An Extended TODIM Based on Cumulative Prospect Theory for Single-Valued Neutrosophic Multi-Attribute Decision-Making

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Abstract—**The single-valued neutrosophic sets area unit powerful tool to describe uncertain data. TODIM method is usually accustomed solve multi-attributes decision-making issues. supported the cumulative prospect theory, this paper proposes an extended TODIM method that comprehensively reflects the psychological characteristics of decision makers. Firstly, we in short explain the definitions of cumulative prospect theory and single-valued neutrosophic sets. Secondly, we introduce the steps of the classical TODIM method of resolution multiple attributes decision-making issues. On the idea, we propose an extended TODIM method to comprehensively mirror the psychological state of decision makers. Finally, through the case analysis, it's evidenced that extended TODIM method will higher think about the psychological characteristics of decision makers.**

Index Terms—**multi-attribute decision-making; cumulative prospect theory; single-valued neutrosophic number; TODIM method**

I. Introduction

With the complicated decision environment, Zadeh offered Mitgliedschaft said uncertain fuzzy sets of information, so that multiple attributes decision making (MADM) problem is becoming increasingly popular. On the basis, Atanassov [1] defined the intuitionistic fuzzy set, which generated a new variable false membership. Subsequently, Torra [2] defined the hesitating fuzzy set, which made the membership of elements expressed by a finite set and the number whose value is between 0 and 1 in the finite set. However, there are still many unsolved problems of uncertainty of our life, As a result, Smarandache [3] introduced the neutrosophic set (NS) of fuzzy decision information, which is represented by true membership function, uncertainty membership function, and false membership function. In order to be used in practical problems, Wang et al. [4] and Ye [5] defined the single-valued neutrosophic sets (SVNSs), and Majumdar et al. [6] defined the distance between two single-valued neutrosophic numbers (SVNNs), making the decision makers (DMs) process more reasonable.

DMs look at a variety of factors to find the most efficient solution to the MADM problem, including TODIM (TOmada de Decisão Iterativa Multicritério) [7], VIKOR (Vlsekriterijumska optimizacija I KOmpromisno Resenje) [8], TOSIS (Techique for Order Prefernce by Similarity to an Ideal Solution) [9], ELECTRE (ELimination Et Choix Traduisant Ia REalité) [10], PROMETHEE (Preference Ranking O-ranization METhod for Enrichment Evaluations) [11], [12], and many other methods. Among them, on the basis of prospect theory, the TODIM approach is proposed [13], which makes it take the psychological state of DMs into account in solving MADM problems. This makes sense, because the risk preference for DMs can really influence the decision making result in the real decision process, which fits the characteristics of cumulative prospect theory (CPT) [14]. In CPT, the DMs' behavior is represented by the product of the transformation weight function and the value function, with the weight function indicating that the DMs use nonlinear probabilities rather than objective probabilities to make judgments [15] [16]. The value function shows that DMs have diverse perspectives on wins and losses [17] [18]. The objective weight of each attribute is frequently specified in the traditional TODIM technique. Therefore, according to the basic ideas of and CPT [19]. We propose the extended TODIM approach, which combines CPT with the classical TODIM method.

The weighting function is used in the extended TODIM approach developed in this paper to estimate the relative weight of the dominant function [20], and uses the value function of CPT to explain the attitude to the DMs when facing the gain or loss, which makes the decision process closer to reality. The main contents of this paper are as follows: (1) The related definitions and theories of SVNSs and CPT are introduced; (2) The classical TODIM method is briefly introduced; (3) The extended TODIM method is proposed by combining CPT and classical TODIM method; (4) We use illustrative examples to verify the validity of the proposed method, and then write and compare it with traditional TODIM method; (5) The conclusions of this study are summarized and the feasibility of the new method is demonstrated.

II. Preliminaries

A. Neutrosophic Sets and Single-Valued Neutrosophic Sets

Definition 1: [3] [21]. X is a finite points(objects), and the neutrosophic set (NS) A defined in the field X is composed of true membership function $T_{A(x)}$, false membership function $F_{A(x)}$ and uncertainty function $I_{A(x)}$. $T_A(x), I_A(x), F_A(x) : X \to]^{-}0, 1^{+}[$, $T_{A(x)}$ represents the degree to which the element x in the field X belongs

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to set A, $F_{A(x)}$ represents the degree to which the element x in the field X does not belong to set A. $I_{A(x)}$ represents the degree to which the element x in the field X is uncertain whether it belongs to set A or not, and the three membership functions of the NS are independent of each other, so there is no restriction on the sum of the three membership degrees of the NS, i.e. $0^{-} \leq \sup T_{A(x)} + \sup I_{A(x)} + \sup F_{A(x)} \leq 3^{+}$.

In order to facilitate the calculation in practical application. Wang [4] develops the SNSs

Definition 2: [4]. X is a finite points (objects); the SVNSs A defined on the points X is composed of:

$$A = \left\{ \left(x, T_{A(x)}, I_{A(x)}, F_{A(x)} \right) | x \in X \right\} \tag{1}$$

which is mainly composed of true membership function $T_{A(x)}$, uncertainty membership $I_{A(x)}$ and false membership function $F_{A(x)}$. Respectively represent the extent to which the element x in the field X belongs to set A, the extent to which it does not belong to set A and the degree of uncertainty, where

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

and $0 \leq T_{A(x)} + I_{A(x)} + F_{A(x)} \leq 3$. For writing convenience, A SVNNs can be expressed as $a = \{T, I, F\}$.

Definition 3: [22]. Suppose a is a SVNN, then the scoring function of a is :

$$S(a) = \frac{(2 + T - I - F)}{3} \tag{2}$$

Where $S(a)$ is the scoring function of a. Suppose there are two a_1 and a_2, if $S(a_1) > S(a_2)$, then $a_1 > a_2$. If we have $S(a_1) = S(a_2)$, we have $a_1 = a_2$.

Definition 4: [23]. Assuming that a is SVNN, Then the precision function of a is:

$$H(a) = (T - F), H \in [-1, 1]. \tag{3}$$

Where $H(a)$ is an precision function of a, let two SVNN be a_1 and a_2, if $H(a_1) < H(a_2)$, then $a_1 < a_2$. If we have $H(a_1) = H(a_2)$, we have $a_1 = a_2$.

Definition 5: [19]. Assuming that a_1 and a_2 is two SVNNs, $S(a_1)$ and $S(a_2)$ are the scoring functions of a_1 and a_2 respectively, and $H(a_1)$ and $H(a_2)$ are the precision function value of a_1 and a_2 respectively, then: if $S(a_1) < S(a_2)$, then $a_1 < a_2$; if $S(a_1) = S(a_2)$, then:

(1) if $H(a_1) = H(a_2)$, then $a_1 = a_2$;
(2) if $H(a_1) < H(a_2)$, then $a_1 < a_2$.

Definition 6: [4]. Suppose a_1 and a_2 are SVNNs. Define the following calculation rules:

(1) $\lambda a_1 = \left\langle 1 - (1 - T_1)^{\lambda}, (I_1)^{\lambda}, (F_1)^{\lambda} \right\rangle; \lambda > 0.$
(2) ${a_1}^{\lambda} = \left\langle (T_1)^{\lambda}, 1 - (1 - I_1)^{\lambda}, 1 - (1 - F_1)^{\lambda} \right\rangle; \lambda > 0.$
(3) $a_1 \oplus a_2 = \langle T_1 + T_2 - T_1 \cdot T_2, I_1 \cdot I_2, F_1 \cdot F_2 \rangle.$
(4) $a_1 \otimes a_2 = \langle T_1 \cdot T_2, I_1 + I_2 - I_1 \cdot I_2, F_1 + F_2 - F_1 \cdot F_2 \rangle.$
(5) ${a_1}^{c} = \langle F_1, 1 - I_1, T_1 \rangle.$

Definition 7: [24]. Assuming that a_1 and a_2 are SVNNs, the normalized Hamming distance of a_1 and a_2 is:

$$d(a_1, a_2) = \frac{1}{3} \left(|T_1 + T_2| + |I_1 + I_2| + |F_1 + F_2| \right) \tag{4}$$

B. Cumulative Prospect Theory

Tversy and Kahneman [19] proposed the well-known CPT theory and used it to tackle decision-making problems in uncertain situations. The foreground function of this theory $V(x_j)$ is defined by the following formula:

which is the product of two functions: the value function $v(x_j)$ and the transformed probability weighting function $\pi(p_j)$.

$$V(x_j) = \sum_{j=1}^{m} v(x_j) \pi(p_j) \tag{5}$$

In the above formula: $v(x_j)$ is the value function, which is the preference choice of decision-makers, and $\pi(p_j)$, which is the probability weighting function after conversion.

The number of alternative attributes is represented by m: The jth attribute is represented as j; The value function $v(x_j)$ represents the decision-maker's preference in the face of risk and seeking risk in the face of loss. It is defined as follows:

$$v(x_j) = \begin{cases} (x_j - x_0)^{\alpha}, & if \quad x_j - x_0 \geq 0, \\ -\lambda (x_0 - x_j)^{\beta}, & if \quad x_j - x_0 > 0, \end{cases} \tag{6}$$

In the above formula, $x_j - x_0$ is the numerical difference between the decision value and the reference point, $x_j - x_0 > 0$ means that the decision is relatively profitable, and $x_j - x_0 < 0$ means the opposite situation. α, δ, are the decreasing coefficients of loss sensitivity. The loss avoidance coefficient is λ, and the smaller the value, the less sensitive the decision maker is to the loss; otherwise, the decision maker is more sensitive to the loss.

If $x_j - x_0 \geq 0$, the weighting function is represented by the following formula:

$$\varpi^{+}(\omega_j) = \omega_j^{\gamma} / \left(\omega_j^{\gamma} + (1 - \omega_j)^{\gamma} \right)^{\frac{1}{\gamma}} \tag{7}$$

otherwise,

$$\varpi^{-}(\omega_j) = \omega_j^{\delta} / \left(\omega_j^{\delta} + (1 - \omega_j)^{\delta} \right)^{\frac{1}{\delta}} \tag{8}$$

In the above formula p_j is the probability of x_j; λ and δ they are income attitude coefficient and loss attitude coefficient.

C. For SVN MADM problems, the classical TODIM method is used.

Suppose $A = \{A_1, A_2, \cdots A_m\}$ is m options, and $G = \{G_1, G_2, \cdots G_n\}$ indicates that there are n attributes. $\omega = \{\omega_1, \omega_2, \cdots \omega_m\}$ expressed as weights of attributes, and these weights $\omega_j \in [0, 1]$, $\sum_{j=1}^{n} \omega_j = 1$.

Step 1: Identify the single-valued neutrosophic matrix $R = (r_{ij})_{m \times n} = (T_{ij}, I_{ij}, F_{ij})_{m \times n}$. The weight of alternative A_i under G_j is given by experts. Among then $T_{ij}, I_{ij}, F_{ij} \in [0, 1]$, and $0 \leq T_{ij} + I_{ij} + F_{ij} \leq 3$, $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$.

Step 2: The relative weight of each attribute G_j is calculated by the following formula:

$$\omega_{jr} = \omega_j / \omega_r, \qquad (j, r = 1, 2, \cdots, n). \tag{9}$$

The weight of G_j attribute is determined by ω_j represents, $\omega_r = \max(\omega_j | j = 1, 2, \cdots, n)$ and $0 \leq \omega_{jr} \leq 1$.

Step 3: The A_i dominance $\phi_j(A_i, A_k)$ of each alternative A_k under attribute G_j is calculated by the (10);

$$\phi_j = (A_i, A_k) = \begin{cases} \sqrt{\omega_{jr} d(r_{ij}, r_{kj}) / \sum_{j=1}^{n} \omega_{jr}}, & if \quad r_{ij} > r_{kj} \\ 0, & if \quad r_{ij} = r_{kj} \\ -\frac{1}{\theta}\sqrt{\left(\sum_{j=1}^{n} \omega_{jr}\right) d(r_{ij}, r_{kj}) / \omega_{jr}}, & if \quad r_{ij} < r_{kj} \end{cases} \tag{10}$$

Step 4: The overall dominance degree $\delta(A_i, A_k)$ of alternative A_i and each alternative A_k is calculated by (11);

$$\delta(A_i, A_k) = \sum_{j=1}^{n} \phi_j(A_i, A_k), \quad (i, k = 1, 2, \cdots, m) \tag{11}$$

Step 5: The overall value $\delta(A_i)$ of each alternative A_i is calculated through (12);

$$\delta(A_i) = \frac{\sum_{k=1}^{m} \delta(A_i, A_k) - \min_i \left\{ \sum_{k=1}^{m} \delta(A_i, A_k) \right\}}{\max_i \left\{ \sum_{k=1}^{m} \delta(A_i, A_k) \right\} - \min_i \left\{ \sum_{k=1}^{m} \delta(A_i, A_k) \right\}}, \tag{12}$$

where $(i = 1, 2, \cdots, m)$.

Step 6: The order of alternatives is determined by $\delta(A_i)$ $(i = 1, 2, \cdots, m)$.

D. A CPT-based Extended TODIM Method

Suppose, the alternative is represented by $A = \{A_1, A_2, \cdots A_m\}$, and the attribute is represented by $G = \{G_1, G_2, \cdots G_n\}$. The weight of the attribute is $\omega = \{\omega_1, \omega_2, \cdots \omega_m\}$, where $\omega_j \in [0, 1]$, $\sum_{j=1}^{n} \omega_j = 1$.

For convenience, let $N = \{1, 2, \cdots n\}$ and $M = \{1, 2, \cdots m\}$.

Step 1: Determine the decision matrix and the relative importance of the attributes listed below.:

$$R = (r_{ij})_{n \times m} = \begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{pmatrix}.$$

Step 2: Work out the transformed probability of the alternative A_i to A_k, $k \in M$ and $k \neq i$ according to (13) or (14).

When $r_{ij} \geq r_{kj}$, the transformed probability weight is acquired by (13):

$$\varpi_{ikj}^{+}(\omega_j) = \omega_j^{\gamma} / \left(\omega_j^{\gamma} + (1 - \omega_j)^{\gamma}\right)^{\frac{1}{\gamma}}. \tag{13}$$

Otherwise, the transformed probability weight is calculated by (14):

$$\varpi_{ikj}^{-}(\omega_j) = \omega_j^{\delta} / \left(\omega_j^{\delta} + (1 - \omega_j)^{\delta}\right)^{\frac{1}{\delta}}. \tag{14}$$

The parameters γ and δ are defined in Section 2.2.

Step 3: The A_i dominance ϖ_{ikj^*} of each alternative A_k under attribute G_j is calculated by the (15);

$$\varpi_{ikj^*} = \varpi_{ikj}(\omega_j) / \varpi_{ikr}(\omega_r), r, j \in M, \forall (i, k). \tag{15}$$

where $\varpi_{ikj}(\omega_j)$ and $\varpi_{ikr}(\omega_r)$ are all acquired from (12) or (13) depending on the value of $r_{ij} \geq r_{kj}$ for the alternative A_i to A_k: while $\varpi_{ikj}(\omega_j)$ for the alternative A_i, denotes the converted weight of the jth attribute; $\varpi_{ikr}(\omega_r)$ denotes the modified weight of the reference attribute for the A_i to A_k alternative fulfilling $\varpi_{ikr}(\omega_r) = \max(\varpi_{ikj}(\omega_j) | j \in M)$.

Step 4: Alternative A_i relative prospect dominance over A_k under attribute j is calculated using (16):

$$\varphi_{j^*}(A_i, A_k) = \begin{cases} \varpi_{ikj^*} d(r_{ij}, r_{kj})^{\alpha} / \sum_{j^*=1}^{m} \varpi_{ikj^*}, & if \ r_{ij} > r_{kj} \\ 0, & if \ r_{ij} = r_{kj} \\ -\lambda \left(\sum_{j^*=1}^{m} \varpi_{ikj^*}\right) d(r_{kj}, r_{ij})^{\delta} / \varpi_{ikj^*}, & if \ r_{ij} < r_{kj} \end{cases} \tag{16}$$

where α, δ, and γ are the parameters defined in Section II-B.

Step 5: According to (17), the relative anticipated dominance of alternative A_i over A_k for all qualities is as follows:

$$\psi(A_i, A_k) = \sum_{j=1}^{m} \varphi_{j^*}(A_i, A_k), \forall (i, k) \tag{17}$$

Step 6: The overall prospect advantage of alternative A_i is obtained by (12).

Step 7: Through understanding, we know the overall prospect value $\psi(A_i)$, the greater the project A_i, the better. So $\psi(A_i), i \in N$, according to the order we can find the optimal solution.

The altered probability weighting function and the related CPT value function are included in the above steps of the enhanced TODIM technique developed by us, which makes the decision-making process more congruent with the decision maker's psychological behavior. In terms of practical applicability, it is more reasonable. An example is presented in the next part to demonstrate the efficacy of the proposed method.

III. Numerical Example and Comparative Analysis

We introduce an example of [23], in which experts evaluate the commercialization potential of five emerging technology enterprises (ETEs) A_i $(i = 1, 2, 3, 4, 5)$ from four attributes, and give an evaluation matrix based on SVNNs. Thus, the EYES with the most potential are selected, where the properties are respectively expressed as: (1) G_1 represents job creation; (2) G_2 represents research and technology development; (3) G_3 represents technological advancement; and (4) G_4 represents industrialization infrastructure. The five ETEs A_i $(i = 1, 2, 3, 4, 5)$ should be evaluated using the SVNNs under the aforementioned four characteristics (whose weighting vector $\omega = (0.2, 0.1, 0.3, 0.4)^T$), as shown in the matrix below.

$$R = \begin{bmatrix} (0.5, 0.8, 0.1), (0.6, 0.3, 0.3), \\ (0.7, 0.2, 0.1), (0.7, 0.2, 0.2), \\ (0.6, 0.7, 0.2), (0.5, 0.7, 0.3), \\ (0.8, 0.1, 0.3), (0.6, 0.3, 0.4), \\ (0.6, 0.4, 0.4), (0.4, 0.8, 0.1), \end{bmatrix}$$

$$\begin{bmatrix} (0.3, 0.6, 0.1), (0.5, 0.7, 0.2), \\ (0.7, 0.2, 0.4), (0.8, 0.2, 0.1), \\ (0.5, 0.3, 0.1), (0.6, 0.3, 0.2), \\ (0.3, 0.4, 0.2), (0.5, 0.6, 0.1), \\ (0.7, 0.6, 0.1), (0.5, 0.8, 0.2), \end{bmatrix}$$

A. For SVN MADM problems, the traditional TODIM approach is used.

To choose the optimum ETE, we apply the TODIM approach from SVN MADM Problems.

To begin, $\omega_4 = \max(\omega_1, \omega_2, \omega_3, \omega_4)$. The reference attribute has a weight of $\omega_r = 0.4$, and the reference attribute is G_4. The relative weights of the properties $G_j\,(j = 1, 2, 3, 4)$ are $\omega_{1r} = 0.50, \omega_{2r} = 0.25, \omega_{3r} = 0.75, \omega_{4r} = 1.00$. With $\theta = 2.5$, the dominance degree matrix $\phi_j(A_i, A_k)\,(j = 1, 2, 3, 4)$ with respect to G_j can be calculated as follows:

$$\phi_1 = \begin{bmatrix} 0.0000 & -0.4619 & -0.2828 & -0.5657 & -0.4619 \\ 0.2309 & 0.0000 & 0.2160 & 0.1633 & 0.2000 \\ 0.1414 & -0.4320 & 0.0000 & -0.4899 & -0.3651 \\ 0.2828 & -0.3266 & 0.2449 & 0.0000 & 0.2000 \\ 0.2309 & -0.4000 & 0.1826 & -0.4000 & 0.0000 \end{bmatrix}$$

$$\phi_2 = \begin{bmatrix} 0.0000 & -0.4000 & 0.1291 & 0.0577 & 0.1732 \\ 0.1000 & 0.0000 & 0.1633 & 0.1155 & 0.1826 \\ -0.5164 & -0.6532 & 0.0000 & -0.5657 & -0.4619 \\ -0.2309 & -0.4619 & 0.1414 & 0.0000 & 0.1826 \\ -0.6928 & -0.7303 & 0.1155 & -0.7303 & 0.0000 \end{bmatrix}$$

$$\phi_3 = \begin{bmatrix} 0.0000 & -0.4422 & -0.2981 & -0.2309 & -0.2667 \\ 0.3317 & 0.0000 & -0.3266 & 0.2828 & 0.2646 \\ 0.2236 & 0.2449 & 0.0000 & 0.2000 & 0.2236 \\ 0.1732 & -0.3771 & -0.2667 & 0.0000 & -0.3528 \\ 0.2000 & -0.3528 & -0.2981 & 0.2646 & 0.0000 \end{bmatrix}$$

$$\phi_4 = \begin{bmatrix} 0.0000 & -0.3464 & -0.2582 & -0.1633 & 0.1155 \\ 0.3464 & 0.0000 & 0.2309 & 0.3055 & 0.3651 \\ 0.2582 & -0.2309 & 0.0000 & 0.2582 & 0.2828 \\ 0.1633 & -0.3055 & -0.2582 & 0.0000 & 0.2000 \\ -0.1155 & -0.3651 & -0.2828 & -0.2000 & 0.0000 \end{bmatrix}$$

The overall dominance degree $\delta(A_i)\,(i = 1, 2, 3, 4, 5)$ can be calculated by (12):

$$\delta(A_1) = 0.0000, \delta(A_2) = 1.0000, \delta(A_3) = 0.2648$$

$$\delta(A_4) = 0.3944, \delta(A_5) = 0.0187$$

Finally, we may use $\delta(A_i)(i = 1, 2, 3, 4, 5)$ to order ETEs: $A_2 \succ A_4 \succ A_3 \succ A_5 \succ A_1$, with A_2, with A_2 being the most desirable ETE.

B. A CPT-based Extended TODIM Method

After we've established the R matrix, we'll use the alternative A_1 as an example to determine its overall prospect dominance.

The converted probability weight is determined using (13) or (14), and it is based on the relative value of the alternative A_1 in each attribute compared to the others, as shown in Table I

$\gamma = 0.61, \delta = 0.69$ in (13) and (14), respectively. The figures come from a research by Tversy and Kahneman [25], and they're largely accepted among scientists.

TABLE I
THE TRANSFORMED PROBABILITY WEIGHT FOR EACH ATTRIBUTE

	G_1	G_2	G_3	G_4
ϖ_{12}	0.26	0.19	0.33	0.39
ϖ_{13}	0.26	0.17	0.33	0.37
ϖ_{14}	0.26	0.17	0.33	0.37
ϖ_{15}	0.26	0.17	0.33	0.37

TABLE II
THE RELATIVE WEIGHT FOR EACH ATTRIBUTE

	G_{1^*}	G_{2^*}	G_{3^*}	G_{4^*}
ϖ_{12}	1.00	1.00	1.00	1.00
ϖ_{13}	1.00	0.91	1.00	1.00
ϖ_{14}	1.00	0.91	1.00	1.00
ϖ_{15}	1.00	0.91	1.00	0.94

TABLE III
THE RELATIVE PROSPECT DOMINANCE FOR EACH ATTRIBUTE

	G_{1^*}	G_{2^*}	G_{3^*}	G_{4^*}
$\varphi_{j^*}(A_1, A_2)$	-2.7515	-1.2991	-3.7222	-3.0766
$\varphi_{j^*}(A_1, A_3)$	-1.1607	0.0517	-1.8599	-1.5071
$\varphi_{j^*}(A_1, A_4)$	-3.9313	0.0125	-1.1864	-0.8189
$\varphi_{j^*}(A_1, A_5)$	-2.7515	0.0867	-1.5282	0.01200

TABLE IV
THE RELATIVE PROSPECT DOMINANCE

$\psi(A_1, A_2)$	$\psi(A_1, A_3)$	$\psi(A_1, A_4)$	$\psi(A_1, A_5)$
-10.8494	-4.4760	-5.9241	-4.1811

TABLE V
THE OVERALL PROSPECT DOMINANCE

$\psi(A_1)$	$\psi(A_2)$	$\psi(A_3)$	$\psi(A_4)$	$\psi(A_1)$
0.0000	1,0000	0.2480	0.3567	0.0089

Step 2 returns the converted probability weight, and (15) may be used to compute the relative weight ϖ_{1kj^*} of the alternative A_1 relative to other characteristics under each attribute. This is depicted in table II.

According to (16), the relative prospect dominance of the alternative A_1 for each characteristic will be assessed, and the findings will be given in Table III.

$\alpha = 0.88, \beta = 0.88, \lambda = 2.25$ are employed in (16). The figures come from a research by Tversy and Kahneman [25], and they're largely accepted among scientists.

According to (17), the alternative A_1 has a relative potential dominance over other alternatives, as shown in Table IV.

To calculate the foreground dominance of each option, repeat steps 2-5, and the results are given in the table V.

By looking at table VI, we can get $\psi(A_2) > \psi(A_4) > \psi(A_3) > \psi(A_5) > \psi(A_1)$, therefore, the order of the five alternatives is $A_2 \succ A_4 \succ A_3 \succ A_5 \succ A_1$.

C. Comparative Analysis

As shown in Table VI, the ranking results are the same for the two methods. It is obvious that A_2 is the most potential emerging technology enterprise. Theoretically speaking, the extended TODIM method combines the value function of the converted weight function, which makes the decision

TABLE VI
THE RESULTS OF BOTH METHODS

Method	Ranking	Optimal
The traditional TODIM	$A_2 \succ A_4 \succ A_3 \succ A_5 \succ A_1$	A_2
The proposed TODIM	$A_2 \succ A_4 \succ A_3 \succ A_5 \succ A_1$	A_2

situation more reasonable. Furthermore, the CPT-based extended TODIM technique can better describe the objective psychological state of DMs. This successfully proves the method described in this paper's rationale and effectiveness. Therefore, this method is feasible for DMs to make decisions on complex environments.

IV. CONCLUSIONS

CPT analyzes the unreasonable factors of the uncertainty of scheme optimization decision-making influence, so accumulated comprehensive prospect of each scheme established maximum dynamic nonlinear model of index weight constraint. This paper on the idea of CPT and extends the classic TODIM method. This method is a lot of totally considering the objective state of mind of DMs. The proposed method is applied to SVNS multiple attribute decision making issues, and therefore the results show the practicableness and relevancy. With traditional methods.Through comparison, we can see that though the results of the two methods are constant, the largest distinction within the TODIM method based on CPT proposed to the present paper lies of the distinction between the weight function and also the value function. As are often seen from Table VI, the overall advantages of the two methods are also totally different. Though extended TODIM incorporates a sensible advantage within the selection of emerging technology enterprises, we have a tendency to ignore the role of DMs psychological science of different fields. Therefore, in future analysis, we should further to expand the decision-making method of DMs in fuzzy decision-making atmosphere.

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