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# Green Logistic Provider Selection with a Hesitant Fuzzy Linguistic Thermodynamic Method Integrating Cumulative Prospect Theory and PROMETHEE

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**Abstract:** In the process of evaluating the green levels of cold-chain logistics providers, experts may hesitate between several linguistic terms rather than give precise values over the alternatives. Due to the potential profit and risk of business decisions, decision-making information is often based on experts' expectations of programs and is expressed as hesitant fuzzy linguistic terms. The consistency of evaluation information of an alternative can reflect the clarity of the alternative in the mind of experts and its own controversy. This paper proposes a method to use the value transfer function in the cumulative prospect theory to convert the original hesitant fuzzy linguistic terms into evaluation information based on reference points. We also introduce the parameters related to the disorder of the system in the hesitant fuzzy thermodynamic method to describe the quantity and quality characteristics of the alternatives. In these kinds of multi-criteria decision-making problems, the weights of criteria are of great importance for decision-making results. Considering the conflicting cases among criteria, the weights were obtained by utilizing the PROMETHEE method. An illustrative example concerning green logistics provider selection was operated to show the practicability of the proposed method.

**Keywords:** green logistics; hesitant fuzzy linguistic term sets; cumulative prospect theory; hesitant fuzzy linguistic thermodynamic method; PROMETHEE

## 1. Introduction

Multi-criteria decision-making (MCDM) is a process of ranking a finite set of alternatives with respect to a list of criteria. It has been extensively studied and also applied in various areas, such as transportation management [1], human resource selection [2], and military affair [3]. With the rapid development of cold chain logistics, evaluating the suppliers of cold chain logistics, as a typical MCDM problem, is crucial for fresh food service industry and pharmaceutical industry. In the process of evaluating the green-level of logistics, it is difficult for decision-makers (DMs) to obtain sufficient and accurate information because of the incompleteness, complexity and uncertainty of the problems. In addition, it is universally acknowledged that people are usually hesitant and irresolute to give their judgments due to the fuzziness thought. Rodríguez et al. [4] proposed the hesitant fuzzy linguistic term set (HFLTS), which allows experts to flexibly express their judgments in linguistic expressions such as "between medium and good" and "at least performance well". The HFLTS has attracted many scholars' attention and many achievements have been obtained [5–8]. For more information, readers can refer to the survey paper Ref. [9].

Traditional MCDM methods, such as TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and ELECTRE (ELimination and Choice Expressing REality), rank alternatives according to the "quantity" information, not accounting for the "quality" of the ratings by DMs. In some cases, however, the discrete degree of numerical values evaluated by different experts contains the quality information of the system. The analogies of thermodynamic indicators energy, exergy, and entropy can depict both the "quantity" information and the "quality" characteristic of the system comprehensively [2]. Verma and Rajasankar [2] first introduced the thermodynamic method to solve MCDM problems. Inspired by Verma and Rajasankar's [2] innovative work, Ren et al. [10,11] extended the thermodynamic method to intuitionistic fuzzy context and hesitant fuzzy context.

The prospect theory, initiated by Kahneman and Tversky [12], is a behavioral theory to indicate the psychological behaviors when each alternative has probabilistic gains and risks. The cumulative prospect theory is proposed based on the original prospect theory and makes up for the original version which fails to explain the stochastic dominance phenomenon. The value function based on the reference point in the cumulative prospect theory is significant in comprehensively depicting the psychological characteristic in reality.

In Ref. [11], Ren et al. established the hesitant fuzzy prospect decision matrix (HFPDM) based on the value function of the cumulative prospect theory, and then obtained the thermodynamic decision-making parameters, including the hesitant fuzzy energy, the hesitant fuzzy entropy and the potential hesitant fuzzy exergy according to the HFPDM. However: (1) it only utilizes the hesitant fuzzy set (HFS) to represent the hesitant cognition of the experts; (2) some computational processes are illogical such as the conversion process of the subscript of hesitant linguistic term when the evaluation level is equal to the reference point; (3) the definition of the center value of evaluations also has unconscionable part; and (4) the priority weights were derived from the hesitant fuzzy preference relations (HFPRs), but, in reality, there are often cases where the comparisons between criteria are incomparable and thus HFPRs cannot be constructed.

To correct these flaws and make the method more consistent with the evaluation of the green-levels of cold chain logistics, we developed a hesitant fuzzy linguistic thermodynamic method based on the cumulative prospect theory and the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method, given that DMs make evaluations over the suppliers of cold chain logistics under the influence of the potential gains and losses. This method allows the experts to express judgments in HFLTSs, and improves the calculation process by enhancing the function in thermodynamic decision-making parameters calculation process to obtain creditable results. Moreover, the PROMETHEE method [13] was applied to get dependable weights of criteria.

The rest of this paper is organized as follows: Section 2 reviews the HFLTS, the cumulative prospect theory, the PROMETHEE method and the thermodynamic methods for the MCDM problems. Section 3 introduces the hesitant fuzzy linguistic thermodynamic method based on the cumulative prospect theory and the PROMETHEE method. Section 4 applies the proposed method to evaluate the green level of a cold chain logistics suppliers and comparative analysis is conducted. The paper ends with Section 5.

## 2. Preliminaries

### *2.1. Hesitant Fuzzy Linguistic Term Set*

The HFLTS is a kind of ordered set, which consists of continuous linguistic terms. It reflects the hesitation of the experts among multiple linguistic terms. Liao et al. [14] gave a concise mathematical definition of HFLTS. Let $S = \{s_t | t = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$ be a linguistic term set. A HFLTS on $X$, $H_S$, is in mathematical terms of $H_S = \{\langle x, h_S(x)\rangle | x \in X\}$ where $h_S(x)$ is a set of elements in $S$ and can be expressed as $h_S(x) = \left\{ s_{\phi l}(x) \middle| s_{\phi l}(x) \in S, l = 1, \cdots, L \right\}$ with $L$ being the number of linguistic terms in $h_S(x)$. $h_S(x)$ denotes the possible degrees of the linguistic variable $x$. For convenience, $h_S(x)$ is called the hesitant fuzzy linguistic element (HFLE).

### 2.2. Cumulative Prospect Theory

The cumulative prospect theory is a descriptive theory that manifests the decision characteristics when people make choices under the influence of potential losses and gains [12]. The reference point is fundamental to describe the DMs' mental activities in the cumulative prospect theory. Some scholars have tried to combine the cumulative prospect theory with the traditional MCDM methods [15,16]. The TODIM is a MCDM method based on the cumulative prospect theory [15]. Besides, Wang et al. [16] combined the cumulative prospect theory with TOPSIS by transforming the original decision information by the value function according to interval reference point. Cumulative prospect theory indicates that the whole value of an alternative is determined by both the value function and the weights. The general form of the value function can be represented as [12]:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x)^{\beta}, & x < 0 \end{cases} \tag{1}$$

where $v(x)$ is the potential gains (when $x > 0$) or losses (when $x < 0$) of the alternative. $\alpha$ $(0 < \alpha < 1)$ and $\beta$ $(0 < \beta < 1)$ are risk preference coefficients, representing the risk appetites of the DMs. When the DMs are risk neutral parties, $\alpha = \beta = 1$. $\lambda$ $(\lambda \geq 1)$ is a coefficient of risk aversion. When the value of $\lambda$ increases, the DM is more sensitive to the loss. It has been verified by Tversky and Kahneman [17] that, when $\lambda = 2.25$ and $\alpha = \beta = 0.88$, the calculated result is consistent with the original data. Equation (1) incarnates the psychological characteristics of the DMs in the cumulative prospect theory: (1) they tend to be risk-averse when faced with earnings (in the profit area, the value function is concave and, as the distance from the reference point increases gradually, the marginal influence decreases); (2) they usually have more preferences for risk faced with the loss (in the area of loss, the value function is convex and, as the distance from the reference point increases gradually, the marginal influence also decreases); and (3) they are more sensitive to losses than to gains (the loss aversion coefficient $\lambda = 2.25$ indicates that the pain of the same numerical loss is far greater than the pleasure of the benefit of the dry income, about 2.25 times).

### 2.3. PROMETHEE

PROMETHEE is an important MCDM method developed by Brans et al. [13]. It has been applied in many areas, such as waste treatment [18] and transportation management [19]. Regarding the problem of selecting the logistics suppliers, Chen et al. [20] combined the linguistic PROMETHEE method with maximum deviation method to determine the ranking order of logistics suppliers. Bansal [21] used an integrated approach named AHP (Analytic Hierarchy Process)-PROMETHEE as a selection methodology to select efficient and requisite third-party logistics.

PROMETHEE is based on the following indexes: the leaving flow $\phi^{+}$, the entering flow $\phi^{-}$, and the net flow $\phi$. The net flow can not only rank the alternatives but also can be used to represent the weights of criteria. The net flow shows the difference between the entering flow $\phi^{+}(x)$ and the leaving flow $\phi^{-}(x)$, and thus $\varphi(x) = \phi^{+}(x) - \varphi^{-}(x)$ where $x$ represents an object. Considering the strength of PROMETHEE in comparing conflicting objects, we introduce the PROMETHEE into the hesitant fuzzy linguistic thermodynamics method, and further extend it to acquire the weights of criteria.

### 2.4. Thermodynamics

Thermodynamics is a branch of physics that studies the thermal motion of matter and its laws from a macroscopic perspective. Verma and Rajasankar [2] innovatively proposed a thermodynamically consistent model for MCDM using the analogies for thermodynamic indicators. Ren et al. [10,11] extended the thermodynamic method to some fuzzy context and applied it for emergency decision making. Thermodynamic method is based on three laws of thermodynamics: the concepts of energy, exergy, and entropy [2]. Energy used to characterize the power of a system, is extended to represent the status of objects when ignore the quality of evaluation. When the system reversibly changes from an arbitrary state to a state that is in balance with the given environment, the part of energy can be infinitely converted into energy of any other form theoretically is termed exergy, also called available energy. It can be defined as the evaluation status when considering the quality of the object evaluation. Entropy is a thermodynamic parameter, which indicates the degree of disorder in the system. It can be extended to an indicator of the overall status of inhomogeneity comprehensively.

In the evaluation process, the information obtained has quantitative characteristics and qualitative characteristics. Quantitative characteristics refer to the overall state of the information display. Quality characteristics refer to the structural characteristics of the information, including consistency and the average distance from the center value. The more concentrated the DMs' evaluation values on a certain indicator over the alternatives are, the stronger the representativeness of the evaluation information is and the less controversial the evaluation would be. In the MCDM process, the energy in thermodynamics may be interpreted as quantitative indicator when the quality of evaluation is ignored. The exergy index depicts the quantitative and qualitative characteristics of the alternatives. The entropy is defined as a comprehensive indicator of the alternatives and instability of information in the MCDM process.

The entropy defined in Ren et al. [11] denoted the deviation of the evaluations under a criterion. However, it cannot depict the controversies about an alternative among different experts. Hence, we redefine the calculation process of the entropy in the following section.

## 3. The Hesitant Fuzzy Linguistic Thermodynamic Method based on Cumulative Prospect Theory and PROMETHEE

### *3.1. Hesitant Fuzzy Linguistic Prospect Decision Matrix*

In the process of decision making, utilizing reference point in the cumulative prospect theory, the DMs often have expectations of the alternatives under a certain criterion. Considering the different expectations of the DMs, and the fact that the DMs tend to make evaluations based on their psychological anticipations, different DMs may have the same perception of a certain object but give different evaluation levels, and vice versa.

The hesitant fuzzy linguistic prospect decision matrix (HFLPDM) that contains the evaluation information has been transferred by value function according to the reference point. It is also the basis to calculate the hesitant fuzzy linguistic energy and hesitant fuzzy linguistic exergy. Using the reference point to depict the evaluation levels of different DMs can accurately reflect their actual perceptions and eliminate the deviations caused by different expectations. Hence, to obtain the HFLPDM, the original evaluation information needs to be compared with the expected level of each DM under each criterion.

The subscripts of the original hesitant fuzzy linguistic terms are computed through the value function of the cumulative prospect theory. If the evaluation level is higher than the reference point, the difference between the evaluation level and the reference point is viewed as income; if the evaluation level is lower than the reference point, the difference between the two values is regarded as loss. The value $v_{ij}^{k\,\sigma(t)}$ of the $\sigma(t)$ th linguistic term can be defined as follows according to the value function in the cumulative prospect theory and the reference point of the DMs in terms of different cases:

$$v_{ij}^{k\sigma(t)} = \begin{cases} \left[\frac{r_{ij}^{k\sigma(t)} - \widetilde{r}_j^k}{\tau - \widetilde{r}_j^k}\right]^{\beta}, & \text{if } r_{ij}^{k\sigma(t)} > \widetilde{r}_j^k \\ v_{ij}^{k\sigma(t)} = MAX\frac{1}{\lambda}\left[e^{-(\frac{\widetilde{r}_j^k - r_{ij}^{k\sigma(t)}}{\tau - \widetilde{r}_j^k})} - e^{-1}\right]^{\beta} = 0.2968, & \text{if } r_{ij}^{k\sigma(t)} = \widetilde{r}_j^k \\ v_{ij}^{k\sigma(t)} = \frac{1}{\lambda}\left[e^{-(\frac{\widetilde{r}_j^k - r_{ij}^{k\sigma(t)}}{\tau - \widetilde{r}_j^k})} - e^{-1}\right]^{\beta}, & \text{if } r_{ij}^{k\sigma(t)} < \widetilde{r}_j^k \end{cases} \tag{2}$$

where $r_{ij}^{k\,\sigma(t)}$ is the subscript of the $\sigma(t)$ th original linguistic term in the HFLE given by the DM $d_k$ regarding to the alternative $A_i$ under the criterion $C_j$. $\widetilde{r}_j^k$ denotes the anticipation of the DM $d_k$ under the criterion $C_j$.

**Remark 1.** *If the prospect of the alternative is superior to the expectation-level, the prospect value of gain* $x = \frac{r_{ij}^{k\,\sigma(t)} - \widetilde{r}_j^k}{\tau - \widetilde{r}_j^k}$ *is the normalized distance between decision value* $r_{ij}^{k\,\sigma(t)}$ *and reference point* $\widetilde{r}_j^k$.

**Remark 2.** *When the level of evaluation value is lower than the reference point, the value function of loss should satisfy two characteristics: (1) It is a monotonically decreasing function as the distance between the evaluation value and the reference point decreases. (2) The prospect value is nonnegative for there does not exist negative expression in hesitant fuzzy linguistic environment, and it ranges from 0 to 1. Hence, the loss can be expressed as* $e^{-(\frac{\widetilde{r}_j^k - r_{ij}^{k\,\sigma(t)}}{\tau - \widetilde{r}_j^k})} - e^{-1}$. *The outcome* $r_{ij}^{k\sigma(t)}$ *is transferred into the monotone decreasing function* $\frac{\widetilde{r}_j - r_{ij}^{k\sigma(t)}}{\tau - \widetilde{r}_j}$, *which reflects the normalized distance between decision value and reference point. Then, we introduce the negative exponential function to reflect the diminishing marginal utility.* $0 = e^{-1} - e^{-1} \leq e^{-(\frac{\widetilde{r}_j^k - r_{ij}^{k\,\sigma(t)}}{\tau - \widetilde{r}_j^k})} - e^{-1} \leq e^0 - e^{-1} \leq 1$ *satisfies the range of values.*

The negative exponential function transfers loss (negative number) to non-negative number as there does not exist negative expression in hesitant fuzzy linguistic environment. Moreover, with its value range and marginal diminishing effect, the negative exponential function can reflect the diminishing marginal utility of the problems in reality.

**Remark 3.** *In Ren et al. [11], when the evaluation level is equal to the reference point,* $v_{ij}^{k\,\sigma(t)} = 0$, *which may lead to the result that* $s_0$ *indicates a lower level of evaluation than some terms whose subscripts are negative. It may be illogical given that it will bring certain benefits when the evaluation level is lower than the reference point. For this reason,* $v_{ij}^{k\,\sigma(t)}$ *is assigned the maximum value of 0.2968 for the function when* $r_{ij}^{k\,\sigma(t)} > \widetilde{r}_j^k$.

### *3.2. The Indexes in the Hesitant Fuzzy Thermodynamic Method*

Assume that there are $K$ DMs who evaluate $m$ alternatives under $n$ criteria. Suppose that they use the HFLTS under the given linguistic term set $S = \{s_t | t = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$ to represent their qualitative assessments.

**Definition 1.** *The hesitant fuzzy linguistic energy index* ($e_{ij}^k$) *is defined as the energy of the comprehensive hesitant fuzzy linguistic utility of the program evaluation level, which is derived based on the original evaluation information and the weights of criteria and*

$$e_{ij}^k = \widetilde{\omega}_j \hat{h}_{ij}^k \tag{3}$$

*where $\widetilde{\omega}_j$ is the weight of the criterion $C_j$, and $\hat{h}^k_{ij}$ is the set of subscripts of the linguistic terms in the HFLE for the alternative $A_i$ with the respect of the criterion $C_j$ given by the DM $d_k$. Then, a hesitant fuzzy linguistic energy matrix $E_k$ associated to the $k$ th DM is constructed as:*

$$E_k = \left(e^k_{ij}\right)_{m\times n} = \begin{pmatrix} e^k_{11} & e^k_{12} & \cdots & e^k_{1n} \\ e^k_{21} & e^k_{22} & \cdots & e^k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e^k_{m1} & e^k_{m2} & \cdots & e^k_{mn} \end{pmatrix} \tag{4}$$

The quality of the information refers to the degree of unevenness of the HFLEs among different experts. The more desperate the evaluation levels distribute, the lower the quality of the evaluations is.

**Definition 2**. *The averaging matrix $\overline{V}$ consisting of the average HFLEs is as follows:*

$$\overline{V} = \left(\overline{v}_{ij}\right)_{m\times n} = \begin{pmatrix} \overline{v}_{11} & \overline{v}_{12} & \cdots & \overline{v}_{1n} \\ \overline{v}_{21} & \overline{v}_{22} & \cdots & \overline{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{v}_{m1} & \overline{v}_{m2} & \cdots & \overline{v}_{mn} \end{pmatrix} \tag{5}$$

*where $\overline{v}_{ij}$ is the mean of the subscripts of all DMs' evaluations of the alternative $A_i$ with the respect of the criterion $C_j$ and*

$$\overline{v}_{ij} = \frac{1}{\sum\limits_{k=1}^{\mu} T^k_{ij}} \left[ \sum_{k=1}^{\mu} \sum_{t=1}^{T^k_{ij}} v^{k\,\sigma(t)}_{ij} \right] \tag{6}$$

*where $T^k_{ij}$ is the number of linguistic terms in the original HFLE and $v^{k\,\sigma(t)}_{ij}$ is the subscript of the $\sigma(t)$ th HFLE.*

**Remark 4.** *Verma and Raiasankar [2] defined the mean value as the average of the evaluations of all alternatives by a DM under a certain criterion. Inspired by this idea, Ren et al. [11] defined the hesitant fuzzy potential (HFP) as the energy of an alternative with respect to a criterion and the mean HFP as the average of an expert's assessments of all criteria for an alternative. Accordingly, the entropy represents the degree of uniformity of the evaluations under the criteria.*

To manifest the degree of unevenness of the evaluations among different alternatives with respect to a specific criterion, we obtain the quality matrix $Q_K$ as follows:

$$Q_k = \left(q^k_{ij}\right)_{m\times n} = \begin{pmatrix} q^k_{11} & q^k_{12} & \cdots & q^k_{1n} \\ q^k_{21} & q^k_{22} & \cdots & q^k_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ q^k_{m1} & q^k_{m2} & \cdots & q^k_{mn} \end{pmatrix} \tag{7}$$

where

$$q^k_{ij} = 1 - \frac{1}{T^k_{ij}} \sum_{t=1}^{T^k_{ij}} \frac{\left| v^{k\,\sigma(t)}_{ij} - \overline{v}^k_{ij} \right|}{\overline{v}^k_{ij}} \tag{8}$$

It is considered that the uniformity of evaluations of different DMs for a given alternative should be attached importance to, as it reflects the degrees of controversy over the evaluations of the alternative by different DMs under specific guidelines. From this point of view, it reflects the quality of the evaluation information more accurately.

**Definition 3.** *The hesitant fuzzy linguistic exergy indicator ($x_{ij}^k \in [0,1]$) reflects the quality of the evaluation information. The hesitant fuzzy linguistic exergy matrix $X_k$ is constructed as:*

$$X_k = \left(x_{ij}^k\right)_{m\times n} = \begin{bmatrix} q_{11}^k e_{11}^k & q_{12}^k e_{12}^k & \cdots & q_{1n}^k e_{1n}^k \\ q_{21}^k e_{21}^k & q_{22}^k e_{22}^k & \cdots & q_{2n}^k e_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ q_{m1}^k e_{m1}^k & q_{m2}^k e_{m2}^k & \cdots & q_{mn}^k e_{mn}^k \end{bmatrix} \tag{9}$$

**Definition 4**. *The hesitant fuzzy linguistic entropy means the unevenness of the evaluations of a particular alternative. It ranges from 0 to 1. The entropy 0 means all DMs give the same evaluation values. On the contrary, 1 indicates that the DMs have great controversies about the evaluation values of an alternative under a criterion.*

The process to calculate the hesitant fuzzy linguistic entropy is clarified as follows:

Firstly, the average evaluation value of each item (here "item" means the value of an alternative under a criterion) is computed according to the HFLEs in the hesitation fuzzy energy matrix. The energy of the alternative $A_i$ under the criterion $C_j$ with respect to the DM $d_k$ can be calculated as follows:

$$f(e_{ij}^k) = \sqrt{\frac{1}{T_{ij}{}^K}[(v_{ij}^{k\,\sigma(1)})^2 + (v_{ij}^{k\,\sigma(2)})^2 + \cdots + (v_{ij}^{k\,\sigma(T_{ij}{}^K)})^2]} \tag{10}$$

After that, the average hesitant fuzzy linguistic energy $\widetilde{E}_i^k$ and the average hesitant fuzzy linguistic exergy $\widetilde{X}_i^k$ are computed, and they reflect the comprehensive evaluation of the alternative $A_i$ under all criteria.

$$\widetilde{E}_i^k = \frac{1}{n}(f(e_{i1}^k) + f(e_{i2}^k) + \cdots f(e_{in}^k)) \tag{11}$$

$$\widetilde{X}_i^k = \frac{1}{n}\left(x_{i1}^k + x_{i2}^k + \cdots + x_{in}^k\right) \tag{12}$$

Next, the integrated hesitant fuzzy linguistic energy $E_i$ and the integrated hesitant fuzzy linguistic exergy $X_i$ reflecting the comprehensive evaluations of alternatives under all criteria can be, respectively, calculated by

$$E_i = \frac{1}{\mu}\left(\widetilde{E}_i^1 + \widetilde{E}_i^2 + \cdots + \widetilde{E}_i^\mu\right) \tag{13}$$

$$X_i = \frac{1}{\mu}\left(\widetilde{X}_i^1 + \widetilde{X}_i^2 + \cdots + \widetilde{X}_i^\mu\right) \tag{14}$$

The entropy $SR_i$ is the difference between the integrated energy value $E_i$ and the integrated exergy value $X_i$ of the alternatives, which depicts the comprehensive grade of the alternative.

$$SR_i = E_i - X_i \tag{15}$$

### *3.3. The Algorithm of the Hesitant Fuzzy Linguistic Thermodynamic Method based on Cumulative Prospect Theory and PROMETHEE*

For the simplicity of application, we set out the algorithm of the hesitant fuzzy linguistic thermodynamic method integrating cumulative prospect theory and PROMETHEE.

**Input:**

(1) The hesitate fuzzy linguistic decision matrices $H_k$ $(k = 1, 2, \cdots, \mu)$ of all experts;
(2) The pairwise comparison matrix $\Xi$ of criteria; and
(3) The experts' reference points of the alternatives under each criterion.

**Output:**

(1) The hesitant fuzzy linguistic energies, exergies, and entropies of the alternatives; and
(2) The complete partial order of the alternatives.

**Step 1.** Let the hesitant fuzzy linguistic decision matrices $H_k(k = 1, 2, \cdots, \mu)$ and the reference points $L_k$ of the expert $d_k$ be represented as:

$$H_k = \begin{pmatrix} h_{11}^k & h_{12}^k & \cdots & h_{1n}^k \\ h_{21}^k & h_{22}^k & \cdots & h_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ h_{m1}^k & h_{m2}^k & \cdots & h_{mn}^k \end{pmatrix}$$

$$L_k = \left( \widetilde{s}_{\widetilde{r}_1^k}, \widetilde{s}_{\widetilde{r}_2^k}, \cdots, \widetilde{s}_{\widetilde{r}_n^k} \right)$$

where $h_{ij}^k = \left\{ s_{r_{ij}^{k}1} \cdots s_{r_{ij}^{k}\sigma(t)} \cdots s_{r_{ij}^{k}\sigma(T_{ij}^k)} \right\}$ with $T_{ij}^k$ being the number of linguistic terms in $h_{ij}^k$. According to Equation (2), calculate each expert's HFLPDM $\hat{\mathrm{H}}_k$ as:

$$\hat{\mathrm{H}}_k = \begin{pmatrix} \hat{h}_{11}^k & \hat{h}_{12}^k & \cdots & \hat{h}_{1n}^k \\ \hat{h}_{21}^k & \hat{h}_{22}^k & \cdots & \hat{h}_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ \hat{h}_{m1}^k & \hat{h}_{m2}^k & \cdots & \hat{h}_{mn}^k \end{pmatrix}$$

where $\hat{h}_{ij}^k = \left\{ s_{v_{ij}^{k}\sigma(1)} \cdots s_{v_{ij}^{k}\sigma(t)} \cdots s_{v_{ij}^{k}\sigma(T_{ij}^k)} \right\}$ and $v_{ij}^{k\,\sigma(t)}$ is calculated using Equation (2).

**Step 2**. Establish the averaging matrix

$$\overline{V} = \begin{pmatrix} \overline{v}_{11} & \overline{v}_{12} & \cdots & \overline{v}_{1n} \\ \overline{v}_{21} & \overline{v}_{22} & \cdots & \overline{v}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \overline{v}_{m1} & \overline{v}_{m2} & \cdots & \overline{v}_{mn} \end{pmatrix}$$

where $\overline{v}_{ij}$ is calculated using Equation (6).

**Step 3.** Compute the quality matrix

$$Q_k = \begin{pmatrix} q_{11}^k & q_{12}^k & \cdots & q_{1n}^k \\ q_{21}^k & q_{22}^k & \cdots & q_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ q_{m1}^k & q_{m2}^k & \cdots & q_{mn}^k \end{pmatrix}$$

where $q_{ij}^k$ is calculated by Equation (8).

**Step 4.** Determine the weights of criteria. According to the pairwise comparison matrix $\Xi = \left(\varepsilon_{jj'}\right)_{n\times n}$ of criteria given by the experts in which $\varepsilon_{jj'}$ is the degree to which the criterion $C_j$ is more important than the criterion $C_{j'}$, calculate the entering flow $\phi^+(C_j)$ and the leaving flow $\phi^-(C_j)$ by:

$$\phi^+(C_j) = \sum_{j'=1}^{n} \varepsilon_{jj'} \tag{16}$$

$$\phi^-(C_j) = \sum_{j=1}^{n} \varepsilon_{jj'} \tag{17}$$

Then, the net flow $\phi(C_j)$ is calculated by.

$$\phi(C_j) = \phi^+(C_j) - \phi^-(C_j) \tag{18}$$

Convert the importance represented by net flows into the weight $\widetilde{\omega}_j$ of criterion:

$$\omega_j = \frac{\phi_j - (-\eta \times n)}{2 \times (\eta \times n)}, j = 1, 2, \cdots, n \tag{19}$$

After normalizing, we obtain

$$\widetilde{\omega}_j = \omega_j \Big/ \sum_{j=1}^{n} \omega_j, j = 1, 2, \cdots, n \tag{20}$$

**Step 5.** Construct the hesitant fuzzy linguistic energy matrix $E_k$ based on the criterion weights and the HFLPDM using Equation (3).

**Step 6.** Based on the quality matrix $Q_k$ and the hesitant fuzzy linguistic energy matrix $E_k$, calculate the hesitant fuzzy linguistic exergy matrix $X_k$ using Equation (9).

**Step 7.** Compute the average hesitant fuzzy linguistic energy $\widetilde{E}_i^k$ and the average hesitant fuzzy linguistic exergy $\widetilde{X}_i^k$ using Equations (11) and (12), respectively.

**Step 8.** Calculate the integrated hesitant fuzzy linguistic energy value $E_i$ and the integrated hesitant fuzzy linguistic entropy value $X_i$ of each alternative using Equations (13) and (14), respectively. Then, compute the entropy index $SR_i$ of each alternative using Equation (15).

**Step 9.** Rank the alternatives in the ascending order of their entropy indexes and ends the algorithm.

## 4. Apply the Proposed Method to Evaluate the Green Level of Cold Chain Logistics Companies

### *4.1. Case Description*

In recent years, environmental problem is a threat to the development of human society and has received more and more attention. Many countries have adopted policies to constraint environmental pollution, such as carbon tax [22]. Many enterprises also attached great importance to environmental issues. They not only reduce emissions in the process of their own production, but also apply environmental protection concepts to supplier selection. For instance, Yang et al. [23] investigated the green supplier selection based on carbon footprint under dynamic environment. Banaeian et al. [24] utilized some fuzzy group decision making methods for green supplier selection. Green supply chain has become a hot topic in recent years.

With the development of economy and the improvement of people's living standard, people's demand for food freshness is higher and higher. This greatly promotes the development of cold chain logistics. Cold chain logistics refers to frozen foods in the production, storage, transportation, and sales, to the consumption of each link in low temperature environment to ensure the food quality and reduce loss of food. It is a system engineering. As an important part of the transportation industry, cold chain logistics mainly serves medicine and food, which play a key role in promoting the development of industry and people's life. Many scholars have done researches related to cold chain logistics. Gogou et al. [25] used the cold chain database for the cold chain management and food quality evaluation. Hariga et al. [26] studied the multi-stage cold supply chain under carbon tax regulation by considering economic and environmental factors.

How to evaluate the green level of a cold chain logistics company and choose the most suitable company to realize the green supply chain naturally becomes the concern of many enterprises. Defraeye et al. [27] proposed a method to evaluate the performance of the fresh-produce cold chain. Zarbakhshnia et al. [28] used fuzzy SWARA and fuzzy COPRAS to evaluate sustainable third-part reverse logistics provider, and the results showed that environmental and social indicators become dominant when selecting third-part logistics providers. Prakash and Barua [29] developed an integrated model under fuzzy environment for third-part logistics provider selection. Aguezzoul [30] provided a literature review on criteria and methods in third-part logistics selection. Yazdani et al. [31] proposed an integrated method to select green suppliers by considering various environmental performance requirements and criteria.

The enterprise F is a food company whose main business involves fresh food such as shrimp, steak, chicken and all kinds of quick-frozen food. It also has its own food brand and enjoys a reputation in the market. Its downstream firms are chain supermarkets in the province. F enterprise has established a stable cooperative relationship with them. The distribution service is managed by F company.

With the rising demand for environmental protection, the government declared a series of policies to reduce pollution. F enterprise hopes to access to high service from green cold-chain logistics suppliers. Meanwhile, customer requirements for the freshness of food should be meet for the returns caused by food spoilage will lead to loss borne by the enterprise. It is hoped that the logistics service can rapidly respond to the changes of market, minimize the pollution discharge and eliminate food contamination. As a result, F enterprise proposed the following four requirements:

1. The freshness of the product must be guaranteed to avoid spoilage.
2. The logistics suppliers should be able to deliver on time, avoiding delay and advance delivery.
3. There should be the ability to obtain, transfer logistics information and share logistics information with F company.
4. There should be less environmental pollution and energy consumption such as refrigerant leakage of refrigeration equipment, high power consumption in the logistics process and automobile exhaust emission.

According to Chen and Lan [32] and the actual situation of green cold chain logistics supplier selection in this case, this paper proposes four main evaluation criteria. The main criteria and their related capabilities of cold chain suppliers are shown in Table 1.

**Table 1.** The main criteria and the capabilities required.

| First-Level | No. | Secondary-Level | No. | The Capabilities Required |
|---|---|---|---|---|
| Evaluation of the green cold-chain logistics providers | 1 | Resource | 1 | Visible quality of service (Facilities, Equipment, Personnel) |
| | | | 2 | Quality authentication |
| | 2 | Growth ability | 1 | Product qualification ratio |
| | | | 2 | Delivery just-in-time |
| | | | 3 | Cost Performance |
| | | | 4 | Response speed |
| | 3 | Performance | 1 | Business process support |
| | | | 2 | Information acquisition and transformation |
| | | | 3 | Information sharing ability |
| | 4 | Environmental | 1 | Microbial contamination |
| | | | 2 | CO emissions of refrigerated vehicle |
| | | | 3 | Utilization of refrigerant |

In the process of actual evaluation, however, an important issue is that many indicators cannot be given an accurate answer, such as the resource criterion and the performance criterion. This kind of fuzziness in the evaluation process is the inevitable reflection of people in dealing with social information. Likert scale is a widely used summated rating scale, which was proposed by an American social psychologist Likert in 1932. The Likert scale requires the participants to indicate whether they agree or disagree with each statement related to the specific attitude. The Likert scale typically contains five- or seven-scale-point version, which can effectively and accurately measure the participants' psychological cognition. In this paper, when the experts are asked to give an evaluation, we give the following description of the semantics according to the seven-point Likert scale: "very unsatisfied", "unsatisfied", "less satisfied", "general, satisfied", "more satisfied", "very satisfied", "unsatisfied", "satisfied" or "very satisfied", to represent the performance of a supplier.

Suppose that three experts $\mu_k$ $(K = 1, 2, 3)$, whose weights are supposed to be the same, now evaluate the green level of four cold chain logistics companies $D_i$ $(i = 1, 2, 3, 4)$. Company 1 does a good job in carbon emissions and microbial contamination, but it is poor in timeliness and often fails to deliver on time. Company 2 has a good performance in business process and information processing, which has strong development potential and relatively balanced performance in other aspects. Company 3 has more abundant resources, such as facilities, equipment, personnel, etc. Besides, Company 3 has a relatively general performance in other aspects. Company 4 is relatively balanced in all aspects. Relatively speaking, Company 4 is excellent in the storage of facilities, equipment and personnel. After investigating the real situation of the four companies, they evaluate the four secondary-level indicators of cold chain logistics enterprises' green level evaluation index system [32] ($\mu_1$, resource; $\mu_2$, growth ability; $\mu_3$, environment; and $\mu_4$, performance). The linguistic term set $S = \{s_{-3}, \cdots, s_3\}$ = {very unsatisfied, unsatisfied, less satisfied, general, satisfied, more satisfied, very satisfied} is used to evaluate these four secondary-level indicators. These three experts are asked to give their expectation level for each indicator, which can be represented by a linguistic term due to that people always know their expectations. The expectation levels of indicators given by the experts are: $L_1 = (s_0, s_1, s_0, s_{-1})$, $L_2 = (s_1, s_0, s_1, s_0)$, $L_3 = (s_0, s_0, s_1, s_0)$, and the original hesitant fuzzy linguistic decision matrices are provided as:

$$H_1 = \begin{pmatrix} \{s_1\} & \{s_2\} & \{s_2\} & \{s_{-2}\} \\ \{s_0\} & \{s_1, s_2\} & \{s_1\} & \{s_1\} \\ \{s_1\} & \{s_1\} & \{s_0\} & \{s_2\} \\ \{s_1, s_2\} & \{s_0\} & \{s_1\} & \{s_1\} \end{pmatrix}$$

$$H_2 = \begin{pmatrix} \{s_2\} & \{s_1\} & \{s_1, s_2\} & \{s_{-1}\} \\ \{s_1\} & \{s_1\} & \{s_1\} & \{s_0\} \\ \{s_1, s_2\} & \{s_0, s_1\} & \{s_0\} & \{s_{-1}\} \\ \{s_0\} & \{s_{-1}, s_0\} & \{s_1\} & \{s_0\} \end{pmatrix}$$

$$H_3 = \begin{pmatrix} \{s_1\} & \{s_1\} & \{s_2\} & \{s_0\} \\ \{s_1\} & \{s_1\} & \{s_0\} & \{s_0, s_1\} \\ \{s_2\} & \{s_0\} & \{s_1\} & \{s_0\} \\ \{s_1\} & \{s_0\} & \{s_1\} & \{s_1\} \end{pmatrix}$$

The three experts are asked to give their preference indices toward these four indicators, which are listed in Table 2.

**Table 2.** The preference indices over the criteria.

| | $\mu_1$ | $\mu_2$ | $\mu_3$ | $\mu_4$ |
|---|---|---|---|---|
| | **Resource** | **Growth Ability** | **Environment-Friendly** | **Performance** |
| $\mu_1$ | 0 | 2 | 1 | 2 |
| $\mu_2$ | 1 | 0 | 3 | -1 |
| $\mu_3$ | −1 | −2 | 0 | 3 |
| $\mu_4$ | 1 | 3 | 1 | 0 |

### 4.2. Solve the Case by the Cumulative Prospect Theory and PROMETHEE Based Hesitant Fuzzy Linguistic Thermodynamic Method

Then, we construct the corresponding HFLPDMs. Considering that Tversky and Kahneman [17] pointed out that the outcome is consistent with the original data when $\alpha = \beta = 0.88$ and $\lambda = 2.25$, the same values of these parameters are utilized in this case study. Hence, the HFPDMs can be obtained:

$$\hat{H}_1 = \begin{pmatrix} \{s_{0.3803}\} & \{s_{0.5434}\} & \{s_{0.6910}\} & \{s_{0.3032}\} \\ \{s_{0.2968}\} & \{s_{0.2968}, s_{0.5439}\} & \{s_{0.3803}\} & \{s_{0.5434}\} \\ \{s_{0.3803}\} & \{s_{0.2968}\} & \{s_{0.2968}\} & \{s_{0.7763}\} \\ \{s_{0.3803}, s_{0.6999}\} & \{s_{0.1758}\} & \{s_{0.3803}\} & \{s_{0.5434}\} \end{pmatrix}$$

$$\hat{H}_2 = \begin{pmatrix} \{s_{0.5434}\} & \{s_{0.3803}\} & \{s_{0.5434}\} & \{s_{0.1758}\} \\ \{s_{0.2968}\} & \{s_{0.3803}\} & \{s_{0.1260}\} & \{s_{0.2968}\} \\ \{s_{0.2468}, s_{0.5434}\} & \{s_{0.2968}, s_{0.3803}\} & \{s_{0.1260}\} & \{s_{0.1758}\} \\ \{s_{0.1260}\} & \{s_{0.4758}, s_{0.3803}\} & \{s_{0.2968}\} & \{s_{0.2968}\} \end{pmatrix}$$

$$\hat{H}_3 = \begin{pmatrix} \{s_{0.3803}\} & \{s_{0.3803}\} & \{s_{0.5434}\} & \{s_{0.2968}\} \\ \{s_{0.3803}\} & \{s_{0.3803}\} & \{s_{0.1260}\} & \{s_{0.2968}, s_{0.3803}\} \\ \{s_{0.7}\} & \{s_{0.2968}\} & \{s_{0.2968}\} & \{s_{0.2968}\} \\ \{s_{0.3803}\} & \{s_{0.2968}\} & \{s_{0.2968}\} & \{s_{0.3803}\} \end{pmatrix}$$

Using Equation (6), we can derive the matrix $\overline{V}$ as:

$$\overline{V} = \begin{pmatrix} s_{0.4346} & s_{0.4346} & s_{0.5926} & s_{0.2263} \\ s_{0.3246} & s_{0.4002} & s_{0.2108} & s_{0.3793} \\ s_{0.4929} & s_{0.3177} & s_{0.2399} & s_{0.4163} \\ s_{0.3966} & s_{0.3322} & s_{0.3546} & s_{0.4068} \end{pmatrix}$$

The quality matrix $Q_K$ can be calculated using Equation (8), and thus we obtain:

$$Q_1 = \begin{pmatrix} 0.8751 & 0.7447 & 0.8340 & 0.9014 \\ 0.9144 & 0.6919 & 0.1954 & 0.5674 \\ 0.7034 & 0.9342 & 0.7628 & 0.1352 \\ 0.5634 & 0.7646 & 0.9275 & 0.6642 \end{pmatrix}$$

$$Q_2 = \begin{pmatrix} 0.7947 & 0.8751 & 0.9170 & 0.7803 \\ 0.9144 & 0.9503 & 0.5977 & 0.7825 \\ 0.7498 & 0.8686 & 0.5252 & 0.4223 \\ 0.4582 & 0.4920 & 1 & 0.7296 \end{pmatrix}$$

$$Q_3 = \begin{pmatrix} 0.8751 & 0.8751 & 0.9170 & 0.7591 \\ 0.8284 & 0.9503 & 0.5977 & 0.8899 \\ 0.5498 & 0.9246 & 0.7628 & 0.7129 \\ 0.9589 & 0.8807 & 0.8370 & 0.9349 \end{pmatrix}$$

By the PROMETHEE method, we can derive the priority vector of the indicators, which is: $W = \{0.361, 0.25, 0.111, 0.278\}^T$. Then, the hesitant fuzzy linguistic energy matrices are calculated using Equation (3) as:

$$E_1 = \begin{pmatrix} \{s_{0.1373}\} & \{s_{0.1359}\} & \{s_{0.0767}\} & \{s_{0.0565}\} \\ \{s_{0.1091}\} & \{s_{0.0742}, s_{0.1359}\} & \{s_{0.0422}\} & \{s_{0.1511}\} \\ \{s_{0.1373}\} & \{s_{0.0742}\} & \{s_{0.0324}\} & \{s_{0.2159}\} \\ \{s_{0.1373}, s_{0.2527}\} & \{s_{0.0440}\} & \{s_{0.0422}\} & \{s_{0.1511}\} \end{pmatrix}$$

$$E_2 = \begin{pmatrix} \{s_{0.1963}\} & \{s_{0.0951}\} & \{s_{0.0603}\} & \{s_{0.0989}\} \\ \{s_{0.1091}\} & \{s_{0.0951}\} & \{s_{0.0140}\} & \{s_{0.0825}\} \\ \{s_{0.1071}, s_{0.1962}\} & \{s_{0.0742}, s_{0.0951}\} & \{s_{0.0140}\} & \{s_{0.0489}\} \\ \{s_{0.0455}\} & \{s_{0.0490}, s_{0.0951}\} & \{s_{0.0329}\} & \{s_{0.0825}\} \end{pmatrix}$$

$$E_3 = \begin{pmatrix} \{s_{0.0455}\} & \{s_{0.0951}\} & \{s_{0.0603}\} & \{s_{0.0825}\} \\ \{s_{0.1373}\} & \{s_{0.0951}\} & \{s_{0.0140}\} & \{s_{0.1057}, s_{0.0825}\} \\ \{s_{0.2527}\} & \{s_{0.0742}\} & \{s_{0.0324}\} & \{s_{0.0825}\} \\ \{s_{0.1373}\} & \{s_{0.0742}\} & \{s_{0.0329}\} & \{s_{0.1057}\} \end{pmatrix}$$

According to Equation (9), the hesitant fuzzy linguistic exergy matrices can be obtained as:

$$X_1 = \begin{pmatrix} \{0.1202\} & \{0.1019\} & \{0.640\} & \{0.0510\} \\ \{0.0979\} & \{0.0513, 0.094\} & \{0.0083\} & \{0.0857\} \\ \{0.0966\} & \{0.0693\} & \{0.0251\} & \{0.0292\} \\ \{0.0774, 0.1424\} & \{0.0336\} & \{0.0391\} & \{0.1004\} \end{pmatrix}$$

$$X_2 = \begin{pmatrix} \{0.1096\} & \{0.0832\} & \{0.0563\} & \{0.0382\} \\ \{0.0979\} & \{0.0904\} & \{0.0084\} & \{0.0646\} \\ \{0.0803, 0.1471\} & \{0.0645, 0.0826\} & \{0.0074\} & \{0.0207\} \\ \{0.0208\} & \{0.0219, 0.0473\} & \{0.0324\} & \{0.0602\} \end{pmatrix}$$

$$X_3 = \begin{pmatrix} \{0.0398\} & \{0.0958\} & \{0.0553\} & \{0.0626\} \\ \{0.1137\} & \{0.0904\} & \{0.0084\} & \{0.0941, 0.0734\} \\ \{0.1465\} & \{0.690\} & \{0.0251\} & \{0.0588\} \\ \{0.1317\} & \{0.0653\} & \{0.0275\} & \{0.0988\} \end{pmatrix}$$

According to Equations (11)–(15), the hesitant fuzzy linguistic entropies of the companies are calculated as $SR_1 = 0.0222$, $SR_2 = 0.0187$, $SR_3 = 0.0391$, and $SR_4 = 0.0217$. We know that smaller values of hesitant fuzzy linguistic entropy mean better green level. Thus, the ranking of the cold chain logistic companies is $D_2 \succ D_4 \succ D_1 \succ D_3$, which implies that $D_2$ has the highest green level among these cold chain logistic companies.

### 4.3. Result Discussion

The results of hesitant fuzzy linguistic energy value reflect the overall state of the evaluation information to display each cold chain logistics provider, which includes the quantity of experts' information. The results of hesitant fuzzy linguistic exergy value reflect the quality of experts' evaluation information of each cold chain logistics provider. The difference between energy and exergy is our final result called hesitant fuzzy linguistic entropy. Thus, it includes both quantity and quality of evaluation information, and the value can reflect the instability of information, which means that higher value a cold chain logistic provider obtains, the more instability the provider is. In case study, we find that Company 2 is more stable than other companies because most of its evaluation criteria are satisfied and more satisfied. As for Company 3, although its resources are very good, other indicators are average, so it is ranked low. Due to these properties regarding to the results, this method can be widely applied in MCDM problems and can reflects more information than other traditional methods.

### 4.4. Comparative Analysis

We use the cumulative prospect theory-based interval TOPSIS method introduced by Wang et al. [16] to solve the case and then compare it with the proposed method. It is noted that we also use the PROMETHEE method to determine the weights of criteria.

With information in the above section, the interval-valued hesitant fuzzy linguistic PIS $\widetilde{A}^{+}$ and the interval-valued hesitant fuzzy linguistic PIS $\widetilde{A}^{-}$ can be, respectively, determined as:

$$\widetilde{A}^{-} = \{(S_1, S_1, S_0, S_0), (S_0, S_0, S_0, S_1), (S_1, S_0, S_0, S_0), (S_0, S_{-1}, S_{-2}, S_{-2})\}$$

$$\widetilde{A}^{+} = \{(S_2, S_2, S_1, S_1), (S_2, S_1, S_1, S_1), (S_2, S_2, S_2, S_1), (S_2, S_1, S_0, S_0)\}$$

The following calculation results derived by the cumulative prospect theory-based interval TOPSIS method can be listed in Table 3.

**Table 3.** The result driven by the cumulative prospect theory-based interval TOPSIS method.

| | $d_i^+$ | $d_i^-$ | $c_i$ | Rank |
|---|---|---|---|---|
| $P_1$ | $s_{0.7365}$ | $s_{0.8835}$ | 0.5454 | 3 |
| $P_2$ | $s_{0.6468}$ | $s_{0.9520}$ | 0.5955 | 2 |
| $P_3$ | $s_{0.6328}$ | $s_{0.9453}$ | 0.5990 | 1 |
| $P_4$ | $s_{0.9433}$ | $s_{0.8857}$ | 0.4843 | 4 |

In Table 2, we can see that different rankings of companies are obtained by the cumulative prospect theory-based interval TOPSIS method. Given that these two methods have different essences and computational processes, the advantages of our method can be summarized as follows:

1. By extending the prospect method into the situations with HFLTSs, this method can reflect experts' psychology behaviors and attitude towards risk, which is more reasonable under limited rationality.
2. By extending the knowledge of thermodynamics theory to accommodate the HFLTSs, our research reflects the quantity and quality of decision-making information. The utilization of the hesitant fuzzy linguistic energy and the hesitant fuzzy linguistic exergy can help this method make full use of the value of information.

Based on the above two advantages, we can know that our model is more reasonable and accurate in solving real decision-making problems.

## 5. Conclusions

This study took advantage of the HFLTS to represent the fuzziness of objects and the hesitant thoughts of experts. Combining the cumulative prospect theory, the PROMETHEE II method and the knowledge of thermodynamics, this study developed an integrating method to solve hesitant fuzzy linguistic MCDM problems. The negative exponential function developed based on the cumulative prospect theory and the process of transferring the hesitant fuzzy linguistic decision matrices into the HFLPDMs can both reflect the psychological behaviors of experts. With the marginal diminishing effect, the negative exponential function reflects the diminishing marginal utility of each expert in reality. We transferred the matrices based on this function, so each expert's psychological behavior on a certain criterion for each alternative can be reflected. The PROMETHEE II method was used to derive the priority vector of criteria, which is more innovative and understandable than traditional method such as the entropy weighting method. We obtained the pairwise comparison matrix of criteria from expert directly. Thus, more information was contained and the concepts of entering flow and leaving flow are easy to understand. Moreover, this study utilized the energy and exergy in thermodynamics to consider both quantity and quality of the decision information. Hesitant fuzzy linguistic energy refers to the overall state of the information display, which reflects the quantity of information. Hesitant fuzzy linguistic exergy refers to the quantity and quality of the alternatives. What is more, hesitant fuzzy linguistic entropy is defined as a comprehensive indicator of the alternatives and the instability of information. Our results of application were obtained from hesitant fuzzy linguistic energy and hesitant fuzzy linguistic exergy, so both quantity and quality of information in MCDM process were included. After providing the whole procedure of our method, we applied it to access the green levels of cold chain logistic suppliers, which demonstrated the practicability of this method.

In the future, our method can be used to solve other hesitant fuzzy linguistic MCDM problems. Moreover, it can also be extended to other decision-making environments, such as the probabilistic linguistic environment [33,34]. Our next work is to investigate new methods in different decision-making environment based on typical MADM methods such as VIKOR [35] and ELECTRE [36].

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