A Multi-attribute Group Decision-making Method Based on a New Scoring Function and Its Application

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Abstract: A way of decision making is specifically designed to handle complex problems involving some decision-makers and multiple evaluation attributes. Evaluating educational performance involves multiple dimensions and requires the input of numerous experts or relevant stakeholders to avoid the subjective bias of a single decision-maker. At the same time, the evaluation process often involves uncertainty and a need for precision. Fuzzy mathematics has a natural advantage in handling uncertainty and precision. Using MAGDM in the context of fuzzy mathematics proves to be an extremely effective method. The scoring function is the final step in the evaluation and ranking process. However, in practice, some scoring functions fail, leading to unsuccessful decisions. To address this issue, a new scoring function is designed to alleviate these problems and provide more options. Experiments conducted using existing open-source data show the ability of the proposed scoring function.

Keywords: New Scoring Function, MAGDM, Fuzzy mathematics, Evaluating educational performance

1. Introduction

With the rapid advancement of technology, educational informatization has also made significant progress at an astonishing speed [1]. The widespread application of digital technologies has brought unprecedented changes to the education sector. Advanced technologies such as virtual reality, artificial intelligence, and big data are gradually being integrated into the educational system, providing students with more personalized, flexible, and diverse learning experiences [2]. For example, the rise of online education platforms has removed the constraints of time and space on the dissemination of knowledge, enabling students to more conveniently access high-quality educational resources worldwide [3]. At the same time, innovative educational methods and tools have not only improved students' learning efficiency but also fostered their innovation awareness and problem-solving abilities [4].

However, the current evaluation of students in higher education institutions often relies on periodic exams and tests. While this method can reflect the students' level of understanding to a certain extent, it fails to comprehensively assess their overall abilities and the practical application of knowledge. In today's rapidly changing and highly complex educational environment, accurate and comprehensive educational evaluation has become particularly important [5]. Multi-attribute group decision-making (MAGDM) methods have been widely applied in educational evaluation to comprehensively consider multiple dimensions and the opinions of multiple stakeholders [6-7]. However, traditional multi-attribute decision-making methods have certain limitations in handling fuzzy information. Traditional educational evaluation methods often rely on clear and definite data and standards, but in reality, evaluation data are often uncertain and fuzzy.

The learning process of learners is influenced by many complex factors. Learning interest factors involve the learners' interest level in different subjects or fields, which is a manifestation of subjective feelings and is difficult to measure with clear numerical values. Learning style factors include individuals' preferences for receiving and processing information, which often show fuzziness in different contexts. Personality attributes and cognitive abilities involve the learners' unique traits and intellectual levels, which are also challenging to describe with precise numerical values. Additionally, the complexity and variability of the external environment add to the challenges of learning evaluation, as external factors are often uncertain and fuzzy. These factors often have a certain degree of fuzziness, making them difficult to describe accurately with precise numerical values.

Fuzzy intelligence, by introducing concepts such as fuzzy sets and fuzzy logic, can more flexibly handle the fuzzy characteristics of learners, comprehensively consider and deal with various fuzzy factors in the learning process, and become an effective way to understand and evaluate the learning process. MAGDM in a fuzzy environment can better simulate human thinking and judgment processes, not only handling fuzzy information but also integrating evaluations from multiple decision-makers, providing more comprehensive and fair evaluation results.

The scoring function, as the final step in the evaluation and ranking process, plays a crucial role in MAGDM in a fuzzy environment. However, in practice, some scoring functions fail, leading to unsuccessful decision-making processes and ultimately affecting the accuracy and reliability of evaluation results. The reasons for the failure of scoring functions may include improper handling of fuzzy information, inability to effectively integrate multiple opinions, sensitivity to abnormal data, and more. Therefore, designing a more effective scoring function to address these challenges has become a direction of effort for many researchers.

To address the shortcomings of existing methods and provide more options for the process, a new scoring function is proposed. It can better handle fuzzy information, effectively integrate evaluations from multiple decision-makers, and provide more comprehensive and fair evaluation results. To verify practicable and effective ability, existing open-source data is used to conduct experiments. Experimental results show that the proposed scoring function performs excellently across multiple evaluation metrics, significantly improving the accuracy and reliability of educational evaluations.

By integrating fuzzy mathematics with MAGDM, our approach aims to enhance the accuracy and reliability of educational evaluations, providing a robust framework that can better manage the inherent uncertainties and complexities of the process. This new scoring function not only improves decision-making outcomes but also broadens the range of applicable scenarios, ensuring more comprehensive and balanced evaluations. Ultimately, this research can provide strong support for educational evaluations and promote the continuous improvement of education quality.

2. Preliminaries

In modern decision science and fuzzy mathematics, handling uncertainty and fuzziness is one of the key challenges. As complex decision problems increase, traditional fuzzy numbers and orthogonal fuzzy numbers have gradually shown limitations in certain application scenarios. Particularly in cases involving multiple evaluation criteria and uncertain factors, traditional methods often struggle to accurately capture and represent these complex fuzzy information. Therefore, researchers have introduced the concept of interval-valued q-rung orthopair fuzzy sets (IVq- ROFSs)to more comprehensively address fuzziness and uncertainty.

Interval-Valued Generalized Orthogonal Fuzzy Numbers extend the classic fuzzy numbers and orthogonal fuzzy numbers by integrating the advantages of interval-valued representation and generalized orthogonality. Unlike traditional fuzzy numbers, IVq-ROFSs use an interval form to represent fuzzy data, which more effectively captures the range of uncertainty in the data. For example, in decision analysis, IVq-ROFSs can handle uncertainty arising from different decision-makers or evaluation criteria, making the representation of fuzzy information more realistic and comprehensive.

Generalized orthogonality is another important feature of IVq-ROFSs. It extends the orthogonality of fuzzy numbers across different attributes to a broader context, allowing for the handling of more complex fuzzy relationships and correlations between data. This extension enablesIVq-ROFSs not only to represent the range of fuzzy data but also to reveal interactions and independencies among fuzzy numbers, thus providing a deeper analysis.

With the advancement of technology and

increasing application demands, IVq-ROFSs have demonstrated strong application potential in various fields. In complex problems such as decision analysis, risk assessment, and resource allocation, IVq-ROFSs provide a more precise and comprehensive method for handling fuzziness. By converting complex multidimensional data into easily understandable fuzzy intervals, researchers and decision-makers can better compare and rank options, leading to more reliable and effective decisions.

Definition 2.1 [8] Given the domain of discourse X, an IVq-ROFSs A in X is defined as:

$$A = \{\langle x, \mu_a(x), v_a(x)\rangle | x \epsilon X\} \quad (1)$$

$\mu_a(x)$ and $v_a(x)$ satisfy $\mu_a(x) = [\mu_a^-(x), \mu_a^+(x)] \subseteq [0,1]$ and $v_a(x) = [v_a^-(x), v_a^+(x)] \subseteq [0,1]$ for $0 \leq \left(\mu_a^+(x)\right)^q + \left(v_a^+(x)\right)^q \leq 1, q \geq 1$.

$$\pi_A(x) = [\pi_A^-(x), \pi_A^-(x)] = \left[\sqrt[q]{1 - (\mu_a^+(x))^q - (v_a^+(x))^q}, \sqrt[q]{1 - (\mu_a^-(x))^q - (v_a^-(x))^q}\right] \quad (2)$$

Definition 2.2[8] Let $a = ([\mu^-, \mu^+,], [v^-, v^+])$, $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [v_{a_1}^-, v_{a_1}^+])$ and $a_2 = ([\mu_{a_2}^-, \mu_{a_2}^+], [v_{a_2}^-, v_{a_2}^+])$ be three IVq-ROFNs with $q \geq 1$, the basic operations of IVq-ROFNs can be defined as:

$$a_1 \oplus a_2 = \langle \begin{matrix} \left[\begin{matrix} \sqrt[q]{(\mu_{a_1}^-)^q + (\mu_{a_2}^-)^q - (\mu_{a_1}^-)^q (\mu_{a_2}^-)^q}, \\ \sqrt[q]{(\mu_{a_1}^+)^q + (\mu_{a_2}^+)^q - (\mu_{a_1}^+)^q (\mu_{a_2}^+)^q} \end{matrix}\right], \\ [v_{a_1}^- v_{a_2}^-, v_{a_1}^+ v_{a_2}^+] \end{matrix} \rangle, \quad (3)$$

$$a_{1 \otimes a_2}: [\mu_{a_1}^- \mu_{a_2}^-, \mu_{a_1}^+ \mu_{a_2}^+], \sqrt[q]{(v_{a_1}^-)^q + (v_{a_2}^-)^q - (v_{a_1}^-)^q (v_{a_2}^-)^q}, \sqrt[q]{(v_{a_1}^+)} \quad (4)$$

$$\lambda a =< \left[\begin{matrix} \sqrt[q]{1 - (1 - (\mu^-)^q)^\lambda}, \\ \sqrt[q]{1 - (1 - (\mu^+)^q)^\lambda} \end{matrix}\right], [(v^-)^\lambda, (v^+)^\lambda] > \quad (5)$$

$$a^\lambda = \langle [(\mu^-)^\lambda, (\mu^+)^\lambda], \rangle \left[\begin{matrix} \sqrt[q]{1 - (1 - (v^-)^q)^\lambda}, \\ \sqrt[q]{1 - (1 - (v^+)^q)^\lambda} \end{matrix}\right] \quad (6)$$

Definition 2.3[8] Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [v_{a_1}^-, v_{a_1}^+])$ and $a_2 = ([\mu_{a_2}^-, \mu_{a_2}^+], [v_{a_2}^-, v_{a_2}^+])$ be two interval-valued q-rung orthopair fuzzy numbers (IVq-ROFNs) with $q \geq 1$, the distance measure between them is introduced as follows:

$$\begin{aligned} d(a_1, a_2) = \frac{1}{4}(&|(u_{a_1}^+)^q - (u_{a_2}^+)^q| + |(u_{a_1}^-)^q \\ &- (u_{a_2}^-)^q| + |(v_{a_1}^+)^q \\ &- (v_{a_2}^+)^q| + |(v_{a_1}^-)^q - (v_{a_2}^-)^q| \\ &+ + |(\pi_{a_1}^+)^q - (\pi_{a_2}^+)^q| \\ &+ |(\pi_{a_1}^-)^q - (\pi_{a_2}^-)^q| \end{aligned} \quad (7)$$

Here is an algorithmic flow for MAGDM presented in a structured format:

Algorithm 1

Input:

- A=$\{A_1, A_2, A_3, \cdots, A_m\}$: Set of alternatives
- C= $\{C_1, C_2, C_3, \cdots, C_n\}$: Set of evaluation attributes
- W =$\{w_1, w_2, w_3, \cdots, w_n\}$: Weights for each evaluation attribute
- D = $\{d_{ij}\}$:Decision matrix, where dij is the score of alternative A_i on attribute C_j

Method: Fuzzy information processing method

Aggregation Method: Method for computing overall scores

Output: Ranked alternatives

Algorithm Steps:

1) Initialization:
- input the set of alternatives A
- Input the set of evaluation attributes C
- Input the attribute weights W
- Collect the decision makers' opinions and form the decision matrix D

2) Process Fuzzy Information
- Apply fuzzy logic tools to handle uncertainty and fuzziness in the decision matrix D
- Determine the fuzzy information processing

3) Normalize the Decision Matrix:
- Standardize the scores in the decision matrix to eliminate the influence of different attribute scales

4) Weighted Decision Matrix:
- Compute the weighted scores

5) Compute Overall Scores:
- Use the selected aggregation method
- Aggregation Method to compute overall scores

6) Rank Alternatives:
- Rank alternatives based on their overall scores Si

7) Generate Decision Recommendations;

Based on the ranking and sensitivity analysis results, provide final decision recommendations

3. New Score Function of IVq-ROFNs

In modern decision science and evaluation systems, scoring functions play a crucial role. As a core component of the evaluation and ranking process, the main function of a scoring function is to convert various evaluation criteria into a quantifiable score, allowing for effective comparison and ranking of different options or solutions. Scoring functions must not only accurately reflect the actual conditions of each evaluation criterion but also consider the degree of factors contribution to ensure the objectivity and fairness of the evaluation results.

In MAGDM, decision-makers need to integrate information from different options, which is often represented as fuzzy numbers. In the final decision matrix, each option's fuzzy number includes uncertainties and ambiguities related to the decision. Therefore, effectively comparing the sizes of these fuzzy numbers has become a significant research topic. Traditional scoring functions are widely used tools for comparing fuzzy numbers, and many effective scoring functions have been proposed and applied in practical decision-making.

However, existing scoring functions still have limitations when dealing with certain types of fuzzy numbers. These limitations may arise from inflexible handling of fuzzy information, sensitivity to abnormal data, or the inability to effectively integrate multiple opinions. To address these challenges, a new scoring function is created. This new method aims to use an improved mathematical model to convert complex, multi-dimensional data into an easily understandable score, thereby simplifying the comparison and decision-making process. Using this scoring function accurately calculate the scores of different options, clarify the optimal solution, and consequently enhance the accuracy and reliability of decisions.

Definition 3.1 [9] Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [\nu_{a_1}^-, \nu_{a_1}^+])$ be an interval-valued q-rung orthopair fuzzy numbers (IVq-ROFNs) with $q \geq 1$,the score function S_X(a):

$$S_X(a) = \frac{(\mu_a^+)^q + (\mu_a^-)^q - (v_a^+)^q - (v_a^-)^q}{2} \tag{8}$$

Example $a_1 = ([0.42,0.6],[0.31,0.38])$ and $a_2 = ([0.42,0.57],[0.25,0.41])$ is calculated using the score function, getting a result S_X(a_1)= S_X(a_2)=0.165. It fails to compare $a_1$with a_2。

Definition 3.2[9] Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [\nu_{a_1}^-, \nu_{a_1}^+])$,the score function S_{WC}(a):

$$S_{WC}(a) = \frac{1}{2}(\mu_a^+)^q + (\mu_a^-)^q))((\mu_a^-)^q + (v_a^-)^q) - \frac{1}{2}((v_a^+)^q + (v_a^-)^q)((\mu_a^+)^q + (v_a^+)^q) \tag{9}$$

Example $a_1 = ([0.46,0.46],[0.12,0.46])$ and $a_2 = ([0.12,0.79],[0.08,0.12]$ is counted the score function getting a result S_{WC}(a_1)= S_{WC} (a_2)=0. This means that can't tell a_1 from a_2.

Definition 3.3[9] Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [\nu_{a_1}^-, \nu_{a_1}^+])$,the score function S_{GM}(a):

$$S_{GM}(a) = \frac{1}{2}[(v_a^+)^q + (v_a^-)^q - (\mu_a^+)^q + (\mu_a^-)^q] + \frac{(\mu_a^+)^q + (\mu_a^-)^q + 2((\mu_a^+)^q(\mu_a^-)^q - (v_a^+)^q(v_a^-)^q)}{(v_a^+)^q + (v_a^-)^q + (\mu_a^+)^q + (\mu_a^-)^q} \tag{10}$$

Example $a_1 = ([0.11,0.25],[0.29,0.37])$ and $a_2 = ([0.18,0.28],[0.36,0.54])$ uses the score function getting a result S_{GM}(a_1)= S_{GM} (a_2)=0.3465. It cannot differentiate between a_1 *and* a_2

Definition 3.4 Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [\nu_{a_1}^-, \nu_{a_1}^+])$,the new score function of a ins developed as below:

$$S(a) = \arcsin\left(\frac{(\mu_a^-)^q + (\mu_a^-)^q + \frac{((\mu_a^-) + (\mu_a^-))^q}{2}}{3}\right) + \arccos\left(\frac{(v_a^-)^q + (v_a^-)^q + \frac{((v_a^-) + (v_a^-))^q}{2}}{3}\right) \tag{11}$$

Theorem 3.1

Let $a_1 = ([\mu_{a_1}^-, \mu_{a_1}^+], [\nu_{a_1}^-, \nu_{a_1}^+])$,and S(a) regard as new score function ,where is its properties：

0≤ $S(a) \leq \pi$.

The function $g(x)$ is defined, $g(x) = arcsinx, x \in [0,1]$. Obviously, $g(x)$ is differentiable within its domain. Always, $g^{'}(x) = \frac{1}{\sqrt{(1-x^2)}} > 0, x \in [0,1]$. Thus $g(x)$ is monotonically increasing over its domain.

Additionally, The function $h(x)$ is defined, $h(y) = arccosx, y \in [0,1]$. Obviously, $h(y)$ is differentiable within its domain. Always, $h^{'}(y) = \frac{-1}{\sqrt{(1-y^2)}} < 0, y \in [0,1]$. Thus $h(y)$ is monotonically decreasing over its domain.

The function S(a) is defined, S(a)=g(x)+h(y). For g(x), which is continuous and monotonically increasing over its domain, and given that S(a) is a bounded function with its maximum lower bound as Max(g(x))+Max(h(y)) and minimum upper bound as Min(g(x))+Min(h(y)). Therefore, $0 \leq S(a) \leq \pi$.

(2)if amin=[[0,0],[1,1]],then S(amin)=0.

When amin=[[0,0],[1,1]], getting a result is $x = \frac{(u_a^-)^q + (u_a^+)^q + (u_a^-)^q (u_a^+)^q}{3}$ =0 and y= $\frac{(v_a^-)^q + (v_a^+)^q + (v_a^-)^q (v_a^+)^q}{3} = 1$ .Thus, S(amin)= Min(g(x))+Min(h(y))=0

(3)if amax=[[1,1],[0,0]],then S(amax)= π

When amax=[[1,1],[0,0]], getting a result x= $\frac{(u_a^-)^q + (u_a^+)^q + (u_a^-)^q (u_a^+)^q}{3}$ =1, y= $\frac{(v_a^-)^q+(v_a^+)^q+(v_a^-)^q(v_a^+)^q}{3}$ =0. Thus, S(max)= Max(g(x))+Max(h(y))= π

(4)Let $a_1=([\mu_{a_1}^-,\mu_{a_1}^+],[v_{a_1}^-,v_{a_1}^+])$ and $a_2=([\mu_{a_2}^-,\mu_{a_2}^+],[v_{a_2}^-,v_{a_2}^+])$,and S(ai) is used(i=1,2), if $\mu_{a_1}^->\mu_{a_2}^-$, $\mu_{a_1}^+>\mu_{a_2}^+$, $v_{a_1}^-<v_{a_2}^-$, $v_{a_1}^+<v_{a_2}^+$, then S(a1)> S(a2). S(a1)= g(x1)+h(y1), S(a2)= g(x2)+h(y2), S(a1)> S(a2) equivalent to S(a1)-S(a2)= g(x1)-g(x2)+ h(y1)-h(y2)>0.

Where:

x1=$\frac{(u_{a1}^-)^q+(u_{a1}^+)^q+(u_{a1}^-)^q(u_{a1}^+)^q}{3}$,

y1=$\frac{(v_{a1}^-)^q+(v_{a1}^+)^q+(v_a^-1)^q(v_{a1}^+)^q}{3}$,

x2= $\frac{(u_{a2}^-)^q+(u_{a2}^+)^q+(u_{a2}^-)^q(u_{a2}^+)^q}{3}$,

y2=$\frac{(v_{a2}^-)^q+(v_{a2}^+)^q+(v_{a2}^-1)^q(v_{a2}^+)^q}{3}$,

because of $\mu_{a_1}^->\mu_{a_2}^-$, $\mu_{a_1}^+>\mu_{a_2}^+$, $v_{a_1}^-<v_{a_2}^-$, $v_{a_1}^+<v_{a_2}^+$,drawing a conclusion x1> x2, y2> y1. According to the properties of g(x), g(x1)-g(x2)>0, h(y1)-h(y2) >0 is clear. Thus, S(a1)-S(a2) >0 is established.

Theorem 3.2 Let $a=([\mu^-,\mu^+,],[v^-,v^+])$,here is its properties:

If μ^-,v^-,v^+ remain unchanged, then $\frac{dS(a)}{d(u^+)^q}>0$.

If μ^+,v^-,v^+ remain unchanged, then $\frac{dS(a)}{d(\mu^-)^q}>0$.

If μ^+,μ^-,v^+ remain unchanged, then $\frac{dS(a)}{d(v^-)^q}<0$.

If μ^+,μ^+,v^- remain unchanged, then $\frac{dS(a)}{d(v^+)^q}<0$.

The above properties can be proven by taking the derivative of S(a)

Theorem 3.3 Let $a_1=([\mu_{a_1}^-,\mu_{a_1}^+],[v_{a_1}^-,v_{a_1}^+])$ and $a_2=([\mu_{a_2}^-,\mu_{a_2}^+],[v_{a_2}^-,v_{a_2}^+])$, the comparison law of these two IVQ-ROFNs is proposed as below:

If S(a_1) > S(a_1), then a_1>a_2.

If S(a_1) < S(a_2), then a_2>a_1.

If S(a_1) = S(a_2) , then a_2=a_1.

To validate the effectiveness and reliability of the proposed scoring function, this study utilized Wan's learning outcome data [10] and conducted experiments to assess its performance. The experimental results are shown in Figure 1, while Wan's results are presented in Figure 2 [10] for direct comparison. To ensure fair and consistent evaluations, the fundamental arithmetic operations of IVq-ROFSs (Interval-Valued q-Rough Fuzzy Sets), as described in Equations 1 to 7, were applied. These operations provide a basis for reasonable comparison of alternatives within a fuzzy data environment, enabling researchers to maintain high analytical accuracy even when handling data with significant uncertainty.

The experimental results showed that the ranking results of the alternatives remained consistent even when different scoring functions were applied. This finding confirms the robustness of the proposed scoring function, indicating that it can provide stable analytical results across various scenarios. This consistency is crucial for the scoring function's application, as obtaining the same conclusions under different scoring standards or computational methods implies that the scoring function itself has high reliability and robustness. Therefore, it can be widely applied in real-world decision-making scenarios with inherent fuzziness or uncertainty

Using IVq-ROFSs offers a more refined approach to managing uncertainty in complex decision-making problems. In real applications, data typically comes with varying degrees of uncertainty and fuzziness, which traditional decision-making methods often struggle to capture adequately. However, by applying the interval-valued representation and fundamental arithmetic operations of IVq-ROFSs, we can better capture subtle changes within the data, making the decision-making analysis process more aligned with real-world conditions.

Moreover, the controlled application of these fundamental arithmetic operations ensures that comparisons between different alternatives are both fair and precise, further enhancing the validity of the experimental results. The experiment demonstrated that the ranking results remained consistent across different scoring functions, indicating not only the robustness of the scoring function but also its ability to accommodate complex data integration and analysis needs. As such, this scoring function holds potential application value in various complex decision-making environments, especially in scenarios where decision accuracy is critical. This robustness ensures that the decision-making process remains reliable when faced with different evaluative perspectives or varying levels of uncertainty, providing a solid theoretical foundation for practical applications.

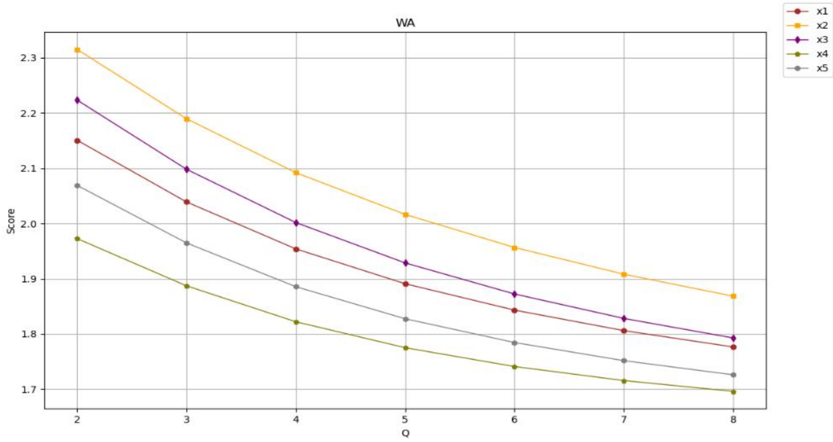

Figure 1. New Score Function of Rank

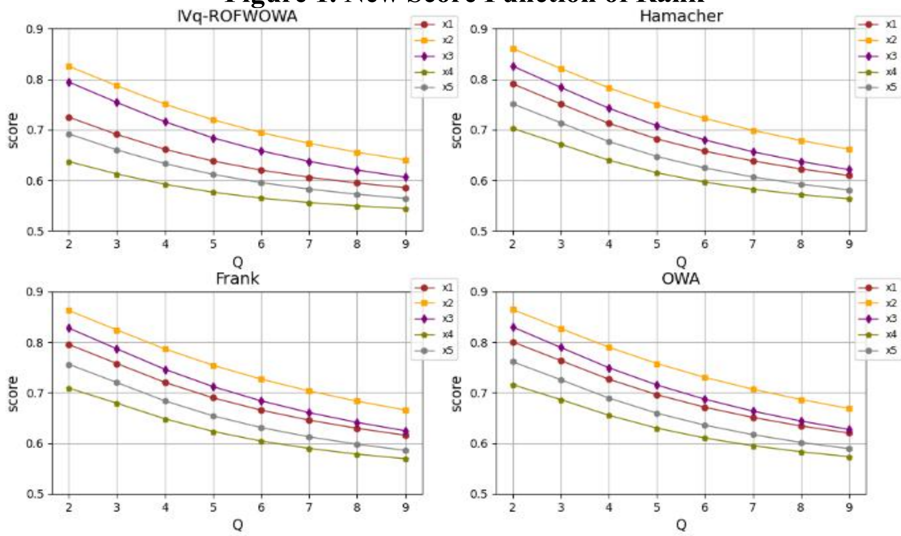

Figure 2. Result of Comparing

4. Conclusion

The proposed MAGDM method, based on a new scoring function and IVq-ROFSs, provides a robust and reliable framework for decision-making in uncertain and fuzzy environments. By integrating multiple attributes and fuzzy values, this method can ensure the accuracy and consistency of decision outcomes even under conditions of data ambiguity and variability. Therefore, it demonstrates great potential for real-world applications requiring precise and consistent analysis, offering an effective solution for diverse decision-making needs.

Application results using actual data indicate that this method not only has scientific rigor in theory but also demonstrates strong applicability and versatility in practice. It effectively addresses various complex scenarios, performing exceptionally well in cases where multiple uncertain factors and fuzzy attributes need to be considered. This method provides solid support for complex decision environments, allowing decision-makers to make reasonable and reliable judgments under uncertain and fuzzy data conditions. Consequently, it shows broad application prospects in fields requiring multi-attribute evaluation, such as healthcare, finance, and engineering.

The next research objective is to apply this method to other decision-making scenarios, especially those involving more complex and diverse sets of attributes. For instance, in fields dealing with higher-dimensional data or requiring the management of multiple uncertainty factors, this method may offer new approaches to improve decision-making accuracy and scientific rigor. Additionally, as application scenarios expand, we will explore the possibility of optimizing the scoring function to better accommodate different types of fuzzy numbers, including triangular and trapezoidal fuzzy numbers. Such optimizations will further enhance this method's applicability, ensuring that it remains robust across a wider range of data types and more complex decision-making challenges.

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