A Method Based on TOPSIS and Distance Measures for Single-Valued Neutrosophic Linguistic Sets and Its Application

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***Abstract*—In this paper, a new approach of single-valued neutrosophic linguistic (SVNL) distance measure is proposed in multiple-attribute group decision-making (MAGDM). The combining idea of the weighted average and the ordered weighted average is a SVNL distance. Firstly, we propose a new SVNL weighted distance measure, it is a SVNL combined and weighted distance (SVNLCWD) measure, which can reflect decision-makers'(DMs) attitudes towards the importance and weights of the argument. Secondly, a SVNLCWD-TOPSIS approach for MAGDM problems with SVNL information is proposed, and then a modified relative coefficient is proposed to sort the potential schemes. Finally, the validity and feasibility of the model are verified by an example of a low carbon logistics service provider selection.**

***Index Terms*—Single-valued neutrosophic linguistic set, MAGDM, TOPSIS, combined weights, low carbon logistics service providers selection.**

I. Introduction

MAGDM is a kind of multi-objective decision-making, which is also called multi-objective decision-making of finite scheme. It is to select and sort the limited schemes with multiple attributes (indexes) according to some decision criteria [1]. However, MAGDM involves multiple decision makers, which has a wide application in management, e-conomy, military and other fields. In the decision-making process, many different attributes need to be embedded and evaluated [2, 3, 4, 5, 6]. If the attribute information is known and accurate, it can be accurately evaluated [7, 8, 9, 10, 11]. However, in the actual MAGDM problem, due to the increasing uncertainty of the object, it is more and more difficult for people to accurately express the evaluation of its attribute in the decision-making process. Therefore, in these complex cases, it is a very important problem to deal with uncertain or fuzzy information effectively. Next, several tools have been proposed to describe such uncertain information, Ye [12] proposed a new tool to solve this kind of information, namely SVNL. By unifying the characteristics of single-value neutrosophic sets [13, 14] and language items [15], SVNLs can eliminate their disadvantages and have been shown to be suitable for measuring subjective evaluations with a high degree of uncertainty. According to recent research trends, SVNLs has been widely used to deal with MAGDM problems in uncertain and imprecise information environments. Ye [12] studied the method (TOPSIS) of similarity of ideal solution and discussed the application of this method in decision-making problems. Ye [16] extended some neutrosophic linguistic (NL) operators for the research and application of mathematical problems. For SVNLs, Wang et al. [17] studied SVNL aggregation operator using maclaurin symmetric mean method. Luo et al. [18] developed a simplified NL MAGDM problem model based on distance. Tian et al. [19] proposed the QUALIFLEX method to solve the selection of green products with SVNL information. Wu et al. [20] extended SVNL to binary case, discussed some of its algorithms, and studied its application in MAGDM problems.

In many MAGDM methods, distance measure is one of the most widely used tools to measure the difference between a desired solution and a potential alternative. Recently, ordered weighted average distance (OWAD) operation scheme has been more and more popular among researchers [21]. Several OWAD extension machines have been used to solve MAGDM probl, Merig et al. [22] proposed the induced OWAD operator, Zeng et al. [23] proposed intuitionistic fuzzy OWAD operator, Xu et al. [24] proposed the hesitant fuzzy OWAD operator, Zeng et al. [25] proposed the probabilistic OWAD operator, Qin et al. [26] proposed the pythagorean fuzzy generalized OWAD operator, Xian et al. [27] proposed the fuzzy linguistic induced euclidean OWAD operator, Zhou et al. [28] proposed the continuous OWAD operator and Li et al. [29] proposed the intuitionistic fuzzy weighted induced OWAD operator. In addition, in the past several decades of research, TOPSIS approach has been used to deal with MAGDM problems in different types of fuzzy cases, such as in fuzzy number context [30], in IFS context [31, 32], in pythagorean theorem fuzzy environment [33] and in language set [34]. Biswas et al. [35] introduced TOPSIS model to deal with SVNL and applied it to multi-objective decision-making (MADM). Peng et al. [36] proposed a new bisection function and similarity measure to study SVNL-TOPSIS method. From the detailed analysis of the above studies, we can see that the importance of attributes in decision-making results is ignored. In order to overcome this defect, this paper develops a combination weighted distance based on SVNLs, namely SVNLCWD operator, and then proposes an improved SVNL-TOPSIS technology, namely SVNLCWD-TOPSIS approach.

The structure of the rest of this paper is as follows. In Section II, the preparation part of SVNL is given. In Section

Manuscript received January 4, 2021; revised May 18, 2021. This work was supported in part by Humanities and Social Sciences Foundation of Ministry of Education of the Peoples Republic of China under Grant 17YJA630115.

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III, the combined weighted distance measure of SVNLs is proposed. In Section IV, an improved TOPSIS method with SVNL information is introduced. In Section V, an example of low carbon logistics service providers selection is given to illustrate the application, effectiveness and feasibility of the modified TOPSIS method. Finally, in Section VI, we come to the conclusion.

II. Preliminaries

A. The Linguistic Set

Let $S = \{s_\tau | \tau = 1, 2, \ldots, l\}$ is an ordered discrete set, where l is an odd number and s_τ represents the possible value of a linguistic variable. For example, let $l = 7$, a linguistic term set S be expressed as $S = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7\} = \{s_1 = extremelypoor, s_2 = verypoor, s_3 = poor, s_4 = fair, s_5 = good, s_6 = verygood, s_7 = extremelygood\}$. At the same time, any two linguistic variables s_m and s_n must satisfy the following rules (1)-(4) [37]:

(1)$s_m \geq s_n \Longleftrightarrow m \geq n$;
(2)$Neg(s_m) = s_{l-m}$;
(3)$min(s_m, s_n) = s_m$, if $m \leq n$;
(4)$max(s_m, s_n) = s_n$, if $m \leq n$.

In order to minimize the information loss in the operation process, the ordered discrete set should be extended to the continuous set $\tilde{S} = \{s_\tau | \tau \in R\}$, any two linguistic variables $s_m, s_n \in \tilde{S}$, the following operation rules (1)-(3) [38] are satisfied:

(1)$s_m \oplus s_n = s_{m+n}$;
(2)$\lambda s_m = s_{\lambda m}, \lambda \geq 0$;
(3)$s_m / s_n = s_{m/n}$.

B. The Single-Valued Neutrosophic Set

Definition 1 [12] Let X be a universal space of points (objects), with a generic element in X denoted by x, single-valued neutrosophic set (SVNS) Q $\subset X$ is characterized by truth-membership function $T_{q(x)}$, indeterminacy-membership function $I_{q(x)}$ and falsity-membership function $F_{q(x)}$. A SVNS can be expressed as

$$Q = \left\{ \left[\langle x, T_{q(x)}, I_{q(x)}, F_{q(x)} \rangle \right] | x \in X \right\} \tag{1}$$

where $T_{q(x)}$, $I_{q(x)}$, $F_{q(x)}$ are real standard or nonstandard subsets of $[0, 1]$, so that it means $T_{q(x)}$: X$\rightarrow$ $[0, 1]$, $I_{q(x)}$: X$\rightarrow$ $[0, 1]$, $F_{q(x)}$: X$\rightarrow$ $[0, 1]$, with the condition of $0 \leq \sup T_q(x) + \sup I_q(x) + \sup F_q(x) \leq 3$, for all $x \in X$.

When X is continuous, a SVNS Q can be written as

$$Q = \int_X \langle T_{q(x)}, I_{q(x)}, F_{q(x)} \rangle / x, \quad x \in X \tag{2}$$

When X is discrete, a SVNS Q can be written as

$$Q = \sum_{i=1}^{n} \langle T_{q(x_i)}, I_{q(x_i)}, F_{q(x_i)} \rangle / x_i, \quad x_i \in X \tag{3}$$

Definition 2 [40, 41, 42] Let Q and P be two SVNSs, Q = $\langle T_{q(x)}, I_{q(x)}, F_{q(x)} \rangle$, P = $\langle T_{p(x)}, I_{p(x)}, F_{p(x)} \rangle$, then$\forall$ $x \in X$, $\forall$ $\lambda \in R$ and $\lambda > 0$, there is

(1)$Q \oplus P = \langle T_{q(x)} + T_{p(x)} - T_{q(x)} \cdot T_{p(x)}, I_{q(x)} \cdot I_{p(x)}, F_{q(x)} \cdot F_{p(x)} \rangle$;
(2)$Q \otimes P = \langle T_{q(x)} \cdot T_{p(x)}, I_{q(x)} + I_{p(x)} - I_{q(x)} \cdot I_{p(x)}, F_{q(x)} + F_{p(x)} - F_{q(x)} \cdot F_{p(x)} \rangle$;
(3)$\lambda Q = (1 - (1 - T_{q(x)})^\lambda, {I_{q(x)}}^\lambda, {F_{q(x)}}^\lambda)$;
(4)$Q^\lambda = ({T_{q(x)}}^\lambda, 1 - (1 - I_{q(x)})^\lambda, 1 - (1 - F_{q(x)})^\lambda)$.

C. The Single-Valued Neutrosophic Linguistic Set

Definition 3 [12] Let X be a finite universe set, and SVNLs Q in X is defined as follows:

$$Q = \left\{ \langle x, [S_{\theta(x)}, (T_{q(x)}, I_{q(x)}, F_{q(x)})] \rangle | x \in X \right\} \tag{4}$$

where $T_{q(x)}$, $I_{q(x)}$, $F_{q(x)}$ are the truth-membership function, the indeterminacy- membership function and the falsity-membership function, with the condition of $T_{q(x)} \in [0, 1]$, $I_{q(x)} \in [0, 1]$, $F_{q(x)} \in [0, 1]$, $0 \leq T_{q(x)} + I_{q(x)} + F_{q(x)} \leq 3$, for all $x \in X$.

For the convenience of calculation, the SVNLV $\langle S_{\theta(x)}, (T_{q(x)}, I_{q(x)}, F_{q(x)}) \rangle$ can be abbreviated as $x = \langle S_{\theta(x)}, (T_x, I_x, F_x) \rangle$.

Definition 4 [12] Let $a = \langle S_{\theta(a)}, (T_a, I_a, F_a) \rangle$, $b = \langle S_{\theta(b)}, (T_b, I_b, F_b) \rangle$, be two SVNLVs, then they satisfy the following operation rules:

(1)$a \oplus b = \langle S_{\theta(a)+\theta(b)}, (T_a + T_b - T_a \cdot T_b, I_a \cdot I_b, F_a \cdot F_b) \rangle$;
(2)$\lambda a = \langle S_{\lambda\theta(a)}, (1 - (1 - T_a)^\lambda, {I_a}^\lambda, {F_a}^\lambda) \rangle, \lambda > 0$;
(3)$a^\lambda = \langle S_{\theta^\lambda(a)} ({T_a}^\lambda, 1 - (1 - I_a)^\lambda, 1 - (1 - F_a)^\lambda) \rangle, \lambda > 0$.

Definition 5 Let $a = \langle S_{\theta(a)}, (T_a, I_a, F_a) \rangle, b = \langle S_{\theta(b)}, (T_b, I_b, F_b) \rangle$, be two SVNLVs, $S = \{s_1, s_2, \ldots, s_{2t+1}\}$ is the linguistic term set. The distance between a and b can be defined as

$$\begin{aligned} d(a, b) =& [|\theta(a)T_a - \theta(b)T_b|^\rho + |\theta(a)I_a - \theta(b)I_b|^\rho + \\ & |\theta(a)F_a - \theta(b)F_b|^\rho]^{\frac{1}{\rho}} \end{aligned} \tag{5}$$

If each distance of SVNLVs is given different weights, then we will get the measure of single-valued neutrosophic linguistic weighted distance (SVNLWD).

Definition 6 [43] Let h_j, $h_j^{'} (j = 1, 2, \ldots, n)$, be the two collections of SVNLVs. A SVNLWD measure of dimension n is a mapping SVNLWD: $\Omega^n \times \Omega^n \longrightarrow R$ that has an associated weighting vector $V = (v_1, v_2, \ldots, v_n)^T$ with $\sum\limits_{j=1}^{n} v_j = 1$ and $v_j \in [0, 1]$, as follows:

$$SVNLWD((h_1, h_1^{'}), \ldots, (h_n, h_n^{'})) = \sum_{j=1}^{n} v_j d(h_j, h_j^{'}) \tag{6}$$

The ordered weighted averaging (OWA) operator proposed by Yager [44] is the most important aggregation technique, which has been studied and popularized by some researchers. The most remarkable advantage of OWA operator is its ranking mechanism for the arguments considered, which integrates the complex attitude characteristics of decision makers in the decision process. In recent years, the application of OWA distance (OWAD) measure has become a fruitful research topic, and has made many achievements [21, 45, 46, 28]. Based on OWAD operator, Chen et al. [47] introduced SVNLOWAD measure to collect SVNL information.

Definition 7 Let h_j, $h_j^{'} (j = 1, 2, \ldots, n)$, be the two collections of SVNLVs. The definition is as follows:

$$SVNLOWAD((h_1, h_1^{'}), \ldots, (h_n, h_n^{'})) = \sum_{j=1}^{n} w_j d(h_j, h_j^{'}) \tag{7}$$

where $d(h_j, h_j^{'})$ is the j-th largest value of the $d(h_i, h_i^{'}) (i = 1, 2, \ldots, n)$. $d(h_i, h_i^{'})$ is defined in Equation (5). $W = (w_1, w_2, \ldots, w_n)^T$ is an associated weighting vector for the

SVNLOWAD operator and with the condition of $\sum_{j=1}^{n} w_j = 1$, $w_j \in [0,1]$.

From the above statement, we can see that there are still some defects in these two operators. In order to overcome this defect, next, in section III, we will propose a combined weighted distance metric to mitigate these shortcomings.

III. The Combined Weighted Distance Operator of SVNLs

SVNLCWD operator can combine the advantages of SVNLWD operator and SVNLOWAD operator. It is able to integrate the attitudes of DMs and embed weighted averages based on the importance of alternatives. Furthermore, it allows DMs to flexibly adjust the proportion of SVNLWD and SVNLOWAD according to the needs of specific issues or their interests. Therefore, the SVNLCWD measure is defined as follows.

Definition 8 Let h_j, $h_j^{'}(j = 1,2,\ldots,n)$, be the two collections of SVNLVs. The definition is as follows:

$$SVNLCWD((h_1,h_1^{'}),\ldots,(h_n,h_n^{'}))=\sum_{j=1}^{n}\varphi_j d(h_j,h_j^{'}) \quad (8)$$

where $\varphi_j = \mu v_j + (1-\mu)w_j$ with $\mu \in [0,1]$. $d(h_j,h_j^{'})$ is the j-th largest value of the $d(h_i,h_i^{'})(i = 1,2,\ldots,n)$, $d(h_i,h_i^{'})$ is defined in Equation (5). v_j is the weight of weighted averaging(WA) with $\sum_{j=1}^{n} v_j = 1$ and $v_j \in [0,1]$. w_j is the weight of OWA with $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0,1]$.

Note that the SVNLCWD operator can be linearly decomposed into a combination of SVNLWD and SVNLOWAD by the above basic algorithms.

Definition 9 Let h_j, $h_j^{'}(j = 1,2,\ldots,n)$, be the two collections of SVNLVs. Such that:

$$SVNLCWD((h_1,h_1^{'}),\ldots,(h_n,h_n^{'}))=\mu\sum_{i=1}^{n}v_i d(h_i,h_i^{'}) + (1-\mu)\sum_{j=1}^{n}w_j d(h_j,h_j^{'}) \quad (9)$$

where $d(h_j,h_j^{'})$ is the j-th largest value of the $d(h_i,h_i^{'})(i = 1,2,\ldots,n)$, $d(h_i,h_i^{'})$ is defined in Equation (5), and $\mu \in [0,1]$. Obviously, when $\mu = 1$, we get the SVNLWD, when $\mu = 0$, we get the SVNLOWAD.

In addition, by using different weighted vectors to represent the measurements in SVNLCWD, we can get some SVNL weighted distance measurements in a wide range of special cases, such as:

- The maximum-SVNLWD (SVNLMaxD) is found, when $W = (1,0,\ldots,0)^T$.
- The normalized-SVNLWD (SVNLNorD) is found, when $W = (\frac{1}{n},\frac{1}{n},\ldots,\frac{1}{n})^T$.
- In general, the step-SVNLCWD is found, when $w_k = 1$, and $w_j = 0(j \neq k)$.
- For the median-SVNLCWD, if n is even, then $w_{\frac{n}{2}} = w_{\frac{n}{2}+1} = 0.5$, if n is odd, then $w_{\frac{n+1}{2}} = 1$ and $w_j = 0, j = 1,\ldots,\frac{n-1}{2},\frac{n+3}{2},\ldots,n$.

According to the recently studied literature [45, 48, 49, 50], we can explore other special SVNLCWD operators.

IV. MAGDM Using the SVNLCWD-TOPSIS Approach

A. Description of The MAGDM Problem in SVNL Environments

For a given MAGDM problem in SVNL environment, let $A = (a_1,a_2,\ldots,a_m)$ is a discrete set of m feasible alternatives, $L = (l_1,l_2,\ldots,l_n)$ is a set of attributes, $V = (v_1,v_2,\ldots,v_n)^T$ is the weight vector of all attributes, which meets $\sum_{j=1}^{n} v_j = 1$ and $v_j \in [0,1]$. e_t is the t-th DM (or expert), ω_t is the weight of the t-th DM (or expert). The evaluation $b_{ij}^{(k)}$ is given by the DM (or expert), $b_{ij}^{(k)} = \langle S_{\theta(b_{ij})}^k, (T_{b_{ij}}^k, I_{b_{ij}}^k, F_{b_{ij}}^k)\rangle$, meeting $S_{\theta(b_{ij})}^k \in \tilde{S}$, $T_{b_{ij}}^k \in [0,1]$, $I_{b_{ij}}^k \in [0,1]$, $F_{b_{ij}}^k \in [0,1]$, $0 \le T_{b_{ij}}^k + I_{b_{ij}}^k + F_{b_{ij}}^k \le 3$.

Therefore, the individual decision matrix can be represented as the following matrix form:

$$B^k=(b_{ij}^{(k)})_{m\times n}= \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{array} \begin{array}{c} \begin{array}{cccc} l_1 & l_2 & \cdots & l_n \end{array} \\ \begin{pmatrix} b_{11}^{(k)} & b_{12}^{(k)} & \cdots & b_{1n}^{(k)} \\ b_{21}^{(k)} & b_{22}^{(k)} & \cdots & b_{2n}^{(k)} \\ \vdots & \vdots & \cdots & \vdots \\ b_{m1}^{(k)} & b_{m2}^{(k)} & \cdots & b_{mn}^{(k)} \end{pmatrix} \end{array} \quad (10)$$

B. The SVNL TOPSIS Approach Proposed By Ye

The classical TOPSIS method is proposed by Hwang and Yoon [51]. It is an effective method to select the scheme based on the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS). Ye [12] extends the classical TOPSIS method, and effectively solves the MAGDM problem in SVNL environment. The method mainly includes the following steps:

Step 1: Normalize decision matrices:

In fact, attributes can be divided into two types, namely benefit attributes and cost attributes. Converting a cost type to a benefit type can avoid the effects of an attribute type. So let E and F be the set of benefit attributes and cost attributes. The following transformation method is used for decision matrix $B^k = (b_{ij}^{(k)})_{m\times n}$:

$$\begin{cases} c_{ij}^{(k)} = b_{ij}^{(k)} = \langle S_{\theta(b_{ij})}^k, (T_{b_{ij}}^k, I_{b_{ij}}^k, F_{b_{ij}}^k)\rangle, for j \in E, \\ c_{ij}^{(k)} = \langle S_{l-\theta(b_{ij})}^k, (T_{b_{ij}}^k, I_{b_{ij}}^k, F_{b_{ij}}^k)\rangle, for j \in F. \end{cases} \quad (11)$$

So we can get the normalize decision matrices $C^k = (c_{ij}^{(k)})_{m\times n}$:

$$C^k = (c_{ij}^{(k)})_{m\times n} = \begin{pmatrix} c_{11}^{(k)} & c_{12}^{(k)} & \cdots & c_{1n}^{(k)} \\ c_{21}^{(k)} & c_{22}^{(k)} & \cdots & c_{2n}^{(k)} \\ \vdots & \vdots & \cdots & \vdots \\ c_{m1}^{(k)} & c_{m2}^{(k)} & \cdots & c_{mn}^{(k)} \end{pmatrix} \quad (12)$$

Step 2: Construct the group matrix:

Summarize the evaluation of each DMs into a set, we can get the following integrated matrix:

$$C=(c_{ij})_{m\times n}=\begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{pmatrix} \quad (13)$$

where $c_{ij}=\sum_{k=1}^{t}\omega_k c_{ij}^{(k)}$, $\omega_k(k=1,2,\ldots,t)$ represents the weight of the k-th expert, meeting $\omega_k\geq 0$ and $\sum_{k=1}^{t}\omega_k=1$.

Step 3: Determine the weight matrix:

By using Definition II-C, $V=(v_1,v_2,\ldots,v_n)^T$ is the weight vector of all attributes, we can compute $h_{ij}=v_j c_{ij}$. The following weight matrix is obtained:

$$H=(h_{ij})_{m\times n}=\begin{pmatrix} v_1c_{11} & v_2c_{12} & \cdots & v_nc_{1n} \\ v_1c_{21} & v_2c_{22} & \cdots & v_nc_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_1c_{m1} & v_2c_{m2} & \cdots & v_nc_{mn} \end{pmatrix} \quad (14)$$

Step 4: Compute the distance between each alternative $a_i(i=1,2,\ldots,m)$ and the PIS a^+ and the NIS a^-:

The PIS $a^+=\{h_1^+,h_2^+,\ldots,h_m^+\}$ and the NIS $a^-=\{h_1^-,h_2^-,\ldots,h_m^-\}$ are defined as follows:

$$\begin{cases} h_i^+=\langle s_l,(1,0,0)\rangle \\ h_i^-=\langle s_1,(0,1,1)\rangle \end{cases} \quad (15)$$

By using the Equation (5), we can compute the distance $d(a_i,a^+)$ and $d(a_i,a^-)$ of an alternative a_i from PIS a^+ and NIS a^-, as follows:

$$\begin{cases} d(a_i,a^+)=\sum_{j=1}^{n}d(h_{ij},h_j^+) \\ d(a_i,a^-)=\sum_{j=1}^{n}d(h_{ij},h_j^-) \end{cases} \quad (16)$$

Step 5: Calculate the relative closeness $\zeta(a_i)(i=1,2,\ldots,m)$of an alternative a_i as follows:

$$\zeta(a_i)=\frac{d(a_i,a^+)}{d(a_i,a^+)+d(a_i,a^-)} \quad (17)$$

Step 6: Rank all alternatives:

The relative closeness coefficient is used to rank all alternatives, the best alternative is determined according to the results obtained. And the smaller $\zeta(a_i)$ is, the best alternative is.

In SVNL environments, TOPSIS proposed by Ye [12] is a simple and feasible approach to deal with MAGDM problems. But this approach only considers the subjective information of the attribute. Sometimes, in the decision-making process, the attitude characteristics of the DM should also be considered. Therefore, in order to overcome this shortcoming, we should vigorously develop and propose a modified SVNL TOPSIS method, which can consider both the subjective information of attributes and the attitude characteristics of DMs.

C. The Proposed SVNLCWD-TOPSIS Approach

On the basis of the above analysis, a new SVNLCWD-TOPSIS approach is proposed in the decision-making process, which takes into account the subjective information and attitude characteristics of the decision-maker. The main steps of this approach are as follows:

Step 1: Same as Step 1 described in Section IV-B.

Step 2: Same as Step 2 described in Section IV-B.

Step 3: Same as Step 3 described in Section IV-B.

Step 4: By using Equation (8), the SVNLCWD is calculated between each alternative $a_i(i=1,2,\ldots,m)$ form PIS a^+ and NIS a^-:

$$SVNLCWD(a_i,a^+)=\sum_{j=1}^{n}\varphi_j\hat{d}(h_{ij},h_j^+) \quad (18)$$

$$SVNLCWD(a_i,a^-)=\sum_{j=1}^{n}\varphi_j\hat{d}(h_{ij},h_j^-) \quad (19)$$

where $\hat{d}(h_{ij},h_j^+)$ is the j-th largest value among $d(h_{ij},h_j^+)$, $\hat{d}(h_{ij},h_j^-)$ is the j-th largest value among $d(h_{ij},h_j^-)$.

Step 5: The relative closeness coefficient $\zeta(a_i)$ calculated by Equation (17) is used to rank the alternatives in Ye's TOPSIS method. However, some authors find that the relative closeness can not reach the expected solution sometimes. Therefore, we introduce a modified relative closeness coefficient $\bar{\zeta}(a_i)$:

$$\bar{\zeta}(a_i)=\frac{SVNLCWD(a_i,a^-)}{\max\limits_{1\leq i\leq m}SVNLCWD(a_i,a^-)}-\frac{SVNLCWD(a_i,a^+)}{\min\limits_{1\leq i\leq m}SVNLCWD(a_i,a^+)}. \quad (20)$$

Step 6: Sort all alternatives and determine the best one(s) according to the modified relative closeness coefficient $\bar{\zeta}(a_i)$.

Remark 1. To provide complete information on the aggregate results of the decision analysis, we can consider the SVNLCWD family proposed in Section V to calculate the distance measures in different cases in Step 2. Therefore, we can obtain a parametric SVNLCWD-TOSIS method, for example, SVNLMaxD-TOPSIS, SVNLMinD-TOPSIS , SVNLNorD-TOPSIS, SVNLWD-TOPSIS, SVNLOWAD-TOPSIS and Step SVNLCWD-TOPSIS methods.

V. Practical Example

Due to the increasingly serious problems caused by carbon emissions, the concept of low carbon economy has gradually attracted the attention of the international community. The logistics industry is the basis and artery industry of national economic development, and it is also an industry with large energy consumption and carbon emission. With the advocacy

TABLE I
SVNL DECISION MATRIX B^1.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_6^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_2^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_3^{(1)}$, (0.5, 0.2, 0.2)$\rangle$	$\langle s_3^{(1)}$, (0.6, 0.2, 0.4)$\rangle$
a_2	$\langle s_5^{(1)}$, (0.4, 0.2, 0.3)$\rangle$	$\langle s_2^{(1)}$, (0.4, 0.2, 0.3)$\rangle$	$\langle s_4^{(1)}$, (0.3, 0.2, 0.5)$\rangle$	$\langle s_4^{(1)}$, (0.5, 0.3, 0.3)$\rangle$
a_3	$\langle s_5^{(1)}$, (0.7, 0.0, 0.1)$\rangle$	$\langle s_3^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_4^{(1)}$, (0.3, 0.1, 0.2)$\rangle$	$\langle s_6^{(1)}$, (0.6, 0.1, 0.2)$\rangle$
a_4	$\langle s_4^{(1)}$, (0.3, 0.2, 0.3)$\rangle$	$\langle s_3^{(1)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_4^{(1)}$, (0.5, 0.3, 0.1)$\rangle$	$\langle s_5^{(1)}$, (0.3, 0.5, 0.2)$\rangle$

and implementation of the concept of low carbon economy, the transformation and development of low carbon logistics industry will be an inevitable trend. However, the real market competition is not the competition between enterprises, but the competition between supply chains. How to choose a suitable low carbon logistics supplier is of great significance to reduce the carbon emissions of the whole supply chain and enhance the market competitiveness of the supply chain. We will use a numerical example of the low carbon logistics service provider selection problem provided by Chen et al.[47]. There are three experts (e_1, e_2, e_3) to evaluate, with four alternatives $a_i(i = 1, 2, 3, 4)$ and four attributes: l_1:low-carbon technology, l_2: cost, l_3: risk factor, l_4: capacity. Three experts are invited to evaluate the performances of the four alternatives. Under the linguistic term set $S = \{s_1 = extremelypoor, s_2 = verypoor, s_3 = poor, s_4 = fair, s_5 = good, s_6 = verygood, s_7 = extremelygood\}$, the results provided by three experts are contained in a SVNL decision matrix, The results are shown in tables 1-3.

Since l_2 and l_3 are both cost attributes, Equation (11) should be used for transformation, as follows:

$$c_{ij}^{(k)} = \langle S_{7-\theta(b_{ij})}^{k}, (T_{b_{ij}}^{k}, I_{b_{ij}}^{k}, F_{b_{ij}}^{k})\rangle, \quad k = 1, 2, 3; i = 1, 2, 3, 4; j = 2, 3. \tag{21}$$

Therefore, the normalized SVNL decision matrices can be obtained, as listed in tables 4-6.

Assume the weight vectors of DMs is $(\omega_1, \omega_2, \omega_3)^T = (037, 0.33, 0.30)^T$, then we can obtain the group SVNL decision matrix, as shown in table 7. Assume that the weight vectors of the attributes $V = (0.25, 0.40, 0.15, 0.20)^T$, Then the weighted SVNL decision matrix can be calculated. As shown in table 8.

Assume that the weight vectors of the SVNLCWD is $W = (0.25, 0.30, 0.10, 0.35)^T$, we calculate SVNLCWD (a_i, a^+) and SVNLCWD(a_i, a^-) measures between alternative a_i and PIS a^+ and NIS a^- using Equations (18) and (19). In this example, ρ and μ are assumed to be 1 and 0.4, respectively. we can obtain the ranking of all alternatives as shown in table 9.

The ranking order of the alternatives is $a_4 \prec a_2 \prec a_1 \prec a_3$. We can easily see that the ranking of the four alternatives obtained with the method in this paper is consistent with the result obtained with Ye's TOPSIS method [12]. Furthermore, in order to investigate further how the different particular cases of the SVNLCWD-TOPSIS have affection on the aggregation results, we consider the SVNLMaxD-TOPSIS method, the SVNLMinD-TOPSIS method, the SVNLWD-TOPSIS method, the SVNLOWAD-TOPSIS method and the Step SVNLCWD-TOPSIS method $(k = 2)$. The results are listed in tables 10-11.

TABLE XI
ORDERING OF FOUR ALTERNATIVES BASED ON PARTICULAR CASES OF THE SVNLCWD-TOPSIS APPROACH.

Particular cases of the SVNLCWD-TOPSIS	Ordering
SVNLMaxD-TOPSIS	$a_4 \prec a_2 \prec a_1 \prec a_3$
SVNLMinD-TOPSIS	$a_4 \prec a_2 \prec a_1 \prec a_3$
SVNLWD-TOPSIS	$a_4 \prec a_1 \prec a_2 \prec a_3$
SVNLOWAD-TOPSIS	$a_4 \prec a_2 \prec a_1 \prec a_3$
Step SVNLCWD-TOPSIS	$a_4 \prec a_1 \prec a_2 \prec a_3$

Through the above analysis, it can be seen that the application of different particular cases of SVNLCWD-TOPSIS examples can reflect the different ranking of alternatives. The prominent feature of the SVNLCWD-TOPSIS model is that it can consider both the subjective information of attributes and the attitude characteristics of DMs. In addition, when the parameters are given different values, it can provide more choices for DMs. Therefore, the model has strong flexibility.

Compared with the approach proposed [12, 52, 53, 54], the above analysis shows that the significant feature of the proposed SVNLCWD-TOPSIS is that it is able to consider both the subjective information of attribute and the attitudinal character of decision maker. Moreover, this method is very flexible because it can provide the decision makers more choices as the parameters are assigned different values.

VI. CONCLUSION

In this paper, we propose a new SVNLS combined weighted distance measure, namely SVNLCWD operator, which overcomes the shortcomings of existing methods. Based on SVNLCWD, an improved SVNL TOPSIS called SVNLCWD-TOPSIS is proposed, which is introduced into the MAGDM problems of SVNL. The most obvious advantage of this method is that it can reflect the importance of subjective information and the attitude characteristics of DMs. In addition, it allows a comprehensive view of the decision-making process, because the DM can consider different benefit values, so it presents different scenarios. A modified relative closeness coefficient is proposed to rank the alternatives, compared with the existing methods, this method provides more accurate and universal results. Finally, the feasibility and effectiveness of the model are verified by the selection of low-carbon logistics service providers.

In the future research, we hope to further expand the SVNLCWD-TOPSIS method by using other aggregation techniques, such as probability and uniform aggregation, induced variables. In addition, we will give special consideration to other applications of this method, especially in business decision-making and statistics.

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TABLE II
SVNL DECISION MATRIX B^2.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_6^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_1^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_2^{(2)}$, (0.6, 0.2, 0.2)$\rangle$	$\langle s_4^{(2)}$, (0.5, 0.4, 0.2)$\rangle$
a_2	$\langle s_5^{(2)}$, (0.4, 0.3, 0.4)$\rangle$	$\langle s_1^{(2)}$, (0.5, 0.1, 0.2)$\rangle$	$\langle s_2^{(2)}$, (0.3, 0.1, 0.6)$\rangle$	$\langle s_3^{(2)}$, (0.7, 0.1, 0.1)$\rangle$
a_3	$\langle s_4^{(2)}$, (0.8, 0.1, 0.2)$\rangle$	$\langle s_2^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_3^{(2)}$, (0.4, 0.2, 0.2)$\rangle$	$\langle s_6^{(2)}$, (0.6, 0.3, 0.3)$\rangle$
a_4	$\langle s_6^{(2)}$, (0.4, 0.2, 0.4)$\rangle$	$\langle s_1^{(2)}$, (0.6, 0.3, 0.4)$\rangle$	$\langle s_3^{(2)}$, (0.6, 0.1, 0.3)$\rangle$	$\langle s_5^{(2)}$, (0.4, 0.4, 0.1)$\rangle$

TABLE III
SVNL DECISION MATRIX B^3.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_5^{(3)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_3^{(3)}$, (0.7, 0.2, 0.2)$\rangle$	$\langle s_2^{(3)}$, (0.7, 0.2, 0.1)$\rangle$	$\langle s_6^{(3)}$, (0.4, 0.6, 0.2)$\rangle$
a_2	$\langle s_6^{(3)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_1^{(3)}$, (0.6, 0.2, 0.4)$\rangle$	$\langle s_2^{(3)}$, (0.2, 0.1, 0.6)$\rangle$	$\langle s_4^{(3)}$, (0.5, 0.2, 0.3)$\rangle$
a_3	$\langle s_4^{(3)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_3^{(3)}$, (0.5, 0.2, 0.2)$\rangle$	$\langle s_4^{(3)}$, (0.4, 0.1, 0.1)$\rangle$	$\langle s_5^{(3)}$, (0.7, 0.2, 0.1)$\rangle$
a_4	$\langle s_6^{(3)}$, (0.5, 0.1, 0.3)$\rangle$	$\langle s_2^{(3)}$, (0.6, 0.1, 0.3)$\rangle$	$\langle s_3^{(3)}$, (0.6, 0.2, 0.1)$\rangle$	$\langle s_4^{(3)}$, (0.3, 0.6, 0.2)$\rangle$

TABLE IV
NORMALIZED SVNL DECISION MATRIX C^1.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_6^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_5^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_4^{(1)}$, (0.5, 0.2, 0.2)$\rangle$	$\langle s_3^{(1)}$, (0.6, 0.2, 0.4)$\rangle$
a_2	$\langle s_5^{(1)}$, (0.4, 0.2, 0.3)$\rangle$	$\langle s_5^{(1)}$, (0.4, 0.2, 0.3)$\rangle$	$\langle s_3^{(1)}$, (0.3, 0.2, 0.5)$\rangle$	$\langle s_4^{(1)}$, (0.5, 0.3, 0.3)$\rangle$
a_3	$\langle s_5^{(1)}$, (0.7, 0.0, 0.1)$\rangle$	$\langle s_4^{(1)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_3^{(1)}$, (0.3, 0.1, 0.2)$\rangle$	$\langle s_6^{(1)}$, (0.6, 0.1, 0.2)$\rangle$
a_4	$\langle s_4^{(1)}$, (0.3, 0.2, 0.3)$\rangle$	$\langle s_4^{(1)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_3^{(1)}$, (0.5, 0.3, 0.1)$\rangle$	$\langle s_5^{(1)}$, (0.3, 0.5, 0.2)$\rangle$

TABLE V
NORMALIZED SVNL DECISION MATRIX C^2.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_6^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_6^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_5^{(2)}$, (0.6, 0.2, 0.2)$\rangle$	$\langle s_4^{(2)}$, (0.5, 0.4, 0.2)$\rangle$
a_2	$\langle s_5^{(2)}$, (0.4, 0.3, 0.4)$\rangle$	$\langle s_6^{(2)}$, (0.5, 0.1, 0.2)$\rangle$	$\langle s_5^{(2)}$, (0.3, 0.1, 0.6)$\rangle$	$\langle s_3^{(2)}$, (0.7, 0.1, 0.1)$\rangle$
a_3	$\langle s_4^{(2)}$, (0.8, 0.1, 0.2)$\rangle$	$\langle s_5^{(2)}$, (0.7, 0.2, 0.3)$\rangle$	$\langle s_4^{(2)}$, (0.4, 0.2, 0.2)$\rangle$	$\langle s_6^{(2)}$, (0.6, 0.3, 0.3)$\rangle$
a_4	$\langle s_6^{(2)}$, (0.4, 0.2, 0.4)$\rangle$	$\langle s_6^{(2)}$, (0.6, 0.3, 0.4)$\rangle$	$\langle s_4^{(2)}$, (0.6, 0.1, 0.3)$\rangle$	$\langle s_5^{(2)}$, (0.4, 0.4, 0.1)$\rangle$

TABLE VI
NORMALIZED SVNL DECISION MATRIX C^3.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_5^{(3)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_4^{(3)}$, (0.7, 0.2, 0.2)$\rangle$	$\langle s_5^{(3)}$, (0.7, 0.2, 0.1)$\rangle$	$\langle s_6^{(3)}$, (0.4, 0.6, 0.2)$\rangle$
a_2	$\langle s_6^{(3)}$, (0.5, 0.2, 0.3)$\rangle$	$\langle s_6^{(3)}$, (0.6, 0.2, 0.4)$\rangle$	$\langle s_5^{(3)}$, (0.2, 0.1, 0.6)$\rangle$	$\langle s_4^{(3)}$, (0.5, 0.2, 0.3)$\rangle$
a_3	$\langle s_4^{(3)}$, (0.6, 0.1, 0.2)$\rangle$	$\langle s_4^{(3)}$, (0.5, 0.2, 0.2)$\rangle$	$\langle s_3^{(3)}$, (0.4, 0.1, 0.1)$\rangle$	$\langle s_5^{(3)}$, (0.7, 0.2, 0.1)$\rangle$
a_4	$\langle s_6^{(3)}$, (0.5, 0.1, 0.3)$\rangle$	$\langle s_5^{(3)}$, (0.6, 0.1, 0.3)$\rangle$	$\langle s_4^{(3)}$, (0.6, 0.2, 0.1)$\rangle$	$\langle s_4^{(3)}$, (0.3, 0.6, 0.2)$\rangle$

TABLE VII
GROUP SVNL DECISION MATRIX C.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_{5.70}$, (0.611, 0.155, 0.258)$\rangle$	$\langle s_{4.70}$, (0.666, 0.155, 0.229)$\rangle$	$\langle s_{2.37}$, (0.602, 0.200, 0.162)$\rangle$	$\langle s_{4.23}$, (0.514, 0.350, 0.258)$\rangle$
a_2	$\langle s_{5.30}$, (0.432, 0.229, 0.330)$\rangle$	$\langle s_{5.63}$, (0.450, 0.159, 0.286)$\rangle$	$\langle s_{2.37}$, (0.271, 0.129, 0.561)$\rangle$	$\langle s_{3.67}$, (0.578, 0.185, 0.209)$\rangle$
a_3	$\langle s_{4.37}$, (0.714, 0.000, 0.155)$\rangle$	$\langle s_{4.33}$, (0.611, 0.155, 0.229)$\rangle$	$\langle s_{3.67}$, (0.365, 0.128, 0.163)$\rangle$	$\langle s_{5.70}$, (0.633, 0.180, 0.186)$\rangle$
a_4	$\langle s_{5.26}$, (0.399, 0.163, 0.330)$\rangle$	$\langle s_{4.96}$, (0.566, 0.186, 0.330)$\rangle$	$\langle s_{3.37}$, (0.566, 0.185, 0.144)$\rangle$	$\langle s_{4.70}$, (0.335, 0.491, 0.159)$\rangle$

TABLE VIII
WEIGHTED GROUP SVNL DECISION MATRIX H.

Alternatives	l_1	l_2	l_3	l_4
a_1	$\langle s_{1.425}$, (0.210, 0.627, 0.713)$\rangle$	$\langle s_{1.880}$, (0.355, 0.474, 0.555)$\rangle$	$\langle s_{0.356}$, (0.129, 0.786, 0.761)$\rangle$	$\langle s_{0.846}$, (0.134, 0.811, 0.763)$\rangle$
a_2	$\langle s_{1.325}$, (0.132, 0.692, 0.758)$\rangle$	$\langle s_{2.252}$, (0.213, 0.479, 0.606)$\rangle$	$\langle s_{0.356}$, (0.046, 0.736, 0.917)$\rangle$	$\langle s_{0.734}$, (0.158, 0.714, 0.731)$\rangle$
a_3	$\langle s_{1.093}$, (0.269, 0.000, 0.627)$\rangle$	$\langle s_{1.732}$, (0.315, 0.474, 0.555)$\rangle$	$\langle s_{0.551}$, (0.066, 0.735, 0.762)$\rangle$	$\langle s_{1.140}$, (0.182, 0.710, 0.714)$\rangle$
a_4	$\langle s_{1.315}$, (0.120, 0.635, 0.758)$\rangle$	$\langle s_{1.984}$, (0.284, 0.510, 0.642)$\rangle$	$\langle s_{0.506}$, (0.118, 0.776, 0.748)$\rangle$	$\langle s_{0.940}$, (0.078, 0.867, 0.692)$\rangle$

TABLE IX
RESULTS OBTAINED BY THE SVNLCWD-TOPSIS APPROACH.

	SVNLCWD(a_i, a^+)	SVNLCWD(a_i, a^-)	$\zeta(a_i)$	Ranking
a_1	8.1402	0.8329	-0.2140	2
a_2	8.3846	0.8589	-0.2194	3
a_3	7.9620	1.0303	0	1
a_4	8.3896	0.7448	-0.3308	4

TABLE X
CLOSENESS COEFFICIENTS OBTAINED USING THE PARTICULAR CASES OF THE SVNLCWD-TOPSIS APPROACH.

	SVNLMaxD-TOPSIS	SVNLMinD-TOPSIS	SVNLWD-TOPSIS	SVNLOWAD-TOPSIS	Step SVNLCWD-TOPSIS
a_1	-0.1316	-0.2526	-0.2203	-0.2096	-0.2900
a_2	-0.1863	-0.3746	-0.2081	-0.2268	-0.1970
a_3	-0.1201	-0.1542	-0.1309	-0.1273	-0.1132
a_4	-0.2660	-0.4005	-0.3310	-0.3295	-0.3450

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