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EDAS Method for Multiple Attribute Group Decision Making with Probabilistic Uncertain Linguistic Information and Its Application to Green Supplier Selection

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ABSTRACT

In order to adapt to the development of the new times, enterprises should not only care for the economic benefits, but also properly cope with environmental and social problems to achieve the integration of environmental, economic and social performance of sustainable development, so as to maximize the efficiency of resource use and minimize the negative effects of environmental pollution. Hence, in order to select a proper green supplier, integration of the information entropy and Evaluation based on Distance from Average Solution (EDAS) under probabilistic uncertain linguistic sets (PULTSs) offered a novel integrated model, in which information entropy is used for deriving priority weights of each attribute and EDAS with PULTSs is employed to obtain the final ranking of green supplier. Furthermore, in order to show the applicability of the proposed method, it is validated by a case study for green supplier selection along with some comparative analysis. Thus, the advantage of this proposed method is that it is simple to understand and easy to compute. The proposed method can also contribute to the selection of suitable alternative successfully in other selection issues.

1. INTRODUCTION

The Evaluation based on Distance from Average Solution (EDAS) method was initially designed by Keshavarz Ghorabaee, Zavadskas, Olfat and Turskis [1] to tackle the multi-criteria inventory classification (MCIC) problems which can also be employed for Multiple attribute decision making (MADM) or Multiple attribute group decision making (MAGDM) issues. The main advantage of the EDAS method has high efficiency and needs less computation in comparison with other decision making and classification methods. Stevic, Vasiljevic, Zavadskas, Sremac and Turskis [2] proposed fuzzy EDAS method to select the carpenter manufacturer. Keshavarz Ghorabaee, Zavadskas, Amiri and Turskis [3] presented the EDAS method to cope with the MADM problems under the fuzzy environment for supplier selection. Keshavarz Ghorabaee, Amiri, Zavadskas and Turskis [4] gave the extended EDAS method for dealing with MAGDM with interval type-2 fuzzy sets. Kahraman, Keshavarz Ghorabaee, Zavadskas, Onar, Yazdani and Oztaysi [5] employed the interval-valued intuitionistic fuzzy EDAS method based on the membership, hesitance degrees and non-membership. Keshavarz Ghorabaee, Amiri, Zavadskas, Turskis and Antucheviciene [6] proposed the stochastic EDAS method for MADM with normally distributed data. Keshavarz-Ghorabaee, Amiri, Zavadskas, Turskis and Antucheviciene [7] analyzed the rank reversal (RR) phenomenon in EDAS method which is compared with TOPSIS method by using a simulation-based analysis. Peng and Dai [8] designed the algorithms for interval neutrosophic EDAS method for MADM based on the MABAC and similarity measure. Zhang, Gao, Wei, Wei and Wei [9] developed the EDAS method for MAGDM with picture 2-tuple linguistic information. Feng, Wei and Liu [10] defined the EDAS method to solve the Hesitant Fuzzy Linguistic MADM. Mi and Liao [11] utilized the hesitant fuzzy BWM and hesitant fuzzy EDAS method for choosing commercial endowment insurance products. Zhang, Wei, Gao, Wei and Wei [12] proposed the EDAS method for multiple criteria group decision making with picture fuzzy information for green suppliers selections.

In many decision-making problems [13], it has been traditionally supposed that all information is depicted in the form of crisp numbers. However, most of decision makers' assessment information is imprecise or uncertain [14–18]. For example, the DMs may utilize the linguistic terms such as "bad," "medium" and "good" when the satisficing degree of a car is appraised [19]. In order to assess the qualitative information easily, Herrera and Martinez [20] defined the linguistic term sets (2TLTSs) for computing with words. Furthermore, Rodriguez, Martinez and Herrera [21] proposed the hesitant fuzzy linguistic term sets (HFLTSs) on the basis of hesitant fuzzy sets [22] and LTSs [23] which allow DMs to provide several possible linguistic variable. Liao, Yang and Xu [24]

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proposed the ELECTRE II method under HFLTS environment and developed two novel methods named score-deviation-based ELECTRE II model and positive and negative ideal-based ELECTRE II model. Zhang, Liang and Zhang [25] provided a new consensus reaching process in multiple attribute group decision making (MAGDM) with HFLTSs. Wei [26] gave the generalized dice similarity measures for MADM with hesitant fuzzy linguistic information. However, in most existing researches on HFLTSs, all possible values are treated by the DMs have same weight or importance. Clearly, it is inconsistent with the real life. In both personal MADM and MAGDM issues, the DMs may give possible linguistic terms so that these offered information may have not equal probability distributions. Thus, Pang, Wang and Xu [27] proposed the probabilistic linguistic term sets (PLTSs) to overcome this limits and defined a framework for ranking PLTSs with the score or deviation degree of each PLTS. Gou and Xu [28] formed the operational laws for HFLEs and PLTSs based on two equivalent transformation functions. Zhang, Xu and Liao [29] developed a consensus algorithm to analyze the GDM with probabilistic linguistic preference relations. Kobina, Liang and He [30] constructed some Probabilistic linguistic power operators for MAGDM with classical power aggregation operators [31–33]. Liao, Jiang, Xu, Xu and Herrera [34] came up with linear programming method to deal with the MADM with probabilistic linguistic information. Chen, Wang and Wang [35] proposed probabilistic linguistic MULTIMOORA for cloud-based Enterprise Resource Planning (ERP) system selection. Liang, Kobina and Quan [36] proposed the probabilistic linguistic gray relational analysis (PL-GRA) for MAGDM based on geometric Bonferroni mean [37,38]. Bai, Zhang, Qian and Wu [39] used more appropriate comparison method and proposed a more efficient way to handle PLTSs. Cheng, Gu and Xu [40] investigated the venture capital group decision-making with interaction under probabilistic linguistic environment. Lu, Wei, Wu and Wei [41] designed the TOPSIS method for probabilistic linguistic MAGDM for supplier selection of new agricultural machinery products.

In some practical situations, a set of DMs may have their preferences to express their assessment information by using uncertain linguistic terms [42] in the 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 PLTSs [27] and uncertain linguistic term [42], Lin, Xu, Zhai and Yao [43] came up with a new concept of probabilistic uncertain linguistic term set (PULTS) in order to model and operate the uncertain linguistic information in the GDM issues. Xie, Ren, Xu and Wang [44] built the probabilistic uncertain linguistic preference relation (PULPR) and the normalized PULPR and designed the distance measure and similarity degree measure the consensus degree. But there are no studies on the EDAS method for MAGDM under PULTSs in the existing literature. Therefore, it is necessary to pay attention to this issue. The goal of such paper is to design the EDAS method to tackle the MAGDM with the PULTSs. The originality of the paper can be highlighted as follows: (1) the EDAS method is modified by PULTSs; (2) the probabilistic uncertain linguistic EDAS (PUL-EDAS) method is designed to tackle the MAGDM issues with PULTSs; (3) a case study for green supplier selection is designed to proof the developed method; (4) some comparative studies are given with the PULWA operator, PUL-TOPSIS method and uncertain linguistic weighted average (ULWA) operator to verify the rationality of PUL-EDAS method.

The remainder section of such paper is designed as follows. Section 2 reviews some basic concepts related to PULTSs. In Section 3, the EDAS method is designed for MAGDM issues under PULTSs. In Section 4, a detailed case study for green supplier selection is designed and some comparative analysis is investigated. The study ends with some meaningful conclusions in Section 5.

2. PRELIMINARIES

Firstly, Xu [45]defined the additive linguistic evaluation scale and Gou, Xu and Liao [46] defined the corresponding transformation function between the linguistic terms and $[0,1]$.

Definition 1. [45,46] Let $L=\{l_\alpha|\alpha=-\theta,\cdots,-2,-1,0,1,2,\cdots\theta\}$ be an LTS [45], the linguistic terms l_α can express the equivalent information to β is derived by the transformation function g [46]:

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

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

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

In order to strengthen the modeling capability of HFLTSs, Pang, Wang and Xu [27] proposed the definition of PLTSs to link each linguistic term with a probability value.

Definition 2. [27] Given an LTS $L=\left\{l_j|j=-\theta,\cdots,-2,-1,0,1,2,\cdots\theta\right\}$, a PLTS is defined as:

$$\begin{aligned}L(p)=&\left\{l^{(\phi)}\left(p^{(\phi)}\right)|l^{(\phi)}\in L,p^{(\phi)}\geq0,\phi\right.\\&\left.=1,2,\cdots,\#L(p),\sum_{\phi=1}^{\#L(p)}p^{(\phi)}\leq1\right\}\end{aligned} \tag{3}$$

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.

In order to depict the DMs' uncertainty accurately, Lin, Xu, Zhai and Yao [43] put forward a novel concept called PULTS based on uncertain linguistic term [42] and PLTSs.

Definition 3. [43] A PULTS could be defined as follows:

$$\begin{aligned}PULTS(p)=&\left\{\left[L^\phi,U^\phi\right]\left(p^\phi\right)|p^\phi\geq0,\phi\right.\\&\left.=1,2,\cdots,\#PULTS(p),\sum_{\phi=1}^{\#PULTS(p)}p^\phi\leq1\right\}\end{aligned} \tag{4}$$

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

In order to easy computation, Pang, Wang and Xu [27] normalized the PLTS $L(p)$ as $\tilde{L}(p) = \left\{ l^{(\phi)}\left(\tilde{p}^{(\phi)}\right) | l^{(\phi)} \in L, \tilde{p}^{(\phi)} \geq 0, \phi = 1, 2, \cdots, \#L\left(\tilde{p}\right), \sum_{\phi=1}^{\#L(p)} \tilde{p}^{(\phi)} = 1 \right\}$, where $\tilde{p}^{(\phi)} = p^{(\phi)} / \sum_{\phi=1}^{\#L(p)} p^{(\phi)}$ for all $\phi = 1, 2, \cdots, \#L\left(\tilde{p}\right)$.

Definition 4. [43] Let $PULTS_1(p) = \left\{\left[L_1^{\phi}, U_1^{\phi}\right]\left(p_1^{\phi}\right) | \phi = 1, 2, \cdots, \#PULTS_1(p)\right\}$ and $PULTS_2(p) = \left\{\left[L_2^{\phi}, U_2^{\phi}\right]\left(p_2^{\phi}\right) | \phi = 1, 2, \cdots, \#PULTS_2(p)\right\}$ 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. [43] For a PULTS $PULTS(p) = \{[L^{\phi}, U^{\phi}](p^{\phi}) | \phi = 1, 2, \cdots, \#PULTS(p)\}$, the expected value $E\left(PULTS(p)\right)$ and deviation degree $\sigma\left(PULTS(p)\right)$ of $PULTS(p)$ is defined:

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

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

By using the Eqs. (4) and (5), the order relation between two PULTSs is defined as: (1) if $E\left(PULTS_1(p)\right) > E\left(PULTS_2(p)\right)$, then $PULTS_1(p) > PULTS_2(p)$; (2) if $E\left(PULTS_1(p)\right) = E\left(PULTS_2(p)\right)$, then if $\sigma\left(PULTS_1(p)\right) = \sigma\left(PULTS_1(p)\right)$, then $PULTS_1(p) = PULTS_2(p)$; if $\sigma\left(PULTS_1(p)\right) < \sigma\left(PULTS_1(p)\right)$, then, $PULTS_1(p) > PULTS_2(p)$.

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

$$d\left(PULTS_1\left(p\right), PULTS_2\left(p\right)\right) = \frac{\sum_{\phi=1}^{\#\tilde{L}_1(\tilde{p})} \left(\left(g\left(L_1^{\phi}\right)p^{\phi} - g\left(L_2^{\phi}\right)p^{\phi}\right) + \left(g\left(U_1^{\phi}\right)p^{\phi} - g\left(U_2^{\phi}\right)p^{\phi}\right)\right)}{2\#PULTS\left(p\right)} \tag{7}$$

3. EDAS METHOD FOR PROBABILISTIC UNCERTAIN LINGUISTIC MAGDM PROBLEMS

In such section, we design a new probabilistic uncertain linguistic EDAS (PUL-EDAS) method for MAGDM issues. The following mathematical notations are employed to cope with the probabilistic uncertain linguistic MAGDM problems. Let $A = \{A_1, A_2, \cdots, A_m\}$ be a discrete set of chosen alternatives, and $G = \{G_1, G_2, \cdots, G_n\}$ with weight vector $w = (w_1, w_2, \cdots, w_n)$, where $w_j \in [0, 1]$, $j = 1, 2, \cdots, n$, $\sum_{j=1}^{n} w_j = 1$, and a set of experts $E = \{E_1, E_2, \cdots, E_q\}$. Suppose that G_j are assessed by expert E_k for A_i and depicted as uncertain linguistic expressions $\left[L_{ij}^k, U_{ij}^k\right]$ $\left(i = 1, 2, \cdots, m, j = 1, 2, \cdots, n, k = 1, 2, \cdots, q\right)$.

Then, PUL-EDAS method is proposed to solve the MAGDM problems. The designed calculating steps are involved as follows:

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

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

Step 3. Calculate the normalized PULDM $NPULDM = \left(NPULDM_{ij}(p)\right)_{m \times n}$.

Step 4. Compute the weight values for attributes.

Entropy [47] is a conventional term from information theory which is also famous as the average amount of information contained in each attribute. The larger the value of entropy in a given attribute is, the smaller the differences in the ratings of alternatives with respect to this attribute. In turn, this means that this kind of attribute supplies less information and has a smaller weight. Firstly, the normalized decision matrix $NPULNDM_{ij}(p)$ is derived as follows:

$$NPULNDM_{ij}\left(p\right) = \frac{\sum_{\phi=1}^{\#NPULDM_{ij}(p)} \left(\frac{g(L_{ij}^{\phi})p_{ij}^{\phi} + g(U_{ij}^{\phi})p_{ij}^{\phi}}{2}\right)}{\sum_{i=1}^{m} \sum_{\phi=1}^{\#NPULDM_{ij}(p)} \left(\frac{g(L_{ij}^{\phi})p_{ij}^{\phi} + g(U_{ij}^{\phi})p_{ij}^{\phi}}{2}\right)}, \quad j = 1, 2, \cdots, n \tag{8}$$

Then, the vector of Shannon entropy $E = (E_1, E_2, \cdots, E_n)$ is computed:

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} NPULNDM_{ij}(p) \ln NPULNDM_{ij}(p) \tag{9}$$

and $NPULNDM_{ij}(p)\ln NPULNDM_{ij}(p)$ is defined as 0, if $NPULNDM_{ij}(p) = 0$.

Finally, the vector of attribute weights $w = (w_1, w_2, \cdots, w_n)$ is computed:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)}, j = 1, 2, \cdots, n \tag{10}$$

Step 5. Determine the probabilistic uncertain linguistic average values in accordance with all attributes, shown as follows:

$$PULAV = (PULAV_j)_{1\times n} \tag{11}$$

$$PULAV_j = \left\{\left[L_j^{\phi}, U_j^{\phi}\right]\left(p_j^{\phi}\right) | \phi = 1, 2, \cdots, \#NPULDM_{ij}(p)\right\} \tag{12}$$

$$\left[L_j^{\phi}, U_j^{\phi}\right]\left(p_j^{\phi}\right) = \left[\frac{\sum_{i=1}^{m} L_{ij}^{\phi}}{m}, \frac{\sum_{i=1}^{m} U_{ij}^{\phi}}{m}\right]\left(\frac{\sum_{i=1}^{m} p_{ij}^{\phi}}{m}\right) \tag{13}$$

Step 6. The probabilistic uncertain linguistic positive distance from average (PULPDA) and probabilistic uncertain linguistic negative distance from average (PULNDA) matrix can be got by Eqs. (14–19) on the basis of attribute type (benefit or cost).

$$PULPDA = \left[PULPDA_{ij}\right]_{m\times n} \tag{14}$$

$$PULNDA = \left[PULNDA_{ij}\right]_{m\times n} \tag{15}$$

If jth attribute is beneficial type,

$$PULPDA_{ij} = \frac{\max\left(0, d\left(NPULDM_{ij}(p), PULAV_j\right)\right)}{E\left(PULAV_j\right)} \tag{16}$$

$$PULNDA_{ij} = \frac{\max\left(0, d\left(PULAV_j, NPULDM_{ij}(p)\right)\right)}{E\left(PULAV_j\right)} \tag{17}$$

If jth attribute is cost type,

$$PULPDA_{ij} = \frac{\max\left(0, d\left(PULAV_j, NPULDM_{ij}(p)\right)\right)}{E\left(PULAV_j\right)} \tag{18}$$

$$PULNDA_{ij} = \frac{\max\left(0, d\left(NPULDM_{ij}(p), PULAV_j\right)\right)}{E\left(PULAV_j\right)} \tag{19}$$

Step 7. The weighted sum of PULPDA and PULNDA can be calculated by Eqs. (20) and (21), respectively.

$$PULSP_i = \sum_{j=1}^{m} w_j PULPDA_{ij} \tag{20}$$

$$PULSN_i = \sum_{j=1}^{m} w_j PULNDA_{ij} \tag{21}$$

Step 8. The value of probabilistic uncertain linguistic weighted sum of PULPDA (PULSP) and probabilistic uncertain linguistic weighted sum of PULNDA (PULSN) for each alternative can be normalized by Eqs. (22) and (23), respectively:

$$PULNSP_i = \frac{PULSP_i}{\max_i (PULSP)_i} \tag{22}$$

$$PULNSN_i = 1 - \frac{PULSN_i}{\max_i (PULSN_i)} \tag{23}$$

Step 9. The probabilistic uncertain linguistic appraisal score (PULAS) for all alternatives can be got by Eq. (24).

$$PULAS_i = \frac{PULNSP_i + PULNSN_i}{2} \tag{24}$$

where $0 \le PULAS_i \le 1$.

Step 10. Rank the alternatives according to the decreasing values of assessment score $PULAS_i$, the alternative with maximum value is the best choice.

As aforementioned, firstly, the uncertain linguistic information is transformed into PULDM. Then, normalized PULDM is derived from the PULDM. in order to select optimal alternative, integration of the information entropy and EDAS method under probabilistic uncertain linguistic sets (PULTSs) offered a novel integrated model, in which information entropy is used for deriving priority weights of each attribute and EDAS with PULTSs is employed to obtain the final ranking of all alternatives.

4. A CASE STUDY AND COMPARATIVE ANALYSIS

4.1. A Case Study

The choice of long-term stable suppliers is the most important problem to build a green supply chain under the green supply chain management mode, which directly affects the competitiveness of enterprises in the market. How can enterprises grasp the changeable internal and external environment, determine reasonable evaluation indicators according to their own needs, and choose suitable green suppliers becomes an urgent problem to be solved. The selection process of green suppliers should not place too much emphasis on environmental protection factors or economic benefits. Only by coordinating the development of the two can the long-term cooperation between enterprises and suppliers be promoted. Green supplier selection is a very complex decision problem [48–53]. Due to the complexity of the green supply chain system and the uncertainty and hesitation of human thinking, the evaluation of green suppliers will be affected by many uncertain factors, which makes it difficult to describe the evaluation index with exact values. In order to better conform to the thinking mode and cognitive mode of decision makers, this paper adopts language expression to describe attribute values. With the rapid development of science and technology, many decision-making problems in life have become more and more complex. It is difficult to solve these problems simply by one decision-maker. Multiple decision makers making decisions together can not only reduce errors, but also improve the accuracy of decisions [54–59]. Therefore, it is of great significance to apply the MAGDM method of PULTS to green supplier selection. Thus, in this section we present a numerical example for green supplier selection to illustrate the proposed method in this paper. There is a panel with five possible green suppliers $A_i\,(i = 1, 2, 3, 4, 5)$ to select. The experts selects four beneficial attribute to evaluate the five possible green suppliers: ①G_1 is environmental improvement quality; ②G_2 is transportation cost of suppliers; ③G_3 is green image and financial conditions; ④G_4 is environmental competencies. The transportation cost (G_2) is cost attribute, others are beneficial attributes. The five possible green suppliers $A_i\,(i = 1, 2, 3, 4, 5)$ are to be evaluated by using the LTS

$$S = \{s_{-3} = extremely\,poor\,(EP)\,, s_{-2} = very\,poor\,(VP)\,,\\ s_{-1} = poor\,(p)\,, s_0 = medium\,(M)\,,\ s_1 = good\,(G)\,,\\ s_2 = very\,good\,(VG)\,, s_3 = extremely\,good\,(EG)\}$$

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

In the following, we utilize the PUL-EDAS method developed for green supplier 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 PULDM (Table 11).

Table 1 Uncertain linguistic decision matrix by the first DM.

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

DM = decision maker.

Table 2 Uncertain linguistic decision matrix by the second DM.

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

DM = decision maker.

Table 3 Uncertain linguistic decision matrix by the third DM.

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

DM = decision maker.

Table 4 Uncertain linguistic decision matrix by the fourth DM.

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

DM = decision maker.

Table 5 Uncertain linguistic decision matrix by the fifth DM.

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

DM = decision maker.

Table 6 Uncertain linguistic decision matrix by the first DM.

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

DM = decision maker.

Table 7 Uncertain linguistic decision matrix by the second DM.

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

DM = decision maker.

Table 8 Uncertain linguistic decision matrix by the third DM.

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

DM = decision maker.

Table 9 Uncertain linguistic decision matrix by the fourth DM.

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

DM = decision maker.

Table 10 Uncertain linguistic decision matrix by the fifth DM.

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

DM = decision maker.

Table 11 Probabilistic uncertain linguistic decision matrix.

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

Step 3. Calculate the normalized PULDM (Table 12).

Step 4. Compute the weight values for attributes from Eqs. (8–10): $w_1 = 0.1195, w_2 = 0.3955, w_3 = 0.0954, w_4 = 0.3896$.

Step 5. Determine the $PULAV_i\,(i = 1, 2, 3, 4, 5)$ for all attributes (Table 13).

Step 6. Compute the PULPDA and PULNDA matrix by Eqs. (14–19), which are listed in Tables 14 and 15.

Step 7. Calculate the $PULSP_i, PULSN_i\,(i = 1, 2, 3, 4, 5)$ by using Eqs. (20) and (21). The calculating results are derived in Table 16.

Step 8. Calculate the $PULNSP_i, PULNSN_i\,(i = 1, 2, 3, 4, 5)$ by using Eqs. (22) and (23). The calculating results are derived in Table 17.

Step 9. Calculate the $PULAS_i\,(i = 1, 2, 3, 4, 5)$ by using Eq. (24) which is depicted in Table 18.

Step 10. According to the $PULAS_i\,(i = 1, 2, 3, 4, 5)$, we can rank all the green suppliers. Obviously, the rank is: $A_2 > A_4 > A_1 > A_5 > A_3$ and the best green supplier is A_2.

4.2. Comparative Analysis

In such subsection, we shall compare our proposed method with PULWA operator[43], probabilistic uncertain linguistic TOPSIS method (PUL-TOPSIS method) [43] and ULWA operator [42].

4.2.1. Compared with PULWA operator

Firstly, we compare our proposed method with probabilistic uncertain linguistic weighted average (PULWA) operator [43], the weight vector of attributes is derived as: $w_1 = 0.1195, w_2 = 0.3955, w_3 = 0.0954, w_4 = 0.3896$, then the overall attribute value of each alternative $Z_i(w)\,(i = 1, 2, 3, 4, 5)$ is obtained by employing PULWA operator.

$$Z_1(w) = \{[l_{-0.1558}, l_{0.0994}], [l_{0.0604}, l_{0.4621}], [l_{0.2846}, l_{0.6277}]\}$$

$$Z_2(w) = \{[l_{-0.1101}, l_{0.0000}], [l_{0.1558}, l_{0.5078}], [l_{0.7717}, l_{1.3097}]\}$$

$$Z_3(w) = \{[l_{-0.3294}, l_{-0.2036}], [l_{-0.4329}, l_{0.1241}], [l_{0.2163}, l_{0.5335}]\}$$

$$Z_4(w) = \{[l_{-0.0381}, l_{0.1607}], [l_{0.1973}, l_{0.6715}], [l_{0.5354}, l_{0.8624}]\}$$

$$Z_5(w) = \{[l_{-0.1257}, l_{0.0477}], [l_{-0.4460}, l_{-0.0154}], [l_{0.0986}, l_{0.4946}]\}$$

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 [43] as follows:

$$E(Z_1(w)) = l_{0.2297}, E(Z_2(w)) = l_{0.4391}, E(Z_3(w)) = l_{-0.0154}$$

$$E(Z_4(w)) = l_{0.3982}, E(Z_5(w)) = l_{0.0090}$$

Furthermore, we can derive the ranking result: $A_2 > A_4 > A_1 > A_5 > A_3$. Thus, we have the same optimal green supplier of coal enterprises A_2.

4.2.2. Compared with PUL-TOPSIS method

Then, we compare our proposed method with probabilistic uncertain linguistic TOPSIS method (PUL-TOPSIS method) [43], then we can acquire the calculating results and sorting results (Table 19). Thus, we have the same optimal green supplier of coal enterprises A_4.

Table 12 Normalized probabilistic uncertain linguistic decision matrix.

Alternatives	G_1	G_2	G_3	G_4
A_1	$\{\langle[l_0,l_1],0\rangle,\langle[l_0,l_1],0.9\rangle,\langle[l_1,l_2],0.1\rangle\}$	$\{\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.4\rangle,\langle[l_2,l_3],0.2\rangle\}$	$\{\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.2\rangle,\langle[l_2,l_3],0.6\rangle\}$	$\{\langle[l_{-2},l_{-1}],0.2\rangle,\langle[l_{-1},l_0],0.3\rangle,\langle[l_0,l_1],0.5\rangle\}$
A_2	$\{\langle[l_{-1},l_0],0.1\rangle,\langle[l_0,l_1],0.5\rangle,\langle[l_1,l_2],0.4\rangle\}$	$\{\langle[l_{-1},l_0],0.2\rangle,\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.6\rangle\}$	$\{\langle[l_{-1},l_0],0.2\rangle,\langle[l_0,l_1],0.6\rangle,\langle[l_1,l_2],0.2\rangle\}$	$\{\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0.4\rangle,\langle[l_2,l_3],0.6\rangle\}$
A_3	$\{\langle[l_{-2},l_{-1}],0.4\rangle,\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.2\rangle\}$	$\{\langle[l_{-1},l_0],0\rangle,\langle[l_{-1},l_0],0.6\rangle,\langle[l_0,l_1],0.4\rangle\}$	$\{\langle[l_1,l_2],0\rangle,\langle[l_1,l_2],0.4\rangle,\langle[l_2,l_3],0.6\rangle\}$	$\{\langle[l_{-3},l_{-2}],0.2\rangle,\langle[l_{-1},l_0],0.6\rangle,\langle[l_1,l_2],0.2\rangle\}$
A_4	$\{\langle[l_0,l_1],0.2\rangle,\langle[l_1,l_2],0.6\rangle,\langle[l_2,l_3],0.2\rangle\}$	$\{\langle[l_0,l_1],0\rangle,\langle[l_0,l_1],0.7\rangle,\langle[l_1,l_2],0.3\rangle\}$	$\{\langle[l_{-2},l_{-1}],0.2\rangle,\langle[l_1,l_2],0.5\rangle,\langle[l_2,l_3],0.3\rangle\}$	$\{\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.2\rangle,\langle[l_2,l_3],0.4\rangle\}$
A_5	$\{\langle[l_{-1},l_0],0.4\rangle,\langle[l_0,l_1],0.4\rangle,\langle[l_1,l_2],0.2\rangle\}$	$\{\langle[l_{-2},l_{-1}],0.0\rangle,\langle[l_{-2},l_{-1}],0.6\rangle,\langle[l_{-1},l_0],0.4\rangle\}$	$\{\langle[l_0,l_1],0.5\rangle,\langle[l_1,l_2],0.3\rangle,\langle[l_2,l_3],0.2\rangle\}$	$\{\langle[l_{-1},l_0],0.2\rangle,\langle[l_0,l_1],0.3\rangle,\langle[l_1,l_2],0.5\rangle\}$

Table 13 PULAV in accordance with all attributes.

	G_1	G_2	G_3	G_4
PULAV	$\{\langle[l_{-0.80},l_{0.20}],0.22\rangle,\langle[l_{0.20},l_{1.20}],0.56\rangle,\langle[l_{1.20},l_{2.20}],0.22\rangle\}$	$\{\langle[l_{-0.80},l_{0.20}],0.12\rangle,\langle[l_{-0.40},l_{0.60}],0.50\rangle,\langle[l_{0.60},l_{1.60}],0.38\rangle\}$	$\{\langle[l_{-0.40},l_{0.60}],0.22\rangle,\langle[l_{0.80},l_{1.80}],0.40\rangle,\langle[l_{1.80},l_{2.80}],0.38\rangle\}$	$\{\langle[l_{-1.00},l_{0.00}],0.20\rangle,\langle[l_{0.00},l_{1.00}],0.36\rangle,\langle[l_{1.20},l_{2.20}],0.44\rangle\}$

PULAV = probabilistic uncertain linguistic average value.

Table 14 PULPDA matrix.

Alternatives	G_1	G_2	G_3	G_4
A_1	0.0000	0.0843	0.0365	0.0000
A_2	0.0090	0.0455	0.0000	0.1108
A_3	0.0000	0.0000	0.0516	0.0000
A_4	0.0721	0.0357	0.0000	0.0585
A_5	0.0000	0.0000	0.0000	0.0000

PULPDA = probabilistic uncertain linguistic positive distance from average.

Table 15 PULNDA matrix.

Alternatives	G_1	G_2	G_3	G_4
A_1	0.0090	0.0000	0.0000	0.0895
A_2	0.0000	0.0000	0.0691	0.0000
A_3	0.0721	0.0517	0.0000	0.1156
A_4	0.0000	0.0000	0.0163	0.0000
A_5	0.0360	0.1488	0.0163	0.0024

PULNDA = probabilistic uncertain linguistic negative distance from average.

Table 16 PULSP and PULSN values.

Alternatives	A_1	A_2	A_3	A_4	A_5
PULSP	0.0386	0.0622	0.0049	0.0455	0.0000
PULSN	0.0360	0.0066	0.0741	0.0016	0.0657

Table 17 PULNSP and PULNSN values.

Alternatives	A_1	A_2	A_3	A_4	A_5
PULNSP	0.5920	1.0000	0.0791	0.7322	0.0000
PULNSN	0.5148	0.9110	0.0000	0.9790	0.1139

PULNSP = probabilistic uncertain linguistic normalized PULSP; PULNSN = probabilistic uncertain linguistic normalized PULSN.

Table 18 PULAS value.

Alternatives	A_1	A_2	A_3	A_4	A_5
PULAS	0.5534	0.9555	0.0396	0.8556	0.0569

PULAS = probabilistic uncertain linguistic appraisal score.

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 [42] with equal weight information to fuse all the uncertain linguistic decision matrices provided by the DMs into a group uncertain linguistic decision matrix (See Table 20).

The weight vector of attributes is derived as: $w_1 = 0.1195, w_2 = 0.3955, w_3 = 0.0954, w_4 = 0.3896$, then the overall attribute value of each alternative $Z_i(w)\,(i = 1, 2, 3, 4, 5)$ is obtained by employing ULWA operator [42].

$$Z_1(w) = [l_{0.0603}, l_{1.6492}], Z_2(w) = [l_{0.8055}, l_{2.1379}],$$
$$Z_3(w) = [l_{-0.5461}, l_{0.5453}]\, Z_4(w) = [l_{0.6264}, l_{2.3147}],$$
$$Z_5(w) = [l_{-0.6186}, l_{0.8932}]$$

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 [43] as follows:

$$E(Z_1(w)) = l_{0.8548}, E(Z_2(w)) = l_{1.5106}, E(Z_3(w)) = l_{0.0092}$$
$$E(Z_4(w)) = l_{1.4705}, E(Z_5(w)) = l_{0.1373}$$

Furthermore, we can derive the ranking result: $A_2 > A_4 > A_1 > A_5 > A_3$. Thus, we have the same optimal green supplier of coal enterprises A_2.

Table 19 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	$d_1^+ = 0.5882, d_2^+ = 0.2384, d_3^+ = 0.6912, d_4^+ = 0.3386, d_5^+ = 0.6864$
The distances of each alternative from PULNIS	$d_1^- = 0.6597, d_2^- = 0.8499, d_3^- = 0.4622, d_4^- = 0.7921, d_5^- = 0.5294$
Closeness coefficients	$CI_1 = -1.6944, CI_2 = -0.0000, CI_3 = -2.3555, CI_4 = -0.4882, CI_5 = -2.2564$
Ordering	$A_2 > A_4 > A_1 > A_5 > A_3$

PUL-TOPSIS = probabilistic uncertain linguistic TOPSIS; PULPIS = probabilistic uncertain linguistic positive ideal solution; PULNIS = probabilistic uncertain linguistic negative ideal solution.

Table 20 Group uncertain linguistic decision matrix.

Alternatives	G_1	G_2	G_3	G_4
A_1	$[l_{0.0}, l_{1.2}]$	$[l_{0.8}, l_{1.8}]$	$[l_{1.4}, l_{2.4}]$	$[l_{-1}, l_{0.6}]$
A_2	$[l_{0.2}, l_{1.4}]$	$[l_{0.4}, l_{1.4}]$	$[l_0, l_1]$	$[l_{1.6}, l_{2.6}]$
A_3	$[l_{-0.6}, l_{0.4}]$	$[l_{-0.6}, l_{0.4}]$	$[l_{1.6}, l_{2.6}]$	$[l_{-1}, l_0]$
A_4	$[l_1, l_2]$	$[l_{0.2}, l_{1.4}]$	$[l_{0.4}, l_2]$	$[l_1, l_2]$
A_5	$[l_{-0.2}, l_{0.8}]$	$[l_{-1.6}, l_{-0.6}]$	$[l_{0.4}, l_2]$	$[l_0, l_{1.6}]$

From the above analysis, it can be seen that the ordering results obtained from the PUL-EDAS method, PUL-TOPSIS method, the PULWA operator are the same as that is obtained by the ULWA operator method under the uncertain linguistic setting. It implies that the PULTS is feasible and meaningful. However, their values of the score function are different when the aggregation-based method is used. The PULTS can not only consider the uncertain linguistic assessment information, but also contain the probabilities of each uncertain linguistic term. Therefore, it could take full advantage of the uncertain linguistic assessment information and their score values are more reasonable and interpretable than those obtained under the uncertain linguistic setting where the probabilities of uncertain linguistic terms are not taken in consideration and partial information is heavily lost. But, these four methods have their advantages: (1) PUL-TOPSIS method emphasizes the distance closeness degree from the positive and negative ideal solution; (2) PULWA operator can not only consider the uncertain linguistic assessment information, but also contain the probabilities of each uncertain linguistic term; (3) ULWA operator emphasis group influences degree and can't consider the probabilities of uncertain linguistic terms and partial information is heavily lost; (4) our proposed PUL-EDAS method only emphasizes the distance closeness degree from average solution for all attributes.

5. CONCLUSION

In this paper, we designed the EDAS method to tackle MAGDM issues with PULTSs. Firstly, the basic definition, comparative formula and Hamming distance of PULTSs are briefly reviewed. Then, on the basis of the conventional EDAS method, the EDAS method is proposed to deal with MAGDM problems with PULTSs and its significant characteristic is that it only highlights the distance closeness degree from average solution for all attributes. Finally, a practical case study for green supplier selection is used to illustrate the developed method and some comparative analysis is also designed to show the applicability in MAGDM issues. In such research, the EDAS method, which is also an efficient MADM or MAGDM method, has been designed to deal with other uncertain decision-making problems. In the future, PULTSs could be expanded to derive the weight information of each DM. Moreover, the basic idea behind PULTSs can be used to extend other fuzzy sets by associating each membership degree with its probability [60–66]. Furthermore, the application of the proposed methods with PULTSs needs to be investigated along with the other uncertain decision making and many other uncertain and fuzzy environments [67–71].

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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