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Multi-Attribute Decision-Making Method Based on Prospect Theory in Heterogeneous Information Environment and Its Application in Typhoon Disaster Assessment

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ABSTRACT

Aiming at the decision-making problem in heterogeneous information environment and considering the influence of decision makers' psychological behavior on decision-making results, this paper proposes a multi-attribute decision-making method based on prospect theory in heterogeneous information environment. The heterogeneous information in this paper indicates that the decision attribute value is represented by various types of data forms, including exact number, interval number, linguistic term, intuitionistic fuzzy number, interval intuitionistic fuzzy number, neutrosophic numbers, and trapezoidal fuzzy neutrosophic numbers, and so on. Firstly, the distance and similarity measure of various heterogeneous data are introduced, and the heterogeneous information attribute weights are obtained using the deviation maximization method. Then, the psychological expectation value of each attribute given by the decision maker is used as a reference point, thereby calculating the gain and loss of each attribute value relative to the reference point, and establishing a gain matrix and a loss matrix. On this basis, the prospect theory is used to obtain the comprehensive prospect value of each alternative, so as to obtain the alternative ordering result and optimal alternative. Finally, an illustrative example about typhoon disaster assessment is presented to show the feasibility and effectiveness of the proposed method, and the advantages of the proposed method are illustrated by comparison with other methods.

1. INTRODUCTION

Multi-attribute decision-making is a problem in which a decision-maker evaluates a finite set of alternatives associated with multiple attributes [1]. It has been widely applied in many practical problems, such as supplier selection [2,3], pattern recognition [4], medical diagnosis [5,6], emergency decision [7,8], water allocation [9], disaster assessment [10–12], and so on. Therefore, the multi-attribute decision-making method has become the focus of scholars and has been extensively studied. However, the decision-making problem has become more and more complicated because of the increasing amount of decision information and alternatives, and the inherent uncertainty and complexity of decision problems, and the fuzzy nature of human thinking [12]. Especially in some sudden, complicated situations, some decision information is often not accurately represented, often expressed as fuzzy, vague, hesitant, incomplete, indeterminate, and inconsistent. So the fuzzy set (FS) [13], hesitant fuzzy set (HFS) [14], rough set [15], grey theory [16], intuitionistic fuzzy set (IFS) [17], and neutrosophic set (NS) [18] are used to model the decision information. Throughout the existing research literature, most of the multi-attribute decision-making methods are based on a single type of data, and there are few studies on multiple data types. However, in some complicated situations, the decision is faced with heterogeneous data. For example, in our typhoon disaster assessment study, the representation of the assessment information is diverse. The number of population death is usually accurately obtained, which is expressed as an exact number (EN). The number of population affected can usually obtain its approximate range, which can be expressed as an interval number. Again, the severity of economic loss tends to be expressed in linguistic terms (LTS). If the assessment of traffic flow after disaster can get the maximum possible range and possible fluctuation range, TrFNNs can be generally used.

Heterogeneity indicates that the type and nature of information or data is different [19]. In view of the high risk, complexity, and ambiguity of typhoon disasters, evaluation information cannot always be expressed as ENs, and often has the characteristics of interval, ambiguity, and hesitation, and is more appropriately expressed as interval numbers (IVNs), fuzzy numbers (FNs), and intuitionistic fuzzy numbers (IFNs). In addition, due to the ambiguity of human thinking, it is difficult to use the quantitative numerical representation of decision information in the decision-making process, and it is more inclined to use qualitative LTs to evaluate attributes. At the same time, typhoon disasters also have great uncertainty. Such

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evaluation information can be characterized as neutrosophic numbers (NNs), trapezoidal fuzzy neutrosophic numbers (TrFNNs), and so on. So, the processing heterogeneous information is a key point in the decision-making process [1,19–21]. Sun *et al.* [1] proposed a MADM with grey multi-source heterogeneous data including ENs, interval grey numbers, and extend grey numbers. Yu *et al.* [19] proposed a heterogeneous MADM considering four types of data: ENs, IVNs, triangular fuzzy numbers (TFNs), and IFNs. Pan *et al.* [20] proposed a hybrid MADM based on VIKOR with multi-granularity LNs, ENs, IVNs. Wan *et al.* [21] proposed a MADM for heterogeneous infromation including ENs, IVNs, TFNs, and trapezoidal fuzzy numbers (TrFNs). Lourenzutti *et al.* [22] proposed a generalized TOPSIS method for MADM with heterogeneous information including crisp numbers, IVNs, FNs, IFNs, and random vectors. Zhang *et al.* [23] proposed a risk-based MADM based on three heterogeneous data: ENs, IVNs, and TFNs. Fanet *et al.* [24] proposed a hybrid MADM based on cumulative prospect theory (PT) with heterogeneous data including ENs, IVNs, and LTs. Qi *et al.* [25] proposed a MADM based on heterogeneous data such as multi-granularity language numbers, IFNs, and interval intuitionistic fuzzy numbers (IVIFNs) into IVIFNs to calculate the comprehensive evaluation value of the alternative. However, looking at the existing research literature, we have not seen the study of heterogeneous data including the NN. On the other hand, in terms of practical applications, the assessment of post-typhoon disasters is a very complicated issue, and it is sometimes difficult for experts to make clear decisions. For example, we invited the expert group to assess the severity of social impact, 30% vote "Yes," 20% vote "No," 10% give up, and 40% are undecided. Such a vote is beyond the scope of IFS to distinguish the information between "giving up" and "undecided." Such a scenario indicates that the NN needs to be studied in depth. Therefore, we studies the MADMs in heterogeneous information environment including the ENs, IVNs, LTs, IFNs, IVIFNs, NNs, and TrFNNs, and so on.

NSs proposed by Smarandache [26] are a powerful tool to deal with incomplete, indeterminate, and inconsistent information in the real world. And it is the generalization of the theory of FSs [13], interval-valued fuzzy sets, and IFSs [17], and so on. NSs are characterized by a truth-membership degree (T), an indeterminacy-membership degree (I), and a falsity-membership degree (F), which can represent more information than other FSs. In recent years, scholars have proposed various forms of NNs. For example, Wang *et al.* [27] introduced the concept of single-valued neutrosophic sets (SVNSs). Ye [28] introduced the simplified neutrosophic sets (SNSs). SVNS is an extension of FN and IFN. Wang and Li [29] also defined multi-valued neutrosophic sets (MVNSs). Wang *et al.* [30] proposed interval neutrosophic sets (INSs). Yang and Pang [31] defined multi-valued interval neutrosophic sets (MVINSs). Deli *et al.* [32] proposed the concept of the bipolar NSs, and applied it to MADM. Deli *et al.* proposed neutrosophic refined sets [33] and bipolar neutrosophic refined sets [34] and applied them to medical diagnosis. Tian *et al.* [35] proposed the concept of the simplified neutrosophic linguistic and applied it to MADM. Broumi *et al.* [36–38] and Tan *et al.* [39] combined the NSs and graph theory to propose neutrosophic graphs, and used for the shortest path solving problem. Ye [40] proposed trapezoidal fuzzy NSs and applied them to MADM. There are many forms of NN, which are suitable for different decision-making environments. The heterogeneous data of typhoon disaster assessment we studied include single-valued neutrosophic numbers (SVNNs) and TrFNN.

Sorting method is a research hotspot in decision-making including method based on scoring function and exact function, similarity measure method, VIKOR method, TOPSIS method, grey theory, TODIM method, and so on, and most of the methods are based on the assumption that the decision maker is completely rational. But some studies about behavioral experiments have shown that the decision maker is bounded rational in decision processes and his behavior plays an important role in decision analysis [41]. In the face of emergencies, especially after the disaster, the psychological factors of decision makers play a key role in decision-making, and the research on this aspect is still rare. PT introduced by Kahneman *et al.* [42,43] provides a simple and clear computation process to describe the psychological behavior using reference points, losses, gains, and overall prospect values [44]. So it has been widely applied in the various fields to solve the practical problems considering human being's psychological behavior. Gao *et al.* [45] and Best *et al.* [46] applied PT to solve asset allocation. Attema *et al.* [47] studied the application of PT in the field of health domains. Tian *et al.* [48] studied the park-and-ride behavior in a cumulative PT-based model. Van Tol *et al.* [49] studied the application of cumulative PT in option valuation and portfolio management. Zou *et al.* [50] studied the optimal investment with transaction costs under cumulative PT. Liu *et al.* [51] and Zhang *et al.* [52] proposed emergency decision-making methods based on PT. Tao *et al.* [53] proposed the brain mechanism of economic management risk decision based on PT. Ning *et al.* [54] studied the disruption management strategy based on PT. Sullivan *et al.* [55] examined the forest certification problem based on PT. Yu *et al.* [56] studied the typhoon disaster emergency scheme generation and dynamic adjustment based on CBR and PT. However, given the existing research, there is still little literature on the application of PT in typhoon disaster assessment. Taking into account the uncertainty of typhoon disasters and the psychological feelings of decision makers, the PT can well consider the psychological factors of decision makers to the assessment of typhoon disasters, which can make disaster assessment more reasonable and effective. So, this paper studies typhoon disaster assessment based on PT.

Natural disasters often lead to death and enormous property damage. Various types of natural disasters occur in China every year. And the typhoon is one of the biggest disasters facing humanity. Its destructive power exceeds that of the earthquake, but it has never been avoided. Meteorological disasters such as typhoon accounted for more than 70% of the natural disasters [57]. In China, typhoons primarily impact the eastern coastal regions of the country, where the population is extremely dense, the economy is highly developed, and social wealth is notably concentrated. Once the typhoon comes, it will cause huge property and economic losses, casualties, and environmental damage to this area. Therefore, typhoon disaster assessment is a very important issue. However, the influencing factors of the typhoon disasters are completely hard to describe accurately. Taking economic loss, for example, it includes many aspects such as the building's collapse, the number and extent of damage to housing, and the affected local economic conditions [10], the degree of environmental damage, and the negative impact on society. The evaluation information is often hesitant, ambiguous, incomplete, inconsistent, indeterminate, and so on. Therefore, FSs, HFSs, and IFSs have been used for typhoon disaster assessment in recent years. For example, Shi *et al.* [57] proposed a fuzzy MADM hybrid approach to evaluate the damage level of typhoon based on FNs. He *et al.* [11] proposed a typhoon disaster assessment

method based on Dombi HFNs. Li *et al.* [58] and Yu [10] proposed evaluating typhoon disasters method based on IFNs. Throughout the existing literature, most of the typhoon disaster assessment studies are based on a single data form, and have not yet been conducted under heterogeneous data environment containing the NNs. We believe that NS will be a powerful theory and method to enhance typhoon disaster assessment. So we study the MADM based on PT in heterogeneous information environment and apply it to the typhoon disaster assessment. First we use the deviation maximization method based on heterogeneous information to get the evaluation index weights, then use the extended PT to calculate the overall prospect value of each alternative to sort the alternatives in a heterogeneous information environment.

This paper is organized as the following: Section 2 briefly presents some basic definitions of heterogeneous information. Section 3 gives the distance formula and similarity measure of various heterogeneous data, a MADM method based on the PT, and the compatibility and consistency measures for heterogeneous information. Section 4 uses a typhoon disaster evaluation example to illustrate the applicability of the proposed method and verifies the advantages of the proposed method by comparative analysis. Finally, Section 5 gives the conclusions.

2. PRELIMINARIES

In this section, we briefly introduce the basic concepts of various heterogeneous data used in this paper, including the NNs, IFNs, FNs, ENs, and so on. At the same time, PT will be briefly reviewed so that unfamiliar readers can understand our proposed method easily.

2.1. SVNN, Trapezoidal Fuzzy NN

Definition 1. [27] ***Let*** *X be a universal set. A SVNS A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. Then, a SVNS A can be denoted by*

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle | x \in X\}. \tag{1}$$

where $T_A(x), I_A(x), F_A(x) \in [0,1]$ for each x in X. Then, the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$ satisfies the condition $0 \leqslant T_A(x) + I_A(x) + F_A(x) \leqslant 3$. For convenience, we can use $n^s = \langle T, I, F\rangle$ to represent a SVNN.

Definition 2. [40] *Let X be a universe of discourse, then a trapezoidal fuzzy NS $\tilde{N}$ in X has the following form:*

$$\tilde{N} = \{\langle x, T_{\tilde{N}}(x), I_{\tilde{N}}(x), F_{\tilde{N}}(x)\rangle | x \in X\}, \tag{2}$$

where $T_{\tilde{N}}(x) \subset [0,1]$, $I_{\tilde{N}}(x) \subset [0,1]$ and $F_{\tilde{N}}(x) \subset [0,1]$ are three TrFNs, $T_{\tilde{N}}(x) = \left(t^1_{\tilde{N}}(x), t^2_{\tilde{N}}(x), t^3_{\tilde{N}}(x), t^4_{\tilde{N}}(x)\right) : X \to [0,1]$, $I_{\tilde{N}}(x) = \left(i^1_{\tilde{N}}(x), i^2_{\tilde{N}}(x), i^3_{\tilde{N}}(x), i^4_{\tilde{N}}(x)\right) : X \to [0,1]$, and $F_{\tilde{N}}(x) = \left(f^1_{\tilde{N}}(x), f^2_{\tilde{N}}(x), f^3_{\tilde{N}}(x), f^4_{\tilde{N}}(x)\right) : X \to [0,1]$ with the condition $0 \leqslant t^4_{\tilde{N}}(x) + i^4_{\tilde{N}}(x) + f^4_{\tilde{N}}(x) \leqslant 3, x \in X$.

For simplicity of calculation, a TrFNN $\tilde{n}$ can be expressed as $n^{Tr} = \langle (a_1, a_2, a_3, a_4), (b_1, b_2, b_3, b_4), (c_1, c_2, c_3, c_4)\rangle$, the parameters can satisfy the following relationship: $a_1 \leqslant a_2 \leqslant a_3 \leqslant a_4$, $b_1 \leqslant b_2 \leqslant b_3 \leqslant b_4$, and $c_1 \leqslant c_2 \leqslant c_3 \leqslant c_4$. When $a_2 = a_3$, $b_2 = b_3$, $c_2 = c_3$, the TrFNN becomes triangle fuzzy neutrosophic number (TFN), and TFN number is a special case of TrFNN.

2.2. IFNs, IVIFNs, and Interval Numbers

Definition 3. [17] *Let a set X be fixed. An IFS A in X is an object having the form:*

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\}. \tag{3}$$

where the functions $\mu_A : X \to [0,1]$ and $\nu_A : X \to [0,1]$ define the degree of membership and the degree of nonmembership of the element $x \in X$ to A, respectively, and for every $x \in X : 0 \leqslant \mu_A(x) + \nu_A(x) \leqslant 1$. For each IFS A in X, if $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$, for all $x \in X$, then $\pi_A(x)$ is called the degree of indeterminacy of x to A. For convenience, we can use $\alpha^I = \langle \mu, \nu\rangle$ to represent an IFN.

Definition 4. [59] *An interval-valued intuitionistic fuzzy set (IVIFS) $\tilde{A}$ in the set X is an object having the following form:*

$$\begin{aligned}\tilde{A} &= \{\langle x, \tilde{\mu}_{\tilde{A}} \tilde{\nu}_{\tilde{A}}\rangle | x \in X\} \\ &= \{\langle x, \left[inf\tilde{\mu}_{\tilde{A}}(x), sup\tilde{\mu}_{\tilde{A}}(x)\right], \rangle \\ &\quad \langle \left[inf\tilde{\nu}_{\tilde{A}}(x), sup\tilde{\nu}_{\tilde{A}}(x)\right], | x \in X\rangle\}.\end{aligned} \tag{4}$$

where $\tilde{\mu}_{\tilde{A}}(x) \subset [0,1]$ and $\tilde{\nu}_{\tilde{A}}(x) \subset [0,1]$ are called the degree of membership and the degree of nonmembership of the element $x \in X$ to $\tilde{A}$, respectively, and with the condition: $sup\tilde{\mu}_{\tilde{A}}(x) + sup\tilde{\nu}_{\tilde{A}}(x) \leqslant 1$. And $\tilde{\pi}_{\tilde{A}}(x) = \left[inf\pi_{\tilde{A}}(x), sup\pi_{\tilde{A}}(x)\right]$ is called the degree of indeterminacy of x to $\tilde{A}$, and $inf\pi_{\tilde{A}}(x) = 1 - sup\mu_{\tilde{A}}(x) - sup\nu_{\tilde{A}}(x)$, $sup\pi^u_{\tilde{A}}(x) = 1 - inf\mu_{\tilde{A}}(x) - inf\nu_{\tilde{A}}(x)$.

For convenience, we can use $\alpha^{Iv} = \langle [\mu^l, \mu^u], [\nu^l, \nu^u]\rangle$ to represent an interval-valued intuitionistic fuzzy number (IvIFN). If $\nu^l = \nu^u = 0$, then the IVIFN becomes a general interval number (IN): $IN = [\mu^l, \mu^u]$.

2.3. Language Term

Definition 5. [60,61]: *Let $S = \left\{s_\theta | \theta = -\frac{\tau-1}{2}, \cdots, -1, 0, 1, \cdots \frac{\tau-1}{2}\right\}$ be a finite and totally ordered discrete term set, where τ is odd value and s_θ represents a possible value for a linguistic variable. For example, when $l = 9$, a set S could be given as follows:*

$$\begin{aligned}S &= \{s_{-4}, s_{-3}, s_{-2}, s_{-1}, s_0, s_1, s_2, s_3, s_4\} \\ &= \{extremely\ poor,\ very\ poor,\ poor,\ slightly \\ &\quad poor,\ fair,\ slightly\ good,\ good,\ very\ good, \\ &\quad extremely\ good\}.\end{aligned}$$

In these cases, it is usually required that there exist the following:

1. A negation operator: $Neg(s_i) = s_{-i}$.
2. The set is ordered: $s_i \leqslant s_j$ if and only if $i \leqslant j$.
3. Maximum operator: $\max(s_i, s_j) = s_i$, if $i \geqslant j$.
4. Minimum operator: $\min(s_i, s_j) = s_i$, if $i \leqslant j$.

In order to preserve all the given information, extending the discrete term set S to a continuous term set $\overline{S} = \{s_\theta | \theta \in [0, q]\}$, where, if $s_\theta \in S$, then we call s_θ the original term, otherwise, we call s_θ the virtual term. In general, the decision maker uses the original LNs to evaluate alternatives, and the virtual LNs can only appear in the actual calculation.

The so-called different granularity language information refers to the preference information given by the decision makers in the group decision-making according to the language evaluation set represented by the granularity of the number of different language phrases. Let $S^q = \left\{s_\theta^q | \theta = -\frac{q-1}{2}, \cdots, -1, 0, 1, \cdots \frac{q-1}{2}\right\}$ be an arbitrary language evaluation set, and its granularity is q. If the value of q is different in the same decision process, it becomes a multi-granular language decision.

2.4. Prospect Theory

PT is a theory that describes and predicts behaviors that are inconsistent with traditional expectations theory and expected utility theory in the face of risk decision-making. The theory finds that people's risk preference behaviors are inconsistent in the face of gains and losses, and they become risk-seeking in the face of "missing," but they are risk-averse in the face of "getting." The establishment and change of reference points affect people's feelings of gain and loss, and thus influence people's decision-making.

In MADM problems, the attributes can be classified into two types: benefits and costs. The higher a benefit attribute is, the better the situation is, while the higher a cost attribute is, the worse the situation is. According to different types of attributes, reference points changes with people's expectations with respect to the predefined amounts to gain or lose [62]. For example, if there is a possibility to lose some money and predefined amounts are USD 5, 10 and 20, then assuming that 10 is an acceptable loss amount to an individual (reference point of possible losses), if the final outcome is 5, he/she feels gains because the final losses are lower than his/her expectation. Benefit attributes can be assessed in a similar way [52].

Gains and losses are determined by the reference point and the final outcome with respect to different types of attributes. For measuring the magnitude of gains and losses, an S-shaped value function is provided in PT [42]. The value function is expressed in the form of a power law [42]:

$$v(x) = \begin{cases} x^\alpha, & x \geqslant 0; \\ -\lambda(-x)^\beta, & x < 0, \end{cases} \tag{5}$$

where x denotes the gains when $x \geqslant 0$, and x denotes the losses when $x < 0$, respectively; α and β are power parameters related to gains and losses, respectively; and $0 \leqslant \alpha \leqslant 1$, $0 \leqslant \beta \leqslant 1$; λ is the risk aversion parameter, which has a characteristic of being steeper for losses than for gains, and $\lambda > 1$. Here, the values of α, β, and λ are determined through experiments [43,63,64]. For example, Abdellaoui *et al.* [63] suggest $\alpha = 0.725$, $\beta = 0.717$, and $\lambda = 2.04$, Liu *et al.* [64] suggest $\alpha = 0.850$, $\beta = 0.850$, and $\lambda = 4.1$, and Tversky *et al.* [43] suggest $\alpha = 0.89$, $\beta = 0.92$, $\lambda = 2.25$.

3. DECISION-MAKING METHOD BASED ON HETEROGENEOUS INFORMATION AND PT

3.1. Distance Measure of Heterogeneous Information

The basic idea of PT is to first use the expectation of the decision maker as a reference point, and establish the risk return matrix and the risk loss matrix, respectively, by calculating the gain and loss of the program attribute value relative to the reference point, and then to establish the prospect decision matrix. On this basis, the alternatives are ranked by calculating the comprehensive prospect values of each alternative. In the disaster assessment, after the typhoon disaster occurs, the decision makers will form a certain psychological expectation according to the report of the relevant personnel and their own situation, also known as the psychological reference point. At the same time, the degree of disaster of each assessment object is compared with the psychological reference point of the decision maker to judge the extent to which the decision maker's psychological perception is "gain" or "loss." Among them, the calculation of the gain and loss mainly involves the distance calculation of various heterogeneous information.

Let x_{ij} represents the expert's evaluation of the alternative i under the attribute j, r_j represents the reference point of attribute j, and $D_{ij}\left(x_{ij}, r_j\right)$ denote the distance between the attribute value and the reference point. The attribute values of different attributes are not the same type of data, but heterogeneous information, including ENs, IVNs, LTs, IFNs, IVIFNs, NNs, and TrFNNs, and so on, and their distance calculation formulas are as follows:

1. When the attribute value is an EN, its distance $D_{ij}\left(x_{ij}, r_j\right)$ from the reference point is calculated as follows [65]:

$$D_{ij}\left(x_{ij}, r_j\right) = 1 - Sim_{ij}\left(x_{ij}, r_j\right) \tag{6}$$
$$\text{Where } Sim_{ij}\left(x_{ij}, r_j\right) = \exp\left[\frac{-|x_{ij} - r_j|}{d_j^{\max} - d_j^{\min}}\right],$$
$$i \in m,\ j \in n,\ \text{and } d_j^{\max} = \left\{r_j, \max\left\{x_{ij} | j \in n\right\}\right\},$$
$$d_j^{\min} = \left\{r_j, \min\left\{x_{ij} | j \in n\right\}\right\}, i \in m.$$

2. When the attribute value is an IVN, that is $x_{ij} = \left[x_{ij}^l, x_{ij}^u\right]$, $r_j = \left[r_j^l, r_j^u\right]$, then its distance $D_{ij}\left(x_{ij}, r_j\right)$ from the reference point is calculated as follows:

$$D_{ij}\left(x_{ij}, r_j\right) = 1 - Sim_{ij}\left(x_{ij}, r_j\right) \tag{7}$$
$$\text{where } Sim_{ij}\left(x_{ij}, r_j\right)$$
$$= \exp\left[-\frac{\sqrt{\left(x_{ij}^l - r_j^l\right)^2 + \left(x_{ij}^u - r_j^u\right)^2}}{\max_i\left\{\sqrt{\left(x_{ij}^l - r_j^l\right)^2 + \left(x_{ij}^u - r_j^u\right)^2}\right\}}\right],$$
$$i \in m, j \in n.$$

3. When the attribute value is an IFN, that is, $x_{ij} = \langle \mu_{ij}, \nu_{ij} \rangle$, $r_j = \langle \mu_j, \nu_j \rangle$, the distance formula based on cosine similarity [66] is as follows:

$$\begin{aligned} D_{ij}\left(x_{ij}, r_j\right) &= 1 - Sim_{ij}\left(x_{ij}, r_j\right), \\ Sim_{ij}\left(x_{ij}, r_j\right) &= \frac{\mu_i\mu_{ij} + \nu_i\nu_{ij}}{\sqrt{\mu_i^2 + \nu_i^2}\sqrt{\mu_{ij}^2 + \nu_{ij}^2}}, \\ & i \in m, j \in n. \end{aligned} \tag{8}$$

4. When the attribute value is a language term, that is, $x_{ij} = s_\theta^{ij}$, $r_j = s_\theta^j$, and $s_\theta^{ij}, s_\theta^i \in s^q = \left\{s_\theta^q | \theta = -\frac{q-1}{2}, \cdots, -1, 0, 1, \cdots \frac{q-1}{2}\right\}$, it will first be converted into IVIFN [25], then use the distance formula of IVIFNs. When the value of q is different, it means evaluation information is expressed as multi-granularity linguistic. However, our paper only considers one granularity, because different granularity linguistic can be converted to IVIFN by a formula [25], the conversion formula is as follows:

$$\begin{aligned} \mu^q &= \left(\mu^q_{-\frac{q-1}{2}}, \mu^q_{-\frac{q-1}{2}+1}, \cdots, \mu^q_0, \cdots, \mu^q_{\frac{q-1}{2}-1}, \mu^q_{\frac{q-1}{2}}\right) \\ &= \left(\left(\mu_0^q\right)^{\frac{q+1}{2}}, \left(\mu_0^q\right)^{\frac{q+1}{2}-1}, \cdots, \mu_0^q, \cdots, \right. \\ &\quad \left. \left(\mu_0^q\right)^{1/\left(\frac{q+1}{2}-1\right)}, \left(\mu_0^q\right)^{1/\frac{q+1}{2}}\right), \end{aligned}$$

$$\begin{aligned} \nu^q &= \left(\nu^q_{-\frac{q-1}{2}}, \nu^q_{-\frac{q-1}{2}+1}, \cdots, \nu^q_0, \cdots, \nu^q_{\frac{q-1}{2}-1}, \nu^q_{\frac{q-1}{2}}\right) \\ &= \left(1 - \left(1 - \nu_0^q\right)^{\frac{q+1}{2}}, 1 - \left(1 - \nu_0^q\right)^{\frac{q+1}{2}-1}, \cdots, \nu_0^q, \right. \\ &\quad \left. \cdots, 1 - \left(1 - \nu_0^q\right)^{1/\left(\frac{q+1}{2}-1\right)}, 1 - \left(1 - \nu_0^q\right)^{1/\frac{q+1}{2}}\right), \end{aligned}$$

where,

$$\begin{aligned} \mu_0^q = \nu_0^q &= \left[0.5 - \frac{1}{2q}, 0.5\right], \\ \left(\mu_0^q\right)^{\frac{q+1}{2}} &= \left[\left(0.5 - \frac{1}{2q}\right)^{\frac{q+1}{2}}, 0.5^{\frac{q+1}{2}}\right], \\ \left(\mu_0^q\right)^{1/\frac{q+1}{2}} &= \left[\left(0.5 - \frac{1}{2q}\right)^{1/\frac{q+1}{2}}, 0.5^{1/\frac{q+1}{2}}\right], \\ 1 - \left(1 - \nu_0^q\right)^{\frac{q+1}{2}} &= \left[1 - \left(0.5 + \frac{1}{2q}\right)^{\frac{q+1}{2}}, 1 - 0.5^{\frac{q+1}{2}}\right], \\ 1 - \left(1 - \nu_0^q\right)^{1/\frac{q+1}{2}} &= \left[1 - \left(0.5 + \frac{1}{2q}\right)^{1/\frac{q+1}{2}}, \right. \\ &\quad \left. 1 - 0.5^{1/\frac{q+1}{2}}\right]. \end{aligned}$$

5. When the attribute value is an IVIFN, that is, $x_{ij} = \langle [\mu_{ij}^l, \mu_{ij}^u], [\nu_{ij}^l, \nu_{ij}^u] \rangle$, $r_j = \langle [\mu_j^l, \mu_j^u], [\nu_j^l, \nu_j^u] \rangle$, then its distance $D_{ij}\left(x_{ij}, r_j\right)$ from the reference point is calculated as follows:

$$\begin{aligned} & d\left(z_{ij} - t_i\right) \\ &= \sqrt{\begin{aligned} & 1/6\left[\left(\mu_i^l - \mu_{ij}^l\right)^2 + \left(\mu_i^u - \mu_{ij}^u\right)^2 + \left(\nu_i^l - \nu_{ij}^l\right)^2 \right. \\ & \left. + \left(\nu_i^u - \nu_{ij}^u\right)^2 + \left(\pi_i^l - \pi_{ij}^l\right)^2 + \left(\pi_i^u - \pi_{ij}^u\right)^2\right]. \end{aligned}} \end{aligned} \tag{9}$$

6. When the attribute value is a NN, that is, $x_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle$, $r_j = \langle T_j, I_j, F_j \rangle$, we use the distance measure formula proposed by Ye [67] as follows:

$$\begin{aligned} & D_{ij}\left(x_{ij}, r_j\right) \\ &= \sqrt{1/3\left(|T_{ij} - T_i|^2 + |I_{ij} - I_i|^2 + |F_{ij} - F_i|^2\right)}. \end{aligned} \tag{10}$$

7. When the attribute value is a TrFNN, that is, $x_{ij} = \langle (a_1^{ij}, a_2^{ij}, a_3^{ij}, a_4^{ij}), (b_1^{ij}, b_2^{ij}, b_3^{ij}, b_4^{ij}), (c_1^{ij}, c_2^{ij}, c_3^{ij}, c_4^{ij}) \rangle$, $t_j = \langle (a_1^j, a_2^j, a_3^j, a_4^j), (b_1^j, b_2^j, b_3^j, b_4^j), (c_1^j, c_2^j, c_3^j, c_4^j) \rangle$, we use the distance formula based on the cosine similarity measure [36] proposed by Tan *et al.* [68] as follows:

$$\begin{aligned} & D\left(x_{ij}, r_j\right) = 1 - S_{TrFNN}\left(x_{ij}, r_j\right) \\ &= \frac{k - \sum_{h=1}^4 a_h^{ij} a_h^i + \sum_{h=1}^4 b_h^{ij} b_h^i + \sum_{h=1}^4 c_h^{ij} c_h^i}{k}. \\ &= \left(k = \left(\sqrt{\sum_{h=1}^4 \left(a_h^{ij}\right)^2 + \sum_{h=1}^4 \left(b_h^{ij}\right)^2 + \sum_{h=1}^4 \left(c_h^{ij}\right)^2}\right) \right. \\ &\quad \left. \times \left(\sqrt{\sum_{h=1}^4 \left(a_h^i\right)^2 + \sum_{h=1}^4 \left(b_h^i\right)^2 + \sum_{h=1}^4 \left(c_h^i\right)^2}\right)\right) \\ &\quad i \in N, j \in M, h = 1, 2, 3, 4. \end{aligned} \tag{11}$$

3.2. Determination of Attribute Weights in Heterogeneous Information Environment

For the objective of decision-making, this paper uses the method of maximizing deviations to calculate the attribute weights. Due to the complexity of objective things and the ambiguity of human thinking, it is often difficult to give explicit attribute weights. Sometimes there is an extreme situation where the weight is completely unknown. In the multi-attribute decision-making (MADM) of the finite alternatives, the smaller the difference of the alternative under the attribute c_j, the smaller the effect of the attribute on the decision of the alternative, otherwise it plays an important role in the ranking and selection of the alternatives. Therefore, the deviation of the attribute value of the alternative is larger. The greater the attribute weight should be given. So, the study of determining attribute weight by maximizing deviation draws the attention of scholars [69,70]. In addition, Xu and Da [71] and Xu [72] put forward some similar methods, namely maximizing standard deviation method and maximizing mean deviation method, to determine attribute weights for different data forms. Based on the idea of maximizing deviations in literature [69], this paper determines the

attribute weights in the heterogeneous information environment. The specific formula is as follows:

The weight vector ω can be obtained by solving the following optimization models:

$$\begin{cases} \max\ d(\omega) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \omega_j D\left(x_{ij} - x_{kj}\right) \\ s.t.\ \sum_{j=1}^{n} \omega_j^2 = 1,\ \ \omega_j^2 \geqslant 0,\ \ i = 1, 2, \cdots, m, \\ j = 1, 2, \cdots, n, j \neq k, \end{cases} \tag{12}$$

where $D\left(x_{ij} - x_{kj}\right)$ represents the attribute value difference of any two alternatives under the same attribute, and the distance calculation of the heterogeneous attribute information uses the distance measure of Section 3.1. Then, solve and normalize the above optimization models to get the attribute weights as follows:

$$\omega_j = \frac{\sum_{i=1}^{m}\sum_{k=1}^{m} D\left(x_{ij} - x_{kj}\right)}{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} D\left(x_{ij} - x_{kj}\right)},\ \ j = 1, 2, \cdots, n. \tag{13}$$

3.3. MADM Method Based on Heterogeneous Information and PT

3.3.1. Problem description and method steps

This section introduces a novel MADM method based on heterogeneous information and PT that considers decision makers' psychological behavior and deals with different types of assessment information. To achieve our objectives, the proposed method consists of the following several phases, depicted graphically in Figure 1.

Consider a MADM problem, let $X = \{x_1, x_2, \cdots, x_m\}$ be a discrete set of m alternatives, and $C = \{c_1, c_2, \cdots, c_n\}$ be the set of n attributes. ω_j is the weight of the attribute $c_j\left(j = 1, 2, \cdots, n\right)$, where $\omega_j \in [0, 1]\left(j = 1, 2, \cdots, n\right)$, and $\sum_{j=1}^{n} \omega_j = 1$. Suppose that $R = \left(x_{ij}\right)_{m\times n}$ is the decision matrix, where x_{ij} represents a different form of data. Due to the high risk, complexity, and uncertainty of typhoon disasters, decision makers have vagueness, uncertainty, and heterogeneity in the description of each attribute. In this paper, attribute information is represented by heterogeneous information such as ENs, IVNs, LTs, IFNs, IVIFNs, NNs, and TrFNNs, and the same attribute value is the same information form. For convenience, the attribute set is denoted as $C = C_1^{EN} \cup C_2^{IVN} \cup C_3^{IFN} \cup C_4^{LT} \cup C_5^{IVIFN} \cup C_6^{TrFNN} \cup C_7^{NN}$, and $C_i \cap C_j = \varnothing$, $\left(i, j = 1, 2, \cdots, 7; i \neq j\right)$. Where C_1^{EN} denotes that the attribute value is expressed as a set of ENs, C_2^{IVN} denotes that the attribute value is expressed as a set of interval numbers, and C_3^{IFN} denotes that the attribute value is expressed as a set

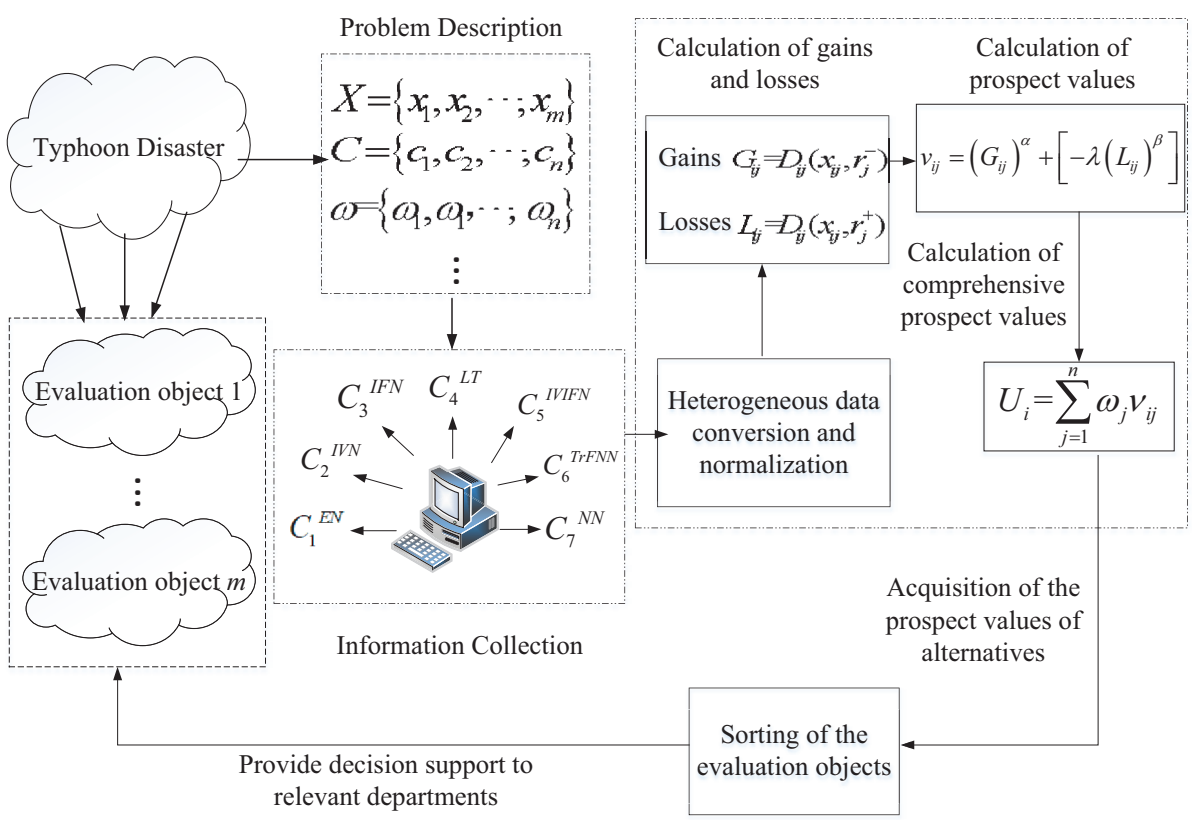


Figure 1 Framework of the proposed multi-attribute decision making (MADM) based on heterogeneous information and prospect theory.

of IFNs, C_4^{LT} denotes that the attribute value is expressed as a set of LNs, C_5^{IVIFN} denotes that the attribute value is expressed as a set of IVIFNs, C_6^{TrFNN} denotes that the attribute value is expressed as a set of TrFNNs, and C_7^{NN} denotes that the attribute value is expressed as a set of the NNs. The decision-making method steps based on PT in a heterogeneous information environment are as follows:

Step 1: Collect heterogeneous data and get the evaluation matrix $R = (x_{ij})_{m\times n}$, then convert LNs into data information to quantify calculations.

Step 2: Get the normalized evaluation matrix $R' = \left(x'_{ij}\right)_{m\times n}$. To eliminate the differences between dimensions, the attributes are normalized to ensure their consistency. In this paper, we only need to normalize the ENs and interval numbers, the formula is as follows:

$$x'_{ij} = \begin{cases} \left[x_{ij}^l / x_{\max j}^u, x_{ij}^u / x_{\max j}^u\right] & if c_i \in C_2^{IVN} \\ x_{ij}/x_{\max j} & if c_i \in C_1^{EN}, \end{cases} \tag{14}$$

where $x_{\max j} = \max\left\{x_{ij}^u | i = 1, 2, \cdots, n\right\}$ and $x_{\max j} = \max\{x_{ij} | i = 1, 2, \cdots, n\}$.

Step 3: Determine the reference point. Reference point represents the psychological expectations of decision makers for certain evaluation attributes after typhoon disasters. In order to eliminate the subjective influence of the decision maker as much as possible, this paper uses the positive and negative points of each attribute as the reference point. Positive and negative ideal solutions represent the decision makers' maximum and minimum prediction of the disaster extent of the assessed objects. So, for $c_j \in C_1^{EN}$, $r_j^{EN+} = \max\left(x_{ij}^{EN}\right)$, and $r_j^{EN-} = \min\left(x_{ij}^{EN}\right), i = 1, 2, \cdots, m$. For $c_j \in C_2^{IVN}$, $r_j^{IVN+} = \left[\max x_{ij}^{IVN(l)}, \max x_{ij}^{IVN(u)}\right]$, and $r_j^{IVN-} = \left[\min x_{ij}^{IVN(l)}, \min x_{ij}^{IVN(u)}\right], i = 1, 2, \cdots, m$. For $c_j \in C_3^{IFN}$, $r_j^{IFN+} = \left\langle \max \mu_{ij}^{IFN}, \min \nu_{ij}^{IFN}\right\rangle$, and $r_j^{IFN-} = \left\langle \min \mu_{ij}^{IFN}, \max \nu_{ij}^{IFN}\right\rangle, i = 1, 2, \cdots, m$. For $c_j \in C_4^{LT}$, because it is converted to an IVIFN to participate in the calculation, so $c_j \in C_5^{IVIFN}$, $r_j^{IVIFN+} = \left\langle\left[\max \mu_j^{IVIFN(l)}, \max \mu_j^{IVIFN(u)}\right], \left[\min \nu_{ij}^{IVIFN(l)}, \min \nu_{ij}^{IVIFN(u)}\right]\right.$, and $r_j^{IVIFN-} = \left\langle\left[\min \mu_j^{IVIFN(l)}, \min \mu_j^{IVIFN(u)}\right], \left[\max \nu_{ij}^{IVIFN(l)}, \max \nu_{ij}^{IVIFN(u)}\right]\right., i = 1, 2, \cdots, m$. For $c_j \in C_6^{TrFNN}$, $r_j^{TrFNN+} = \left\langle\left(\max a_1^{ij}, \max a_2^{ij}, \max a_3^{ij}, \max a_4^{ij}\right), \left(\min b_1^{ij}, \min b_2^{ij}, \min b_3^{ij}, \min b_4^{ij}\right), (\min c_1^{ij}, \min c_2^{ij}, \min c_3^{ij}, \min c_4^{ij}),\right.$ and $r_j^{TrFNN-} = \left\langle(\min a_1^{ij}, \min a_2^{ij}, \min a_3^{ij}, \min a_4^{ij}), \left(\max b_1^{ij}, \max b_2^{ij}, \max b_3^{ij}, \max b_4^{ij}\right), \left(\max c_1^{ij}, \max c_2^{ij}, \max c_3^{ij}, \max c_4^{ij}\right)\right., i = 1, 2, \cdots, m$. For C_7^{NN}, $r_j^{NN+} = \left\langle \max T_{ij}^{NN}, \min I_{ij}^{NN}, \min F_{ij}^{NN}\right\rangle$, and $r_j^{NN-} = \left\langle \min T_{ij}^{NN}, \max I_{ij}^{NN}, \max F_{ij}^{NN}\right\rangle, i = 1, 2, \cdots, m$.

Step 4: Calculate the gains and losses. Based on the gain value and the loss value, a gain matrix GM and a loss matrix LM are established. Where $GM = [G_{ij}]_{m\times n}$, $G_{ij} = D_{ij}\left(x_{ij}, r_j^-\right)$, and $LM = [L_{ij}]_{m\times n}, L_{ij} = D_{ij}(x_{ij}, r_j^+)$. The distance between each attribute value and the positive and negative ideal points represents the area of gain and loss in the value function. The positive ideal distance $D_{ij}\left(x_{ij}, r_j^+\right)$ represents the distance of the attribute value x_{ij} from the positive ideal reference point r_j^+, representing the loss area. And the less the value, the more serious the assessment object is affected. The ideal distance $D_{ij}\left(x_{ij}, r_j^-\right)$ represents the distance of the attribute value x_{ij} from the negative ideal reference point r_j^-, which represents the income area. And the larger the value, the larger the assessment object is affected.

Step 5: Calculation of prospect values. According to PT, the magnitude of gains and losses is measured by value function. Let $V = \left(v_{ij}\right)_{m\times n}$ be the prospect value matrix, it can be obtained by using Equation (15) based on GM and LM, that is,

$$\begin{aligned} v_{ij} &= \left(G_{ij}\right)^\alpha + \left[-\lambda\left(L_{ij}\right)^\beta\right], \quad i = 1, 2, \cdots, m; \\ j &= 1, 2, \cdots, n. \end{aligned} \tag{15}$$

The prospect values indicate the earned value of each evaluation object for each evaluation attribute based on the decision-maker's psychological reference point. In the assessment of the typhoon disaster, they indicate the severity of the evaluation objects in a certain aspect.

Step 6: Calculate the weights and calculate the attribute weights of the heterogeneous information using Equation (13).

Step 7: The comprehensive prospect value U_i of each alternative is calculated, and all alternatives are ranked according to the magnitude of the U_i value. The larger the U_i value, the higher the order of the alternative, where $U_i = \sum_{j=1}^n \omega_j v_{ij}$.

3.3.2. The compatibility and consistency of heterogeneous information

Measuring the level of consistency of different opinions of experts in group decision-making is a key issue. The consistency problem mainly includes two types: the consistency of the judgment matrix given by each expert and the consistency of the preference relationship between experts. Related to our research is the latter, which is the compatibility and consistency of information in group decision-making. When a group of decision-makers' preference relationships are similar, there is consistency among decision makers. In the absence of basic compatibility, unsatisfactory or incorrect results may result in group decision problems, and the evaluation information needs to be adjusted. The research on the compatibility and consistency of information including uncertain information has yielded rich results [73–75], but there are not many related researches on heterogeneous information, especially including NNs. We have been inspired by the literature [73] to propose the judgment method and adjustment strategy of compatibility and consistency for heterogeneous information are as follows:

Step 1: We first convert the multiple evaluation matrices $R^k = \left(x_{ij}^k\right)_{m\times n}$ $(k = 1, 2, \cdots, e)$ given by the e experts into unified representation, that is, the heterogeneous data evaluation matrix is uniformly converted into TrFNNs matrices $\overline{R}'^k = \left(\overline{x}_{ij}'^k\right)_{m\times n}$ $(k = 1, 2, \cdots, e)$ based on the relationship between heterogeneous data and the conversion method proposed in [21].

Step 2: We use the TNNWAA operator to assemble the group evaluation matrices into a comprehensive evaluation matrix $\overline{\overline{R}} = \left(\overline{\overline{x}}_{ij}\right)_{m\times n}$.

Step 3: We calculate the compatibility index $SI(\overline{R}'^{k}, \overline{\overline{R}})(k = 1, 2, \cdots, e)$ for each evaluation matrix $\overline{R}'^{k}$ and comprehensive evaluation matrix $\overline{\overline{R}}$. Here $SI\left(\overline{R}'^{k}, \overline{\overline{R}}\right) = \frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n} c\left(\overline{x}_{ij}'^{k}, \overline{\overline{x}}_{ij}\right)$ and $c\left(\overline{x}_{ij}', \overline{\overline{x}}_{ij}\right)$ is the compatibility measure of two TrFNNs, and $c\left(\overline{x}_{ij}', \overline{\overline{x}}_{ij}\right) = D\left(\overline{x}_{ij}', \overline{\overline{x}}_{ij}\right)$.

Step 4: We predetermine the critical value $\overline{SI}$, if $SI^{k} < \overline{SI}$, then a satisfactory consistency is obtained, otherwise the corresponding evaluation matrix is adjusted.

Step 5: If there is an expert evaluation matrix R^{k_0} that satisfies $SI^{k_0} > \overline{SI}$, then the compatibility $c\left(\overline{x}_{ij}'^{k_0}, \overline{\overline{x}}_{ij}\right)$ of each pair of elements $\overline{x}_{ij}'^{k_0}$ in R^{k_0} and $\overline{\overline{x}}_{ij}$ in $\overline{\overline{R}}$ needs to be calculated separately. If $c\left(\overline{x}_{ij}'^{k_0}, \overline{\overline{x}}_{ij}\right)$ does not meet the critical value $\overline{SI}$, the elements $\overline{x}_{ij}'^{k_0}$ are adjusted accordingly, and the adjustment strategy is to replace $\overline{x}_{ij}'^{k_0}$ with $\overline{\overline{x}}_{ij}$ in the corresponding comprehensive evaluation matrix, or to reevaluate the k_0 expert matrix.

In particular, we only give compatibility and consistency judgment methods and adjustment strategies for heterogeneous information, and our case study section does not make specific calculations.

4. CASE STUDY AND COMPARISON WITH OTHER APPROACHES

4.1. Case Study

With the rapid development of China's economy and the growing development of coastal cities, the losses caused by typhoon disasters have become increasingly serious. Take Fujian Province as an example. It is located in the southeast coastal area of China. It is close to the typhoon source and is on the path of typhoon movement. Typhoon is often landed. When the typhoon landed, it brought disasters such as storms and storm surges. Therefore, this paper evaluates the typhoon disasters in Fujian Province. Taking a strong typhoon "Maria" in Fujian Province in July 2018 as an example, "Maria" landed on the coast of Lianjiang River at 9:10 on November 11. When landing, the maximum wind force near the center was 14 levels (42/sec, strong typhoon level), and the lowest central pressure was 960 hPa. It was the strongest typhoon landing in Fujian since July with meteorological records. It was strong, fast moving, and destructive. After the disaster, we quickly obtains heterogeneous data from multiple sources for disaster assessment, which provides decision support for disaster relief in relevant departments. This paper synthesizes the literature [56] and [10] to construct an assessment indicator system. The assessment indicators $C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7\}$ include population death (c_1), population affected (c_2), agricultural damage (c_3), economic loss (c_4), environmental impact (c_5), social impact (c_6), and other impact (c_7). Several experts and crawler software are responsible for this assessment, and the evaluation information is expressed by heterogeneous information. Here, the population death can be accurately obtained through the lower-level government departments, which can be expressed by the ENs, that is, $c_1 \in C_1^{EN}$; and population affected can estimate the upper and lower limits, which can be expressed by the IVNs, that is, $c_2 \in C_2^{IVN}$; and agricultural damage has fuzziness and hesitation, which can be expressed by IFNs, that is, $c_3 \in C_4^{IFN}$; and for economic loss, the evaluation expert tends to use qualitative language information to evaluate its severity, which can be expressed in LTs, that is, $c_4 \in C_3^{LT}$; and environmental impact has ambiguity and interval, which can be expressed by the number of IVIFNs, that is, $c_5 \in C_5^{IVIFN}$; and social impact can be assessed by experts in the range of maximum possible values and possible fluctuations, which can be expressed by TrFNNs, that is, $c_6 \in C_6^{TrFNN}$; and other impact factors are wide and unclear, and there is great uncertainty in expert evaluation. Some experts may vote for support and vote against it at the same time, the sum of the ratios is greater than 1, exceeding IFSs represent ranges, which can be expressed as NNs, that is, $c_7 \in C_7^{NN}$. So the assessment matrix $R = \left(x_{ij}\right)_{m\times n}$ are given in the form of heterogeneous information including ENs, IVNs, LTs, IFNs, IVIFNs, NNs, and TrFNNs (see Table 1). Here LN sets are expressed as

$S = \{s_{-3}, s_{-2}, s_{-1}, s_0, s_1, s_2, s_3\}$ = {Absolutely low, Low, Fairly low, Medium, Fairly high, High, Absolutely high}. So the evaluation data is shown in Table 1:

Step 1: For the convenience of calculation, the language term is converted into IVIFN according to the literature [25], and the transformed data is shown in Table 2.

Step 2: We use Equation (14) to get the normalized evaluation matrix R' as shown in Table 3.

Step 3: Determine the reference point. For c_1, $r_1^{EN+} = 1.000$ and $r_1^{EN-} = 0.200$. For c_2, $r_2^{IVN+} = [0.500, 1.000]$ and $r_2^{IVN-} = [0.001, 0.095]$. For c_3, $r_3^{IFN+} = \langle 0.90, 0.05\rangle$ and $r_3^{IFN-} = \langle 0.05, 0.90\rangle$. For c_4, $r_4^{LT+} = \langle [0.8091, 0.8409], [0.1344, 0.1591]\rangle$ and $r_4^{LT-} = \langle [0.0337, 0.0625], [0.9007, 0.9375]\rangle$. For c_5, $r_5^{IVIFN+} = \langle [0.8500, 0.9000], [0.0500, 0.1000]\rangle$ and $r_5^{IVIFN-} = \langle [0.1000, 0.3000], [0.5500, 0.6000]\rangle$. For C_6^{TrFNN}, $r_6^{TrFNN+} = \langle (0.7, 0.8, 0.9, 1.0), (0.0, 0.1, 0.2, 0.3), (0.0, 0.1, 0.2, 0.3)\rangle$ and $r_6^{TrFNN-} = \langle (0.0, 0.1, 0.2, 0.3), (0.7, 0.8, 0.9, 1.0), (0.7, 0.8, 0.9, 1.0)\rangle$. For C_7^{NN},$r_7^{NN+} = \langle 1.00, 0.00, 0.00\rangle$ and $r_7^{NN-} = \langle 0.10, 0.66, 0.85\rangle$.

Table 1 | Evaluation Matrix R.

Cities \ Index	c_1	c_2	c_3	c_4
Nanping (NP)	3	[2,100–200,000]	$\langle 0.05, 0.90\rangle$	s_{-3}
Ningde (ND)	10	[65,000–1,900,000]	$\langle 0.80, 0.15\rangle$	s_3
Sanming (SM)	2	[2,000–190,000]	$\langle 0.05, 0.90\rangle$	s_{-3}
Fuzhou (FZ)	7	[180,000–600,000]	$\langle 0.50, 0.45\rangle$	s_2
Putian (PT)	5	[1,000,000–2,000,000]	$\langle 0.80, 0.15\rangle$	s_1
Longyan (LY)	3	[5,000–300,000]	$\langle 0.15, 0.80\rangle$	s_0
Quanzhou (QZ)	4	[18,000–500,000]	$\langle 0.05, 0.90\rangle$	s_{-1}
Xiamen (XM)	3	[2,300–190,000]	$\langle 0.30, 0.65\rangle$	s_{-2}
Zhangzhou (ZZ)	6	[500,000–2,000,000]	$\langle 0.90, 0.05\rangle$	s_2

Cities \ Index	c_5	c_6	c_7
Nanping (NP)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.0, 0.1, 0.2, 0.3), (0.7, 0.8, 0.9, 1.0), (0.7, 0.8, 0.9, 1.0)\rangle$	$\langle 0.20, 0.60, 0.75\rangle$
Ningde (ND)	$\langle[0.85, 0.90], [0.05, 0.10]\rangle$	$\langle(0.7, 0.8, 0.9, 1.0), (0.0, 0.1, 0.2, 0.3), (0.0, 0.1, 0.2, 0.3)\rangle$	$\langle 0.50, 0.50, 0.45\rangle$
Sanming (SM)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.0, 0.1, 0.2, 0.3), (0.7, 0.8, 0.9, 1.0), (0.7, 0.8, 0.9, 1.0)\rangle$	$\langle 0.10, 0.66, 0.85\rangle$
Fuzhou (FZ)	$\langle[0.55, 0.65], [0.30, 0.35]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.80, 0.20, 0.15\rangle$
Putian (PT)	$\langle[0.70, 0.80], [0.15, 0.20]\rangle$	$\langle(0.5, 0.6, 0.7, 0.8), (0.0, 0.2, 0.3, 0.4), (0.0, 0.2, 0.3, 0.4)\rangle$	$\langle 0.70, 0.25, 0.20\rangle$
Longyan (LY)	$\langle[0.45, 0.50], [0.35, 0.45]\rangle$	$\langle(0.1, 0.2, 0.3, 0.4), (0.4, 0.6, 0.7, 0.9), (0.4, 0.6, 0.7, 0.9)\rangle$	$\langle 0.30, 0.55, 0.60\rangle$
Quanzhou (QZ)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.90, 0.10, 0.05\rangle$
Xiamen (XM)	$\langle[0.20, 0.40], [0.45, 0.50]\rangle$	$\langle(0.1, 0.2, 0.3, 0.4), (0.4, 0.6, 0.7, 0.9), (0.4, 0.6, 0.7, 0.9)\rangle$	$\langle 1.00, 0.00, 0.00\rangle$
Zhangzhou (ZZ)	$\langle[0.85, 0.90], [0.05, 0.10]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.80, 0.20, 0.15\rangle$

Table 2 Converted evaluation matrix R.

Cities \ Index	c_1	c_2	c_3	c_4
Nanping (NP)	3	[2,100–200,000]	$\langle 0.05, 0.90\rangle$	$\langle[0.0337, 0.0625], [0.9007, 0.9375]\rangle$
Ningde (ND)	10	[65,000–1,900,000]	$\langle 0.80, 0.15\rangle$	$\langle[0.8091, 0.8409], [0.1344, 0.1591]\rangle$
Sanming (SM)	2	[2,000–190,000]	$\langle 0.05, 0.90\rangle$	$\langle[0.0337, 0.0625], [0.9007, 0.9375]\rangle$
Fuzhou (FZ)	7	[180,000–600,000]	$\langle 0.50, 0.45\rangle$	$\langle[0.7540, 0.7937], [0.1751, 0.2063]\rangle$
Putian (PT)	5	[1,000,000–2,000,000]	$\langle 0.80, 0.15\rangle$	$\langle[0.6547, 0.7071], [0.2507, 0.2929]\rangle$
Longyan (LY)	3	[5,000–300,000]	$\langle 0.15, 0.80\rangle$	$\langle[0.4286, 0.5000], [0.4286, 0.5000]\rangle$
Quanzhou (QZ)	4	[18,000–500,000]	$\langle 0.05, 0.90\rangle$	$\langle[0.1837, 0.2500], [0.6848, 0.7500]\rangle$
Xiamen (XM)	3	[2,300–190,000]	$\langle 0.30, 0.65\rangle$	$\langle[0.0787, 0.1250], [0.8231, 0.8750]\rangle$
Zhangzhou (ZZ)	6	[500,000–2,000,000]	$\langle 0.90, 0.05\rangle$	$\langle[0.7540, 0.7937], [0.1751, 0.2063]\rangle$

Table 3 Normalized evaluation matrix R'.

Cities \ Index	c_1	c_2	c_3	c_4
Nanping (NP)	0.300	[0.001, 0.100]	$\langle 0.05, 0.90\rangle$	$\langle[0.0337, 0.0625], [0.9007, 0.9375]\rangle$
Ningde (ND)	1.000	[0.033, 0.950]	$\langle 0.80, 0.15\rangle$	$\langle[0.8091, 0.8409], [0.1344, 0.1591]\rangle$
Sanming (SM)	0.200	[0.001, 0.095]	$\langle 0.05, 0.90\rangle$	$\langle[0.0337, 0.0625], [0.9007, 0.9375]\rangle$
Fuzhou (FZ)	0.700	[0.090, 0.300]	$\langle 0.50, 0.45\rangle$	$\langle[0.7540, 0.7937], [0.1751, 0.2063]\rangle$
Putian (PT)	0.500	[0.500, 1.000]	$\langle 0.80, 0.15\rangle$	$\langle[0.6547, 0.7071], [0.2507, 0.2929]\rangle$
Longyan (LY)	0.300	[0.003, 0.150]	$\langle 0.15, 0.80\rangle$	$\langle[0.4286, 0.5000], [0.4286, 0.5000]\rangle$
Quanzhou (QZ)	0.400	[0.009, 0.250]	$\langle 0.05, 0.90\rangle$	$\langle[0.1837, 0.2500], [0.6848, 0.7500]\rangle$
Xiamen (XM)	0.300	[0.012, 0.095]	$\langle 0.30, 0.65\rangle$	$\langle[0.0787, 0.1250], [0.8231, 0.8750]\rangle$
Zhangzhou (ZZ)	0.600	[0.250, 1.000]	$\langle 0.90, 0.05\rangle$	$\langle[0.7540, 0.7937], [0.1751, 0.2063]\rangle$

Cities \ Index	c_5	c_6	c_7
Nanping (NP)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.0, 0.1, 0.2, 0.3), (0.7, 0.8, 0.9, 1.0), (0.7, 0.8, 0.9, 1.0)\rangle$	$\langle 0.20, 0.60, 0.75\rangle$
Ningde (ND)	$\langle[0.85, 0.90], [0.05, 0.10]\rangle$	$\langle(0.7, 0.8, 0.9, 1.0), (0.0, 0.1, 0.2, 0.3), (0.0, 0.1, 0.2, 0.3)\rangle$	$\langle 0.50, 0.50, 0.45\rangle$
Sanming (SM)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.0, 0.1, 0.2, 0.3), (0.7, 0.8, 0.9, 1.0), (0.7, 0.8, 0.9, 1.0)\rangle$	$\langle 0.10, 0.66, 0.85\rangle$
Fuzhou (FZ)	$\langle[0.55, 0.65], [0.30, 0.35]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.80, 0.20, 0.15\rangle$
Putian (PT)	$\langle[0.70, 0.80], [0.15, 0.20]\rangle$	$\langle(0.5, 0.6, 0.7, 0.8), (0.0, 0.2, 0.3, 0.4), (0.0, 0.2, 0.3, 0.4)\rangle$	$\langle 0.70, 0.25, 0.20\rangle$
Longyan (LY)	$\langle[0.45, 0.50], [0.35, 0.45]\rangle$	$\langle(0.1, 0.2, 0.3, 0.4), (0.4, 0.6, 0.7, 0.9), (0.4, 0.6, 0.7, 0.9)\rangle$	$\langle 0.30, 0.55, 0.60\rangle$
Quanzhou (QZ)	$\langle[0.10, 0.30], [0.55, 0.60]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.90, 0.10, 0.05\rangle$
Xiamen (XM)	$\langle[0.20, 0.40], [0.45, 0.50]\rangle$	$\langle(0.1, 0.2, 0.3, 0.4), (0.4, 0.6, 0.7, 0.9), (0.4, 0.6, 0.7, 0.9)\rangle$	$\langle 1.00, 0.00, 0.00\rangle$
Zhangzhou (ZZ)	$\langle[0.85, 0.90], [0.05, 0.10]\rangle$	$\langle(0.3, 0.4, 0.5, 0.6), (0.2, 0.4, 0.5, 0.7), (0.2, 0.4, 0.5, 0.7)\rangle$	$\langle 0.80, 0.20, 0.15\rangle$

Step 4: Calculate the gains and losses to get the gain matrix GM and a loss matrix LM as shown in Tables 4 and 5. LM represents the loss matrix, and each data in the matrix represents the loss value of each attribute value of each evaluation object that does not reach the positive ideal reference point (ie, the most severe value). GM denotes a gain matrix, and each data in the matrix represents a earned value for each attribute value of each evaluation object exceeding the negative ideal reference point (ie, the lightest value).

Step 5: Using Equation (15) to calculation of prospect values when $\alpha = 0.89$, $\beta = 0.92$, $\lambda = 2.25$ [43] as shown in Table 6.

Step 6: The weight of the attribute calculated by java programming based on Equation (13) is as follows:

$$\omega_1 = 0.106,\ \omega_2 = 0.156,\ \omega_3 = 0.158,$$
$$\omega_4 = 0.226,\ \omega_5 = 0.114,\ \omega_6 = 0.078,$$
$$\omega_7 = 0.162.$$

Table 4 Loss matrix *LM*.

Cities \ Index	c_1	c_2	c_3	c_4	c_5	c_6	c_7
Nanping (NP)	0.583	0.631	0.889	0.633	0.499	0.618	0.722
Ningde (ND)	0.000	0.365	0.008	0.000	0.000	0.000	0.484
Sanming (SM)	0.632	0.632	0.889	0.633	0.499	0.618	0.810
Fuzhou (FZ)	0.313	0.544	0.221	0.039	0.216	0.232	0.185
Putian (PT)	0.465	0.000	0.008	0.112	0.096	0.027	0.253
Longyan (LY)	0.583	0.614	0.761	0.280	0.301	0.483	0.620
Quanzhou (QZ)	0.528	0.580	0.889	0.483	0.499	0.232	0.087
Xiamen (XM)	0.583	0.630	0.531	0.582	0.421	0.483	0.000
Zhangzhou (ZZ)	0.393	0.215	0.000	0.039	0.000	0.232	0.185

Table 5 Gain matrix *GM*.

Cities \ Index	c_1	c_2	c_3	c_4	c_5	c_6	c_7
Nanping (NP)	0.118	0.005	0.000	0.032	0.000	0.000	0.089
Ningde (ND)	0.632	0.563	0.761	0.633	0.499	0.618	0.339
Sanming (SM)	0.000	0.000	0.000	0.032	0.000	0.000	0.000
Fuzhou (FZ)	0.465	0.194	0.291	0.594	0.289	0.128	0.630
Putian (PT)	0.313	0.632	0.761	0.523	0.404	0.438	0.563
Longyan (LY)	0.118	0.052	0.008	0.356	0.204	0.019	0.195
Quanzhou (QZ)	0.221	0.139	0.000	0.153	0.000	0.128	0.729
Xiamen (XM)	0.118	0.011	0.070	0.055	0.082	0.019	0.810
Zhangzhou (ZZ)	0.393	0.597	0.889	0.594	0.499	0.128	0.630

Table 6 Prospect value matrix *V*.

Cities \ Index	c_1	c_2	c_3	c_4	c_5	c_6	c_7
Nanping (NP)	−1.220	−1.464	−2.019	−1.431	−1.187	−1.445	−1.551
Ningde (ND)	0.665	−0.290	0.758	0.666	0.539	0.652	−0.772
Sanming (SM)	−1.475	−1.475	−2.019	−1.431	−1.187	−1.445	−1.853
Fuzhou (FZ)	−0.267	−1.053	−0.228	0.515	−0.218	−0.426	0.186
Putian (PT)	−0.757	0.665	0.758	0.261	0.186	0.399	−0.036
Longyan (LY)	−1.220	−1.364	−1.736	−0.299	−0.503	−1.123	−1.216
Quanzhou (QZ)	−0.989	−1.190	−2.019	−0.964	−1.187	−0.426	0.517
Xiamen (XM)	−1.220	−1.453	−1.163	−1.292	−0.907	−1.123	0.829
Zhangzhou (ZZ)	−0.517	0.085	0.901	0.515	0.539	−0.426	0.186

Step 7: The comprehensive prospect value U_i of each alternative is calculated are as follows:

$$U_{NP} = -1.499,\ U_{ND} = 0.282,\ U_{SM} = -1.577,$$
$$U_{FZ} = -0.140,\ U_{PT} = 0.249,\ U_{LY} = -1.026,$$
$$U_{QZ} = -0.912,\ U_{XM} = -0.889,\ U_{ZZ} = 0.275.$$

From the above calculation results, we can see that $U_{ND} \succ U_{ZZ} \succ U_{PT} \succ U_{FZ} \succ U_{XM} \succ U_{QZ} \succ U_{LY} \succ U_{NP} \succ U_{SM}$. So the ranking of disaster severity in nine cities is as follows: $ND \succ ZZ \succ PT \succ FZ \succ XM \succ QZ \succ LY \succ NP \succ SM$. The results of this decision can be provided to relevant departments for effective disaster relief and material distribution. Thereby providing security for the people, and establishing the government's action prestige, maintaining social stability, and people's lives are happy.

4.2. Comparative Analysis

4.2.1. Sensitivity analysis

To illustrate the robustness of the algorithm, sensitivity analysis is performed on three parameters in the PT under different values of α, β, and λ. The results are as shown in Tables 7–9.

Table 7 Prospect value matrix *V* when $\alpha = 0.725$, $\beta = 0.717$, $\lambda = 2.04$.

Cities \ Index	$\alpha = 0.725, \beta = 0.717, \lambda = 2.04$. [63]						
	c_1	c_2	c_3	c_4	c_5	c_6	c_7
Nanping (NP)	−1.173	−1.445	−1.875	−1.387	−1.239	−1.445	−1.442
Ningde (ND)	0.717	−0.331	0.756	0.718	0.604	0.705	−0.756
Sanming (SM)	−1.468	−1.468	−1.875	−1.387	−1.239	−1.445	−1.754
Fuzhou (FZ)	−0.313	−1.014	−0.283	0.486	−0.273	−0.490	0.107
Putian (PT)	−0.747	0.717	0.756	0.201	0.138	0.397	−0.102
Longyan (LY)	−1.173	−1.321	−1.647	−0.346	−0.547	−1.154	−1.142
Quanzhou (QZ)	−0.956	−1.141	−1.875	−0.954	−1.239	−0.490	0.441
Xiamen (XM)	−1.173	−1.427	−1.150	−1.262	−0.934	−1.154	0.858
Zhangzhou (ZZ)	−0.536	0.010	0.918	0.486	0.604	−0.490	0.107

Table 8 Prospect value matrix *V* when $\alpha = 0.850$, $\beta = 0.850$, $\lambda = 4.1$.

Cities \ Index	$\alpha = 0.850, \beta = 0.850, \lambda = 4.1$. [64]					
	c_1	c_2	c_4	c_5	c_6	c_7
Nanping (NP)	−2.429	−2.761	−2.726	−2.271	−2.723	−2.980
Ningde (ND)	0.677	−1.127	0.678	0.554	0.664	−1.814
Sanming (SM)	−2.776	−2.776	−2.726	−2.271	−2.723	−3.428
Fuzhou (FZ)	−1.006	−2.196	0.382	−0.766	−1.010	−0.302
Putian (PT)	−1.766	0.677	−0.061	−0.097	0.305	−0.661
Longyan (LY)	−2.429	−2.627	−0.974	−1.219	−2.174	−2.482
Quanzhou (QZ)	−2.105	−2.394	−2.006	−2.271	−1.010	0.250
Xiamen (XM)	−2.429	−2.747	−2.503	−1.846	−2.174	0.836
Zhangzhou (ZZ)	−1.402	−0.465	0.382	0.554	−1.010	−0.302

Table 9 Prospect value matrix *V* when $\alpha = 0.89$, $\beta = 0.92$, $\lambda = 2.25$.

Cities \ Index	$\alpha = 0.89, \beta = 0.92, \lambda = 2.25$ [43]						
	c_1	c_2	c_3	c_4	c_5	c_6	c_7
Nanping (NP)	−1.220	−1.464	−2.019	−1.431	−1.187	−1.445	−1.551
Ningde (ND)	0.665	−0.290	0.758	0.666	0.539	0.652	−0.772
Sanming (SM)	−1.475	−1.475	−2.019	−1.431	−1.187	−1.445	−1.853
Fuzhou (FZ)	−0.267	−1.053	−0.228	0.515	−0.218	−0.426	0.186
Putian (PT)	−0.757	0.665	0.758	0.261	0.186	0.399	−0.036
Longyan (LY)	−1.220	−1.364	−1.736	−0.299	−0.503	−1.123	−1.216
Quanzhou (QZ)	−0.989	−1.190	−2.019	−0.964	−1.187	−0.426	0.517
Xiamen (XM)	−1.220	−1.453	−1.163	−1.292	−0.907	−1.123	0.829
Zhangzhou (ZZ)	−0.517	0.085	0.901	0.515	0.539	−0.426	0.186

Table 10 Comprehensive prospect value U_i and ranking result R_i with different parameter values.

Cities \ Index	$\alpha = 0.725$, $\beta = 0.717$, $\lambda = 2.04$ [63]		$\alpha = 0.850$, $\beta = 0.850$, $\lambda = 4.1$ [64]		$\alpha = 0.89$, $\beta = 0.92$, $\lambda = 2.25$ [43]	
	U_i	R_i	U_i	R_i	U_i	R_i
Nanping (NP)	−1.447	8	−2.845	8	−1.499	8
Ningde (ND)	0.307	1	−0.015	1	0.282	1
Sanming (SM)	−1.532	9	−2.956	9	−1.577	9
Fuzhou (FZ)	−0.178	4	−0.702	4	−0.140	4
Putian (PT)	0.228	3	−0.074	3	0.249	3
Longyan (LY)	−1.006	7	−2.109	7	−1.026	7
Quanzhou (QZ)	−0.899	6	−1.933	6	−0.912	6
Xiamen (XM)	−0.872	5	−1.859	5	−0.889	5
Zhangzhou (ZZ)	0.247	2	−0.057	2	0.275	2

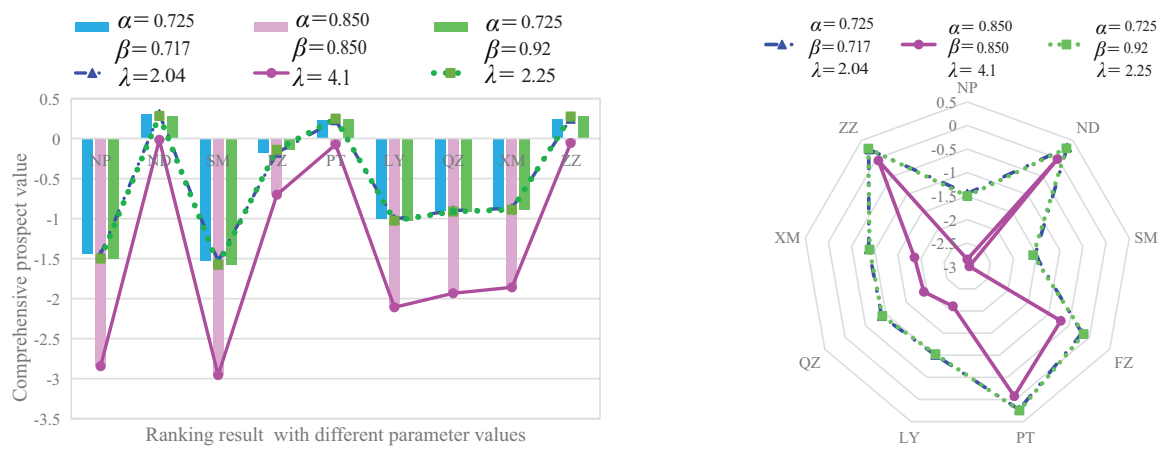


Figure 2 Ranking result with different parameter values α, β, and λ.

The comprehensive prospect value U_i of each alternative is calculated under different values of α, β, and λ are as shown in Table 10.

As can be seen from Table 10 and Figure 2, $U_{ND} \succ U_{ZZ} \succ U_{PT} \succ U_{FZ} \succ U_{XM} \succ U_{QZ} \succ U_{LY} \succ U_{NP} \succ U_{SM}$, so the ranking of disaster severity in nine cities is $ND \succ ZZ \succ PT \succ FZ \succ XM \succ QZ \succ LY \succ NP \succ SM$. Compare the three ranking results when the parameters take different values, the ranking results are exactly the same.

4.2.2. Comparative analysis with different methods

In order to illustrate the validity and rationality of the algorithm, the proposed method is compared with the most widely used operator-based method. Firstly, using the heterogeneous information conversion method [21], and the relationship between the TrFNN and other data, all kinds of heterogeneous data are converted into TrFNNs, and then the weighted comprehensive evaluation value of each city is calculated by using the trapezoidal fuzzy trapezoidal weighted arithmetic average operator (TNNWAA) [40]. Finally, the exact function and scoring function of the neutrosophic in trapezoidal fuzzy are used to rank the degree of city disaster. The TNNWAA operator is as follows:

$$\begin{aligned} &TNNWAA\left(\tilde{n}_1, \tilde{n}_2, \cdots, \tilde{n}_n\right) \\ &= \omega_1 \tilde{n}_1 \oplus \omega_2 \tilde{n}_2 \oplus \cdots \oplus \omega_n \tilde{n}_n \\ &= \left\langle \begin{array}{c} \left(1-\prod_{j=1}^{n}\left(1-a_{1j}\right)^{\omega_j}, 1-\prod_{j=1}^{n}\left(1-a_{2j}\right)^{\omega_j}, \right. \\ \left. 1-\prod_{j=1}^{n}\left(1-a_{3j}\right)^{\omega_j}, 1-\prod_{j=1}^{n}\left(1-a_{4j}\right)^{\omega_j}\right), \\ \left(\prod_{j=1}^{n} b_{1j}^{\omega_j}, \prod_{j=1}^{n} b_{2j}^{\omega_j}, \prod_{j=1}^{n} b_{3j}^{\omega_j}, \prod_{j=1}^{n} b_{4j}^{\omega_j}\right), \\ \left(\prod_{j=1}^{n} c_{1j}^{\omega_j}, \prod_{j=1}^{n} c_{2j}^{\omega_j}, \prod_{j=1}^{n} c_{3j}^{\omega_j}, \prod_{j=1}^{n} c_{4j}^{\omega_j}\right) \end{array} \right\rangle. \end{aligned} \tag{16}$$

The decision-making method steps based on the TNNWAA operator are as follows:

Step 1: By using the data conversion formula [21], the heterogeneous data of Table 3 is uniformly converted into the TrFNNs. The specific data are shown in Table 11:

Step 2: Using the TNNWAA operator, the attribute values of each scheme are assembled to obtain a comprehensive evaluation

Table 11 Unified trapezoidal fuzzy neutrosophic numbers decision matrix $\overline{R}'$.

Cities \ Index	c_1	c_2	c_3	c_4
Nanping (NP)	$\left\langle \begin{matrix}(0.300,0.300,0.300,0.300),\\(0.600,0.600,0.600,0.600),\\(0.700,0.700,0.700,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.051,0.051,0.051,0.051),\\(0.101,0.101,0.101,0.101),\\(0.949,0.949,0.949,0.949)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.050,0.050,0.050,0.050),\\(0.050,0.050,0.050,0.050),\\(0.900,0.900,0.900,0.900)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.0337,0.0337,0.0625,0.0625),\\(0.0000,0.0000,0.0656,0.0656),\\(0.9007,0.9007,0.9375,0.9375)\end{matrix}\right\rangle$
Ningde (ND)	$\left\langle \begin{matrix}(1.000,1.000,1.000,1.000),\\(0.000,0.000,0.000,0.000),\\(0.000,0.000,0.000,0.000)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.491,0.491,0.491,0.491),\\(0.517,0.517,0.517,0.517),\\(0.509,0.509,0.509,0.509)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.800,0.800,0.800,0.800),\\(0.050,0.050,0.050,0.050),\\(0.150,0.150,0.150,0.150)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.8091,0.8091,0.8409,0.8409),\\(0.0000,0.0000,0.0565,0.0565),\\(0.1344,0.1344,0.1591,0.1591)\end{matrix}\right\rangle$
Sanming (SM)	$\left\langle \begin{matrix}(0.200,0.200,0.200,0.200),\\(0.400,0.400,0.400,0.400),\\(0.800,0.800,0.800,0.800)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.048,0.048,0.048,0.048),\\(0.096,0.096,0.096,0.096),\\(0.952,0.952,0.952,0.952)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.050,0.050,0.050,0.050),\\(0.050,0.050,0.050,0.050),\\(0.900,0.900,0.900,0.900)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.0337,0.0337,0.0625,0.0625),\\(0.0000,0.0000,0.0656,0.0656),\\(0.9007,0.9007,0.9375,0.9375)\end{matrix}\right\rangle$
Fuzhou (FZ)	$\left\langle \begin{matrix}(0.700,0.700,0.700,0.700),\\(0.600,0.600,0.600,0.600),\\(0.300,0.300,0.300,0.300)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.195,0.195,0.195,0.195),\\(0.390,0.390,0.390,0.390),\\(0.805,0.805,0.805,0.805)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.500,0.500,0.500,0.500),\\(0.050,0.050,0.050,0.050),\\(0.450,0.450,0.450,0.450)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.7540,0.7540,0.7937,0.7937),\\(0.0000,0.0000,0.0709,0.0709),\\(0.1751,0.1751,0.2063,0.2063)\end{matrix}\right\rangle$
Putian (PT)	$\left\langle \begin{matrix}(0.500,0.500,0.500,0.500),\\(1.000,1.000,1.000,1.000),\\(0.500,0.500,0.500,0.500)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.750,0.750,0.750,0.750),\\(0.500,0.500,0.500,0.500),\\(0.250,0.250,0.250,0.250)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.800,0.800,0.800,0.800),\\(0.050,0.050,0.050,0.050),\\(0.150,0.150,0.150,0.150)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.6547,0.6547,0.7071,0.7071),\\(0.0000,0.0000,0.0946,0.0946),\\(0.2507,0.2507,0.2929,0.2929)\end{matrix}\right\rangle$
Longyan (LY)	$\left\langle \begin{matrix}(0.300,0.300,0.300,0.300),\\(0.600,0.600,0.600,0.600),\\(0.700,0.700,0.700,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.076,0.076,0.076,0.076),\\(0.153,0.153,0.153,0.153),\\(0.924,0.924,0.924,0.924)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.150,0.150,0.150,0.150),\\(0.050,0.050,0.050,0.050),\\(0.800,0.800,0.800,0.800)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.4286,0.4286,0.5000,0.5000),\\(0.0000,0.0000,0.1428,0.1428),\\(0.4286,0.4286,0.5000,0.5000)\end{matrix}\right\rangle$
Quan zhou (QZ)	$\left\langle \begin{matrix}(0.400,0.400,0.400,0.400),\\(0.800,0.800,0.800,0.800),\\(0.600,0.600,0.600,0.600)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.130,0.130,0.130,0.130),\\(0.259,0.259,0.259,0.259),\\(0.871,0.871,0.871,0.871)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.050,0.050,0.050,0.050),\\(0.050,0.050,0.050,0.050),\\(0.900,0.900,0.900,0.900)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.1837,0.1837,0.2500,0.2500),\\(0.0000,0.0000,0.1315,0.1315),\\(0.6848,0.6848,0.7500,0.7500)\end{matrix}\right\rangle$
Xiamen (XM)	$\left\langle \begin{matrix}(0.300,0.300,0.300,0.300),\\(0.600,0.600,0.600,0.600),\\(0.700,0.700,0.700,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.053,0.053,0.053,0.053),\\(0.107,0.107,0.107,0.107),\\(0.947,0.947,0.947,0.947)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.300,0.300,0.300,0.300),\\(0.050,0.050,0.050,0.050),\\(0.650,0.650,0.650,0.650)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.0787,0.0787,0.1250,0.1250),\\(0.0000,0.0000,0.0982,0.0982),\\(0.8231,0.8231,0.8750,0.8750)\end{matrix}\right\rangle$
Zhang zhou (ZZ)	$\left\langle \begin{matrix}(0.600,0.600,0.600,0.600),\\(0.800,0.800,0.800,0.800),\\(0.400,0.400,0.400,0.400)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.625,0.625,0.625,0.625),\\(0.500,0.500,0.500,0.500),\\(0.375,0.375,0.375,0.375)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.900,0.900,0.900,0.900),\\(0.050,0.050,0.050,0.050),\\(0.050,0.050,0.050,0.050)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.7540,0.7540,0.7937,0.7937),\\(0.0000,0.0000,0.0709,0.0709),\\(0.1751,0.1751,0.2063,0.2063)\end{matrix}\right\rangle$

Cities \ Index	c_5	c_6	c_7
Nanping (NP)	$\left\langle \begin{matrix}(0.100,0.100,0.300,0.300),\\(0.100,0.100,0.350,0.350),\\(0.550,0.550,0.600,0.600)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.000,0.100,0.200,0.300),\\(0.700,0.800,0.900,1.000),\\(0.700,0.800,0.900,1.000)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.200,0.200,0.200,0.200),\\(0.600,0.600,0.600,0.600),\\(0.750,0.750,0.750,0.750)\end{matrix}\right\rangle$
Ningde (ND)	$\left\langle \begin{matrix}(0.850,0.850,0.900,0.900),\\(0.000,0.000,0.100,0.100),\\(0.050,0.050,0.100,0.100)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.700,0.800,0.900,1.000),\\(0.000,0.100,0.200,0.300),\\(0.000,0.100,0.200,0.300)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.500,0.500,0.500,0.500),\\(0.500,0.500,0.500,0.500),\\(0.450,0.450,0.450,0.450)\end{matrix}\right\rangle$
Sanming (SM)	$\left\langle \begin{matrix}(0.100,0.100,0.300,0.300),\\(0.100,0.100,0.350,0.350),\\(0.550,0.550,0.600,0.600)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.000,0.100,0.200,0.300),\\(0.700,0.800,0.900,1.000),\\(0.700,0.800,0.900,1.000)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.100,0.100,0.100,0.100),\\(0.660,0.660,0.660,0.660),\\(0.850,0.850,0.850,0.850)\end{matrix}\right\rangle$
Fuzhou (FZ)	$\left\langle \begin{matrix}(0.550,0.550,0.650,0.650),\\(0.000,0.000,0.150,0.150),\\(0.300,0.300,0.350,0.350)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.300,0.400,0.500,0.600),\\(0.200,0.400,0.500,0.700),\\(0.200,0.400,0.500,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.800,0.800,0.800,0.800),\\(0.200,0.200,0.200,0.200),\\(0.150,0.150,0.150,0.150)\end{matrix}\right\rangle$
Putian (PT)	$\left\langle \begin{matrix}(0.700,0.700,0.800,0.800),\\(0.000,0.000,0.150,0.150),\\(0.150,0.150,0.200,0.200)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.500,0.600,0.700,0.800),\\(0.000,0.200,0.300,0.400),\\(0.000,0.200,0.300,0.400)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.700,0.700,0.700,0.700),\\(0.250,0.250,0.250,0.250),\\(0.200,0.200,0.200,0.200)\end{matrix}\right\rangle$
Longyan (LY)	$\left\langle \begin{matrix}(0.450,0.450,0.500,0.500),\\(0.050,0.050,0.200,0.200),\\(0.350,0.350,0.450,0.450)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.100,0.200,0.300,0.400),\\(0.400,0.600,0.700,0.900),\\(0.400,0.600,0.700,0.900)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.300,0.300,0.300,0.300),\\(0.550,0.550,0.550,0.550),\\(0.600,0.600,0.600,0.600)\end{matrix}\right\rangle$
Quanzhou (QZ)	$\left\langle \begin{matrix}(0.100,0.100,0.300,0.300),\\(0.100,0.100,0.350,0.350),\\(0.550,0.550,0.600,0.600)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.300,0.400,0.500,0.600),\\(0.200,0.400,0.500,0.700),\\(0.200,0.400,0.500,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.900,0.900,0.900,0.900),\\(0.100,0.100,0.100,0.100),\\(0.050,0.050,0.050,0.050)\end{matrix}\right\rangle$
Xiamen (XM)	$\left\langle \begin{matrix}(0.200,0.200,0.400,0.400),\\(0.100,0.100,0.350,0.350),\\(0.450,0.450,0.500,0.500)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.100,0.200,0.300,0.400),\\(0.400,0.600,0.700,0.900),\\(0.400,0.600,0.700,0.900)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(1.000,1.000,1.000,1.000),\\(0.000,0.000,0.000,0.000),\\(0.000,0.000,0.000,0.000)\end{matrix}\right\rangle$
Zhangzhou (ZZ)	$\left\langle \begin{matrix}(0.850,0.850,0.900,0.900),\\(0.000,0.000,0.100,0.100),\\(0.050,0.050,0.100,0.100)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.300,0.400,0.500,0.600),\\(0.200,0.400,0.500,0.700),\\(0.200,0.400,0.500,0.700)\end{matrix}\right\rangle$	$\left\langle \begin{matrix}(0.800,0.800,0.800,0.800),\\(0.200,0.200,0.200,0.200),\\(0.150,0.150,0.150,0.150)\end{matrix}\right\rangle$

value $TNNWAA\,(x_i)$, wherein the weights use the above calculated weights, and the result data is as follows:

$$TNNWAA\,(x_1) = \left\langle \begin{matrix}(0.104,0.111,0.150,0.159),\\(0.000,0.000,0.180,0.182),\\(0.796,0.804,0.827,0.834)\end{matrix}\right\rangle,$$

$$TNNWAA\,(x_2) = \left\langle \begin{matrix}(1.000,1.000,1.000,1.000),\\(0.000,0.000,0.000,0.000),\\(0.000,0.000,0.000,0.000)\end{matrix}\right\rangle,$$

$$TNNWAA\,(x_3) = \left\langle \begin{matrix}(0.073,0.081,0.121,0.130),\\(0.000,0.000,0.174,0.183),\\(0.824,0.833,0.856,0.863)\end{matrix}\right\rangle,$$

$$TNNWAA\left(x_4\right)=\left\langle\begin{array}{l}(0.620,0.624,0.654,0.660),\\(0.000,0.000,0.165,0.169),\\(0.286,0.302,0.325,0.333)\end{array}\right\rangle,$$

$$TNNWAA\left(x_5\right)=\left\langle\begin{array}{l}(0.690,0.695,0.726,0.734),\\(0.000,0.000,0.192,0.197),\\(0.000,0.222,0.245,0.251)\end{array}\right\rangle,$$

$$TNNWAA\left(x_6\right)=\left\langle\begin{array}{l}(0.286,0.247,0.328,0.336),\\(0.000,0.000,0.208,0.212),\\(0.576,0.595,0.642,0.654)\end{array}\right\rangle,$$

$$TNNWAA\left(x_7\right)=\left\langle\begin{array}{l}(0.419,0.425,0.460,0.469),\\(0.000,0.000,0.180,0.185),\\(0.425,0.448,0.470,0.483)\end{array}\right\rangle,$$

$$TNNWAA\left(x_8\right)=\left\langle\begin{array}{l}(1.000,1.000,1.000,1.000),\\(0.000,0.000,0.000,0.000),\\(0.000,0.000,0.000,0.000)\end{array}\right\rangle,$$

$$TNNWAA\left(x_9\right)=\left\langle\begin{array}{l}(0.762,0.765,0.787,0.791),\\(0.000,0.000,0.169,0.173),\\(0.151,0.159,0.182,0.187)\end{array}\right\rangle.$$

Step 3: The comprehensive evaluation values are sorted according to different methods including Prospect Theory, TOPSIS and Traditional Function Method (also known as Score Function, Accuracy Function). The calculation results are shown in Table 12 and Figure 3.

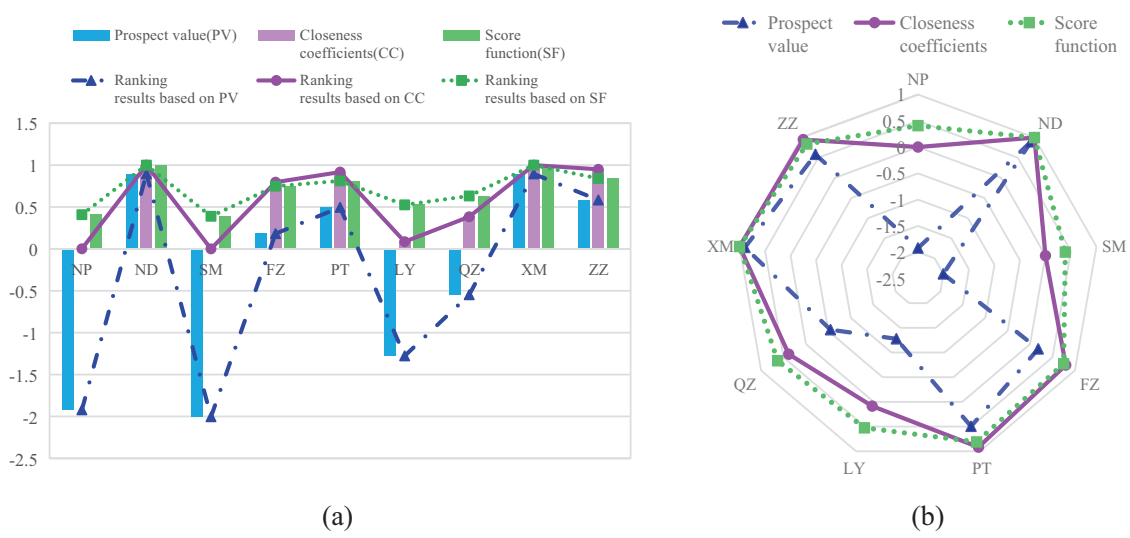
Step 4: It is known from the previous step the three different ranking results are the same, and the ranking of disaster severity in nine cities is $ND \sim XM \succ ZZ \succ PT \succ FZ \succ QZ \succ LY \succ NP \succ SM$.

From the comparison of the two typhoon disaster assessment methods, it can be seen that although the ranking results are not exactly the same, they are basically the same, and the special optimal scheme is the same. In addition, because the TNNWAA operator is sensitive to data 0 when assembling information, the second method, which is based on the TNNWAA algorithm, sometimes cannot fully sort the evaluation objects. For example, the comprehensive evaluation values of ND and SM are the same, that is, $ND \sim XM$, so they cannot be distinguished. However, this phenomenon does not occur in the proposed method based on PT.

Compared with other related researches, the advantages of this algorithm mainly include several aspects:

Table 12 Ranking results of different methods.

Index / Cities	Prospect Theory		TOPSIS		Traditional Function Method		
	Prospect Value	Ranking Results	Closeness Coefficients	Ranking Results	Score Function	Accuracy Function	Ranking Results
Nanping (NP)	−1.921	8	0.0011	8	0.408	−0.684	8
Ningde (ND)	0.895	1	1.0000	1	1.000	1.000	1
Sanming (SM)	−2.004	9	0.0004	9	0.389	−0.743	9
Fuzhou (FZ)	0.182	5	0.7965	5	0.748	0.328	5
Putian (PT)	0.496	4	0.9168	4	0.811	0.532	4
Longyan (LY)	−1.277	7	0.0858	7	0.526	−0.318	7
Quanzhou (QZ)	−0.548	6	0.3834	6	0.632	−0.013	6
Xiamen (XM)	0.895	1	1.0000	1	1.000	1.000	1
Zhangzhou (ZZ)	0.583	3	0.9498	3	0.840	0.606	3



(a) (b)

Figure 3 City ranking results for different ranking methods.

1. The types of heterogeneous information studied in this paper are more comprehensive and more diverse, including ENs, interval numbers, language numbers, IFNs, IVIFNs, SVNNs, and TrFNNs. Compared with the literature [19], the heterogeneous data includes four types of data: real numbers, interval numbers, triangular fuzzy numbers, and IFNs. However, the information representation forms in our paper are more. Compared with the literature [20], the data type of our paper contains the NN and the TrFNN, while the literature [20] does not. Compared with the literature [21], the heterogeneous information includes real numbers, interval numbers, triangular fuzzy numbers, TrFNs, even so, the information representation forms in our paper are more. At the same time, compared with the literatures [22–25], the heterogeneous information in our paper research includes the NN and the TrFNN, however, the literatures [22–25] do not.
2. In this heterogeneous information environment, the attribute weight is determined based on the maximization of deviation. Compared with the subjective reference [76], the decision result of this paper is more objective and fair. Compared with the method [21], our method is easier to understand.
3. This paper adopts the PT to sort the selection is simple and easy to understand, and introduces the psychological behavior of the decision maker. Compared with the evidence reasoning [20], the calculation of our method is relatively small. Compared with the method [21] that transforms heterogeneous information into IvIFNs for information aggregation, our method can fully sort the evaluation objects without juxtaposed results.

5. CONCLUSION

Based on the study of heterogeneous information, this paper proposes a decision-making method based on PT and applies it to typhoon disaster assessment. The distance measures of heterogeneous data such as EN, interval number, linguistic number, IFN, IVIFN, NN, TrFNN, and so on are introduced. The attribute weighting of the heterogeneous information is determined by the deviation maximization method. Considering the uncertainty of typhoon disaster and the psychological perception of decision makers, the PT is used for disaster assessment. Finally, an example is given to verify the feasibility and effectiveness of the decision-making method, and the advantages of this method are compared with other methods. In the future work, the decision-making methods based on the NNs, the decision-making methods in the case of heterogeneous information incomplete situations, the study of compatibility and consistency of decision information, and their application in typhoon disaster assessment will be further studied.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

AUTHORS' CONTRIBUTIONS

All authors have contributed to this paper. The individual responsibilities and contribution of all authors can be described as follows: The idea of this whole thesis was put forward by Ruipu Tan, she also wrote the paper. Wende Zhang analyzed the existing work of the research problem. Lehua Yang collected relevant data and implemented partial calculation through programming. The revision and submission of this paper was completed by Ruipu Tan and Shengqun Chen.

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REFERENCES

[1] H. Sun, Y. Dang, W. Mao, A decision-making method with grey multi-source heterogeneous data and its application in green supplier selection, Int. J. Environ. Res. Pub. Health. 15 (2018), 446.
[2] I. Badi, A.G. Shetwan, A.M. Abdulshahed, Supplier selection using Combinative Distance-Based Assessment (CODAS) method for multi-criteria decision-making, in Proceedings of the 1st International Conference on Management, Engineering and Environment (ICMNEE), ECOR (RABEK), Belgrade, 2017, pp. 395–407.
[3] P. Liu, P. Wang, Some interval-valued intuitionistic fuzzy Schweizer-Sklar power aggregation operators and their application to supplier selection, Int. J. Syst. Sci. 49 (2018), 1188–1211.
[4] A. Peralta, E. Conde, M. García, F.P. Romero, Behavioral pattern recognition and knowledge extraction for decision-making in software project management, in Proceedings of the international Conference on Computational Science & Computational Intelligence, IEEE, Las Vegas, 2017, pp. 865–868.
[5] J. Dhivya, B. Sridevi, Single valued neutrosophic exponential similarity measure for medical diagnosis and multi attribute decision making, Int. J. Pure Appl. Math. 116 (2017), 157–166.
[6] T. Mahmood, K. Ullah, Q. Khan, N. Jan, An approach toward decision-making and medical diagnosis problems using the concept of spherical fuzzy sets, Neural Comput. Appl. 2 (2018), 1–13.
[7] Y. Xu, W. Zhang, H. Wang, A conflict-eliminating approach for emergency group decision of unconventional incidents, Knowl. Based Syst. 83 (2015), 92–104.
[8] Y. Xu, X. Wen, W. Zhang, A two-stage consensus method for large-scale multi-attribute group decision making with an application to earthquake shelter selection, Comput. Ind. Eng. 116 (2018), 113–129.
[9] Y. Xu, F.J. Cabrerizo, E. Herrera-Viedma, A consensus model for hesitant fuzzy preference relations and its application in water allocation management, Appl. Soft Comput. 58 (2017), 265–284.
[10] D.J. Yu, Intuitionistic fuzzy theory based typhoon disaster evaluation in Zhejiang Province, China: a comparative perspective, Nat. Hazards. 75 (2015), 2559–2576.
[11] X.R. He, Typhoon disaster assessment based on Dombi hesitant fuzzy information aggregation operators, Nat. Hazards. 90 (2018), 1153–1175.
[12] M. Abdel-Basset, M. Gunasekaran, M. Mohamed, F. Smarandache, A novel method for solving the fully neutrosophic linear programming problems, Neural Comput. Appl. 31 (2019), 1595–1605.

[13] L.A. Zadeh, Fuzzy sets, Inf. Control. 8 (1965), 338–353.
[14] V. Torra, Y. Narukawa, On hesitant fuzzy sets and decision, in Proceedings of the IEEE International Conference on Fuzzy Systems, Fuzz-IEEE, Jeju Island, 2009, pp. 1378–1382.
[15] W. Ziarko, Variable precision rough set model, J. Comput. Syst. Sci. 46 (1993), 39–59.
[16] J.L. Deng, Introduction to Grey system theory, Sci. Tech. Inf. Serv. 1 (1989), 1–24.
[17] K.T. Atanassov, Intuitionistic fuzzy sets, Fuzzy Sets Syst. 20 (1986), 87–96.
[18] F. Smarandache, A unifying field in logics: neutrosophic logic, Mult. Valued Log. 8 (1999), 489–503.
[19] G.F. Yu, D.F. Li, Y.F. Ye, J.M. Qiu, Heterogeneous multi-attribute variable weight decision making method considering regret aversion, Comput. Integr. Manuf. Syst. 23 (2017), 154–161. (In Chinese).
[20] Y.H. Pan, X.L. Geng, A hybrid multiple attributes group decision making method based on VIKOR, Mach. Des. Res. 34 (2018), 177–182. (In Chinese).
[21] S.P. Wan, J. Xu, J.Y. Dong, Aggregating decision information into interval-valued intuitionistic fuzzy numbers for heterogeneous multi-attribute group decision making, Appl. Soft Comput. 41 (2016), 331–351.
[22] R. Lourenzutti, R.A. Krohling, A generalized TOPSIS method for group decision making with heterogeneous information in a dynamic environment, Inf. Sci. 330 (2016), 1–18.
[23] X. Zhang, Z.P. Fan, Method for risky hybrid multiple attribute decision making based on prospect theory, J. Syst. Eng. 27 (2012), 772–781. (In Chinese).
[24] Z.P. Fan, F.D. Chen, X. Zhang, Method for hybrid multiple attribute decision making based on cumulative prospect theory, J. Syst. Eng. 27 (2012), 295–301. (In Chinese).
[25] X.W. Qi, C.Y. Liang, Y.Q. Huang, Y. Ding, Multi-attribute group decision making method based on hybrid evaluation matrix, Syst. Eng. Theory Pract. 33 (2013), 473–481. (In Chinese).
[26] F. Smarandache, Neutrosophic set - a generalization of the intuitionistic fuzzy set, J. Defense Resources Manag. 1 (2010), 38–42.
[27] H. Wang, F. Smarandache, Y.Q. Zhang, R. Sunderraman, Single valued neutrosophic sets, Multispace Multistructure. 4 (2010), 410–413. https://www.researchgate.net/publication/262034561
[28] J. Ye, A multicriteria decision-making method using aggregation operators for simplified neutrosophic sets, J. Fuzzy Syst. 26 (2014), 2459–2466.
[29] J.Q. Wang, X.E. Li, TODIM method with multi-valued neutrosophic sets, Control Decis. 30 (2015), 1139–1142. (In Chinese).
[30] H. Wang, F. Smarandache, Y.Q. Zhang, R. Sunderraman, Interval Neutrosophic Sets and Logic: Theory and Applications in Computing, Hexis, Phoenix, 2005.
[31] W. Yang, Y. Pang, New multiple attribute decision making method based on DEMATEL and TOPSIS for multi-valued interval neutrosophic sets, Symmetry. 10 (2018), 115.
[32] I. Deli, M. Ali, F. Smarandache, Bipolar neutrosophic sets and their applications based on multicriteria decision making problems, in Proceedings of the International Conference on Advanced Mechatronic Systems, IEEE, Beijing, (2015), pp. 249–254.
[33] I. Deli, S. Broumi, F. Smarandache, On neutrosophic refined sets and their applications in medical diagnosis, J. N. Theory. 6 (2015), 88–89.
[34] İ. Deli, Y. Şubaş, Bipolar neutrosophic refined sets and their applications in medical diagnosis international, in Proceedings of the Conference on Natural Science and Engineering (ICNASE'16), Kilis, (2016), pp. 1121–1132.
[35] Z.P. Tian, J. Wang, H.Y. Zhang, X.H. Chen, J.Q. Wang, Simplified neutrosophic linguistic normalized weighted Bonferroni mean operator and its application to multi-criteria decision-making problems, Filomat. 30 (2016), 3339–3360.
[36] P. Biswas, S. Pramanik, B.C. Giri, Cosine similarity measure based multi-attribute decision-making with trapezoidal fuzzy neutrosophic numbers, Neutrosophic Sets Syst. 8 (2014), 46–56.
[37] S. Broumi, F. Smarandache, M. Talea, A. Bakali, An introduction to bipolar single valued neutrosophic graph theory, Appl. Mech. Mater. 841 (2016), 184–191.
[38] S. Broumi, F. Smarandache, M. Talea, A. Bakali, Single valued neutrosophic graphs: degree, order and size, in Proceedings of the 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver, 2016, pp. 2444–2451.
[39] R.P. Tan, W.D. Zhang, S. Broumi, Solving methods of the shortest path problem based on the trapezoidal fuzzy neutrosophic numbers, Control and Decision, 34 (2019), 851–860. (In Chinese).
[40] J. Ye, Trapezoidal neutrosophic set and its application to multiple attribute decision-making, Neural Comput. Appl. 26 (2015), 1157–1166.
[41] C. Wei, Z. Ren, R.M. Rodríguez, A hesitant fuzzy linguistic TODIM method based on a score function, Int. J. Comput. Intell. Syst. 8 (2015), 701–712.
[42] D. Kahneman, A. Tversky, Prospect theory: an analysis of decision under risk, Econom. 47 (1979), 263–292.
[43] A. Tversky, D. Kahneman, Advances in prospect theory: cumulative representation of uncertainty, J. Risk Uncertain. 5 (1992), 297–323.
[44] Z.X. Zhang, L. Wang, Y.M. Wang, An emergency decision making method for different situation response based on game theory and prospect theory, Symmetry. 10 (2018), 476.
[45] J. Gao, D. Li, J. Yao, When Prospect Theory Preference Meets Mean-Reverting Asset Returns: a Dynamic Asset Allocation Model, Social Science Electronic Publishing, New York, USA, 2018.
[46] M.J. Best, R.R. Grauer, Prospect theory and portfolio selection, J. Behav. Exp. Financ. 11 (2016), 13–17.
[47] A.E. Attema, W.B. Brouwer, O. Haridon, Prospect theory in the health domain: a quantitative assessment, J. Health Econ. 32 (2013), 1057–1065.
[48] L.J. Tian, C.R. Lyu, Y.X. Zhao, The park-and-ride behavior in a cumulative prospect theory-based model, J. Oper. Res. Soc. China. 5 (2017), 363–376.
[49] L.J.M. VanTol, Cumulative prospect theory in option valuation and portfolio management, M. D. Techische Universiteit Delft, 2018. http://repository.tudelft.nl/.
[50] B. Zou, R. Zagst, Optimal investment with transaction costs under cumulative prospect theory in discrete time, Math. Financ. Econ. 11 (2015), 1–29.
[51] W. Liu, L. Li, Emergency decision-making combining cumulative prospect theory and group decision-making, Granular Comput. 4 (2018), 39–52.
[52] Z.X. Zhang, L. Wang, Y.M. Wang, An emergency decision making method based on prospect theory for different emergency situations, Int. J. Disaster Risk Sci. 10 (2018), 1–14.

[53] G. Tao, Brain mechanism of economic management risk decision based on Kahneman's prospect theory, NeuroQuantology. 16 (2018), 401–406.
[54] T. Ning, X.P. Wang, study on disruption management strategy of job-shop scheduling problem based on prospect theory, J. Clean. Prod. 194 (2018), 174–178.
[55] K.A. Sullivan, E. Uchida, T.W. Sproul, J. Xu, Prospect theory and tenure reform: impacts on forest management, Land Econ. 94 (2018), 405–424.
[56] X.B. Yu, Y.Q. Lu, X.M. Wang, X. Luo, M. Cai, Typhoon disaster emergency scheme generation & dynamic adjustment based on CBR and prospect theory, Fuzzy Syst. Math. 31 (2017),182–190.
[57] Y. Shi, G. Kou, Y. Li, G. Wang, Y. Peng, FMCDM: a fuzzy multi-criteria decision-making hybrid approach to evaluate the damage level of typhoon: integration of fuzzy AHP and fuzzy TOPSIS, in Proceeding of the International Conference on Information Sciences & Interaction Sciences, IEEE, Chengdu, 2010, pp. 666–671.
[58] C. Li, L. Zhang, S. Zeng, Typhoon disaster evaluation based on extension of intuitionistic fuzzy TOPSIS method in Zhejiang Province of China, Int. J. Earth Sci. Eng. 8 (2015), 1031–1035.
[59] K. Atanassov, G. Gargov, Interval valued intuitionistic fuzzy sets, Fuzzy Sets Syst. 31 (1989), 343–349.
[60] Z.S. Xu, EOWA and EOWG operators for aggregating linguistic labels based on linguistic preference relations, Int. J. Uncertain. Fuzziness Knowl. Based Syst. 12 (2004), 791–810.
[61] Z.S. Xu, Group decision making based on multiple types of linguistic preference relations, Inf. Sci. 178 (2008), 452–467.
[62] L. Wang, Y.M. Wang, L. Martínez, A group decision method based on prospect theory for emergency situations, Inf. Sci. 418–419 (2017), 119–135.
[63] M. Abdellaoui, H. Bleichrodt, C. Paraschiv, Loss aversion under prospect theory: a parameter-free measurement, Manag. Sci. 53 (2007), 1659–1674.
[64] Y. Liu, Z.P. Fan, Y. Zhang, Risk decision analysis in emergency response: amethod based on cumulative prospect theory, Comput. Oper. Res. 42 (2014), 75–82.
[65] Z.P. Fan, Y.H. Li, X. Wang, Y. Liu, Hybrid similarity measure for case retrieval in CBR and its application to emergency response towards gas explosion, Expert Syst. Appl. 41 (2014), 2526–2534.
[66] J. Ye, Cosine similarity measures for intuitionistic fuzzy sets and their applications, Math. Comput. Model. 53 (2011), 91–97.
[67] J. Ye, Clustering methods using distance-based similarity measures of single-valued neutrosophic sets, J. Intell. Syst. 23 (2014), 379–389.
[68] R. Tan, W. Zhang, Multiple attribute group decision making methods based on trapezoidal fuzzy neutrosophic numbers, J. Intell. Fuzzy Syst. 33 (2017), 2547–2564.
[69] Y.M. Wang, Using the method of maximizing deviations to make decision for multiindices, Syst. Eng. Electron. 20 (1998), 24–26. https://ieeexplore.ieee.org/document/6079108
[70] B. Yang, J. Yuan, Z. Ye, Risk assessment of coal mining above confined aquifer based on maximizing deviation in a GIS environment, Arab. J. Geosci. 11 (2018), 299.
[71] Y.J. Xu, Q.L. Da, Standard and mean deviation methods for linguistic group decision making and their applications, Expert Syst. Appl. 37 (2010), 5905–5912.
[72] Y. Xu, A mean deviation based method for intuitionistic fuzzy multiple attribute decision making, in Proceeding of the International Conference on Artificial Intelligence & Computational Intelligence, IEEE, Sanya, 2010, pp. 12–16.
[73] Y. Chen, S. Jin, Y.N. Yang, A consensus adjustment method for group decision making based on compatibility of interval-valued intuitionistic fuzzy information, Math. Pract. Theory. 48 (2018), 230–239. http://ssjs.cbpt.cnki.net/WKA2/WebPublication/paperDigest.aspx?paperID=d6e2b36b-c02b-4f9c-8e04-cd0db6e8aee6
[74] Y. Sun, P.Y. Yao, L.J. Wan, J. Bai, Multiple attribute decision making method based on weights aggregation and relative dominance relation, Control Decis. 32 (2017), 317–322.
[75] F. Chen, Decision making method based on improving consistency of fuzzy linguistic preference relations, Comput. Eng. Appl. 53 (2017), 165–170.
[76] J. Zheng, Y.M. Wand, Y.E. Xin, Decision method for emergency alternative with considering total superiority degree, Control Decis. 30 (2015), 1239–1244. (In Chinese).