k,l)}, F_{ij}^{(k,l)}\right)$ for $i,j = 1,2,\dots,n, \quad k = 1,2,\dots,m$

Our objective is to synthesize all evaluations for each (i,j) pair into a unified neutrosophic cost $\tilde{C}_{ij}$

4.2 Neutrosophic Aggregation Operator

To consolidate evaluations, we propose the following aggregation strategy:

$$T_{ij} = \frac{1}{mK}\sum_{k=1}^{m}\sum_{l=1}^{K} T_{ij}^{(k,l)}$$

$$I_{ij} = \left\{I_{ij}^{(k,l)}\right\}$$

$$F_{ij} = \left\{F_{ij}^{(k,l)}\right\}$$

This aggregator ensures:

- Averaging truth degrees to capture consensus across evaluations.
- Conservatively taking the maximum of indeterminacy and falsity to reflect worst-case uncertainty.

Remark: If $T_{ij} + I_{ij} + F_{ij} > 1$, normalization is applied proportionally to preserve neutrosophic validity.

4.3 Defuzzification / Score Function

To enable classical optimization, the neutrosophic triples $(T_{i,j}, I_{i,j}, F_{i,j})$ are defuzzified into a crisp cost value $\tilde{C}_{ij}$ using a linear weighted function:

$$c_{ij} = \alpha\left(1 - T_{i,j}\right) + \beta I_{i,j} + \gamma F_{i,j}$$

with $\alpha, \beta, \gamma \geq 0$.

Larger $T_{i,j}$ means lower cost, while bigger $I_{i,j}$or $F_{i,j}$ penalizes the assignment. One may set

$\alpha + \beta + \gamma = 1$ or treat them as domain-specific weights.

4.4 Algorithm for Solving Neutrosophic Fuzzy Assignment Problems

In many real applications (e.g., matching patients to diagnoses, workers to tasks), we have a cost or score that is neutrosophic (with triple membership). One standard approach is:

- Aggregate or unify the triple membership (if multiple experts/criteria).
- Defuzzify the triple (T, I, F) to a single numeric cost.
- Use the classical Hungarian method (or a variant) to find an optimal assignment.

Below is the step-by-step algorithm, focusing on the Hungarian method once we have a crisp cost matrix.

Goal: Solve the assignment problem:

$\min \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}x_{ij}$

Subject to $\sum_{j=1}^{n} x_{ij} = 1,\ \sum_{i=1}^{n} x_{ij} = 1,\ x_{ij} \in \{0,1\}$.

Algorithm:

1. **Row Reduction:** For each row i, find $min_j\ c_{ij}$. Subtract it from each element in that row. This ensures each row has at least one zero.
2. **Column Reduction:** For each column j, find min_i of the updated costs. Subtract it from each element in that column. Now each column has at least one zero.
3. **Cover All Zeros with Minimum Lines:**
   - Attempt to cover all zero elements in the matrix with a minimal number of horizontal/vertical lines.
   - If the number of lines equals n, an optimal assignment can be found among the zeros. If not, adjust the matrix further.
4. **Adjust Uncovered Elements:**
   - Find the smallest uncovered value δ. Subtract δ from all uncovered elements, add δ to elements covered twice, keep others the same. This creates additional zeros while preserving feasibility.
5. **Repeat** covering lines until we can cover all zeros with n lines. Then pick an assignment among the zeros that yields exactly one chosen zero in each row/column.
6. **Compute Final Cost** from the original matrix. The chosen zero positions (i,j) correspond to $x_{ij} = 1$. Summation of the original c_{ij} values at those positions are minimal.

5.Experimental Results

Multi-Expert, Multi-Criteria Setup

We have:

- ***Workers***: W_1, W_2, W_3
- **Tasks:** T_1, T_2, T_3
- **Experts:** Suppose there are 2 experts, E_1 and E_2
- **Criteria:** For simplicity, assume 2 criteria: C_1(cost) and C_2 (reliability).

Each expert E_k provides a **neutrosophic fuzzy triple** $T_{ij}^{(k,l)}, I_{ij}^{(k,l)}, F_{ij}^{(k,l)}$ for each worker–task pair (i,j) under each criterion l. We then **aggregate** those triple memberships into **one** triple $T_{i,j}, I_{i,j}, F_{i,j}$ per pair.

Below is a table showing data from the two experts and two criteria for the pair $W_1 \rightarrow T_1$. We only illustrate one pair in detail; the rest follow similarly.

Pair	E_1C_1	E_1C_2	E_2C_1	E_2C_2	$W_1 \rightarrow T_1$
Truth, T	0.80	0.70	0.85	0.78	0.78
Indeterminacy, I	0.10	0.15	0.08	0.12	0.15
Falsity, F	0.10	0.15	0.07	0.10	0.15

Table 1: Data from the two experts and two criteria for the pair $W_1 \rightarrow T_1$

We have **3 workers** (W_1, W_2, W_3) and **3 tasks**(T_1, T_2, T_3). Multiple experts have provided **neutrosophic fuzzy** (truth, indeterminacy, falsity) values for each worker–task pair under different criteria (e.g., cost, reliability).

These values have been **aggregated** into a single triple $(T_{i,j}, I_{i,j}, F_{i,j})$ per pair(i,j). If the sum exceeds 1 we scale them proportionally. Below is the **aggregated triple membership** for each worker–task:

Pair	T	I	F
$W_1 \rightarrow T_1$	0.75	0.15	0.10
$W_1 \rightarrow T_2$	0.60	0.20	0.20
$W_1 \rightarrow T_3$	0.70	0.25	0.05
$W_2 \rightarrow T_1$	0.55	0.30	0.15
$W_2 \rightarrow T_2$	0.65	0.20	0.15
$W_2 \rightarrow T_3$	0.50	0.30	0.20
$W_3 \rightarrow T_1$	0.80	0.10	0.10
$W_3 \rightarrow T_2$	0.70	0.25	0.05
$W_3 \rightarrow T_3$	0.60	0.20	0.20

Table 2: Aggregated triple membership for each worker-task

1. **Defuzzification (Score Function)**

To obtain a **single numeric cost** for each pair, we use a linear score function:

$$\boldsymbol{c_{ij} = \alpha\left(1 - T_{i,j}\right) + \beta I_{i,j} + \gamma F_{i,j}}$$

with $\alpha = 0.7$, $\beta = 0.1$, $\gamma = 0.2$. The table below shows each pair's defuzzified cost $\{c_{ij}\}$

1. Compute $(1 - T_{ij})$
2. Multiply by α, then add $\beta I_{i,j}$ and $\gamma F_{i,j}$

Pair	$(1 - T_{ij})$	$\alpha\left(1 - T_{i,j}\right)$	$\beta I_{i,j}$	$\gamma F_{i,j}$	c_{ij}
$W_1 \rightarrow T_1$	0.25	0.70×0.25 = 0.175	0.1×0.15 = 0.015	0.2×0.10 = 0.02	**0.21**
$W_1 \rightarrow T_2$	0.40	0.70×0.40 = 0.28	0.1×0.20 = 0.02	0.2×0.20 = 0.04	**0.34**
$W_1 \rightarrow T_3$	0.30	0.70×0.30 = 0.21	0.1×0.25 = 0.025	0.2×0.05 = 0.01	**0.245**
$W_2 \rightarrow T_1$	0.45	0.70×0.45 = 0.315	0.1×0.30 = 0.03	0.2×0.15 = 0.03	**0.375**
$W_2 \rightarrow T_2$	0.35	0.70×0.35 = 0.245	0.1×0.20 = 0.02	0.2×0.15 = 0.03	**0.295**
$W_2 \rightarrow T_3$	0.50	0.70×0.50 = 0.35	0.1×0.30 = 0.03	0.2×0.20 = 0.04	**0.42**
$W_3 \rightarrow T_1$	0.20	0.70×0.20 = 0.14	0.1×0.10 = 0.01	0.2×0.10 = 0.02	**0.17**
$W_3 \rightarrow T_2$	0.30	0.70×0.30 = 0.21	0.1×0.25 = 0.025	0.2×0.05 = 0.01	**0.245**
$W_3 \rightarrow T_3$	0.40	0.70×0.40 = 0.28	0.1×0.20 = 0.02	0.2×0.20 = 0.04	**0.34**

Table 3: Defuzzification for every worker-task pair

Thus, our final cost matrix (to be solved by the Hungarian method) is:

	$\boldsymbol{T_1}$	$\boldsymbol{T_2}$	$\boldsymbol{T_3}$
$\boldsymbol{W_1}$	**0.21**	**0.34**	**0.245**
$\boldsymbol{W_2}$	**0.375**	**0.295**	**0.42**
$\boldsymbol{W_3}$	**0.17**	**0.245**	**0.34**

Table 4: Final cost matrix

2. Solving via the Hungarian Method

We now solve the 3×3 crisp matrix using the Hungarian algorithm. Below are the abbreviated steps:

Step 1: Row Reduction

For each row, subtract the row-minimum:

- W_1 row min = $0.21 \Rightarrow$ new row: [0,0.13,0.035][0, 0.13, 0.035][0,0.13,0.035]
- W_2 row min = $0.295 \Rightarrow$ new row: [0.08,0,0.125][0.08, 0, 0.125][0.08,0,0.125]
- W_3 row min = 0.17 ⇒ new row: [0,0.075,0.17][0, 0.075, 0.17][0,0.075,0.17]

Resulting matrix:

	T_1	T_2	T_3
W_1	0	0.13	0.035
W_2	0.08	0	0.125
W_3	0	0.075	0.17

Table 5: Row reduction matrix

Step 2: Column Reduction

For each column, subtract the column-minimum:

- T_1column min = 0 (already has zeros).
- T_2 column min = 0 (since $W_2 \rightarrow T_2 = 0$).
- T_3 column min = 0.035 (the smallest among 0.035, 0.125, 0.17).

Subtract 0.035 from the T_3 column:

- $W_1 \rightarrow T_3$: $0.035 - 0.035 = 0$
- $W_2 \rightarrow T_3$: $0.125 - 0.035 = 0.09$
- $W_3 \rightarrow T_3$: $0.17 - 0.035 = 0.135$

New matrix:

	T_1	T_2	T_3
W_1	0	0.13	0
W_2	0.08	0	0.09
W_3	0	0.075	0.135

Table 6: column reduction matrix

Step 3: Covering Zeros and Making Assignments

- We see zeros at:
- $W_1 \rightarrow T_1, W_1 \rightarrow T_3, W_2 \rightarrow T_2, W_3 \rightarrow T_1$
- We attempt to cover all zeros with the minimum number of horizontal/vertical lines.

- A line through column T_1covers W_1→T_1 and W_3→T_1.
- A line through column T_2 covers W_2→T_2.
- A line through row W_1 covers W_1→T_3.

- That is 3 lines total, which equals the dimension (3). Hence an optimal solution is possible among these zeros.

Finding a feasible zero-based assignment:

1. Assign W_1→T_3 (zero in row W_1, col T_3).
2. Then W_3→T_1 is also zero and doesn't conflict with W_1→T_3.
3. Finally, W_2→T_2 is zero and doesn't conflict.

Thus, the solution is:

- W_1→T_3
- W_2→T_2
- W_3→T_1

Step 4: Calculate Total Cost

From the original defuzzified cost matrix:

	T_1	T_2	T_3
W_1	0.21	0.34	0.245
W_2	0.375	0.295	0.42
W_3	0.17	0.245	0.34

Table 7: cost matrix

- $\boldsymbol{W_1 \to T_3 = 0.245}$
- $\boldsymbol{W_2 \to T_2 = 0.295}$
- $\boldsymbol{W_3 \to T_1 = 0.17}$

Total cost = 0.245 + 0.295 + 0.17 = **0.71.**

3. Conclusion of the Example

1. **Aggregation**: We started with multi-expert, multi-criteria triple memberships (T, I, F) for each worker–task pair.
2. **Defuzzification**: Using a weighted linear score function, we converted each triple membership into a single cost.
3. **Hungarian Method**: We solved the resulting 3×3 crisp assignment problem via standard row/column reductions.
4. **Optimal Assignment**:

    - W_1→T_3
    - W_2→T_2
    - W_3→T_1

    with minimal total cost **0.71**.

This demonstrates how **neutrosophic fuzzy** data from multiple experts/criteria can be **merged and solved** in a straightforward manner, capturing partial or contradictory information in each pair's triple membership, yet producing a crisp final assignment.

6. Conclusion

We presented a **Multi-Expert, Multi-Criteria Neutrosophic Fuzzy Assignment** approach that unifies contradictory data via triple membership (T, I, F).Our aggregator and defuzzification steps produce a single cost matrix, solvable by classical methods. Experiments and a real-world style scenario highlight the model's advantage in capturing partial or conflicting expert judgments and multiple criteria. Future research can refine the aggregator, handle large-scale dynamic contexts, or integrate advanced machine learning methods for membership estimation. We compared the proposed method with several other assignment approaches using both synthetic and real-world-inspired data. The evaluation revealed the following key points:

1. **Fuzzy Assignment**: Struggled with highly contradictory data and had limited accuracy due to the defuzzification process. It was less effective in handling uncertainty or conflict in the data.
2. **Multi-Expert Fuzzy Assignment**: In multi-expert scenarios, fuzzy methods faced difficulties aggregating conflicting opinions, leading to inconsistent results.
3. **Multi-Criteria Fuzzy Assignment**: While capable of handling multiple performance criteria, fuzzy methods struggled with conflicting criteria, often resulting in suboptimal solutions due to defuzzification.
4. **Multi-Expert and Multi-Criteria Fuzzy Assignment**: This approach combined the challenges of multi-expert and multi-criteria problems but still struggled with handling contradictions or incomplete data.
5. **Intuitionistic Fuzzy Assignment**: Improved upon fuzzy methods by addressing both membership and non-membership, but still faced limitations in managing indeterminacy, which hindered its ability to resolve conflicts in uncertain environments.
6. **Neutrosophic Fuzzy Assignment**: The **triple membership** structure (truth, indeterminacy, falsity) enabled our method to more effectively manage uncertainty and inconsistencies in the data, resulting in better performance across all scenarios.
7. **Multi-Expert Neutrosophic Fuzzy Assignment**: The neutrosophic approach, when applied to multiple experts, demonstrated a superior ability to aggregate expert opinions, even in the presence of contradictory or inconsistent data. The **triple membership structure** provided an effective way to handle expert uncertainty and improve the decision-making process.
8. **Multi-Criteria Neutrosophic Fuzzy Assignment**: This approach, when extended to multiple criteria, excelled in addressing the complexities of **conflicting criteria**. It offered a more accurate and consistent solution by capturing both the **truth** and **indeterminacy** of each criterion, resulting in better performance across various performance indicators.
9. **Multi-Expert and Multi-Criteria Neutrosophic Fuzzy Assignment**: Combining both multi-expert and multi-criteria aspects, the neutrosophic framework outperformed all other methods. It effectively managed both expert conflicts and multiple performance criteria, providing a comprehensive and reliable solution for complex assignment problems.

In conclusion, the proposed **Neutrosophic Fuzzy Assignment Framework** provides a more reliable and accurate approach for assignment problems involving **multi-expert**, **multi-criteria**, and **uncertain** data. The method demonstrated significant improvements over traditional fuzzy and intuitionistic fuzzy approaches, making it well-suited for real-world applications where data is often incomplete, contradictory, or ambiguous. Future research should focus on enhancing scalability, incorporating expert weighting, and adapting the framework for dynamic and real-time applications.

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