# The Best-Worst Method Based on Interval Neutrosophic Sets

Dongsheng Xu, Xue Kang, Xinghai Zhang, Moyi Zhu

***Abstract*—In real-life multi-criteria decision-making problems, decision-making data often exhibit ambiguity due to incomplete information. Additionally, qualitative judgments by decision-makers can introduce fallacies and inaccuracies. Consequently, these problems cannot be resolved using precise values alone. To address this, the present study enhances the Best-Worst Method(BWM) by incorporating interval neutrosophic sets, thereby improving its applicability to real-life multi-criteria decision-making issues. In the modified BWM approach detailed in this study, decision-makers express preferences using linguistic terms, which are then converted into interval neutrosophic numbers. These numbers facilitate the comparative assessment between the best and other criteria, as well as between the other criteria and the worst criterion. All interval neutrosophic numbers are subsequently converted into real numbers using the score function s(a). Furthermore, a new nonlinear constrained optimization model concerning interval neutrosophic numbers is formulated according to the BWM framework. The resultant data, representing the weights of different criteria, do not require further transformation. A consistency ratio for BWM is also introduced to evaluate the reliability of preference comparisons. Comparative analysis of three methods using the same case study confirms the efficacy and viability of the proposed method, namely the interval neutrosophic set based BWM.**

***Index Terms*—Best-worst method, Interval Neutrosophic sets, Consistency Ratio, Multi-criteria Decision-making.**

## I. Introduction

THE Best-Worst Method(BWM) was initially proposed by J. Figueira, S. Greco, and V. Mousseau in 2010, which focused on contrasting the 'best' and 'worst' factors [1], [2], [3], [4]. Subsequently, Rezaei [5] developed a theoretical framework based on BWM and demonstrated its application in addressing real-life multi-criteria decision-making problems. Over time, an increasing number of researchers have explored this method, identifying that the preferences derived from it can be problematic due to data inaccuracies and the heterogeneity among decision-makers, leading to data of limited referential value. To enhance the resolution of these issues, scholars have adapted the BWM to the fuzzy environment. By integrating BWM with fuzzy numbers, a novel approach has been formulated the fuzzy best-worst method [6], [7], which effectively addresses multi-criteria decision-making challenges in fuzzy contexts.

Manuscript received March 29, 2024; revised August 15, 2024. This work was supported by the Natural Science Foundation of Sichuan Province.

Dongsheng Xu is a professor of School of Science, South-west Petroleum University, Sichuan, Chengdu, 610500, PR China (e-mail:xudongsheng1976@163.com).

Xue Kang is a graduate student of School of Science, South-west Petroleum University, Sichuan, Chengdu, 610500, PR China (Corresponding author to provide e-mail:3080924898@qq.com)

Xinghai Zhang is a graduate student of School of Science, South-west Petroleum University, Sichuan, Chengdu, 610500, PR China (e-mail:2789874044@qq.com)

Moyi Zhu is a graduate student of School of Science, South-west Petroleum University, Sichuan, Chengdu, 610500, PR China (e-mail:zhumoyi@foxmail.com)

The multi-criteria decision-making problem [8], [9], often encountered in real-life, refers to the challenge of selecting the optimal alternative or ranking several options when multiple attributes are considered. This problem is a crucial component of modern decision science. Its theories and methods are extensively applied across various fields including engineering [10], technology [11], economics [12], management [13], and military [14]. Over time, with the progression of research, the focus has also expanded to fuzzy multi-criteria decision-making, which has emerged as a significant area of interest within the field. This approach, which utilizes fuzzy numbers [15], [16], intuitionistic fuzzy sets [17], and vague sets [18], has found broad applications in real-world decision-making scenarios. Consequently, it is anticipated that innovation will continue regarding the BWM. As research deepens, the BWM has been increasingly utilized to address multi-criteria decision-making problems both independently and in conjunction with other methods. For instance, BWM is integrated with the fuzzy comprehensive evaluation method [19] to broaden its applicability. In combination with the grey correlation analysis method [20], it enables a comprehensive assessment of each alternative's degree of correlation with each criterion. Furthermore, it is employed alongside the Analytic Hierarchy Process (AHP) [21] to ascertain the relative importance of each alternative per criterion. As previously noted, given the uncertainty and ambiguity inherent in practical problems, BWM has been adapted to fuzzy environments. This paper also situates its discussion within such an environment, aiming to address the inherent fallacies of the problems. It integrates the interval neutrosophic set [22], [23], [24] with the neutrosophic set [25], [26], [27] and the BWM method to propose an extension.

The structure of this paper is as follows. Section 2 discusses interval neutrosophic sets and their scoring functions. Section 3 briefly reviews the specific steps of the classical BWM. Section 4 provides an overview of the fuzzy BWM approach. Section 5 introduces a BWM method based on an interval neutrosophic set, detailing its application to practical examples and a comparison with the previous two methods. The final section summarizes the contents of this paper.

## II. Preliminary

*definition 1:* [23] In the universe $\Omega$, an interval neutrosophic sets (INS) A is

$$A = \{(x(t_A(x), i_A(x), f_A(x))) : x \in U\} \tag{1}$$

and, there are

$$t_A(x), i_A(x), f_A(x) \in [0, 1], t_A(x){=}[\inf t_A(x), \sup t_A(x)],$$

TABLE I
CONSISTENCY INDEX (CI) OF BWM

| $a_{BW}$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| CI (max $\xi$) | 3 | 4.56 | 6 | 7.37 | 8.7 | 10 | 11.27 | 12.53 | 14.28 |

$i_A(x) = [\inf i_A(x), \sup i_A(x)], f_A(x) = [\inf f_A(x), \sup f_A(x)]$.

Therefore, an interval neutrosophic set can be represented as:

$$A = \left(\left[t^i(x), t^s(x)\right], \left[i^i(x), i^s(x)\right], \left[f^i(x), f^s(x)\right]\right) \quad (2)$$

In definition 1 above, $t_A(x)$ denotes the degree of truth or membership, $i_A(x)$ denotes indeterminacy or neutrality, and $f_A(x)$ denotes the degree of falsity or non-membership, called the neutrosophic components of x.

*definition 2:* [24] If $A =< t_A(x), i_A(x), f_A(x) >$ is an interval neutrosophic number. Then its score function s(A) can be expressed as follows:

$$s(A) = \frac{t^i(x) + t^s(x) + 2 - i^i(x) - i^s(x) - f^i(x) - f^i(x)}{2} \quad (3)$$

*definition 3:* [24] If A and B are two interval neutrosophic numbers, the rules for comparing these two interval neutrosophic numbers are as follows:

(1) If the score function of A is greater than the score function of B, i.e., $s(A) > s(B)$, then $A > B$.

(2) If the score function of A is equal to the score function of B, i.e., s(A) = s(B), then A = B.

(3) If the score function of A is less than the score function of B, i.e., $s(A) < s(B)$, then $A < B$.

*definition 4:* [17] If $i$ is the best element and $j$ is the worst element, then a pairwise comparison $\tilde{a}_{ij}$ is a reference comparison.

*definition 5:* [17] To obtain a sufficiently consistent pairwise comparison, the equation $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$ needs to hold, where $\tilde{a}_{BW}$ represents the preference of the best criterion relative to the worst criterion, $\tilde{a}_{Bj}$ represents the preference of the best criterion relative to other criteria, and $\tilde{a}_{jW}$ represents the preference of other criteria relative to the worst criterion.

## III. A BRIEF REVIEW OF THE BWM METHOD

### A. The Specific Steps of the Best-Worst Method

The BWM was first proposed in 2015 and has played a pivotal role in addressing multi-criteria decision-making issues. This method assists decision-makers in evaluating multiple factors by calculating their respective weights, thereby facilitating informed choices. Consequently, it is extensively applied in multi-criteria decision-making scenarios. The following section briefly reviews the weighting steps of the classical BWM. The specific steps [5] are as follows:

Step 1: the decision maker first decides on a decision criterion and determines its collective as $C = \{c_1, c_2, \cdots, c_n\}$.

Step 2: decision makers decide for themselves the best $C_B$ and worst criteria $C_W$.

Step 3: the decision-maker uses the numbers 1-9 to denote the preference of the best criterion relative to other criteria to obtain the best other vectors $A_B = [a_{B1}, a_{B2}, \cdots, a_{Bn}]$. It is noteworthy that $a_{Bj}(j = 1, 2, \cdots, n)$ represents the preference of the best criteria $a_B$ relative to other criterion $a_j(j = 1, 2, \cdots, n)$, and $a_{BB} = 1$.

Step 4: as in the third step, the decision-maker needs to use 1-9 to denote the preference of other criteria relative to the worst criterion, to obtain the other-worst vectors $A_W = [a_{1W}, a_{2W}, \cdots, a_{nW}]$, where $a_{jW}(j = 1, 2, \cdots, n)$ represents the preference of the other vectors $a_j(j = 1, 2, \cdots, n)$ relative to the worst vector $a_W$, and $a_{WW} = 1$.

Step 5: the optimal weight is obtained as $w^* = [w_1^*, w_2^*, \cdots, w_n^*]$, where $w_j^*$ represents the optimal weight of the criterion $c_j$, and $j = 1$, so the following model can be established:

$$\begin{aligned} &\min \max_j \{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{jw} \right| \} \\ &s.t. \begin{cases} \sum_{j=1}^{n} w_j = 1 \\ w_j \geq 0 (j = 1, 2, \cdots n) \end{cases} \end{aligned} \quad (4)$$

By transforming the mathematical model constructed above, the following new model is obtained:

$$\begin{aligned} &\min \xi \\ &s.t. \begin{cases} \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi (j = 1, 2, \cdots n) \\ \left| \frac{w_j}{w_w} - a_{jW} \right| \leq \xi (j = 1, 2, \cdots n) \\ \sum_{j=1}^{n} w_j = 1, w_j \geq 0 (j = 1, 2, \cdots n) \end{cases} \end{aligned} \quad (5)$$

By using the Lingo software to solve the above construction of the programming model, that is, the Eq.(4), the optimal weights $w_1^*, w_2^*, \cdots, w_n^*$ of standard $c_1, c_2, \cdots, c_n$ and can be obtained respectively. At the same time, optimal values $\xi$ can be obtained.

### B. Consistency Ratio of the BWM

In the application of the Best-Worst Method (BWM) to determine optimal weights, the definitions of vector groups $A_B = [a_{B1}, a_{B2}, \cdots, a_{Bn}]$ and $A_W = [a_{1W}, a_{2W}, \cdots, a_{nW}]$ are established in the second and third steps of the methodology. Consistency in comparisons is achieved when the product of $a_{Bj}$ and $a_{jW}$ equals $a_{BW}$ for each $j = 1, 2, \cdots, n$, where $a_{BW}$ quantifies the preference of the best criterion over the worst criterion. However, this equation does not hold for certain values of $j$ [17].

$$a_{Bj} \times a_{jW} \neq a_{BW} (j = 1, 2, \cdots, n) \quad (6)$$

By Eq.(5), if both $a_{Bj}$ and $a_{jw}$ simultaneously attain their maximum values, then maximum inequality is observed. Consequently, in this scenario, a specific value of $\xi$ is considered. This value is subtracted from $a_{Bj}$ and $a_{jw}$ on the left side of the equation and added to $a_{Bw}$ on the right side to manifest the greatest inequality, as described below:

$$(a_{Bj} - \xi) \times (a_{jW} - \xi) = a_{BW} + \xi \quad (7)$$

As for the minimum consistency $a_{Bj} = a_{jW} = a_{BW}$, we can get the following equation:

$$(a_{BW} - \xi) \times (a_{BW} - \xi) = (a_{BW} + \xi) \quad (8)$$

Simplify the above equation and get:

$$\xi^2 - (1 + 2a_{BW})\xi + (a_{BW}^2 - a_{BW}) = 0 \quad (9)$$

TABLE II
TRANSFORMATION RULES OF LINGUISTIC VARIABLES OF DECISION-MAKERS

| Linguistic terms | Membership function |
|---|---|
| Equally Important(EI) | (1,1,1) |
| Weakly Important(WI) | (2/3,1,3/2) |
| Fairly Important(FI) | (3/2,2,5/2) |
| Very Important(VI) | (5/2,3,7/2) |
| Absolutely Important(AI) | (7/2,4,9/2) |

By substituting values from 1 to 9 for $a_{BW}$ in the aforementioned equation, the maximum value of $\xi$ can be determined, which is referred to as the Consistency Index (CI). The specific values of CI are listed in Table 1 [15]. Subsequently, the obtained Consistency Index is utilized in the following formula to compute the Consistency Ratio (CR):

$$CR = \frac{\xi^*}{\xi} \tag{10}$$

The $\xi^*$ in the Eq.(5) is obtained by the formula.

## IV. A BRIEF INTRODUCTION OF FUZZY BEST-WORST METHOD

### A. fuzzy best-worst method

The fuzzy BWM [16] results from researchers adapting the BWM for use in a fuzzy environment to innovate the method. This adaptation aligns with the weighting step of the original BWM. However, a fuzzy number substitutes the constant, resulting in a modification and resolution of the mathematical model. The details are as follows:

Step 1: build the decision criteria system $C = \{c_1, c_2, \cdots, c_n\}$.

Step 2: determine the best (most important) criterion $C_B$ and the worst (least important) criterion $C_W$.

Step 3: execute the fuzzy reference comparisons for the best criterion, $A_B = [a_{B1}, a_{B2}, \cdots, a_{Bn}]$, $a_{Bj}(j = 1, 2, \cdots, n)$ and $a_{BB} = (1, 1, 1)$.

Step 4: execute the fuzzy reference comparisons for the worst criterion, $A_W = [a_{1W}, a_{2W}, \cdots, a_{nW}]$, $a_{jW}(j = 1, 2, \cdots, n)$ and $a_{WW} = (1, 1, 1)$.

Step 5: mathematical modelling.

Note: all elements are triangular fuzzy numbers; the transform table is shown in Table 3 [16].

$$\min \max_j \left\{ \left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right|, \left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW} \right| \right\}$$

$$s.t. \begin{cases} \sum\limits_{j=1}^{n} R(\tilde{w}_j) = 1 \\ l_j^W \leq m_j^W \leq u_j^W \\ l_j^W \geq 0 \\ j = 1, 2, \cdots, n \end{cases} \tag{11}$$

Through the transformation of the previously described mathematical model, a new mathematical model is derived, which is presented as follows:

$$\min \xi^*$$

$$s.t. \begin{cases} \left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum\limits_{j=1}^{n} R(\tilde{w}_j) = 1 \\ l_j^W \leq m_j^W \leq u_j^W \\ l_j^W \geq 0 \\ j = 1, 2, \cdots, n \end{cases} \tag{12}$$

In Eq.(12), $\tilde{w}_B = (l_B^w, m_B^w, u_B^w)$, $\tilde{w}_j = (l_j^w, m_j^w, u_j^w)$, $\tilde{w}_W = (l_W^w, m_W^w, u_W^w)$, $\tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$ ,$\tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$ and we usually think that $l^\xi \leq m^\xi \leq u^\xi$ and $\xi^* = (k^*, k^*, k^*), k^* \leq l^\xi$, then the formula can be substituted into the data and solved by lingo software.

### B. Consistency Ratio of Fuzzy Best-worst Method

Best-to-Other vectors and Other-to-Worst vectors are $\tilde{A}_B = [\tilde{a}_{B1}, \tilde{a}_{B2}, \cdots, \tilde{a}_{Bn}]$, $\tilde{A}_W = [\tilde{a}_{1W}, \tilde{a}_{2W}, \cdots, \tilde{a}_{nW}]$. Where, $\tilde{a}_{Bj}$ and $\tilde{a}_{jW}(j = 1, 2, \cdots n)$ are triangular fuzzy numbers [17]. Moreover, for a comparison to be fully consistent, you have to satisfy $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$, but not all j is satisfy this equation. Therefore, it needs to deform the formula by a triangular fuzzy number $\tilde{\xi} = (\xi^l, \xi^m, \xi^u)$, that is, subtracting $\tilde{\xi}$ from $\tilde{a}_{Bj}$ and $\tilde{a}_{jW}$ on the left side of the equation, and adding $\tilde{\xi}$ on the right side of the equation, so the formula is deformed as follows:

$$(\tilde{a}_{Bj} - \tilde{\xi}) \times (\tilde{a}_{jW} - \tilde{\xi}) = \tilde{a}_{BW} + \tilde{\xi} \tag{13}$$

For the minimum consistency of this equation, this is true if $\tilde{a}_{Bj} = \tilde{a}_{jW} = \tilde{a}_{BW}$ is appropriate, and the equation becomes:

$$(\tilde{a}_{BW} - \tilde{\xi}) \times (\tilde{a}_{BW} - \tilde{\xi}) = \tilde{a}_{BW} + \tilde{\xi} \tag{14}$$

However, since $a^l{}_{BW} \leq a^m{}_{BW} \leq a^u{}_{BW}$, that is, the upper bound of the triangular fuzzy number $a_{BW}$ is $a^u{}_{BW}$, $a^u{}_{BW}$ can be substituted for $\tilde{a}_{BW}$ and use it to represent the consistency index [16]. The formula continues to transform into:

$$(a^u{}_{BW} - \tilde{\xi}) \times (a^u{}_{BW} - \tilde{\xi}) = a^u{}_{BW} + \tilde{\xi} \tag{15}$$

The simplification results in:

$$\xi^2 - (1 + 2a^u{}_{BW})\xi + (a^{u2}{}_{BW} - a^u{}_{BW}) = 0 \tag{16}$$

$\xi$ in the above formula is obtained by degenerating $\tilde{\xi}$ in Eq.(15) into a real number. Different values of $a^u{}_{BW}$ can be known through Table 2, and the so-called CI can be obtained by solving it. The following formula can then obtain the consistency ratio:

$$CR = \frac{k^*}{\xi} \tag{17}$$

TABLE III
CI OF FUZZY BWM

| Linguistic terms | $\tilde{a}_{BW}$ | CI |
|---|---|---|
| Equally Important(EI) | (1,1,1) | 3.00 |
| Weakly Important(WI) | (2/3,1,3/2) | 3.80 |
| Fairly Important(FI) | (3/2,2,5/2) | 5.29 |
| Very Important(VI) | (5/2,3,7/2) | 6.69 |
| Absolutely Important(AI) | (7/2,4,9/2) | 8.04 |

## V. BWM BASED ON INTERVAL NEUTROSOPHIC NUMBERS

### A. The Specific Steps of the BWM Based on Interval Neutrosophic Numbers

This chapter extensively discusses the BWM as applied within the framework of the interval neutrosophic set. It is widely recognized that the BWM method has been adapted for use in fuzzy environments. The interval neutrosophic set, a subset of fuzzy environments, is similarly applicable. Consequently, this chapter integrates the interval neutrosophic set with the BWM to develop a novel approach to the BWM. The procedural steps of this method mirror those of the classical BWM, with the primary modification being the substitution of conventional scalar numbers with interval neutrosophic numbers, resulting in a transformation of the underlying mathematical programming model. Suppose a research object has n criteria that can be paired and compared based on the language variables [22] of the decision maker, such as 'Unimportant (UI)', 'Ordinarily Important (OI)', 'Important (I)', 'Very Important (VI)', and 'Absolutely Important (AI)'. The decision maker's verbal evaluations must then be converted into interval neutrosophic numbers, as detailed in Table 4.

By pairwise comparison, the following nth-order pairwise comparison matrix [16] can be obtained:

$$\dot{A} = \begin{bmatrix} \dot{a}_{11} & \dot{a}_{12} & \cdots & \dot{a}_{1n} \\ \dot{a}_{21} & \dot{a}_{22} & \cdots & \dot{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \dot{a}_{n1} & \dot{a}_{n2} & \cdots & \dot{a}_{nn} \end{bmatrix} \tag{18}$$

In the n-order square matrix presented above, elements such as $\dot{a}_{12}$, are derived according to definition 4, specifically referencing the comparison between criterion 1 and criterion 2. It is also crucial to note that all elements within the matrix are represented as interval neutrosophic numbers. Subsequently, the steps of the BWM based on interval neutrosophic numbers are delineated in detail.

Step 1: determine the decision criteria.

The decision maker initially selects a decision criterion and defines the collective set as $C = \{c_1, c_2 \cdots, c_n\}$. This step is fundamental and establishes the groundwork for subsequent procedures.

Step 2: identify the best and worst decision criteria.

The decision-maker identifies the optimal and least favorable decision criteria based on a range of influencing factors; the best decision criterion is denoted as $c_B$, and the worst criterion is $c_W$.

Step 3: obtained Best-to-Others vector.

According to definition 4, the Best-to-Others vector is derived by comparing the optimal criterion with other criteria. Specifically, this involves a reference comparison denoted as $\dot{a}_{ij}$, where i represents the best criterion and j represents other criteria, with j potentially being equal to i. Subsequently, the Best-to-Others vector is transformed into an interval neutrosophic number using the corresponding reference standard outlined in Table 4 [22].

$$\dot{A}_B = (\dot{a}_{B1}, \dot{a}_{B2}, \cdots, \dot{a}_{Bn}) \tag{19}$$

The vector obtained above is the target vector, which represents the reference comparison of the best standard $c_B$ with other standard $c_j$, and $j = 1, 2, \cdots, n$. In particular, when i=j, $\dot{a}_{Bj}$=$([0.2, 0.4], [0.5, 0.6], [0.4, 0.5])$.

Step 4: obtained Others-to-Worst vector.

In Step 3, the process involves obtaining the Other-to-Worst vector. According to definition 4, this is achieved by comparing other criteria to the worst criterion to derive the most appropriate pair of vectors. Specifically, this comparison is denoted as $\dot{a}_{ij}$, where i represents other criteria and j is the worst criterion, with j potentially being equal to i. Subsequently, following the corresponding reference standards listed in Table 4, these vectors can be converted into interval neutrosophic numbers.

$$\dot{A}_W = (\dot{a}_{1W}, \dot{a}_{2W}, \cdots, \dot{a}_{nW}) \tag{20}$$

The Eq.(20) is the target vector other to the worst vector, which represents the reference comparison of other criteria $c_j$ to the worst criteria $c_W$, as well as $j = 1, 2, \cdots, n$. In particular, when i=j, $\dot{a}_{jW}$=$([0.2, 0.4], [0.5, 0.6], [0.4, 0.5])$.

Step 5: get the optimal weights.

This section primarily derives from solving the established mathematical model. The specific mathematical model is formulated as follows:

$$\min \max_j \left\{ \left| \frac{\dot{w}_B}{\dot{w}_j} - \dot{a}_{Bj} \right|, \left| \frac{\dot{w}_j}{\dot{w}_W} - \dot{a}_{jW} \right| \right\}$$
$$s.t. \begin{cases} \sum\limits_{j=1}^{n} s(\dot{w}_j) = 1 \\ 0 \le \sup\limits_T(\dot{w}_j) + \sup\limits_I(\dot{w}_j) + \sup\limits_F(\dot{w}_j) \le 3 \\ 0 \le \sup\limits_T(\dot{w}_j), \sup\limits_I(\dot{w}_j), \sup\limits_F(\dot{w}_j) \\ 0 \le \inf\limits_T(\dot{w}_j), \inf\limits_I(\dot{w}_j), \inf\limits_F(\dot{w}_j) \\ j = 1, 2, \cdots n \end{cases} \tag{21}$$

In the mathematical programming model mentioned above, $\dot{w}_B, \dot{w}_j, \dot{w}_W, \dot{a}_{Bj} and \dot{a}_{jW}$ are all interval neutrosophic numbers, represented as:

$$\dot{a}_{jW} = ([\inf_T \dot{a}_{jW}, \sup_T \dot{a}_{jW}], [\inf_I \dot{a}_{jW}, \sup_I \dot{a}_{jW}], [\inf_F \dot{a}_{jW}, \sup_F \dot{a}_{jW}])$$

$$\dot{a}_{Bj} = ([\inf_T \dot{a}_{Bj}, \sup_T \dot{a}_{Bj}], [\inf_I \dot{a}_{Bj}, \sup_I \dot{a}_{Bj}], [\inf_F \dot{a}_{Bj}, \sup_F \dot{a}_{Bj}])$$

$$\dot{w}_W = ([\inf_T \dot{w}_W, \sup_T \dot{w}_W], [\inf_I \dot{w}_W, \sup_I \dot{w}_W], [\inf_F \dot{w}_W, \sup_F \dot{w}_W])$$

$$\dot{w}_B = ([\inf_T \dot{w}_B, \sup_T \dot{w}_B], [\inf_I \dot{w}_B, \sup_I \dot{w}_B], [\inf_F \dot{w}_B, \sup_F \dot{w}_B])$$

$$\dot{w}_j = ([\inf_T \dot{w}_j, \sup_T \dot{w}_j], [\inf_I \dot{w}_j, \sup_I \dot{w}_j], [\inf_F \dot{w}_j, \sup_F \dot{w}_j])$$

Simultaneously, this article necessitates the transformation of weights into a precise value, as demonstrated in the referenced study [15]. Consequently, this study employs the scoring function of the interval neutrosophic numbers to convert them into a precise value.

The above mathematical model can be transformed into the following nonlinearly constrained optimization problem:

$$\min \dot{\zeta}$$
$$s.t.\begin{cases} \left|\frac{\dot{w}_B}{\dot{w}_j} - \dot{a}_{Bj}\right| \le \dot{\zeta} \\ \left|\frac{\dot{w}_j}{\dot{w}_W} - \dot{a}_{jW}\right| \le \dot{\zeta} \\ \sum_{j=1}^{n} s(\dot{w}_j) = 1 \\ 0 \le \sup_T(\dot{w}_j) + \sup_I(\dot{w}_j) + \sup_F(\dot{w}_j) \le 3 \\ 0 \le \sup_T(\dot{w}_j), \sup_I(\dot{w}_j), \sup_F(\dot{w}_j) \\ 0 \le \inf_T(\dot{w}_j), \inf_I(\dot{w}_j), \inf_F(\dot{w}_j) \\ j = 1, 2, \cdots n \end{cases} \tag{22}$$

In Eq.(22), $\dot{\zeta}$ is also a interval neutrosophic numbers $\dot{\zeta} = ([\sup_T\dot{\xi}, \inf_T\dot{\xi}], [\sup_I\dot{\xi}, \inf_I\dot{\xi}], [\sup_F\dot{\xi}, \inf_F\dot{\xi}])$, $0 \le \sup_T\dot{\xi} + \sup_I\dot{\xi} + \sup_F\dot{\xi} \le 3$, $\sup_T\dot{\xi}$, $\sup_I\dot{\xi}$, $\sup_F\dot{\xi}$, $\inf_T\dot{\xi}$, $\inf_I\dot{\xi}$, $\inf_F\dot{\xi}$ is greater than 0. Unlike a fuzzy set, an interval neutrosophic set does not define operations for subtraction and division; therefore, the mathematical programming model in question cannot be transformed in the same manner as a fuzzy set. Consequently, this mathematical programming model cannot be solved in its current form, necessitating a transformation of the model. After extensive testing, this paper has chosen to employ the scoring function defined in definition 2 to convert all interval neutrosophic sets in the model into precise values for subsequent computation. Accordingly, Eq.(22) is transformed into the following mathematical programming model:

$$\min \zeta$$
$$s.t.\begin{cases} \left|\frac{s(\dot{w}_B)}{s(\dot{w}_j)} - s(\dot{a}_{Bj})\right| \le s(\dot{\zeta}) \\ \left|\frac{s(\dot{w}_j)}{s(\dot{w}_W)} - s(\dot{a}_{jW})\right| \le s(\dot{\zeta}) \\ \sum_{j}^{n} s(\dot{w}_j) = 1 \\ 0 \le \sup_T(\dot{w}_j) + \sup_I(\dot{w}_j) + \sup_F(\dot{w}_j) \le 3 \\ 0 \le \sup_T(\dot{w}_j), \sup_I(\dot{w}_j), \sup_F(\dot{w}_j) \\ 0 \le \inf_T(\dot{w}_j), \inf_I(\dot{w}_j), \inf_F(\dot{w}_j) \\ j = 1, 2, \cdots n \end{cases} \tag{23}$$

Continue to transform the above mathematical model to obtain the following formulation:

$$\min \zeta$$
$$s.t.\begin{cases} |s(\dot{w}_B) - s(\dot{a}_{Bj})s(\dot{w}_j)| \le s(\dot{\zeta})s(\dot{w}_j) \\ |s(\dot{w}_j) - s(\dot{a}_{jW})s(\dot{w}_W)| \le s(\dot{\zeta})s(\dot{w}_W) \\ \sum_{j}^{n} s(\dot{w}_j) = 1 \\ 0 \le \sup_T(\dot{w}_j) + \sup_I(\dot{w}_j) + \sup_F(\dot{w}_j) \le 3 \\ 0 \le \sup_T(\dot{w}_j), \sup_I(\dot{w}_j), \sup_F(\dot{w}_j) \\ 0 \le \inf_T(\dot{w}_j), \inf_I(\dot{w}_j), \inf_F(\dot{w}_j) \\ j = 1, 2, \cdots n \end{cases} \tag{24}$$

The optimal weight value can be obtained by using Lingo software to solve the transformed mathematical programming model described above.

TABLE IV
THE TRANSFORMATION RULE OF LINGUISTIC VARIABLES OF DECISION-MAKERS WITH INTELLECTUAL CONCENTRATION IN INTERVAL [23]

| Linguistic terms | $\dot{a}_{BW}$ |
|---|---|
| Unimportant (UI) | ([0.1,0.2],[0.4,0.5],[0.6,0.7]) |
| Ordinary Important (OI) | ([0.2,0.4],[0.5,0.6],[0.4,0.5]) |
| Important (I) | ([0.4,0.6],[0.4,0.5],[0.3,0.4]) |
| Very important (VI) | ([0.6,0.8],[0.3,0.4],[0.2,0.3]) |
| Absolutely important (AI) | ([0.7,0.9],[0.2,0.3],[0.1,0.2]) |

### B. *Consistency ratio based on interval neutrosophic numbers*

The Consistency Ratio is commonly used to gauge the level of agreement among decision-makers. A lower value indicates greater consistency in their decisions. This concept is pivotal in decision analysis; for example, when constructing a consistently mixed matrix, it is essential first to identify the criteria for participation in the decision-making process, such as cost, benefit, and feasibility. Subsequently, decision-makers are required to assess each criterion in pairs to ascertain their relative importance. Thus, the CR plays a crucial role in paired comparisons.

In the process of solving the consistency index [17], there may be some j that does not satisfy the equation $\dot{a}_{Bj} \times \dot{a}_{jW} {=} \dot{a}_{BW}$, which leads to inconsistency in criterion j related to the pairwise comparison. Consequently, the subsequent section of the article introduces a new formula for calculating the consistency index to address this issue.

Upon analysis, it is determined that the primary cause of the inconsistency is that the value of $\dot{a}_{Bj} \times \dot{a}_{jW}$ is higher or lower than $\dot{a}_{BW}$. When $\dot{a}_{Bj} = \dot{a}_{jW} = \dot{a}_{BW}$, the inequality achieves its maximum value, leading to the emergence of $\dot{\theta}$. Therefore, subtract an $\dot{\theta}$ from the left side of the inequality and add an $\dot{\theta}$ to the right side. Thus, it is transformed into the following formula:

$$(\dot{a}_{Bj} - \dot{\theta}) \times (\dot{a}_{jW} - \dot{\theta}) = (\dot{a}_{BW} + \dot{\theta}) \tag{25}$$

By adopting the principle of maximizing inequality, we further transform the above formula, resulting in Eq.(26).

$$(\dot{a}_{BW} - \dot{\theta}) \times (\dot{a}_{BW} - \dot{\theta}) = (\dot{a}_{BW} + \dot{\theta}) \tag{26}$$

Simplify Eq.(26) to obtain:

$$\theta^2 - (1 + 2\dot{a}_{BW})\dot{\theta} + (\dot{a}_{BW}^2 - \dot{a}_{BW}) = 0 \tag{27}$$

Obviously, $\dot{a}_{BW} = ([\inf_T\dot{a}_{BW}, \sup_T\dot{a}_{BW}], [\inf_I\dot{a}_{BW}, \sup_I \dot{a}_{BW}], [\inf_F\dot{a}_{BW}, \sup_F\dot{a}_{BW}])$ and $\dot{\theta} = ([\inf_T\dot{\theta}, \sup_T\dot{\theta}], [\inf_I\dot{\theta}, \sup_I\dot{\theta}], [\inf_F\dot{\theta}, \sup_F\dot{\theta}])$ are interval neutrosophic numbers, and they cannot be further calculated. Therefore, it is necessary to use the score function of the interval neutrosophic set to convert it into a clear value before calculation. Eq.(27) was successfully converted to Eq.(28).

$$s^2(\dot{\theta}) - (1 + 2s(\dot{a}_{BW}))s(\dot{\theta}) + (s^2(\dot{a}_{BW}) - s(\dot{a}_{BW})) = 0 \tag{28}$$

Through this series of transformations, the final Eq.(28) can be very convenient for calculating the value of the consistency index. For example, we take $\dot{a}_{BW} = ([0.7, 0.9], [0.2, 0.3], [0.1, 0.2])$, then the specific calculation formula of its score function can get $s(\dot{a}_{BW}) = 5.1$, and

TABLE V
THE LINGUISTIC TERMS FOR PERFERENCES

| criteria | C1 | C2 | C3 |
|---|---|---|---|
| best criterion C3 | AI | I | OI |

TABLE VI
THE LINGUISTIC TERMS FOR PERFERENCES

| criteria | worst criteria C1 |
|---|---|
| C1 | OI |
| C2 | VI |
| C3 | AI |

substitute it into the equation Eq.(28), to get $s(\dot{\theta})$. Therefore, the above calculation method is used to calculate all $\dot{a}_{BW}$ in Table 4, and different $s(\dot{\theta})$ can be obtained. The calculated $s(\dot{\theta})$ is called the consistency index, or CI. Table 5 lists the specific values of CI. The calculation formula of the consistency ratio is similar to the classical BWM [5] calculation method. As shown below:

$$\mathrm{CR} = \frac{s(\dot{\zeta})}{s(\dot{\theta})} \tag{29}$$

*C. Application of BWM Based on Interval Neutrosophic Numbers*

This chapter primarily employs the proposed BWM based on an interval neutrosophic set to address the transportation mode selection problem. A company seeks to identify the optimal transportation mode for supplying goods to a mall, focusing on three critical indicators: flexibility of loading, accessibility, and cost considerations. It is precisely because of the importance of these three factors that businesses must rigorously evaluate them to determine the most suitable mode of transportation. The rationale for selecting this scenario as an example is its mention in references [5] and [17], where it was addressed using the Best-Worst Method (BWM). This paper aims to assess the previously used method and determine whether the newly proposed interval-based neutrosophic set BWM method can effectively resolve the same case. Consequently, this section will outline the application of the method introduced in this study to tackle this issue.

Subsequently, we will demonstrate the problem-solving process using the methods described herein.

Step 1: the decision-maker determines a set of decisions, which in this case are 'loading flexibility (C1)', 'Accessibility (C2)', and 'cost (C3)'. That is, $\{C1, C2, C3\}$.

Step 2: determine the best and worst criteria. Based on the company's perspective, 'cost (C3)' was chosen as the best criterion, while 'flexibility of loading (C1)' was chosen as the worst criterion.

Step 3: obtain the Best-to-Others vector. According to Table 4, it can be obtained that the best to others vector $\dot{A}_B = [\dot{a}_{B1}, \dot{a}_{B2}, \dot{a}_{B3}]$.

Here, $\dot{a}_{B1} = ([0.7, 0.9], [0.2, 0.3], [[0.1, 0.2]), \dot{a}_{B2} = ([0.4, 0.6], [0.4, 0.5], [0.3, 0.4]), \dot{a}_{B3} = ([0.2, 0.4], [0.5, 0.6], [0.4, 0.5])$.

Step 4: obtain the Others-to-Worst vector. From Table 5, we can obtain the Other to worst vector $\dot{A}_W = [\dot{a}_{1W}, \dot{a}_{2W}, \dot{a}_{3W}]$.

Here, $\dot{a}_{1W} = ([0.2, 0.4], [0.5, 0.6], [0.4, 0.5]), \dot{a}_{2W} = ([0.6, 0.8], [0.3, 0.4], [0.2, 0.3], \dot{a}_{3W} = ([0.7, 0.9], [0.2, 0.3], [0.1, 0.2])$.

step5: model construction. The specific mathematical model is as follows:

$$\begin{gathered} \min \dot{\zeta} \\ s.t. \begin{cases} |s(\dot{w}_3) - s(\dot{a}_{31})s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_3) - s(\dot{a}_{32})s(\dot{w}_2)| \le s(\dot{\zeta})s(\dot{w}_2) \\ |s(\dot{w}_3) - s(\dot{a}_{33})s(\dot{w}_3)| \le s(\dot{\zeta})s(\dot{w}_3) \\ |s(\dot{w}_1) - s(\dot{a}_{11})s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_2) - s(\dot{a}_{21})s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_3) - s(\dot{a}_{31})s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ s(\dot{w}_1) + s(\dot{w}_2) + s(\dot{w}_3) = 1 \\ 0 \le \sup_T(\dot{w}_j) + \sup_I(\dot{w}_j) + \sup_F(\dot{w}_j) \le 3 \\ 0 \le \sup_T(\dot{w}_j), \sup_I(\dot{w}_j), \sup_F(\dot{w}_j) \\ 0 \le \inf_T(\dot{w}_j), \inf_I(\dot{w}_j), \inf_F(\dot{w}_j) \\ j = 1, 2, 3. \end{cases} \end{gathered} \tag{30}$$

By substituting the data, the following nonlinear constrained optimization problem is obtained:

$$\begin{gathered} \min \dot{\zeta} \\ s.t. \begin{cases} |s(\dot{w}_3) - 2.4 * s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_3) - 1.7 * s(\dot{w}_2)| \le s(\dot{\zeta})s(\dot{w}_2) \\ |s(\dot{w}_3) - 1.3 * s(\dot{w}_3)| \le s(\dot{\zeta})s(\dot{w}_3) \\ |s(\dot{w}_1) - 1.3 * s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_2) - 2.1 * s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ |s(\dot{w}_3) - 2.4 * s(\dot{w}_1)| \le s(\dot{\zeta})s(\dot{w}_1) \\ s(\dot{w}_1) + s(\dot{w}_2) + s(\dot{w}_3) = 1 \\ 0 \le \sup_T(\dot{w}_1) + \sup_I(\dot{w}_1) + \sup_F(\dot{w}_1) \le 3 \\ 0 \le \sup_T(\dot{w}_2) + \sup_I(\dot{w}_2) + \sup_F(\dot{w}_2) \le 3 \\ 0 \le \sup_T(\dot{w}_3) + \sup_I(\dot{w}_3) + \sup_F(\dot{w}_3) \le 3 \\ \sup_T(\dot{w}_1), \sup_I(\dot{w}_1), \sup_F(\dot{w}_1) \ge 0 \\ \sup_T(\dot{w}_2), \sup_I(\dot{w}_2), \sup_F(\dot{w}_2) \ge 0 \\ \sup_T(\dot{w}_3), \sup_I(\dot{w}_3), \sup_F(\dot{w}_3) \ge 0 \\ \inf_T(\dot{w}_1), \inf_I(\dot{w}_1), \inf_F(\dot{w}_1) \ge 0 \\ \inf_T(\dot{w}_2), \inf_I(\dot{w}_2), \inf_F(\dot{w}_2) \ge 0 \\ \inf_T(\dot{w}_3), \inf_I(\dot{w}_3), \inf_F(\dot{w}_3) \ge 0 \end{cases} \end{gathered} \tag{31}$$

By employing Lingo software to solve the mathematical model that incorporates the specified data, the precise weight values for the three criteria 'load flexibility', 'accessibility', and 'cost' are obtained:

$$s(\dot{w}_1) = 0.17; s(\dot{w}_2) = 0.34; s(\dot{w}_3) = 0.48; s(\dot{\zeta}) = 0.3.$$

The results from Lingo software indicate that the weights of the three criteria "load flexibility," "accessibility," and "cost" are 0.17, 0.34, and 0.48, respectively. And the consistency index can be easily obtained through the previous Table 5. It is clear that due to $\dot{a}_{BW} = ([0.7, 0.9], [0.2, 0.3], [0.1, 0.2])$, the corresponding consistency index is 8.83. Therefore, the consistency ratio $CR = \frac{s(\dot{\zeta})}{s(\dot{\theta})} = \frac{0.3}{8.83} \approx 0.034$ can be calculated by the Eq.(29).

TABLE VII
CONSISTENCY INDEX OF INTERVAL NEUTROSOPHIC NUMBERS

| $\dot{a}_{BW}$ | Consistency Index |
|---|---|
| ([0.1,0.2],[0.4,0.5],[0.6,0.7]]) | 6.14 |
| ([0.2,0.4],[0.5,0.6],[0.4,0.5]]) | 6.69 |
| ([0.4,0.6],[0.4,0.5],[0.3,0.4]]) | 7.51 |
| ([0.6,0.8],[0.3,0.4],[0.2,0.3]]) | 8.31 |
| ([0.7,0.9],[0.2,0.3],[0.1,0.2]]) | 8.83 |

### D. Comparative Analysis

Comparing the above results with the results obtained in [5] and [17], it is found that the weights obtained in [5] are 0.07414, 0.3387, and 0.5899, respectively. The weights calculated with the fuzzy BWM [17] proposed by Guo and Zhao are 0.1431, 0.3496, and 0.5073, respectively. Comparative analysis reveals that although there are variations in the results obtained by these three methods, the results from the proposed method closely align with those from the fuzzy BWM method [17]. Notably, the By employing Lingo software to solve the mathematical model that incorporates the specified data, the precise weight values for the three criteria 'load flexibility', 'accessibility', and 'cost' are obtained. And, ranking results generated by the three methods are consistent.

Similarly, the results are compared with those obtained using the classical BWM and the fuzzy BWM methods. The consistency ratio CR=0.058 is calculated using the classical BWM method [5], while the fuzzy BWM method [17] yields a consistency ratio of CR=0.0559. The CR=0.034 reported in this paper is lower than those achieved by the aforementioned methods; thus, the consistency ratio derived in this study is closer to 0. Consequently, it can be concluded that the BWM method based on interval neutrosophic numbers demonstrates superior consistency.

## VI. CONCLUSION

Building on the traditional BWM [5] and the fuzzy BWM method [17] proposed by Guo and Zhao, this paper addresses the critical factors of fallacy and uncertainty faced by decision-makers in real-world scenarios. It innovatively combines the interval neutrosophic set with the neutrosophic set to enhance the BWM, proposing a BWM method based on interval neutrosophic sets. This approach aims to strengthen the connection between the classical BWM method and interval neutrosophic numbers. The paper highlights challenges in calculating interval neutrosophic numbers; specifically, unlike the fuzzy triangular number, the interval neutrosophic number lacks defined operations for division and subtraction. To resolve this, the interval neutrosophic number is transformed into an exact value using a direct scoring function. Furthermore, the consistency ratio is calculated using the formulas from both the classical and fuzzy BWM methods. The findings reveal that the consistency ratio obtained is smaller than those from the existing methods, indicating enhanced consistency in the proposed method. Thus, the BWM method based on interval neutrosophic sets, as presented in this study, proves beneficial in a fuzzy environment.

## REFERENCES


[1] Qun Wu, Xinwang Liu, Ligang Zhou, Jindong Qin, and Jafar Rezaei. An analytical framework for the best–worst method. *Omega*, 123:102974, 2024.

[2] Jiancheng Tu, Zhibin Wu, and Witold Pedrycz. Priority ranking for the best-worst method. *Information Sciences*, 635:42–55, 2023.

[3] Siamak Kheybari and Alessio Ishizaka. The behavioural best-worst method. *Expert Systems with Applications*, 209:118265, 2022.

[4] Salvatore Greco, Roman Słowiński, José Rui Figueira, and Vincent Mousseau. Robust ordinal regression. *Trends in multiple criteria decision analysis*, pages 241–283, 2010.

[5] Jafar Rezaei. Best-worst multi-criteria decision-making method. *Omega*, 53:49–57, 2015.

[6] Iman Ajripour and Thomas Hanne. Using the fuzzy best worst method for evaluating strategic planning models. *Processes*, 11(4):1284, 2023.

[7] Ayodeji Sulaiman Olawore, Kuan Yew Wong, Azanizawati Ma'aram, and Wahyudi Sutopo. Prioritization of technology commercialization success factors using fuzzy best worst method. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(3):100096, 2023.

[8] Milan Zeleny. Multiple criteria decision making: Eight concepts of optimality. *Human Systems Management*, 17(2):97–107, 1998.

[9] Rukiye Kaya and Barbaros Yet. Building bayesian networks based on dematel for multiple criteria decision problems: A supplier selection case study. *Expert Systems with Applications*, 134:234–248, 2019.

[10] Seyed Reza Nabavi, Zhiyuan Wang, and Gade Pandu Rangaiah. Sensitivity analysis of multi-criteria decision-making methods for engineering applications. *Industrial & Engineering Chemistry Research*, 62(17):6707–6722, 2023.

[11] Hegazy Rezk, Irik Z Mukhametzyanov, Mohammad Ali Abdelkareem, Tareq Salameh, Enas Taha Sayed, Hussein M Maghrabie, Ali Radwan, Tabbi Wilberforce, Khaled Elsaid, and AG Olabi. Multi-criteria decision making for different concentrated solar thermal power technologies. *Sustainable Energy Technologies and Assessments*, 52:102118, 2022.

[12] Aleksandra Król-Badziak, Seyyed Hassan Pishgar-Komleh, Stelios Rozakis, and Jerzy Księżak. Environmental and socio-economic performance of different tillage systems in maize grain production: Application of life cycle assessment and multi-criteria decision making. *Journal of cleaner production*, 278:123792, 2021.

[13] Sabah Khodabocus and Senem Seyis. Multi-criteria decision-making model for risk management in modular construction projects. *International Journal of Construction Management*, 24(2):240–250, 2024.

[14] Beyza Özlem YILMAZ, Hakan TOZAN, and Melis Almula KARADAYI. Multi-criteria decision making (mcdm) applications in military healthcare field. *Journal of Health Systems and Policies*, 2(2):149–181, 2020.

[15] Jiuying Dong, Shuping Wan, and Shyi-Ming Chen. Fuzzy best-worst method based on triangular fuzzy numbers for multi-criteria decision-making. *Information Sciences*, 547:1080–1104, 2021.

[16] Sen Guo and Haoran Zhao. Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge-based systems*, 121:23–31, 2017.

[17] Sen Guo and Haoran Zhao. Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge-based systems*, 121:23–31, 2017.

[18] Jiu-Ying Dong and Shu-Ping Wan. Interval-valued intuitionistic fuzzy best-worst method with additive consistency. *Expert Systems with Applications*, 236:121213, 2024.

[19] Junnan Wu, Xin Liu, Dianqi Pan, Yichen Zhang, Jiquan Zhang, and Kai Ke. Research on safety evaluation of municipal sewage treatment plant based on improved best-worst method and fuzzy comprehensive method. *Sustainability*, 15(11):8796, 2023.

[20] Mahender Singh Kaswan and Rajeev Rathi. Investigation of life cycle assessment barriers for sustainable development in manufacturing using grey relational analysis and best worst method. *International Journal of Sustainable Engineering*, 14(4):672–685, 2021.

[21] Ashis Mitra and Abhijit Majumdar. Determination of quality value of cotton fiber using integrated best-worst method-revised analytic hierarchy process. *Journal of Natural Fibers*, 20(2):2210324, 2023.

[22] Sunay P Pai and Rajesh S Prabhu Gaonkar. The safety assessment in dynamic conditions using interval neutrosophic sets. *Neutrosophic Sets and Systems*, 40(1):5, 2021.

[23] Surapati Pramanik. Interval pentapartitioned neutrosophic sets. *Neutrosophic Sets and Systems*, 55:232–246, 2023.

[24] Ruipu Tan, Wende Zhang, and Shengqun Chen. Exponential aggregation operator of interval neutrosophic numbers and its application in typhoon disaster evaluation. *Symmetry*, 10(6):196, 2018.

[25] Amanna Ghanbari Talouki, Abbas Koochari, and S Ahmad Edalatpanah. Image completion based on segmentation using neutrosophic sets. *Expert Systems with Applications*, 238:121769, 2024.

[26] Michael Gr Voskoglou. *An application of neutrosophic sets to decision making*. Infinite Study, 2023.

[27] Surender Singh and Sonam Sharma. An asymmetric measure of comparison of neutrosophic sets. *Neutrosophic Sets and Systems*, 55(1):15, 2023.