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Algorithms for probabilistic uncertain linguistic multiple attribute group decision making based on the GRA and CRITIC method: application to location planning of electric vehicle charging stations

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ABSTRACT

Electric vehicles (EVs) could be regarded as one of the most innovative and high technologies all over the world to cope with the fossil fuel energy resource crisis and environmental pollution issues. As the initiatory task of EV charging station (EVCS) construction, site selection play an important part throughout the whole life cycle, which is deemed to be multiple attribute group decision making (MAGDM) problem involving many experts and many conflicting attributes. In this paper, a grey relational analysis (GRA) method is investigated to tackle the probabilistic uncertain linguistic MAGDM in which the attribute weights are completely unknown information. Firstly, the definition of the expected value is then employed to objectively derive the attribute weights based on the CRiteria Importance Through Intercriteria Correlation (CRITIC) method. Then, the optimal alternative is chosen by calculating largest relative relational degree from the probabilistic uncertain linguistic positive ideal solution (PULPIS) which considers both the largest grey relational coefficient from the PULPIS and the smallest grey relational coefficient from the probabilistic uncertain linguistic negative ideal solution (PULNIS). Finally, a numerical case for site selection of electric vehicle charging stations (EVCS) is designed to illustrate the proposed method. The result shows the approach is simple, effective and easy to calculate.

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1. Introduction

In many existing multiple attribute group decision making (MAGDM) issues, it has been assumed that almost all assessing information is expressed with crisp numbers

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(Pamucar & Cirovic, 2015). However, in more and more practical MAGDM issues, most of decision makers' (DMs') assessment information is imprecise or uncertain (H. Gao, Ran, Wei, Wei, & Wu, 2020; He, Wei, Lu, Wei, & Lin, 2019; L.P. Wu, Wei, Wu, & Wei, 2020) because of ever growing complexity and uncertainty of MAGDM issues and the fuzziness of human subjective preferences (X. M. Deng & Gao, 2019; H. Gao, Lu, & Wei, 2019; Li & Lu, 2019; J.P. Lu & Wei, 2019). In order to depict these qualitative assessment information easily (J. Wang, Gao, & Lu, 2019; R. Wang, 2019; L.P. Wu, Gao, & Wei, 2019; L.P. Wu, Wang, & Gao et al., 2019), Herrera and Martinez (2000) defined the linguistic term sets (LTSs) for computing with words. Furthermore, Rodriguez, Martinez, and Herrera (2012) proposed the hesitant fuzzy linguistic term sets (HFLTSs) on the basis of hesitant fuzzy sets(Torra, 2010) and linguistic term sets (LTSs) (Zadeh, 1975) which allowed DMs to provide some possible linguistic information. However, in most of the current references on HFLTSs, all possible values are provided by the DMs have equal weight or importance. Thus, Pang, Wang, and Xu (2016) defined the probabilistic linguistic term sets (PLTSs) to overcome this defect. J.P. Lu et al. (2019) designed the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method for probabilistic linguistic MAGDM for supplier selection of new agricultural machinery products. Feng, Liu, and Wei (2019) proposed the probabilistic linguistic QUALItative FLEXible multiple criteria method (QUALIFLEX) method with possibility degree comparison. Chen, Wang, and Wang (2019) employed the probabilistic linguistic MULTIMOORA for cloud-based Enterprise Resource Planning (ERP) system selection. G.W. Wei, Wei, Wu, and Wang (2019) defined the supplier selection of medical consumption products with a probabilistic linguistic multi-attributive border approximation area comparison (MABAC) method. Lei, Wei, Lu, Wei, and Wu (2019) proposed the GRA method for probabilistic linguistic multiple attribute group decision making with incomplete weight information and its application to waste incineration plants location problem. Liao, Jiang, Lev, and Fujita (2019) studied the novel operations of PLTSs to solve the probabilistic linguistic ELimination Et Choix Traduisant la REalité (ELECTRE) III method. In some practical situations, a set of DMs may have their preferences to express their assessment information by using uncertain linguistic terms (Z.S. Xu, 2004) in the group decision making (GDM) processes because of lack of sufficient knowledge and the fuzziness of human's thinking, However, these uncertain linguistic terms are different from each other and also the number of occurrences of each uncertain linguistic term is different. Inspired by the idea based on probabilistic linguistic term sets (Pang et al., 2016) and uncertain linguistic term (Z.S. Xu, 2004), Lin, Xu, Zhai, and Yao (2018) designed a new concept of probabilistic uncertain linguistic term set in order to depict the uncertain linguistic information in the GDM issues. Xie, Ren, Xu, and Wang (2018) defined the probabilistic uncertain linguistic preference relation (PULPR) and the normalized PULPR and designed the distance measure and similarity degree measure the consensus degree. Y. He, Lei, et al. (2019) defined the EDAS method for multiple attribute group decision making with probabilistic uncertain linguistic information and its application to green supplier selection.

The grey relational analysis (GRA) method was firstly developed by J. L. Deng (1989) to solve the MADM issue, which concentrates on selecting the alternative with the largest grey relational degree from the PIS and with the smallest grey relational degree from the NIS. Kuo, Yang, and Huang (2008) utilized GRA method to solve the MADM issues for facility layout and dispatching rules selection. Kung and Wen (2007) used six financial indicators to classify twenty items of financial ratios by GRA method to arrange the total performances of the sample venture capital enterprises in order. Alptekin, Alptekin, and Sarac (2018) assessed the low carbon development of European Union countries and Turkey with GRA model. Tan, Chen, and Wu (2019) studied the green design alternatives and GRA integrated with Analytical Hierarchy Process (AHP). Sun, Guan, Yi, and Zhou (2018) and HFSs slope grey relational degree together to construct the HFSs synthetic grey relational degree which takes both the closeness and the linear fashion into consideration. Malek, Ebrahimnejad, and Tavakkoli-Moghaddam (2017) proposed an improved hybrid GRA method for green resilient supply. G. D. Tian et al. (2018) defined the grey-correlation based hybrid multi-criteria decision making (MCDM) method for green decoration materials selection under interior environment characteristics. G. Tian et al. (2019) designed the fuzzy grey Choquet integral for evaluation of multicriteria decision making problems with interactive and qualitative indices.

But there are no studies on the GRA method for MAGDM under PULTSs in the existing literature. Therefore, it is necessary to pay attention to this issue. The goal of this paper is to extend the GRA method to solve the probabilistic uncertain linguistic MAGDM with unknown weight information on the basis of the CRITIC method. The motivation of such paper can be outlined as follows: (1) the GRA method is extended by PULTSs with unknown weight information; (2) the scoring function of PULTs is employed to objectively derive the attribute weights based on the CRITIC method; (3) the probabilistic uncertain linguistic GRA (PUL-GRA) method is proposed to solve the probabilistic uncertain linguistic MAGDM problems; (4) a case study for site selection of EVCS is supplied to show the developed approach; (5) some comparative studies are provided with the PULWA operator, ULWA operator and PUL-TOPSIS method to give effect to the rationality of PUL-GRA method.

The remainder of this paper is organized as follows. Section 2 supplies some basic concepts of PULTSs. In Sect. 3, the probabilistic uncertain linguistic GRA method is proposed for MAGDM issue with CRITIC-based weight information. In Sect. 4, a case study for site selection of EVCS is given and some comparative analysis is conducted. The study ends with some conclusions in Sect. 5.

2. Preliminaries

Z. S. Xu (2005) designed the additive linguistic evaluation scale and Gou, Xu, and Liao (2017) proposed the corresponding transformation function between the linguistic terms and$[0, 1]$.

Definition 1. (Gou et al., 2017; Z. S. Xu, 2005). Let $L = \{l_\alpha | \alpha = -\theta, \ldots, -2, -1, 0, 1, 2, \ldots \theta\}$ be an LTS (Z. S. Xu, 2005), the linguistic terms l_α can depict the equivalent information to β is obtained by the transformation functiong (Gou et al., 2017):

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

At the same time, β can be expressed the equivalent information to the linguistic terms l_{α}, which is derived by the transformation functioning^{-1} :

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

In order to strengthen the modeling capability of HFLTSs, Pang et al. (2016) designed the definition of PLTSs to link each linguistic term with a probability value.

Definition 2. (Pang, et al., 2016). Given an LTS $L=\{l_j|j=-\theta,\ldots,-2,-1,0,1,2,\ldots\theta\}$, a PLTS is designed as:

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

where $l^{(\phi)}(p^{(\phi)})$ 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.

In order to express the DMs' uncertainty more accurately, Lin et al. (2018) came forward the probabilistic uncertain linguistic term sets (PULTS) based on uncertain linguistic term (Z.S. Xu, 2004) and probabilistic linguistic term sets

Definition 3. (Lin et al., 2018). A PULTS could be designed as follows:

$$PULTS(p)=\{[L^{\phi},U^{\phi}](p^{\phi})|p^{\phi}\geq 0,\phi=1,2,\ldots,\#PULTS(p),\sum_{\phi=1}^{\#PULTS(p)}p^{\phi}\leq 1\} \tag{4}$$

where $[L^{\phi},U^{\phi}](p^{\phi})$ depicts the uncertain linguistic term $[L^{\phi},U^{\phi}]$ associated with the probability p^{ϕ}, L^{ϕ},U^{ϕ} are linguistic term sets, $L^{\phi}\leq U^{\phi}$, and $\#PULT(p)$ is the cardinality of $PULTS(p)$.

In order to convenient computation, Lin et al. (2018) normalized the PULTS $PULTS(p)$ as $NPULTS(p)=\{[L^{\phi},U^{\phi}](\tilde{p}^{\phi})|\tilde{p}^{\phi}\geq 0,\phi=1,2,\ldots,\#NPULTS(\tilde{p}),\sum_{\phi=1}^{\#NPULTS(\tilde{p})}\tilde{p}^{\phi}=1\}$, where $\tilde{p}^{(\phi)}=p^{(\phi)}/\sum_{\phi=1}^{\#L(p)}p^{(\phi)}$ for all$\phi=1,2,\ldots,\#\,NPULTS(\tilde{p})$.

Definition 4. (Lin et al., 2018). Let$PULTS_1(p)=\{[L_1^{\phi},U_1^{\phi}](p_1^{\phi})|\phi=1,2,\ldots,\#PULTS_1(p)\}$ and $PULTS_2(p)=\{[L_2^{\phi},U_2^{\phi}](p_2^{\phi})|\phi=1,2,\ldots,\#PULTS_2(p)\}$ be two PULTSs, where $\#PULTS_1(p)$ and $\#PULTS_2(p)$ are the numbers of PULTSs $PULTS_1(p)$ and $PULTS_2(p)$, respectively. If $\#PULTS_1(p)>\#PULTS_2(p)$, then add $\#PULTS_1(p)-\#\,PULTS_2(p)$ linguistic terms to $PULTS_2(p)$. Moreover, the added uncertain linguistic terms should be the smallest linguistic term in $PULTS_2(p)$ and the probabilities of added linguistic terms should be zero.

Definition 5. (Lin et al., 2018). For the$PULTS(p) = \{[L^{\phi}, U^{\phi}](p^{\phi})|\phi = 1, 2, \ldots, \#PULTS(p)\}$, the expected value $E(PULTS(p))$ and deviation degree $DD(PULTS(p))$ of $PULTS(p)$ is defined:

$$EV\left(PULTS(p)\right) = \frac{\sum_{\phi=1}^{\#PULTS(p)}\left(\frac{g(L^{\phi})p^{\phi}+g(U^{\phi})p^{\phi}}{2}\right)}{\sum_{\phi=1}^{\#PULTS(p)}p^{\phi}} \tag{5}$$

$$DD\left(PULTS(p)\right) = \frac{\sqrt{\sum_{\phi=1}^{\#PULTS(p)}\left(\frac{g(L^{\phi})p^{\phi}+g(U^{\phi})p^{\phi}}{2} - E\left(PULTS(p)\right)\right)^2}}{\sum_{\phi=1}^{\#PULTS(p)}p^{\phi}} \tag{6}$$

By using the Eqs (4)-(5), the order relation between two PULTSs is defined as: (1) if $EV(PULTS_1(p)) > EV(PULTS_2(p))$, then $PULTS_1(p) > PULTS_2(p)$; (2) if $EV(PULTS_1(p)) = EV(PULTS_2(p))$, then if$DD(PULTS_1(p)) = DD(PULTS_1(p))$, then $PULTS_1(p) = PULTS_2(p)$; if $DD(PULTS_1(p)) < DD(PULTS_1(p))$, then, $PULTS_1(p) > PULTS_2(p)$.

Definition 6. Let $PULTS_1(p) = \{[L_1^{\phi}, U_1^{\phi}](p_1^{\phi})|\phi = 1, 2, \ldots, \#PULTS_1(p)\}$ and $PULTS_2(p) = \{[L_2^{\phi}, U_2^{\phi}](p_2^{\phi})|\phi = 1, 2, \ldots, \#PULTS_2(p)\}$ be two PULTSs with $\#PULTS_1(p) = \#PULTS_2(p) = \#PULTS(p)$, then Hamming distance $HD(PULTS_1(p), PULTS_2(p))$ between $PULTS_1(p)$ and $PULTS_2(p)$ is defined as follows:

$$HD\left(PULTS_1(p), PULTS_2(p)\right) = \frac{\sum_{\phi=1}^{\#PULTS(p)}\left(|g(L_1^{\phi})p^{\phi} - g(L_2^{\phi})p^{\phi}| + |g(U_1^{\phi})p^{\phi} - g(U_2^{\phi})p^{\phi}|\right)}{2\#PULTS(p)} \tag{7}$$

3. GRA method for PUL-MAGDM with CRITIC weight

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

Then, PUL-GRA method is designed to solve the MAGDM problems with PULTs and CRITIC weight. The detailed calculating steps are listed as follows:

Step 1. Shift cost attribute into beneficial attribute. If the cost attribute value is $[l_\alpha, l_\beta]$, then the corresponding beneficial attribute value is $[l_{-\beta}, l_{-\alpha}]$.

Step 2. Convert the uncertain linguistic information $[L_{ij}^k, U_{ij}^k](i = 1, 2, \ldots, m, j = 1, 2, \ldots, n, k = 1, 2, \ldots, q)$ into probabilistic uncertain linguistic decision matrix $PULDM = (PULDM_{ij}(p))_{m\times n}$, $PULDM_{ij}(p) = \{[L_{ij}^\phi, U_{ij}^\phi](p_{ij}^\phi)|\phi = 1, 2, \ldots, \#PULDM_{ij}(p)\}$ $(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)$.

Step 3. Obtain the normalized probabilistic uncertain linguistic matrix $NPULDM = (NPULDM_{ij}(p))_{m\times n}$, $NPULDM_{ij}(p) = \{[L_{ij}^\phi, U_{ij}^\phi](p_{ij}^\phi)|\phi = 1, 2, \ldots, \#NPULDM_{ij}(p)\}$ $(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)$. Thus, probabilistic uncertain linguistic information for the alternative $A_i \in A$ can be expressed as: $PULA_i = ([L_{i1}^\phi, U_{i1}^\phi](p_{i1}^\phi), [L_{i2}^\phi, U_{i2}^\phi](p_{i2}^\phi), \ldots, [L_{in}^\phi, U_{in}^\phi](p_{in}^\phi))$, $\phi = 1, 2, \ldots, \#NPULDM_{ij}(p)$.

Step 4. Compute the weight values by CRITIC method.

In such section, an essential method called CRiteria Importance Through Intercriteria Correlation (CRITIC) was initially presented by (Diakoulaki., Mavrotas., & Papayannakis., 1995), will be introduced to decide the objective weights of attributes. Subsequently, the detailed computing procedures of this combined weight method are given as follows.

1. Build the probabilistic uncertain linguistic correlation coefficient matrix $PULCCM = (PULCC_{jt})_{n\times n}$ by computing the correlation coefficient between attributes.

$$PULCC_{jt} = \frac{\sum_{i=1}^{m}\left(\begin{array}{c}\left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)}\frac{\left(g(L_{ij}^\phi)p_{ij}{}^\phi - g(L_j^\phi)p_j^\phi\right) + \left(g(U_{ij}^\phi)p_{ij}{}^\phi - g(U_j^\phi)p_j^\phi\right)}{2}\right)\cdot\\ \left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)}\frac{\left(g(L_{it}^\phi)p_{it}{}^\phi - g(L_t^\phi)p_t^\phi\right) + \left(g(U_{it}^\phi)p_{it}{}^\phi - g(U_t^\phi)p_t^\phi\right)}{2}\right)\end{array}\right)}{\sqrt{\sum_{i=1}^{m}\left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)}\frac{\left(g(L_{ij}^\phi)p_{ij}{}^\phi - g(L_j^\phi)p_j^\phi\right) + \left(g(U_{ij}^\phi)p_{ij}{}^\phi - g(U_j^\phi)p_j^\phi\right)}{2}\right)^2}\cdot\sqrt{\sum_{i=1}^{m}\left(\left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)}\frac{\left(g(L_{it}^\phi)p_{it}{}^\phi - g(L_t^\phi)p_t^\phi\right) + \left(g(U_{it}^\phi)p_{it}{}^\phi - g(U_t^\phi)p_t^\phi\right)}{2}\right)\right)^2}},$$

$$j, t = 1, 2, \ldots, n \tag{7}$$

where $[L_j^\phi, U_j^\phi](p_j^\phi) = \left[\frac{\sum_{i=1}^m L_{ij}^\phi}{m}, \frac{\sum_{i=1}^m U_{ij}^\phi}{m}\right]\left(\frac{\sum_{i=1}^m p_{ij}^\phi}{m}\right)$ and $[L_t^\phi, U_t^\phi](p_t^\phi) = \left[\frac{\sum_{i=1}^m L_{it}^\phi}{m}, \frac{\sum_{i=1}^m U_{it}^\phi}{m}\right]\left(\frac{\sum_{i=1}^m p_{it}^\phi}{m}\right)$.

2. Derive the probabilistic uncertain linguistic standard deviation (PULSD) of attribute.

$$PULSD_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)} \frac{\left(g(L_{ij}^{\phi})p_{ij}{}^{\phi} - g(L_j^{\phi})p_j^{\phi}\right) + \left(g(U_{ij}^{\phi})p_{ij}{}^{\phi} - g(U_j^{\phi})p_j^{\phi}\right)}{2}\right)^2},$$

$$j = 1, 2, \ldots, n, \tag{8}$$

3. Compute the objective weights of attributes.

$$w_j = \frac{PULSD_j \sum_{t=1}^{n}(1 - PULCC_{jt})}{\sum_{j=1}^{n}\left(PULSD_j \sum_{t=1}^{n}(1 - PULCC_{jt})\right)}, j = 1, 2 \ldots, n, \tag{9}$$

where $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$.

Step 5. Define the probabilistic linguistic positive ideal solution (PLPIS) and probabilistic linguistic negative ideal solution (PLNIS):

$$PULPIS = (PULPIS_1, PULPIS_2, \ldots, PULPIS_n) \tag{10}$$

$$PULNIS = (PULNIS_1, PULNIS_2, \ldots, PULNIS_n) \tag{11}$$

where

$$\begin{gathered} PULPIS_j = \{pl_j^{\phi}(p_j^{\phi}) | \phi = 1, 2, \ldots, \#NPULDM_{ij}(p)\}, \\ EV(PULPIS_j) = \{\max_i EV\left(NPULDM_{ij}(p)\right)\} \end{gathered} \tag{12}$$

$$\begin{gathered} PULNIS_j = \{nl_j^{\phi}(p_j^{\phi}) | \phi = 1, 2, \ldots, \#NPULDM_{ij}(p)\}, \\ EV(PULNIS_j) = \{\min_i EV\left(NPULDM_{ij}(p)\right)\} \end{gathered} \tag{13}$$

Step 6. Calculate the grey relational coefficient of each alternative from PULPIS and PULNIS, respectively:

The grey relational coefficient of each alternative from PULPIS is given as

$$PULPIS(\xi_{ij}) = \frac{\min_{1 \le i \le m} \min_{1 \le j \le n} HD(PULA_{ij}, PULPIS_j) + \rho \max_{1 \le i \le m} \max_{1 \le j \le n} HD(PULA_{ij}, PULPIS_j)}{HD(PULA_{ij}, PULPIS_j) + \rho \max_{1 \le i \le m} \max_{1 \le j \le n} HD(PULA_{ij}, PULPIS_j)},$$

$$i = 1, 2, \ldots, m, j \in 1, 2, \ldots, n. \tag{14}$$

Similarly, the grey relational coefficient of each alternative from PULNIS is given as

$$PULNIS(\xi_{ij}) = \frac{\min_{1\le i\le m}\min_{1\le j\le n} HD(PULA_{ij}, PULNIS_j) + \rho \max_{1\le i\le m}\max_{1\le j\le n} HD(PULA_{ij}, PULNIS_j)}{HD(PULA_{ij}, PULNIS_j) + \rho \max_{1\le i\le m}\max_{1\le j\le n} HD(PULA_{ij}, PULNIS_j)},$$

$$i = 1, 2, \ldots, m, j \in 1, 2, \ldots, n. \tag{15}$$

where the identification coefficient$\rho = 0.5$.

$$HD(PULA_{ij}, PULPIS_j) = \frac{\left(\sum_{\phi=1}^{\#NPULDM_{ij}(p)} |p_{ij}^{\phi} g(L_{ij}^{\phi}) - p_j^{\phi} g(L_j^{\phi})| + |p_{ij}^{\phi} g(U_{ij}^{\phi}) - p_j^{\phi} g(U_j^{\phi})|\right)}{2\#NPULDM_{ij}(p)} \tag{16}$$

Step 7. Calculating the degree of grey relational coefficient of each alternative from PULPIS and PULNIS by using the following equation, respectively:

$$PULPIS(\xi_i) = \sum_{j=1}^{n} w_j PULPIS(\xi_{ij}), i = 1, 2, \ldots, m, \tag{18}$$

$$PULNIS(\xi_i) = \sum_{j=1}^{n} w_j PULNIS(\xi_{ij}), i = 1, 2, \ldots, m, \tag{19}$$

The fundamental principle of the GRA method is that the chosen alternative should have the 'largest degree of grey relational coefficient' from the PULPIS and the 'smallest degree of grey relational coefficient' from the PULNIS. Obviously, the larger $PULPIS(\xi_i)$ and the smaller $PULNIS(\xi_i)$, the better alternativeA_i is.

Step 8. Calculate the probabilistic uncertain linguistic relative relational degree (PULRRD) of each alternative from PULPIS.

$$PULRRD(\xi_i) = \frac{PULPIS(\xi_i)}{PULPIS(\xi_i) + PULNIS(\xi_i)}, i = 1, 2, \ldots, m, \tag{20}$$

Step 9. According to $PULRRD(\xi_i)$, the ranking order of all alternatives can be determined. Thus, if any alternative has the largest $PULRRD(\xi_i)$ value, then, it is the optimal alternative.

4. A case study and comparative analysis

4.1. A case study

Along with the convenience of transportation, motor vehicle becomes the primary source of pollution. The issues of energy and environment pollution attract high attention. In view of the adverse effects of the transportation industry on energy and environment, countries have taken the development of new energy vehicles as a national

Table 1. Uncertain linguistic assessing matrix by the DM_1.

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

strategy. As the representative of new energy vehicles, electric vehicles with low energy consumption and zero pollution have been developed rapidly. Therefore, it is imperative to promote electric logistics vehicles in the logistics industry. The use of electric logistics vehicle distribution can not only reduce harmful gas emissions, but also reduce logistics costs. At present, the problem of difficult charging seriously restricts the large-scale operation of electric logistics vehicles. Perfect charging facilities are an important guarantee to promote the large-scale use of electric logistics vehicles, and it is particularly important to reasonably determine the location distribution of charging facilities. At the same time, compared with the distribution of traditional fuel vehicles, the distribution of electric logistics vehicles is faced with difficulties such as limited battery capacity, few charging facilities and long charging time, so the traditional vehicle route distribution method cannot be directly applied to the distribution system of electric logistics vehicles. The location of charging station and the path planning of electric logistics vehicle depend on each other, so it is necessary to combine the site selection and vehicle path planning. The site selection of EVCS is deemed as a kind of MAGDM issue(Li et al., 2019; J. Wang, Lu, Wei, Lin, & Wei, 2019; J. Wang, Wei, et al., 2019; G. W. Wei, Wang, Wei, Wei, & Zhang, 2019; S. Q. Zhang, Wei, Gao, Wei, & Wei, 2019). Thus, in this section we present a numerical example for site selection of EVCS to illustrate the method designed in this paper. There are five possible EVCS sites $A_i(i = 1, 2, 3, 4, 5)$ to select. The experts selects four attribute to evaluate the five possible EVCS sites: ①G_1 is the waste discharge; ②G_2 is the construction cost; ③G_3 is the traffic convenience; ④G_4 is the service capability. The construction cost is not beneficial attribute, others are beneficial attribute. The five possible EVCS sites $A_i(i = 1, 2, 3, 4, 5)$ are to be evaluated by using the linguistic term set

$$\begin{aligned} L = \{ & l_{-3} = extremelypoor(EP), l_{-2} = verypoor(VP), \\ & l_{-1} = poor(P), l_0 = medium(M), l_1 = good(G), \\ & l_2 = verygood(VG), l_3 = extremelygood(EG)\} \end{aligned}$$

by the five decision makers under the above four attributes, as listed in the Tables 1–5.

In the following, we utilize the PUL-GLDS method developed for EVCS site selection.

Step 1. Shift cost attribute G_2 into beneficial attribute. If the cost attribute value is $[s_\alpha, s_\beta](-3 \le \alpha, \beta \le 3)$, then the corresponding beneficial attribute value is $[s_{-\beta}, s_{-\alpha}]$ (See Tables 6–10).

Step 2. Transform the uncertain linguistic variables into probabilistic uncertain linguistic assessing matrix (Table 11).

Table 2. Uncertain linguistic assessing matrix by the DM_2.

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

Table 3. Uncertain linguistic assessing matrix by the DM_3.

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

Table 4. Uncertain linguistic assessing matrix by the DM_4.

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

Table 5. Uncertain linguistic assessing matrix by the DM_5.

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

Table 6. Uncertain linguistic assessing matrix by the DM_1.

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

Table 7. Uncertain linguistic assessing matrix by the DM_2.

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

Step 3. Calculate the normalized probabilistic uncertain linguistic assessing matrix (Table 12).

Step 4. Define the probabilistic linguistic positive ideal solution (PLPIS) and probabilistic linguistic negative ideal solution (PLNIS) (Table 13).

Table 8. Uncertain linguistic assessing matrix by the DM_3.

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

Table 9. Uncertain linguistic assessing matrix by the DM_4.

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

Table 10. Uncertain linguistic assessing matrix by the DM_5.

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

Table 11. Probabilistic uncertain linguistic assessing matrix.

Alternatives	G_1	G_2
A_1	$\left\{\begin{matrix}\langle [l_{-2}, l_{-1}], 0.4\rangle, \langle [l_{-1}, l_0], 0.2\rangle, \\ \langle [l_1, l_2], 0.4\rangle\end{matrix}\right\}$	$\left\{\begin{matrix}\langle [l_0, l_1], 0.4\rangle, \langle [l_1, l_2], 0.4\rangle, \\ \langle [l_2, l_3], 0.2\rangle\end{matrix}\right\}$
A_2	$\left\{\begin{matrix}\langle [l_{-3}, l_{-2}], 0.6\rangle, \langle [l_{-2}, l_{-1}], 0.2\rangle, \\ \langle [l_{-1}, l_0], 0.2\rangle\end{matrix}\right\}$	$\left\{\begin{matrix}\langle [l_0, l_1], 0.6\rangle, \langle [l_1, l_2], 0.2\rangle, \\ \langle [l_2, l_3], 0.2\rangle\end{matrix}\right\}$
A_3	$\left\{\begin{matrix}\langle [l_0, l_1], 0.2\rangle, \langle [l_1, l_2], 0.2\rangle, \\ \langle [l_2, l_3], 0.6\rangle\end{matrix}\right\}$	$\{\langle [l_{-3}, l_{-2}], 1\rangle\}$
A_4	$\{\langle [l_1, l_2], 1\rangle\}$	$\left\{\begin{matrix}\langle [l_{-3}, l_{-2}], 0.2\rangle, \langle [l_{-2}, l_{-1}], 0.2\rangle, \\ \langle [l_{-1}, l_0], 0.6\rangle\end{matrix}\right\}$
A_5	$\left\{\begin{matrix}\langle [l_0, l_1], 0.4\rangle, \langle [l_1, l_2], 0.4\rangle, \\ \langle [l_2, l_3], 0.2\rangle\end{matrix}\right\}$	$\left\{\begin{matrix}\langle [l_{-2}, l_{-1}], 0.2\rangle, \langle [l_{-1}, l_0], 0.6\rangle, \\ \langle [l_0, l_1], 0.2\rangle\end{matrix}\right\}$
Alternatives	G_3	G_4
A_1	$\left\{\begin{matrix}\langle [l_{-2}, l_{-1}], 0.6\rangle, \langle [l_{-1}, l_0], 0.2\rangle, \\ \langle [l_{-1}, l_1], 0.2\rangle\end{matrix}\right\}$	$\left\{\begin{matrix}\langle [l_{-3}, l_{-2}], 0.4\rangle, \langle [l_{-2}, l_{-1}], 0.2\rangle, \\ \langle [l_0, l_1], 0.4\rangle\end{matrix}\right\}$
A_2	$\{\langle [l_{-3}, l_{-2}], 1\rangle\}$	$\{\langle [l_{-2}, l_{-1}], 0.6\rangle, \langle [l_{-1}, l_0], 0.4\rangle\}$
A_3	$\{\langle [l_1, l_2], 0.4\rangle, \langle [l_2, l_3], 0.6\rangle\}$	$\left\{\begin{matrix}\langle [l_0, l_1], 0.2\rangle, \langle [l_1, l_2], 0.2\rangle, \\ \langle [l_2, l_3], 0.6\rangle\end{matrix}\right\}$
A_4	$\{\langle [l_1, l_2], 0.2\rangle, \langle [l_2, l_3], 0.8\rangle\}$	$\{\langle [l_2, l_2], 0.4\rangle, \langle [l_2, l_3], 0.6\rangle\}$
A_5	$\left\{\begin{matrix}\langle [l_0, l_1], 0.4\rangle, \langle [l_1, l_2], 0.4\rangle, \\ \langle [l_2, l_3], 0.2\rangle\end{matrix}\right\}$	$\left\{\begin{matrix}\langle [l_{-1}, l_0], 0.2\rangle, \langle [l_0, l_1], 0.4\rangle, \\ \langle [l_1, l_2], 0.4\rangle\end{matrix}\right\}$

Step 5. Computing the corresponding GRC of each alternative from PULPIS and PULNIS (Tables 14 and 15), let $\rho = 0.5$:

Step 6. the weight vector of attributes can be got: $w = (0.2966, 0.1930, 0.2534, 0.2570)^T$.

Table 12. Normalized probabilistic uncertain linguistic assessing matrix.

Alternatives	G_1	G_2
A_1	$\left\{\begin{array}{c}\langle[l_{-2},l_{-1}],0.4\rangle,\langle[l_{-1},l_0],0.2\rangle,\\ \langle[l_1,l_2],0.4\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.4\rangle,\langle[l_{-2},l_{-1}],0.4\rangle,\\ \langle[l_{-1},l_0],0.2\rangle\end{array}\right\}$
A_2	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.6\rangle,\langle[l_{-2},l_{-1}],0.2\rangle,\\ \langle[l_{-1},l_0],0.2\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.2\rangle,\langle[l_{-2},l_{-1}],0.2\rangle,\\ \langle[l_{-1},l_0],0.6\rangle\end{array}\right\}$
A_3	$\left\{\begin{array}{c}\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_2,l_3],0\rangle,\langle[l_2,l_3],0\rangle,\\ \langle[l_2,l_3],1\rangle\end{array}\right\}$
A_4	$\left\{\begin{array}{c}\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0\rangle,\\ \langle[l_1,l_2],1\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_0,l_1],0.6\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.2\rangle\end{array}\right\}$
A_5	$\left\{\begin{array}{c}\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.4\rangle,\\ \langle[l_2,l_3],0.2\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-1},l_0],0.2\rangle,\langle[l_0,l_1],0.6\rangle,\\ \langle[l_1,l_2],0.2\rangle\end{array}\right\}$
Alternatives	G_3	G_4
A_1	$\left\{\begin{array}{c}\langle[l_{-2},l_{-1}],0.6\rangle,\langle[l_{-1},l_0],0.3\rangle,\\ \langle[l_0,l_1],0.2\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.4\rangle,\langle[l_{-2},l_{-1}],0.2\rangle,\\ \langle[l_0,l_1],0.4\rangle\end{array}\right\}$
A_2	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0\rangle,\langle[l_{-3},l_{-2}],0\rangle,\\ \langle[l_{-3},l_{-2}],1\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-2},l_{-1}],0\rangle,\langle[l_{-2},l_{-1}],0.6\rangle,\\ \langle[l_{-1},l_0],0.4\rangle\end{array}\right\}$
A_3	$\left\{\begin{array}{c}\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0.4\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$
A_4	$\left\{\begin{array}{c}\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.8\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_2,l_2],0\rangle,\langle[l_2,l_2],0.4\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$
A_5	$\left\{\begin{array}{c}\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.4\rangle,\\ \langle[l_2,l_3],0.2\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-1},l_0],0.2\rangle,\langle[l_0,l_1],0.4\rangle,\\ \langle[l_1,l_2],0.4\rangle\end{array}\right\}$

Table 13. PULPIS and PULNIS.

	G_1	G_2
PULPIS	$\left\{\begin{array}{c}\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_2,l_3],0\rangle,\langle[l_2,l_3],0\rangle,\\ \langle[l_2,l_3],1\rangle\end{array}\right\}$
PULNIS	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.6\rangle,\langle[l_{-2},l_{-1}],0.2\rangle,\\ \langle[l_{-1},l_0],0.2\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.4\rangle,\langle[l_{-2},l_{-1}],0.4\rangle,\\ \langle[l_{-1},l_0],0.2\rangle\end{array}\right\}$
	G_3	G_4
PULPIS	$\left\{\begin{array}{c}\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0.2\rangle,\\ \langle[l_2,l_3],0.8\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_2,l_2],0\rangle,\langle[l_2,l_2],0.4\rangle,\\ \langle[l_2,l_3],0.6\rangle\end{array}\right\}$
PULNIS	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0\rangle,\langle[l_{-3},l_{-2}],0\rangle,\\ \langle[l_{-3},l_{-2}],1\rangle\end{array}\right\}$	$\left\{\begin{array}{c}\langle[l_{-3},l_{-2}],0.4\rangle,\langle[l_{-2},l_{-1}],0.2\rangle,\\ \langle[l_0,l_1],0.4\rangle\end{array}\right\}$

Step 7. Calculating the degree of GRC of all possible alternatives from PULPIS and PULNIS, respectively (Table 14):

Step 8. Calculating the $PULRRD(\xi_i)$ of each alternative from PULPIS by Eq.(14) (Table 15).

Step 9. According to the $PULRRD(\xi_i)(i = 1, 2, 3, 4, 5)$, all the waste incineration plants sites can be ranked. Evidently, the order is $A_3 > A_4 > A_5 > A_1 > A_2$ and the most desirable EVCS site among five alternatives isA_3.

At the same time, we conduct the sensitively analysis to show the robustness of the proposed method. The parameter valueρ varies from 0.1 to 1. We could get the

Table 14. GRC of each alternative from PULPIS.

Alternatives	G_1	G_2	G_3	G_4
A_1	0.5068	0.4157	0.4205	0.4805
A_2	0.4353	0.4568	0.4353	0.5362
A_3	1.0000	1.0000	0.6491	0.6981
A_4	0.5362	0.3333	1.0000	1.0000
A_5	0.3978	0.3394	0.4066	0.4933

Table 14. $PULPIS(\xi_i)$ and$PULNIS(\xi_i)$ of each alternative.

Alternatives	$PULPIS(\xi_i)$	$PULNIS(\xi_i)$
A_1	0.4420	0.7413
A_2	0.4619	0.9030
A_3	0.7628	0.3710
A_4	0.8260	0.4205
A_5	0.4124	0.4825

Table 15. GRC of each alternative from PULNIS.

Alternatives	G_1	G_2	G_3	G_4
A_1	0.5909	1.0000	0.5532	1.0000
A_2	1.0000	0.7647	1.0000	0.7647
A_3	0.3514	0.3333	0.3611	0.4333
A_4	0.6190	0.5200	0.3514	0.3939
A_5	0.4483	0.5652	0.4194	0.5652

Table 15. PULRRD of each alternative from PULPIS.

Alternatives	A_1	A_2	A_3	A_4	A_5
$PULRRD(\xi_i)$	0.3735	0.3384	0.6728	0.6626	0.4608

Table 16. The sensitively analysis for PUL-GRA method.

ρ	Order	ρ	Order
$\rho = 0.1$	$A_4 > A_3 > A_5 > A_1 > A_2$	$\rho = 0.6$	$A_3 > A_4 > A_5 > A_1 > A_2$
$\rho = 0.2$	$A_4 > A_3 > A_5 > A_1 > A_2$	$\rho = 0.7$	$A_3 > A_4 > A_5 > A_1 > A_2$
$\rho = 0.3$	$A_3 > A_4 > A_5 > A_1 > A_2$	$\rho = 0.8$	$A_3 > A_4 > A_5 > A_1 > A_2$
$\rho = 0.4$	$A_3 > A_4 > A_5 > A_1 > A_2$	$\rho = 0.9$	$A_3 > A_4 > A_5 > A_1 > A_2$
$\rho = 0.5$	$A_3 > A_4 > A_5 > A_1 > A_2$	$\rho = 1.0$	$A_3 > A_4 > A_5 > A_1 > A_2$

calculating result which is listed in Table 16. The ranking result is same and the order is: $A_3 > A_4 > A_5 > A_1 > A_2$ when The parameter valueρ varies from 0.1 to 1. The optimal alternative is still isA_3 and the worst alternative isA_2. It could be seen that the proposed PUL-GRA method is robust and effective.

4.2. Comparative analysis

In such subsection, we shall compare our proposed method with PULWA operator(Lin et al., 2018), probabilistic uncertain linguistic TOPSIS method (PUL-TOPSIS method) (Lin et al., 2018) and ULWA operator (Z.S. Xu, 2004).

Table 17. The calculating results and sorting results by using PUL-TOPSIS method.

TOPSIS method	calculating results and sorting results
The distances of each alternative from PULPIS	$d_1^+ = 1.2418, d_2^+ = 1.7766, d_3^+ = 0.1392, d_4^+ = 0.6584, d_5^+ = 0.9528$
The distances of each alternative from PULNIS	$d_1^- = 0.6044, d_2^- = 0.2167, d_3^- = 1.6827, d_4^- = 1.4133, d_5^- = 1.0793$
Closeness coefficients	$CI_1 = -8.5622, CI_2 = -12.6347, CI_3 = 0.0000, CI_4 = -3.8902, CI_5 = -0.6203$
Ordering	$A_3 > A_4 > A_5 > A_1 > A_2$

4.2.1. Compared with PULWA operator

Firstly, we compare our proposed method with probabilistic uncertain linguistic weighted average (PULWA) operator (Lin et al., 2018), the weight vector of attributes is derived as: $w_1 = 0.2996, w_2 = 0.1930, w_3 = 0.2534, w_4 = 0.2570$, then the overall attribute value of each alternative $Z_i(w)(i = 1, 2, 3, 4, 5)$ is obtained by employing PULWA operator.

$$Z_1(w) = \{[l_{-0.9656}, l_{-0.5535}], [l_{-0.3925}, l_{-0.1286}], [l_{-0.0613}, l_{0.2626}]\}$$

$$Z_2(w) = \{[l_{-0.6497}, l_{-0.4331}], [l_{-0.5042}, l_{-0.2521}], [l_{-1.0382}, l_{-0.5069}]\}$$

$$Z_3(w) = \{[l_{0.0000}, l_{0.0514}], [l_{0.2121}, l_{0.4242}], [l_{1.4730}, l_{2.2095}]\}$$

$$Z_4(w) = \{[l_{0.0000}, l_{0.1158}], [l_{-0.0452}, l_{0.2655}], [l_{0.6131}, l_{1.1866}]\}$$

$$Z_5(w) = \{[l_{-0.1414}, l_{0.2707}], [l_{0.1693}, l_{0.5572}], [l_{0.3100}, l_{0.5100}]\}$$

Then, the score values of these five overall attribute values of each alternative $Z_i(w)(i = 1, 2, 3, 4, 5)$ are obtained by Definition 9 (Lin et al., 2018) as follows:

$$E\Big(Z_1(w)\Big) = l_{-0.2043}, E\Big(Z_2(w)\Big) = l_{-0.3760}, E\Big(Z_3(w)\Big) = l_{0.4856} E\Big(Z_4(w)\Big) = l_{0.2373}, E\Big(Z_5(w)\Big) = l_{0.1862}$$

Furthermore, we can derive the ranking result: $A_3 > A_4 > A_5 > A_1 > A_2$. Thus, we have the same optimal EVCS siteA_3.

4.2.2. Compared with PUL-TOPSIS method

Then, we compare our proposed method with probabilistic uncertain linguistic TOPSIS method (PUL-TOPSIS method) (Lin et al., 2018), then we can acquire the calculating results and sorting results (Table 17). Thus, we have the same optimal EVCS siteA_2.

4.2.3. Compared with ULWA operator

In this subsection, we further analysis the above example under the uncertain linguistic environment. Use the ULWA operator (Z.S. Xu, 2004) with equal weight

Table 18. Group uncertain linguistic decision matrix.

Alternatives	G_1	G_2	G_3	G_4
A_1	$[l_{-0.6}, l_{0.4}]$	$[l_{-1.8}, l_{-0.8}]$	$[l_{-1.5}, l_{-0.5}]$	$[l_{-2}, l_{-1}]$
A_2	$[l_{-2.4}, l_{-1.4}]$	$[l_{-1.6}, l_{-0.6}]$	$[l_{-0.7}, l_{0.3}]$	$[l_{-1.6}, l_{-0.6}]$
A_3	$[l_{1.8}, l_{2.8}]$	$[l_2, l_3]$	$[l_{1.2}, l_{2.2}]$	$[l_{1.4}, l_{2.4}]$
A_4	$[l_{-1.4}, l_{-0.4}]$	$[l_{-0.4}, l_{0.6}]$	$[l_{1.8}, l_{2.8}]$	$[l_{1.6}, l_{2.6}]$
A_5	$[l_{0.8}, l_{1.8}]$	$[l_0, l_1]$	$[l_{0.6}, l_{1.6}]$	$[l_{-0.2}, l_{0.8}]$

information to fuse all the uncertain linguistic decision matrices provided by the DMs into a group uncertain linguistic decision matrix (See Table 18).

The attributes weight is derived as: $w_1 = 0.2800, w_2 = 0.3200, w_3 = 0.1100, w_4 = 0.2900$, then the overall values of these five alternatives $Z_i(w)(i = 1, 2, 3, 4, 5)$ is obtained by using ULWA operator (Z.S. Xu, 2004).

$$Z_1(w) = [l_{-1.4194}, l_{-0.4194}], Z_2(w) = [l_{-2.1921}, l_{-1.1921}], Z_3(w) = [l_{1.6851}, l_{2.6851}]$$

$$Z_4(w) = [l_{0.5679}, l_{1.5679}], Z_5(w) = [l_{0.3379}, l_{1.3379}]$$

Then, the score values of these five alternatives $Z_i(w)(i = 1, 2, 3, 4, 5)$ are obtained by Definition 9 (Lin et al., 2018) as follows:

$$E\Big(Z_1(w)\Big) = l_{-0.9194}, E\Big(Z_2(w)\Big) = l_{-1.6921}, E\Big(Z_3(w)\Big) = l_{2.1851}$$

$$E\Big(Z_4(w)\Big) = l_{1.0679}, E\Big(Z_5(w)\Big) = l_{0.8379}$$

Furthermore, we can derive the ranking result: $A_3 > A_4 > A_5 > A_1 > A_2$. Thus, we have the same optimal EVCS siteA_3.

5. Conclusion

In this paper, we extend the classical GRA method to the probabilistic uncertain linguistic MAGDM with unknown weight information. Firstly, the basic concept, comparative formula and Hamming distance of PULTs are briefly introduced. Then, the definition of the expected value is employed to objectively compute the attribute weights based on the CRITIC method. Then, the optimal alternative(s) is determined by calculating the 'largest degree of grey relational coefficient' from the PULPIS and the 'smallest degree of grey relational coefficient' from the PULNIS. Finally, a practical case study for site selection of EVCS is provided to validate the proposed algorithm and some comparative analysis is also designed to verify the applicability. In the future, the application of the proposed models and methods with PULTSs needs to be investigated into other practical applicable domains (Stanujkic, Karabasevic, Zavadskas, Smarandache, & Brauers, 2019; Stevic, Vasiljevic, Zavadskas, Sremac, & Turskis, 2018; G. W. Wei, Wang, Wei, et al., 2019; Zavadskas, Antucheviciene, Saparauskas, & Turskis, 2013) and uncertain and fuzzy cognitive environments (Dahooie et al., 2019; Jahan & Zavadskas, 2019; G. Tian et al., 2017; J. Wang, Gao, &

Wei, 2019; G. W. Wei, Wang, Wang, et al., 2019; G.W. Wei, Wu, Wei, Wang, & Lu et al., 2019; K. Zhang et al., 2018). At the same time, we shall continue to investigate the PUL-MAGDM with incomplete weight information.

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