Method for Green Supplier Selection with Probabilistic Linguistic Multiple Attribute Group Decision Making

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Abstract

In this paper, a TOPSIS method is proposed for probabilistic linguistic MAGDM. First, the definition of probabilistic linguistic term sets (PLTSs) is introduced Second, Then, the optimal alternative(s) is determined by calculating the shortest distance from the probabilistic linguistic positive ideal solution (PLPIS) and on the other side the farthest distance of the probabilistic linguistic negative ideal solution (PLNIS). This proposed method extends the applications range of the traditional entropy-weighted method. The calculating results hence tend to be more objective. Finally, a numerical example for green supplier selection is used to illustrate the use of the proposed method. The result shows the approach is simple, effective and easy to calculate.

Keywords

Multiple attribute group decision making (MAGDM); Probabilistic linguistic term sets (PLTSs); TOPSIS method; Green supplier selection.

1. Introduction

In order to depict the qualitative assessment information easily, Herrera and Martinez [1] gave the linguistic term sets (LTSs) for computing with words. Herrera and Martinez [2] combined linguistic and numerical information on the basis of the 2-tuple fuzzy linguistic representation model. Herrera and Martinez [3] defined the linguistic 2-tuples for handling multigranular hierarchical linguistic contexts. Rodriguez, Martinez and Herrera [4] defined the hesitant fuzzy linguistic term sets (HFLTSs) on the basis of hesitant fuzzy sets[5] and linguistic term sets (LTSs) [6] which allow DMs to provide several possible linguistic variable. Pang, Wang and Xu [7] proposed the probabilistic linguistic term sets (PLTSs) to overcome this defect and constructed a framework for ranking PLTSs with the score or deviation degree of each PLTS. Liang, Kobina and Quan [8] developed the probabilistic linguistic grey relational analysis (PL-GRA) for MAGDM based on geometric Bonferroni mean. Liao, Jiang, Xu, Xu and Herrera [9] defined the linear programming method to deal with the MADM with probabilistic linguistic information. Lin, Chen, Liao and Xu [10] proposed the ELECTRE II method to deal with PLTSs for edge computing. Liao, Jiang, Lev and Fujitac [11] studied the novel operations of PLTSs to solve the probabilistic linguistic ELECTRE III method. Chen, Wang and Wang [12] employed the probabilistic linguistic MULTIMOORA for cloud-based ERP system selection. Feng, Liu and Wei [13] proposed the probabilistic linguistic QUALIFLEX method with possibility degree comparison. Kobina, Liang and He [14] proposed some Probabilistic linguistic power operators for MAGDM with classical power aggregation operators.

TOPSIS(Technique for order performance by similarity to ideal solution) method was initially proposed by Hwang and Yoon [15] for solving a MADM problem, which concentrates on choosing the alternative with the smallest distance from the positive ideal solution (PIS) and with the longest distance from the negative ideal solution (NIS). Chen, Li and Liu [16] defined the OWA-TOPSIS method for MADM. Yu, Shao, Wang and Zhang [17] supplied the GDM sustainable supplier selection by utilizing the extended TOPSIS within interval-valued Pythagorean fuzzy environment. Wang, Wang, Xu and Ren [18] extended TOPSIS method to the interval-valued hesitant Pythagorean fuzzy sets. Tang, Shi and Dong [19] used public block-chain evaluation by using entropy and TOPSIS. Baky [20] defined the interactive TOPSIS algorithms to deal with decision-making problems with multi-level non-linear multi-objective. The aim of this paper is to extend the TOPSIS method to solve the probabilistic linguistic MAGDM. The remainder of this paper is set out as follows. Section 2 supplies some basic concepts of PLTSs. In Sect. 3, the TOPSIS method is proposed for probabilistic linguistic MAGDM problems. In Sect. 4, a case study for green supplier selection is given and some comparative analysis is conducted. The study finishes with some conclusions in Sect. 5.

2. Preliminaries

Pang, Wang and Xu [7] proposed the probabilistic linguistic term set (PLTS).

Definition 1[7]. Let $L=\{l_\alpha | \alpha = -\theta,\cdots,-2,-1,0,1,2,\cdots\theta\}$ be an LTS, the linguistic terms l_α can express the equivalent information to β which is expressed with the transformation function g :

$$g:[l_{-\theta},l_{-\theta}]\to[0,1],\ g(l_\alpha)=\frac{\alpha+\theta}{2\theta}=\beta \tag{1}$$

β can also be expressed the equivalent information to the linguistic terms l_α which is denoted with the transformation function g^{-1}:

$$g^{-1}:[0,1]\to[l_{-\theta},l_{-\theta}],\ g^{-1}(\beta)=l_{(2\beta-1)\theta}=l_\alpha \tag{2}$$

Definition 2[7]. Given an LTS $L=\{l_\alpha | \alpha = -\theta,\cdots,-2,-1,0,1,2,\cdots\theta\}$, a PLTS is defined as:

$$L(p)=\left\{l^{(\phi)}\left(p^{(\phi)}\right)\middle| l^{(\phi)}\in L,\ p^{(\phi)}\geq 0,\ \phi=1,2,\cdots,\#L(p),\ \sum_{\phi=1}^{\#L(p)}p^{(\phi)}\leq 1\right\} \tag{3}$$

where $l^{(\phi)}\left(p^{(\phi)}\right)$ is the ϕth linguistic term $l^{(\phi)}$ associated with the probability value $p^{(\phi)}$, and $\#L(p)$ is the length of linguistic terms in $L(p)$. The linguistic term $l^{(\phi)}$ in $L(p)$ are arranged in ascending order.

Definition 3[7]. Let $L=\{l_\alpha | \alpha = -\theta,\cdots,-1,0,1,\cdots\theta\}$ be an LTS, $\tilde{L}_1(\tilde{p})=\left\{l_1^{(\phi)}\left(\tilde{p}_1^{(\phi)}\right)\middle| \phi=1,2,\cdots,\#\tilde{L}_1(\tilde{p})\right\}$ and $\tilde{L}_2(\tilde{p})=\left\{l_2^{(\phi)}\left(\tilde{p}_2^{(\phi)}\right)\middle| \phi=1,2,\cdots,\#\tilde{L}_2(\tilde{p})\right\}$ be two PLTSs, where $\#\tilde{L}_1(\tilde{p})$ and $\#\tilde{L}_2(\tilde{p})$ are the numbers of PLTS $\tilde{L}_1(\tilde{p})$ and $\tilde{L}_2(\tilde{p})$, respectively. If $\#\tilde{L}_1(\tilde{p})>\#\tilde{L}_2(\tilde{p})$, then add $\#\tilde{L}_1(\tilde{p})-\#\tilde{L}_2(\tilde{p})$ linguistic terms to $\tilde{L}_2(\tilde{p})$. Moreover, the added linguistic terms should be the smallest linguistic term in $\tilde{L}_2(\tilde{p})$ and the probabilities of added linguistic terms should be zero.

Definition 5[21]. Let $L=\{l_\alpha | \alpha = -\theta,\cdots,-1,0,1,\cdots\theta\}$ be an LTS. And let $\tilde{L}_1(\tilde{p})=\left\{l_1^{(\phi)}\left(\tilde{p}_1^{(\phi)}\right)\middle| \phi=1,2,\cdots,\#\tilde{L}_1(\tilde{p})\right\}$ and $\tilde{L}_2(\tilde{p})=\left\{l_2^{(\phi)}\left(\tilde{p}_2^{(\phi)}\right)\middle| \phi=1,2,\cdots,\#\tilde{L}_2(\tilde{p})\right\}$ be two PLTSs with $\#\tilde{L}_1(\tilde{p})=\#\tilde{L}_2(\tilde{p})$, then Hamming distance $d\left(\tilde{L}_1(\tilde{p}),\tilde{L}_2(\tilde{p})\right)$ between $\tilde{L}_1(\tilde{p})$ and $\tilde{L}_2(\tilde{p})$ is defined as follows:

$$d\left(\tilde{L}_1(\tilde{p}),\tilde{L}_2(\tilde{p})\right)=\frac{\sum_{\phi=1}^{\#\tilde{L}_1(\tilde{p})}\left|\tilde{p}_1^{(\phi)}g\left(l_1^{(\phi)}\right)-\tilde{p}_2^{(\phi)}g\left(l_2^{(\phi)}\right)\right|}{\#\tilde{L}_1(\tilde{p})} \tag{6}$$

3. TOPSIS method for probabilistic linguistic MAGDM

In this section, we propose the probabilistic linguistic TOPSIS (PL-TOPSIS) method for MAGDM problems. The following notations are used to solve the PL-MAGDM problems. Let $A=\{A_1,A_2,\cdots,A_m\}$ be a discrete set of alternatives, and $G=\{G_1,G_2,\cdots,G_n\}$ with weight vector $w=(w_1,w_2,\cdots,w_n)$, where $\omega_j\in[0,1]$, $j=1,2,\cdots,n$, $\sum_{j=1}^{n}w_j=1$, and a set of experts $E=\{E_1,E_2,\cdots,E_q\}$. Suppose that there are n qualitative attribute $A=\{A_1,A_2,\cdots,A_m\}$ and their values are evaluated by qualified experts and denoted as linguistic expressions information $l_{ij}^{k}\left(i=1,2,\cdots,m,\ j=1,2,\cdots,n,k=1,2,\cdots,q\right)$.

Then, PL-TOPSIS method is designed to solve the MAGDM problems. The detailed calculating steps are given as follows:

Step 1. Convert the linguistic information $l_{ij}^{k}\left(i=1,2,\cdots,m,\ j=1,2,\cdots,n,k=1,2,\cdots,q\right)$ into probabilistic linguistic information $l_{ij}{}^{(\phi)}\left(p_{ij}{}^{(\phi)}\right),\phi=1,2,\cdots,\#L_{ij}(p)$ and construct the probabilistic linguistic decision matrix $L=\left(L_{ij}(p)\right)_{m\times n}$, $L_{ij}(p)=\left\{l_{ij}{}^{(\phi)}\left(p_{ij}{}^{(\phi)}\right)\middle|\ \phi=1,2,\cdots,\#L_{ij}(p)\right\}$ $\left(i=1,2,\cdots,m,\ j=1,2,\cdots,n\right)$.

Step 2. Derive the normalized probabilistic linguistic matrix $\tilde{L}=\left(\tilde{L}_{ij}(\tilde{p})\right)_{m\times n}$, $L_{ij}(\tilde{p})=\left\{l_{ij}{}^{(\phi)}\left(\tilde{p}_{ij}{}^{(\phi)}\right)\middle|\ \phi=1,2,\cdots,\#L_{ij}(\tilde{p})\right\}$ $\left(i=1,2,\cdots,m,\ j=1,2,\cdots,n\right)$. Thus, probabilistic linguistic information for the alternative $A_i\in A$ with respect to the all the attribute G can be expressed as: $PLA_i=\left(l_{i1}^{(\phi)}\left(\tilde{p}_{i1}^{(\phi)}\right),l_{i2}^{(\phi)}\left(\tilde{p}_{i2}^{(\phi)}\right),\cdots,l_{in}^{(\phi)}\left(\tilde{p}_{in}^{(\phi)}\right)\right)$, $\phi=1,2,\cdots,\#L_{ij}(\tilde{p})$.

Step 3. Define the probabilistic linguistic positive ideal solution (PLPIS) and probabilistic linguistic negative ideal solution (PLNIS):

$$PLPIS=\left(PLPIS_1,PLPIS_2,\cdots,PLPIS_n\right) \tag{7}$$

$$PLNIS=\left(PLNIS_1,PLNIS_2,\cdots,PLNIS_n\right) \tag{8}$$

where

$$PLPIS_j=\left\{pl_j^{(\phi)}\left(\tilde{p}_j^{(\phi)}\right)\middle|\ \phi=1,2,\cdots,\#L_{ij}(\tilde{p})\right\}=\left\{\max_i s\left(L_{ij}(\tilde{p})\right)\right\} \tag{9}$$

$$PLNIS_j=\left\{nl_j^{(\phi)}\left(\tilde{p}_j^{(\phi)}\right)\middle|\ \phi=1,2,\cdots,\#L_{ij}(\tilde{p})\right\}=\left\{\min_i s\left(L_{ij}(\tilde{p})\right)\right\} \tag{10}$$

Step 4. Calculate the distances of each alternative from PLPIS and PLNIS, respectively:

$$d\left(PLA_i,PLPIS\right)=\sum_{j=1}^{n}w_j d\left(PLA_{ij},PLPIS_j\right) \tag{11}$$

$$d\left(PLA_i,PLNIS\right)=\sum_{j=1}^{n}w_j d\left(PLA_{ij},PLNIS_j\right) \tag{12}$$

$$d\left(PLA_{ij},PLPIS_j\right)=\left(\sum_{\phi=1}^{\#L_{ij}(\tilde{p})}\left|l_{ij}{}^{(\phi)}\left(p_{ij}{}^{(\phi)}\right)-pl_j^{(\phi)}\left(\tilde{p}_j^{(\phi)}\right)\right|\right)\Big/\#L_{ij}(\tilde{p}) \tag{14}$$

$$d\left(PLA_{ij},PLNIS_j\right)=\left(\sum_{\phi=1}^{\#L_{ij}(\tilde{p})}\left|l_{ij}^{(\phi)}\left(p_{ij}^{(\phi)}\right)-nl_j^{(\phi)}\left(\tilde{p}_j^{(\phi)}\right)\right|\right)\Big/\#L_{ij}\left(\tilde{p}\right) \tag{15}$$

Step 5. Calculate the probabilistic linguistic relative closeness degree (PLRCD) of each alternative from PLPIS.

$$PLRCD\left(PLA_i,PLPIS\right)=\frac{d\left(PLA_i,PLPIS\right)}{d\left(PLA_i,PLPIS\right)+d\left(PLA_i,PLNIS\right)},i=1,2,\cdots,m. \tag{16}$$

Step 6. According to the $PLRCD\left(PLA_i,PLPIS\right)$, the ranking order of all alternatives can be determined. The best alternative is the one closest to PLPIS and farthest from the PLNIS. Thus, if any alternative has the smallest $PLRCD\left(PLA_i,PLPIS\right)$ value, then, it is the most desirable alternative.

4. A case study

Supplier selection in supply chains plays a more and more important strategic role in reducing cost, increasing efficiency and improving service. In view of resource constraints and uncertainties of demand and supply, large enterprises and project construction units usually select several suppliers according to multiple objectives or attributes at first, and then allocate orders among them. In order to reduce the impact of supply chain uncertainties and promote cooperation relationship, suppliers and demanders usually sign some bilateral contracts with each other. As an effective method for disposing the uncertainties in supply chains, setting up safety stock plays an important role in reducing cost and improving customer service. So developing some methods supporting supplier selection, order allocation and safety stock placement is of important academic and practical significance to enrich and perfect supply chain management and decision analysis theories and promote effective operation of supply chains. In this section we present a numerical example for green supplier selection to illustrate the method proposed in this paper. There is a panel with five possible green suppliers $A_i\left(i=1,2,3,4,5\right)$ to select. The experts selects four beneficial attribute to evaluate the five possible green suppliers: ①G_1 is the environmental improvement quality; ②G_2 is the price capability of suppliers; ③G_3 is the green image, human resources and financial conditions; ④G_4 is the environmental competencies. The five possible green suppliers $A_i\left(i=1,2,3,4,5\right)$ are to be evaluated by using the linguistic term set $L=\{l_{-3}=extremely\ poor(EP),l_{-2}=very\ poor(VP),l_{-1}=poor(P),l_0=medium(M),$ $l_1=good(G),l_2=very\ good(VG),l_3=extremely\ good(EG)\}$ by the five decision makers under the above four attributes, as listed in the Table 1-5.

Table 1. linguistic decision matrix by the first DM

Alternatives	G_1	G_2	G_3	G_4
A_1	VG	VP	P	VG
A_2	VP	P	EP	P
A_3	VG	G	EG	P
A_4	P	EG	VP	G
A_5	EP	EP	EG	VG

Table 2. linguistic decision matrix by the second DM

Alternatives	G_1	G_2	G_3	G_4
A_1	VG	EP	M	G
A_2	P	VP	VP	EP
A_3	G	EG	EG	P
A_4	VP	G	EP	VG
A_5	EP	P	G	EG

Table 3. linguistic decision matrix by the third DM

Alternatives	G_1	G_2	G_3	G_4
A_1	G	P	EP	G
A_2	P	P	VP	EP
A_3	VG	EG	EG	VP
A_4	EP	VG	VP	G
A_5	P	P	EG	VG

Table 4. linguistic decision matrix by the fourth DM

Alternatives	G_1	G_2	G_3	G_4
A_1	EG	P	M	VG
A_2	EP	EP	P	P
A_3	EG	G	EG	EP
A_4	P	EG	EP	VG
A_5	VP	EP	G	EG

Table 5. linguistic decision matrix by the fifth DM

Alternatives	G_1	G_2	G_3	G_4
A_1	VG	P	EP	EG
A_2	EP	VP	P	VP
A_3	G	EG	EG	P
A_4	VP	G	EP	VG
A_5	EP	VP	VG	G

In the following, we utilize the PL-TOPSIS method developed for green supplier selection.

Step 1. Transform the linguistic variables into probabilistic linguistic decision matrix (Table 6).

Table 6. Probabilistic linguistic decision matrix

Alternatives	G_1	G_2
A_1	$\{l_1(0.2), l_2(0.6), l_3(0.2)\}$	$\{l_{-3}(0.2), l_{-2}(0.2), l_{-1}(0.6)\}$
A_2	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$	$\{l_{-3}(0.6), l_{-1}(0.4)\}$
A_3	$\{l_1(0.4), l_2(0.4), l_3(0.2)\}$	$\{l_1(0.4), l_3(0.6)\}$
A_4	$\{l_{-3}(0.2), l_{-2}(0.4), l_{-1}(0.4)\}$	$\{l_1(0.4), l_2(0.2), l_3(0.4)\}$
A_5	$\{l_{-3}(0.6), l_{-2}(0.2), l_{-1}(0.2)\}$	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$
Alternatives	G_3	G_4
A_1	$\{l_0(0.4), l_{-1}(0.2), l_{-3}(0.4)\}$	$\{l_1(0.4), l_2(0.4), l_3(0.2)\}$
A_2	$\{l_{-2}(0.4), l_{-1}(0.4), l_{-3}(0.2)\}$	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$
A_3	$\{l_3(1)\}$	$\{l_{-3}(0.2), l_{-2}(0.2), l_{-1}(0.6)\}$
A_4	$\{l_{-3}(0.6), l_{-2}(0.4)\}$	$\{l_1(0.4), l_2(0.6)\}$
A_5	$\{l_1(0.4), l_2(0.2), l_3(0.4)\}$	$\{l_1(0.2), l_2(0.4), l_3(0.4)\}$

Step 2. Calculate the normalized probabilistic linguistic decision matrix (Table 7).

Table 7. Normalized probabilistic linguistic decision matrix

Alternatives	G_1	G_2
A_1	$\{l_1(0.2), l_2(0.6), l_3(0.2)\}$	$\{l_{-3}(0.2), l_{-2}(0.2), l_{-1}(0.6)\}$
A_2	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$	$\{l_{-3}(0), l_{-3}(0.6), l_{-1}(0.4)\}$
A_3	$\{l_1(0.4), l_2(0.4), l_3(0.2)\}$	$\{l_1(0), l_1(0.4), l_3(0.6)\}$
A_4	$\{l_{-3}(0.2), l_{-2}(0.4), l_{-1}(0.4)\}$	$\{l_1(0.4), l_2(0.2), l_3(0.4)\}$
A_5	$\{l_{-3}(0.6), l_{-2}(0.2), l_{-1}(0.2)\}$	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$

Alternatives	G_3	G_4
A_1	$\{l_{-3}(0.4), l_{-1}(0.2), l_0(0.4)\}$	$\{l_1(0.4), l_2(0.4), l_3(0.2)\}$
A_2	$\{l_{-3}(0.2), l_{-2}(0.4), l_{-1}(0.4)\}$	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$
A_3	$\{l_3(0), l_3(0), l_3(1)\}$	$\{l_{-3}(0.2), l_{-2}(0.2), l_{-1}(0.6)\}$
A_4	$\{l_{-3}(0), l_{-3}(0.6), l_{-2}(0.4)\}$	$\{l_1(0), l_1(0.4), l_2(0.6)\}$
A_5	$\{l_1(0.4), l_2(0.2), l_3(0.4)\}$	$\{l_1(0.2), l_2(0.4), l_3(0.4)\}$

Step 3. Determine the PLPIS and PLNIS by Eq.(7)-(10) (Table 8):

Table 8. PLPIS and PLNIS

	G_1	G_2
PLPIS	$\{l_1(0.2), l_2(0.6), l_3(0.2)\}$	$\{l_1(0), l_1(0.4), l_3(0.6)\}$
PLNIS	$\{l_{-3}(0.6), l_{-2}(0.2), l_{-1}(0.2)\}$	$\{l_{-3}(0), l_{-3}(0.6), l_{-1}(0.4)\}$
	G_3	G_4
PLPIS	$\{l_3(0), l_3(0), l_3(1)\}$	$\{l_1(0.2), l_2(0.4), l_3(0.4)\}$
PLNIS	$\{l_{-3}(0), l_{-3}(0.6), l_{-2}(0.4)\}$	$\{l_{-3}(0.4), l_{-2}(0.2), l_{-1}(0.4)\}$

Step 5. Calculate the distances $d(PLA_i, PLPIS)$ and $d(PLA_i, PLNIS)$ of each alternative by Eq.(14-17), respectively (Table 9):

Table 9. $d(PLA_i, PLPIS)$ and $d(PLA_i, PLNIS)$ of each alternative

Alternatives	$d(PLA_i, PLPIS)$	$d(PLA_i, PLNIS)$
A_1	0.1138	0.1622
A_2	0.2546	0.0221
A_3	0.0813	0.2387
A_4	0.2438	0.0970
A_5	0.2904	0.0977

Step 6. Calculating the PLRCD of each alternative from PLPIS by Eq.(18) (Table 10).

Table 10. PLRCD of each alternative from PLPIS

Alternatives	A_1	A_2	A_3	A_4	A_5
$PLRCD(PLA_i, PLPIS)$	0.4344	0.9388	0.2566	0.7565	0.7467

Step 7. According to the $PLRCD(PLA_i, PLPIS)(i=1,2,3,4,5)$, we can rank all the green suppliers. Obviously, the rank is $A_3 > A_1 > A_5 > A_4 > A_2$ and the best green supplier among five alternatives is A_3.

5. Conclusion

In this paper, we extend the TOPSIS method to the PL-MAGDM. Firstly, the basic concept, comparative formula and Hamming distance of PLSs are briefly reviewed. Then, the optimal alternative(s) is determined by calculating the shortest distance from the PLPIS and on the other side the farthest distance of the PLNIS. Finally, a practical case study for green supplier selection is supplied to show the proposed approach.

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