Probabilistic Uncertain Linguistic EDAS Method Based on Prospect Theory for Multiple Attribute Group Decision-Making and Its Application to Green Finance

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Abstract In recent years, some scholars have put forward the concept of green finance, which is to integrate the environmental protection concept of green development into the traditional financial industry. Green credit is one of the important financial services in green finance. In order to construct a more perfect multiple attribute group decision-making (MAGDM) method, this paper proposes a new evaluation based on distance from average solution (EDAS) model based on prospect theory and probabilistic uncertain linguistic term set (PT-PULTS-EDAS model). The PT-PUTLS-EDAS model fully takes the psychological state of decision-makers into account the mathematical logic of the method, which is more suitable for the problem of MAGDM in reality. In addition, the new PT-PULTS-EDAS model reduces the decision-maker's subjective judgment on some objective situations as much as possible. The model uses Criteria Importance Through Intercriteria Correlation (CRITIC) method to obtain the initial attribute weights and makes use of the weighting function to alter the initial weights so that successfully avoids the distortion of subjective judgment to the actual probability to some extent. Moreover, different parameters are introduced in this method to further deal with the part above and below the standard point respectively so that different types of decision-makers' attitudes towards gains and losses are taken into account. In the fifth part, we focus on green finance, prove the usability of this method through an example, and draw a reasonable and scientific conclusion based on the results of comparative analysis. In the future, we will continue to focus on the relevant theories and methods about MADM or MAGDM.

Keywords Multiple attribute group decision-making (MAGDM) · Probabilistic uncertain linguistic term set · EDAS method · Prospect theory

1 Introduction

The emergence of industrial civilization in the eighteenth century has brought us great material satisfaction, but it has also caused increasingly serious problems such as climate change, resource depletion and environmental pollution. In order to solve environmental problems and ensure sustainable economic and social development, international organizations and research institutions have begun to advocate green civilization and vigorously promote the development of green industries and low-carbon economy. As an important link of modern economic development, finance is the key factor to promote economic development and also an important means to change the allocation of resources. Consequently, the concept of green finance, which applies green concept to financial development, is put forward. Green finance includes green credit. While providing green credit services, it is indispensable for banks and other financial institutions to carry out risk assessment on enterprises who are applying for green credit. This phenomenon about green credit risk assessment can be regarded as a kind of MADM [1–5].

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MADM and multiple attribute group decision-making (MAGDM) are hot topics in the field of management decision-making [6–11]. There are many research methods around MADM and MAGDM. Among them, Evaluation Based on Distance from Average Solution (EDAS) method [12] is a relatively simple and easy-to-use. In this method, the relationship between each alternative and the standard point is compared from two aspects of positive distance and negative distance. Finally, the comprehensive score obtained from the positive distance and negative distance is established as the tool to evaluate the merits and demerits of alternatives. Tian et al. [13] applied EDAS method to supplier performance assessment. Based on extended hesitant fuzzy linguistic term environment, Liu and Zhang [14] developed traditional EDAS method and pointed novel possibility degree. Li et al. [15] established interval-valued neutrosophic EDAS model. Ju et al. [16] confirmed a series of picture fuzzy interaction operators which is also as a kind of innovation to traditional EDAS method. Zeng et al. [17] completed 2-tuple linguistic neutrosophic set (2TLNS) and further constructed improved EDAS model on the basis of 2TLNS. Keshavarz Ghorabaee, Amiri, Zavadskas, Turskis and Antucheviciene [18] utilized mul-tivalued neutrosophic number (MVNN) to extend original EDAS method. Feng et al. [19] believed that establishing the EDAS model under IF was a valuable thing for the researches of MADM and MAGDM. Meanwhile, Karasan and Kahraman [20] also focused on IF EDAS model, but the difference was that they demonstrated new parametric divergence measures in their study. Similar to the forms of many researches, Li et al. [21] created new operators under single-valued complex neutrosophic environment and took advantage of these operators as the improved tool for the EDAS method. The contribution of the study of Wang et al. [22] was to construct EDAS models in covering-based variable precision fuzzy rough environment. Huang et al. [23] built the Enhancement EDAS Method Based on Prospect Theory. Han and Wei [24] chose four-branch fuzzy set to describe the uncertainty of the environment and gave the application of EDAS model in this fuzzy set. Wei et al. [25] defined the EDAS method for probabilistic linguistic MAGDM. He et al. [26] built the pythagorean 2-tuple linguistic EDAS method.

Such as intuitionistic fuzzy set (IFS) [27], picture fuzzy set (PFS) [28], and Pythagorean fuzzy set (PyFS) [29], all of these depend on the fuzzy set (FS) mentioned by Zhan et al. [30] firstly in 1965. These traditional fuzzy sets are used to evaluating things directly with numerical values. However, in the reality, for a great number of decision-makers, language is the effective way they are more familiar with and more accustomed to. Therefore, lots of fuzzy sets based on linguistic term set have been developed. Hesitant fuzzy linguistic term set (NWHFLTS) [31], probabilistic linguistic term set (PLTS) [32], probabilistic uncertain linguistic term set (PULTS) and so on are typical representatives. There are some similarities and differences between PULTS and PLTS. PLTS evolved from hesitant fuzzy linguistic term set (HFLTS), but further developed probability of each possible linguistic term. PULTS used a linguistic term in the form of an interval to evaluate, while made use of probability and the conception of linguistic term. Cuong [33] proposed a new Pearson correlation coefficient for PLTS, and compared with traditional cor-relation coefficient, the new one expressed better effect in assessing correlation. Wei et al. [25] defined the proba-bilistic linguistic EDAS method. Yager [34] integrated PLTS with the D number theory. Zadeh [35] developed dual Muirhead mean operators under PLTSs. At the same time, the birth of PULTS is noteworthy as well. Rodriguez, Martinez and Herrera [36] defined the basic concepts, operations and so on about PULTS. For optimizing the operation of PULTS, Pang et al. [37] created new opera-tions, distance measure and operators. Based on a full comprehension of PULTS, Luo et al. [38] confirmed a new preference relation, distance measure and similarity mea-sure about PULTS. Mo [39] emphasized the application of probabilistic uncertain linguistic EDAS model in the choice about the optimal green supplier. Another research from Du and Liu [40] also proposed multi-attributive border approximation area comparison (MABAC) model under PULTS about the issue of green suppliers. Mean-while, Lin et al. [41] constructed PULTS-based QUALI-FLEX (qualitative flexible multiple criteria) model. Wei et al. [42] defined the generalized Dice similarity measures for PUL-MAGDM. Wei et al. [43] built the probabilistic uncertain linguistic combinative distance-based assessment (CODAS) method.

Prospect theory (PT) had a unique insight into the fac-tors affecting decision-making, which differs from tradi-tional expected value theory (TEVT). The proposers of prospect theory, Bashir et al. [44], broke out of the con-straint of TEVT for the first time and divided value into two aspects: gain and loss. In their opinion, there were different types of decision-makers in reality. The percep-tion of profit and loss by decision-makers was not equal to value, but depended on the degree of aversion to risk. In addition, the PT believed that the subjective judgment of decision-maker may be distort the probability of the occurrence of the event, so the weighting function was proposed to eliminate the adverse effects. At present, there are many researches on using PT to make MADM or MAGDM [45–49], which is due to the perfect fit between PT and real decision situation. Zhao et al. [50] took advantage of PT to improve the traditional MABAC method under picture fuzzy environment and put forward a combination of weight determination method. Soon

afterwards, Zhao et al. [51] established a new MAGDM model based on PT and hesitant probabilistic fuzzy set, and created a comprehensive weight determination model as well. Coincidentally, Zhao et al. [52] also researched the blend of MABAC method and PT, but the difference was that they likewise brought another idea in their model. Meanwhile, Fu et al. [53] utilized PT as well as the maximizing deviation method to construct decision model for the fuel options in ocean transportation. From the existing studies, there are many studies that combine PT with TODIM method, and some other studies on MAGDM using PT, but there are few investigations that merge PT and EDAS method together.

In order to make up for this gap and to put forward a more effective and user-friendly MAGDM method to help decision-makers select a reasonable and reliable optimal alternative as soon as possible in an increasingly complex environment of uncertainty, this paper proposes to establish an EDAS model based on prospect theory under probabilistic uncertainty linguistic term set (PT-PULTS-EDAS). In accordance with the analysis of PT and traditional EDAS, this new method will have simple arithmetic logic, which is easy for users to understand and employ. Moreover, the PT-PULTS-EDAS model fully considers the influence of decision-maker's mentality on decision result. Through the application of value function in PT, different parameters are introduced into the decision-making process to deal with the benefits and losses, so as to ensure that the decision-making process conforms to the decision-maker's psychological cognition. What's more, the PT-PULTS-EDAS model not only utilizes CRITIC method to determine initial attribute weights, but also takes advantage of weight function to avoid the influence of decision-maker's cognitive differences on weights. To sum up, there are contributions of this paper: (1) the traditional EDAS method is improved using prospect theory; (2) the new model is a novel solution to the MAGDM problem; (3) the new model is also an extension of PULTS in the MAGDM problem; (4) the realization of the application of the new proposed method in green finance related fields enriches the application fields of MAGDM method. Therefore, there are reasons to believe that the PT-PULTS-EDAS model in this paper has certain significance and value for MAGDM.

This article contains the following contents. In order to help the readers understand PULTS, we review and summarize the basic knowledge of PULTS in the second part of the article. The third part of the article expounds the main basic theory of this paper—the prospect theory. In the Sect. 4, we elaborate the EDAS model based on the prospect theory (PT) in the PULT environment. Finally, in the Sect. 5, an example about green finance is given to prove the usability of this new model, and the conclusion is

drawn that the model presented in this paper is reasonable and scientific in line with the comparative analysis results.

2 Preliminary Knowledge

In fact, people are more likely to rely on language to express their opinions than on numbers. Hence, in this article we select probabilistic uncertain linguistic term set (PULTS) as appraisal tool. Now we introduce some basic knowledge about PULTS.

Definition 1 [54] In order to relate language to numbers, we can define a linguistic term set $\tilde{F} = \{\tilde{f_\Delta} | \Delta = -\xi, \cdots, -2, -1, 0, 1, 2, \ldots, \xi.\}$ such as $\tilde{F} = \{\tilde{f}_{-3} = $ extremely bad, $\tilde{f}_{-2} = $ very bad, $\tilde{f}_{-1} = $ bad, $\tilde{f}_0 = $ medium, $\tilde{f}_1 = $ great, $\tilde{f}_2 = $ very great, $\tilde{f}_3 = $ extremely great$\}$. And the transfer function $\tilde{T}\tilde{F}$ as the bridge help us to realize the transformation of the linguistic term $\tilde{f_\Delta}$ into a crisp $\Re$.

$$\tilde{T}\tilde{F} : [\tilde{f}_{-\xi}, \tilde{f}_\xi] \to [0, 1]$$
$$\tilde{T}\tilde{F}(\tilde{f_\Delta}) = \frac{\Delta + \xi}{2\xi} = \Re, \tag{1}$$

According to Eq. (2) namely function $\tilde{T}\tilde{F}^{-1}$, the crisp $\Re$ can be recovered to the linguistic term $\tilde{f_\Delta}$.

$$\tilde{T}\tilde{F}^{-1} : [0, 1] \to [\tilde{f}_{-\xi}, \tilde{f}_\xi]$$
$$\tilde{T}\tilde{F}^{-1}(\Re) = \tilde{f}_{(2\Re-1)\xi} = \tilde{f_\Delta}, \tag{2}$$

Slightly different from probabilistic linguistic term set (PLTS), Wang, Peng and Wang [55] further developed the probabilistic uncertain linguistic term set (PULTS).

Definition 2 [56] Eq. (3) is the definition of PULTS in line with the LTS $\tilde{F} = \{\tilde{f_\Delta} | \Delta = -\xi, \cdots, -2, -1, 0, 1, 2, \ldots, \xi.\}$.

$$\Im(\tau) = \left\{ [\hbar^\iota, \chi^\iota](\tau^\iota) | \tau^\iota \geq 0; \iota = 1, 2, \ldots, \#\Im(\tau); \sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota \leq 1 \right\}, \tag{3}$$

where $[\hbar^\iota, \chi^\iota]$ is a uncertain linguistic term (ULT), and $\hbar^\iota$ as well as χ^ι respectively represent the limitation of lower and upper ($\hbar^\iota, \chi^\iota \in \tilde{F}$ as well as $\hbar^\iota \leq \chi^\iota$). Moreover, the probability of ULT $[\hbar^\iota, \chi^\iota]$ is evaluated by τ^ι, and the total amount of ULT in PULTS $\Im(\tau)$ is $\#\Im(\tau)$.

In particular, if there is an inclusion or crossover relationship between two different ULTs in $PU(\hat{\pi}) = \{ [\hat{L}^{(m)}, \hat{U}^{(m)}](\hat{\pi}^{(m)}) | m = 1, 2, \ldots, \#PU(\hat{\pi})\}$, it is necessary to reprocess original PULTS. For inclusion, the more extensive ULT is further subdivided, for example, $[v_0, v_2](0.6)$ is divided into $[v_0, v_1](0.3)$ and $[v_1, v_2](0.3)$ in

$PU(\hat{\pi}) = \{[v_0, v_2](0.6), [v_0, v_1](0.4)\}$ so that $PU(\hat{\pi}) = \{[v_0, v_1](0.7), [v_1, v_2](0.3)\}$. For crossover, the same part is separated out from original PULTSs, for instance, $PU(\hat{\pi}) = \{[v_{-1}, v_1](0.6), [v_0, v_2](0.4)\}$ is turned into $PU(\hat{\pi}) = \{[v_{-1}, v_0](0.3), [v_0, v_1](0.5), [v_1, v_2](0.2)\}$.

Definition 3 [14] If $\sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota < 1$, we need to standardize using $\hat{\tau}^\iota = \tau^\iota \Big/ \sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota$ instead of the previous probability τ^ι. In other words, the PULTS $\Im(\tau) = \{[\hbar^\iota, \varkappa^\iota](\tau^\iota) | \iota = 1, 2, \ldots, \#\Im(\tau); \sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota \leq 1\}$ is standardized to $\Im(\hat{\tau}) = \{[\hbar^\iota, \varkappa^\iota](\hat{\tau}^\iota) | \hat{\tau}^\iota \geq 0; \iota = 1, 2, \ldots, \#\Im(\hat{\tau}); \sum_{\iota=1}^{\#\Im(\hat{\tau})} \hat{\tau}^\iota = 1\}$.

For ensuring the comparability between any two PULTS, we need to normalize PULTS in terms of length and form of expression.

Definition 4 [57] Suppose there are two PULTS $\Im_1(\tau_1) = \{[\hbar_1^\iota, \varkappa_1^\iota](\tau_1^\iota) | \iota = 1, 2, \ldots, \#\Im_1(\tau_1)\}$ and $\Im_2(\tau_2) = \{[\hbar_2^\iota, \varkappa_2^\iota](\tau_2^\iota) | \iota = 1, 2, \ldots, \#\Im_2(\tau_2)\}$, if $\#\Im_1(\tau_1) > \#\Im_2(\tau_2)$, then Add $\#\Im_1(\tau_1) - \#\Im_2(\tau_2)$ ULTs which are the smallest ULT of $\Im_2(\tau_2)$ into PULTS $\Im_2(\tau_2)$ with corresponding probabilities of zero.

Definition 5 [58] For a PULTS $\Im(\tau) = \{[\hbar^\iota, \varkappa^\iota](\tau^\iota) | \iota = 1, 2, \ldots, \#\Im(\tau)\}$, each ULT should be independent interval that is neither contained nor intersected in other ULTs. Once the inclusion or crossover relationship exists, the original PULTS need to be rearranged, and new PULTS with each ULT independent of each other is obtained by splitting and remerging. For instance, $\Im(\tau) = \{[\tilde{f}_{-3}, \tilde{f}_0](0.3), [\tilde{f}_{-1}, \tilde{f}_1](0.5)\}$ is rearranged to $\Im(\tau) = \{[\tilde{f}_{-3}, \tilde{f}_{-1}](0.2), [\tilde{f}_{-1}, \tilde{f}_0](0.35), [\tilde{f}_0, \tilde{f}_1](0.25)\}$.

Definition 6 [41] The expected value $\tilde{E}\tilde{V}(\Im(\tau))$ and deviation value $\tilde{D}\tilde{V}(\Im(\tau))$ of PULTS $\Im(\tau) = \{[\hbar^\iota, \varkappa^\iota](\tau^\iota) | \iota = 1, 2, \ldots, \#\Im(\tau)\}$ can be defined as Eqs. (4) and (5) separately.

$$\tilde{E}\tilde{V}(\Im(\tau)) = \frac{\sum_{\iota=1}^{\#\Im(\tau)} \left(\frac{\tilde{T}\tilde{F}(\hbar^\iota) \cdot \tau^\iota + \tilde{T}\tilde{F}(\varkappa^\iota) \cdot \tau^\iota}{2} \right)}{\sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota}, \quad (4)$$

$$\tilde{D}\tilde{V}(\Im(\tau)) = \frac{\sqrt{\sum_{\iota=1}^{\#\Im(\tau)} \left(\frac{\tilde{T}\tilde{F}(\hbar^\iota) \cdot \tau^\iota + \tilde{T}\tilde{F}(\varkappa^\iota) \cdot \tau^\iota}{2} - \tilde{E}\tilde{V}(\Im(\tau)) \right)^2}}{\sum_{\iota=1}^{\#\Im(\tau)} \tau^\iota}. \quad (5)$$

Definition 7 [41] If there are two PULTSs $\Im_1(\tau_1) = \{[\hbar_1^\iota, \varkappa_1^\iota](\tau_1^\iota) | \iota = 1, 2, \ldots, \#\Im_1(\tau_1)\}$ and $\Im_2(\tau_2) = \{[\hbar_2^\iota, \varkappa_2^\iota](\tau_2^\iota) | \iota = 1, 2, \ldots, \#\Im_2(\tau_2)\}$,

(1) when $\tilde{E}\tilde{V}(\Im_1(\tau_1)) > \tilde{E}\tilde{V}(\Im_2(\tau_2))$, there is $\Im_1(\tau_1) > \Im_2(\tau_2)$;

(2) when $\tilde{E}\tilde{V}(\Im_1(\tau_1)) = \tilde{E}\tilde{V}(\Im_2(\tau_2))$ and $\tilde{D}\tilde{V}(\Im_1(\tau_1)) > \tilde{D}\tilde{V}(\Im_2(\tau_2))$, the same consequence can be deduced namely $\Im_1(\tau_1) > \Im_2(\tau_2)$;

(3) when $\tilde{E}\tilde{V}(\Im_1(\tau_1)) = \tilde{E}\tilde{V}(\Im_2(\tau_2))$ and $\tilde{D}\tilde{V}(\Im_1(\tau_1)) = \tilde{D}\tilde{V}(\Im_2(\tau_2))$, we can conclude $\Im_1(\tau_1) = \Im_2(\tau_2)$.

Definition 8 [41] Suppose $\Im_1(\tau_1) = \{[\hbar_1^\iota, \varkappa_1^\iota](\tau_1^\iota) | \iota = 1, 2, \ldots, \#\Im_1(\tau_1)\}$ and $\Im_2(\tau_2) = \{[\hbar_2^\iota, \varkappa_2^\iota](\tau_2^\iota) | \iota = 1, 2, \ldots, \#\Im_2(\tau_2)\}$ are two PULTSs and $\#\Im_1(\tau_1) = \#\Im_2(\tau_2) = \#\Im$, the Hamming distance of these two PULTS are represented as Eq. (6) as follows:

$$\hat{d}(\Im_1(\tau), \Im_2(\tau)) = \frac{1}{2 \cdot \#\Im} \sum_{\iota=1}^{\#\Im} \left(\begin{array}{c} \left(|\tilde{T}\tilde{F}(\hbar_1^\iota) \cdot \tau_1^\iota - \tilde{T}\tilde{F}(\hbar_2^\iota) \cdot \tau_2^\iota| \right) \\ + \left(|\tilde{T}\tilde{F}(\varkappa_1^\iota) \cdot \tau_1^\iota - \tilde{T}\tilde{F}(\varkappa_2^\iota) \cdot \tau_2^\iota| \right) \end{array} \right). \quad (6)$$

3 Prospect Theory

Prospect theory (PT) first confirmed by Tversky and Kahneman [59] contradicted the point of the traditional expected value theory (TEVT) about final assets as the evaluation criteria for decision-makers and selected gains and losses instead of final asset. In addition, the discoverer of PT thought that the characteristic of decision-makers plays a vital role in attitude toward gain and losses. Comprehensively, the more a decision-maker pursues risk, the less he is affected by losses. Moreover, this phenomenon also appears in decision-makers' perception of the probability of occurrence of events and gives rise to distortion. To be more realistic, the prospect function $\tilde{P}(w)$, the value function $\tilde{C}(w_s)$ and the weighting function $\tilde{G}(h_s)$ are created as follows Eqs. (7)–(9):

$$\tilde{P}(w) = \sum_{s=1}^{f} \tilde{C}(w_s) \cdot \tilde{G}(h_s). \quad (7)$$

For the value function $\tilde{C}(w_s)$, if the actual value w_s is no less than the selected standard point w_0, the value $w_s - w_0$ means gains for decision-makers. Otherwise, the value $w_0 - w_s$ means losses for decision-makers. Actually, in a real decision-making, decision-makers with different personality traits have different psychological perception of gain and loss. Hence, the parameters ψ, p and q in Eq. (8) are the mathematical embodiment of the decision-maker's

psychology. To sum up, More risk-seeking decision-makers is with the greater distinct between q and p, and usually their value function has traits that $q > p$ and $\psi < 1$. However, in more cases, the decision-maker is risk averse which means $\psi > 1$ as well as $q \leq p$.

$$\tilde{C}(w_s) = \begin{cases} (w_s - w_0)^q, & \text{if } w_s \geq w_0 \\ -\psi(w_0 - w_s)^p, & \text{if } w_s < w_0 \end{cases}, \tag{8}$$

The weighting function $\tilde{G}(h_s)$ represents a modification of probabilities that have been distorted by the decision-makers' psychology. As far as Lin et al. [41] are concerned, the decision-makers' psychology can affect the decision-maker's cognition about the objective probability of the occurrence of the event. Therefore, in order to make a more accurate judgment, it is necessary to modify the subjective probability value according to the weighting function $\tilde{G}(h_s)$. x and z represent the curvature of the weighting function $\tilde{G}(h_s)$.

$$\tilde{G}(h_s) = \begin{cases} \dfrac{h_s^x}{\left(h_s^x + (1 - h_s)^x\right)^{\frac{1}{x}}}, & \text{if } w_s \geq w_0 \\ \dfrac{h_u^z}{\left(h_u^z + (1 - h_s)^z\right)^{\frac{1}{z}}}, & \text{if } w_s < w_0 \end{cases}. \tag{9}$$

4 PT-Based EDAS Method Under PULTS

As mentioned above, PT is adequate evaluation of decision-maker's emotion and also constructs a reasonable mathematical formula to quantify the effect of such emotion on decision-making. In other words, PT provides a measure to ensure that data are processed in a more realistic way. Consequently, constructing a new-optimized EDAS model based on PT and using PULTS to deal with the increasing uncertainty in the decision-making process will be a very interesting and meaningful way to solve the MAGDM problem. In the following, we will discuss the new model in detail.

First of all, invite ς experts to form a panel of experts $\overleftrightarrow{\wp} = \left\{ \overleftrightarrow{\wp}_1, \overleftrightarrow{\wp}_2, \ldots, \overleftrightarrow{\wp}_\vartheta \right\}$ and each expert is asked to give his opinion in uncertain linguistic terms (ULT) on all alternatives $\overleftrightarrow{\Lambda} = \left\{ \overleftrightarrow{\Lambda}_1, \overleftrightarrow{\Lambda}_1, \ldots, \overleftrightarrow{\Lambda}_\varsigma \right\}$ under different attributes $\overleftrightarrow{\Upsilon} = \left\{ \overleftrightarrow{\Upsilon}_1, \overleftrightarrow{\Upsilon}_2, \ldots \overleftrightarrow{\Upsilon}_\chi \right\}$. All assessment information is stored in the v matrices $\tilde{UL}^{(v)} = \left(\left[\hbar_{\mu\gamma}^{(v)}, \chi_{\mu\gamma}^{(v)} \right] \right)_{\varsigma \times \chi}$ ($\hbar_{\mu\gamma}^{(v)}, \chi_{\mu\gamma}^{(v)} \in \tilde{F}; \hbar_{\mu\gamma}^{(v)} \leq \chi_{\mu\gamma}^{(v)}; \mu = 1, 2, \ldots, \varsigma; \gamma = 1, 2, \ldots, \chi; v = 1, 2, \ldots, \vartheta$).

Phase I: Preprocessing of basic information

Step 1: Judge whether one attribute is negative or not, and it is essential to transform the value of negative attribute $\left[\tilde{f}_a, \tilde{f}_b \right]$ into its corresponding form $\left[\tilde{f}_{-b}, \tilde{f}_{-a} \right]$.

Step 2: According to the above information that has been processed for consistency, we are capable to establish the aggregated and adjusted PULTS matrix $\tilde{PU}\tilde{M} = \left(\Im_{\mu\gamma}(\tau) \right)_{\varsigma \times \chi} = \left(\left\{ \left[^-h_{\mu\gamma}^\iota, \chi_{\mu\gamma}^\iota \right] \left(\tau_{\mu\gamma}^\iota \right) \middle| \iota = 1, 2, \ldots, \#\Im_{\mu\gamma}(\tau) \right\} \right)_{\varsigma \times \chi}$ in which $\tau_{\mu\gamma}^\iota$ is the possibility of ULTS $\left[^-h_{\mu\gamma}^\iota, \chi_{\mu\gamma}^\iota \right]$ appearing in alternative $\overleftrightarrow{\Lambda}_\mu$ under attribute $\overleftrightarrow{\Upsilon}_\gamma$ and satisfies $\sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \tau^\iota = 1$.

Step 3: Take advantage of the CRITIC method [60] to extract the initial objective attribute weights $\overleftrightarrow{\text{Ioa}}_\gamma \left(\overleftrightarrow{\text{Ioa}}_\gamma \geq 0 \text{ and } \sum_{\gamma=1}^{x} \overleftrightarrow{\text{Ioa}}_\gamma = 1 \right)$ from known and aggregated information. And the process is just as Eqs. (10)–(13).

$$\tilde{PC}\tilde{C}_{\gamma\kappa} =$$

$$\sum_{\mu=1}^{\varsigma} \frac{\left(\left(\sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \frac{\left(\tilde{TF}\left(h_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\overline{h}_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right) + \left(\tilde{TF}\left(\chi_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\chi_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right)}{2} \right) \right)}{\sqrt{\sum_{\mu=1}^{\varsigma} \left(\sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \frac{\left(\tilde{TF}\left(h_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\overline{h}_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right) + \left(\tilde{TF}\left(\chi_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\chi_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right)}{2} \right)^2}}$$

$$\cdot \frac{\left(\sum_{\iota=1}^{\#\Im_{\mu\kappa}(\tau)} \frac{\left(\tilde{TF}\left(h_{\mu\kappa}^\iota \right) \cdot \tau_{\mu\kappa}^\iota - \tilde{TF}\left(\overline{h}_\kappa^\iota \right) \cdot \overline{\tau}_\kappa^\iota \right) + \left(\tilde{TF}\left(\chi_{\mu\kappa}^\iota \right) \cdot \tau_{\mu\kappa}^\iota - \tilde{TF}\left(\chi_\kappa^\iota \right) \cdot \overline{\tau}_\kappa^\iota \right)}{2} \right)}{\sqrt{\sum_{\mu=1}^{\varsigma} \left(\sum_{\iota=1}^{\#\Im_{\mu\kappa}(\tau)} \frac{\left(\tilde{TF}\left(h_{\mu\kappa}^\iota \right) \cdot \tau_{\mu\kappa}^\iota - \tilde{TF}\left(\overline{h}_\kappa^\iota \right) \cdot \overline{\tau}_\kappa^\iota \right) + \left(\tilde{TF}\left(\chi_{\mu\kappa}^\iota \right) \cdot \tau_{\mu\kappa}^\iota - \tilde{TF}\left(\chi_\kappa^\iota \right) \cdot \overline{\tau}_\kappa^\iota \right)}{2} \right)^2}}$$

$$\gamma, \kappa = 1, 2, \ldots, \chi \tag{10}$$

where $\overline{\Im}_\gamma(\overline{\tau}) = \left\{ \left[\overline{h}_\gamma^\iota, \chi_\gamma^\iota \right] \left(\overline{\tau}_\gamma^\iota \right) = \left[\frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \hbar_{\mu\gamma}^\iota, \frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \chi_{\mu\gamma}^\iota \right] \left(\frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \tau_{\mu\gamma}^\iota \right) \right\}$ and $\overline{\Im}_\kappa(\overline{\tau}) = \left\{ \left[\overline{h}_\kappa^\iota, \chi_\kappa^\iota \right] \left(\overline{\tau}_\kappa^\iota \right) = \left[\frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \hbar_{\mu\kappa}^\iota, \frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \chi_{\mu\kappa}^\iota \right] \left(\frac{1}{\varsigma} \sum_{\mu=1}^{\varsigma} \tau_{\mu\kappa}^\iota \right) \right\}$.

$$\tilde{PS}\tilde{D}_\gamma = \sqrt{\frac{\sum_{\mu=1}^{\varsigma} \left(\sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \frac{1}{2} \left(\begin{array}{c} \left(\tilde{TF}\left(h_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\overline{h}_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right) \\ + \left(\tilde{TF}\left(\chi_{\mu\gamma}^\iota \right) \cdot \tau_{\mu\gamma}^\iota - \tilde{TF}\left(\chi_\gamma^\iota \right) \cdot \overline{\tau}_\gamma^\iota \right) \end{array} \right) \right)^2}{\varsigma - 1}},$$

$$\gamma = 1, 2, \ldots, \chi \tag{11}$$

$$\Psi_\gamma = \tilde{P}\tilde{S}\tilde{D}_\gamma \cdot \sum_{\kappa=1}^{\chi} \left(1 - \tilde{P}\tilde{C}\tilde{C}_{\gamma\kappa}\right), \gamma = 1, 2, \ldots, \chi \qquad (12)$$

$$\overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}} = \frac{\Psi_\gamma}{\sum_{\gamma=1}^{\chi} \Psi_\gamma}, \gamma = 1, 2, \ldots, \chi \qquad (13)$$

Phase II: Core operation of PT-PULTS-EDAS model

Step 4   Adopt Eq. (14) to alter the initial objective attribute weights by virtue of the viewpoint that the psychology of decision-makers could lead to the distortion of probability. And eventually acquire the altered objective attribute weights $\tilde{A}\tilde{O}\tilde{A}_{\mu\gamma}$ ($\mu = 1, 2, \ldots, \varsigma; \gamma = 1, 2, \ldots, \chi$).

$$\begin{cases} \tilde{A}\tilde{O}\tilde{A}_{\mu\gamma} = \left(\overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^x / \left(\left(\overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^x + \left(1 - \overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^x\right)^{\frac{1}{x}}, & \Im_{\mu\gamma}(\tau) \geq \overline{\Im}_\gamma(\overline{\tau}) \\ \left(\overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^z / \left(\left(\overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^z + \left(1 - \overset{\text{Ioa}}{\underset{\gamma}{\leftrightarrow}}\right)^z\right)^{\frac{1}{z}}, & \Im_{\mu\gamma}(\tau) \geq \overline{\Im}_\gamma(\overline{\tau}) \end{cases}$$
$$(14)$$

where x and z are parameters which represent the curvature of the attribute weight function.

Step 5   Determine the mean value $\overline{\Im}_\gamma(\overline{\tau})$ ($\gamma = 1, 2, \ldots, \chi$) of PULTS under each attribute as the reference point, just as Eq. (15).

$$\overline{\Im}_\gamma(\overline{\tau}) = \left\{ \left[\overline{h}_\gamma^\iota, \chi_\gamma^\iota\right]\left(\overline{\tau}_\gamma^\iota\right) = \left[\frac{1}{\varsigma}\sum_{\mu=1}^{\varsigma} h_{\mu\gamma}^\iota, \frac{1}{\varsigma}\sum_{\mu=1}^{\varsigma} \chi_{\mu\gamma}^\iota\right]\left(\frac{1}{\varsigma}\sum_{\mu=1}^{\varsigma} \tau_{\mu\gamma}^\iota\right) \right\}.$$
$$(15)$$

Step 6   The part more than the average is counted as a gain in the positive distance $\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma}$ ($\mu = 1, 2, \ldots, \varsigma; \gamma = 1, 2, \ldots, \chi$), and the part less than the average is regarded as a loss and included in the negative distance $\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma}$ ($\mu = 1, 2, \ldots, \varsigma; \gamma = 1, 2, \ldots, \chi$), just as Eq. (16) and (17). Importantly, three parameters ψ, q and p are brought in for expounding the phenomenon that decision-makers may be have different attitudes towards gain and loss.

$$\text{if } \sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \left(\left(\tilde{T}\tilde{F}\left(h_{\mu\gamma}^\iota\right) \cdot \tau_{\mu\gamma}^\iota - \tilde{T}\tilde{F}\left(\overline{h}_\gamma^\iota\right) \cdot \overline{\tau}_\gamma^\iota\right)\right.$$
$$\left. + \left(\tilde{T}\tilde{F}\left(\chi_{\mu\gamma}^\iota\right) \cdot \tau_{\mu\gamma}^\iota - \tilde{T}\tilde{F}\left(\chi_\gamma^\iota\right) \cdot \overline{\tau}_\gamma^\iota\right)\right) \geq 0$$
$$\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma} = \frac{\max\left\{0, \left(\hat{d}\left(\Im_{\mu\gamma}(\tau), \overline{\Im}_\gamma(\overline{\tau})\right)\right)^q\right\}}{\tilde{E}\tilde{V}\left(\overline{\Im}_\gamma(\overline{\tau})\right)},$$
$$(16)$$

$$\text{If } \sum_{\iota=1}^{\#\Im_{\mu\gamma}(\tau)} \left(\left(\tilde{T}\tilde{F}\left(\overline{h}_\gamma^\iota\right) \cdot \overline{\tau}_\gamma^\iota - \tilde{T}\tilde{F}\left(h_{\mu\gamma}^\iota\right) \cdot \tau_{\mu\gamma}^\iota\right)\right.$$
$$\left. + \left(\tilde{T}\tilde{F}\left(\chi_\gamma^\iota\right) \cdot \overline{\tau}_\gamma^\iota - \tilde{T}\tilde{F}\left(\chi_{\mu\gamma}^\iota\right) \cdot \tau_{\mu\gamma}^\iota\right)\right) \geq 0$$
$$\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma} = \frac{\max\left\{0, \psi \cdot \left(\hat{d}\left(\overline{\Im}_\gamma(\overline{\tau}), \Im_{\mu\gamma}(\tau)\right)\right)^p\right\}}{\tilde{E}\tilde{V}\left(\overline{\Im}_\gamma(\overline{\tau})\right)},$$
$$(17)$$

where all ψ, q and p are parameters.

Step 6   Gather all $\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma}$ into positive distance matrix $\tilde{P}\tilde{D}\tilde{A}\tilde{M}$ and all $\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma}$ into negative distance matrix $\tilde{N}\tilde{D}\tilde{A}\tilde{M}$.

$$\overset{\overleftrightarrow{\Upsilon}_1 \overleftrightarrow{\Upsilon}_2 \cdots \overleftrightarrow{\Upsilon}_\chi}{\tilde{P}\tilde{D}\tilde{A}\tilde{M}} = \left(\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma}\right)_{\varsigma\times\chi}$$
$$= \begin{matrix} \overset{\leftrightarrow}{\Lambda}_1 \\ \overset{\leftrightarrow}{\Lambda}_1 \\ \vdots \\ \overset{\leftrightarrow}{\Lambda}_\varsigma \end{matrix} \begin{pmatrix} \tilde{P}\tilde{D}\tilde{A}_{11} & \tilde{P}\tilde{D}\tilde{A}_{12} & \cdots & \tilde{P}\tilde{D}\tilde{A}_{1\chi} \\ \tilde{P}\tilde{D}\tilde{A}_{21} & \tilde{P}\tilde{D}\tilde{A}_{22} & \cdots & \tilde{P}\tilde{D}\tilde{A}_{2\chi} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{P}\tilde{D}\tilde{A}_{\varsigma 1} & \tilde{P}\tilde{D}\tilde{A}_{\varsigma 2} & \cdots & \tilde{P}\tilde{D}\tilde{A}_{\varsigma\chi} \end{pmatrix}, \qquad (18)$$

$$\overset{\overleftrightarrow{\Upsilon}_1 \overleftrightarrow{\Upsilon}_2 \cdots \overleftrightarrow{\Upsilon}_\chi}{\tilde{N}\tilde{D}\tilde{A}\tilde{M}} = \left(\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma}\right)_{\varsigma\times\chi}$$
$$= \begin{matrix} \overset{\leftrightarrow}{\Lambda}_1 \\ \overset{\leftrightarrow}{\Lambda}_1 \\ \vdots \\ \overset{\leftrightarrow}{\Lambda}_\varsigma \end{matrix} \begin{pmatrix} \tilde{N}\tilde{D}\tilde{A}_{11} & \tilde{N}\tilde{D}\tilde{A}_{12} & \cdots & \tilde{N}\tilde{D}\tilde{A}_{1\chi} \\ \tilde{N}\tilde{D}\tilde{A}_{21} & \tilde{N}\tilde{D}\tilde{A}_{22} & \cdots & \tilde{N}\tilde{D}\tilde{A}_{2\chi} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{N}\tilde{D}\tilde{A}_{\varsigma 1} & \tilde{N}\tilde{D}\tilde{A}_{\varsigma 2} & \cdots & \tilde{N}\tilde{D}\tilde{A}_{\varsigma\chi} \end{pmatrix}, \qquad (19)$$

Step 7   Figure out the weighted positive distance $\tilde{S}\tilde{P}_\mu$ ($\mu = 1, 2, \ldots, \varsigma$) and the weighted negative distance $\tilde{S}\tilde{N}_\mu$ ($\mu = 1, 2, \ldots, \varsigma$) by utilizing Eqs. (20) and (21).

$$\tilde{S}\tilde{P}_\mu = \sum_{\gamma=1}^{\chi} \tilde{A}\tilde{O}\tilde{A}_{\mu\gamma} \cdot \tilde{P}\tilde{D}\tilde{A}_{\mu\gamma} \, \mu = 1, 2, \ldots, \varsigma. \quad (20)$$

$$\tilde{S}\tilde{N}_\mu = \sum_{\gamma=1}^{\chi} \tilde{A}\tilde{O}\tilde{A}_{\mu\gamma} \cdot \tilde{N}\tilde{D}\tilde{A}_{\mu\gamma} \, \mu = 1, 2, \ldots, \varsigma. \quad (21)$$

Step 8   Integrate $\tilde{S}\tilde{P}_\mu$ and $\tilde{S}\tilde{N}_\mu$ in accordance with Eq. (22) to obtain the overall score $\tilde{A}\tilde{S}_\mu$ ($\mu = 1, 2, \ldots, \varsigma$) of alternative $\overset{\leftrightarrow}{\underset{\mu}{\Lambda}}$. Undisputedly, the alternative with the biggest overall score is affirmed as the best choice.

$$\tilde{A}\tilde{S}_\mu = \frac{1}{2}\left(\frac{\tilde{S}\tilde{P}_\mu}{\max_\mu\{\tilde{S}\tilde{P}_\mu\}} + \left(1 - \frac{\tilde{S}\tilde{N}_\mu}{\max_\mu\{\tilde{S}\tilde{N}_\mu\}}\right)\right).$$
$$\mu = 1, 2, \ldots, \varsigma$$
$$(22)$$

5 Numerical Example

Since the eighteenth century, the advance of industrial civilization has not only brought us great material wealth, but also caused increasingly serious problems such as climate change, resource depletion, environment pollution and so on. In order to prevent the environmental problem from further worsening and adapt to climate change, some government departments, international organizations and academic institutions have begun to advocate green civilization and at the same time vigorously promote the development of green industry and low carbon economy in both policy and public opinion to ensure the sustainable development of economy and society. As an important link of modern economic development, finance is an important means to change the allocation of resources and a key factor to promote economic development. The implementation of green concept into financial development has gradually become the focus of researchers and policy makers, hence the concept of green finance was put forward. Green finance refers to a series of financial services which can improve environment, respond climate change and ensure efficient utilization of resource, including project investment and financing, project operation, risk management and so on. For many enterprises adhering to the concept of green environmental protection, financing difficulties have been perplexing them. Therefore, how to construct an effective evaluation model to help banks select qualified green enterprises to provide green credit has become a very important issue in green finance. A bank needs to evaluate the credit risk and environmental protection of five enterprises. The bank invited five experts to give assessment information in four aspects: (1) $\overset{\leftrightarrow}{\Upsilon}_1$ is the operating conditions; (2) $\overset{\leftrightarrow}{\Upsilon}_2$ is the applicant's credit; (3) $\overset{\leftrightarrow}{\Upsilon}_3$ is the resource consumption; (4) $\overset{\leftrightarrow}{\Upsilon}_4$ is the asset scale. Moreover, five experts $\overset{\leftrightarrow}{\wp}_v (v = 1, 2, 3, 4, 5)$ have given the following evaluative information, just as Tables 1, 2, 3, 4

Table 1 The ULT matrix $\tilde{U}\tilde{L}^{(1)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_2$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_3$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_4$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_5$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$

Table 2 The ULT matrix $\tilde{U}\tilde{L}^{(2)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_2$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VG}{\leftrightarrow},\overset{EG}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_3$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_4$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_5$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$

Table 3 The ULT matrix $\tilde{U}\tilde{L}^{(3)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_2$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_3$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{EB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{VG}{\leftrightarrow},\overset{EG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_4$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_5$	$\left[\overset{B}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$

Table 4 The ULT matrix $\tilde{U}\tilde{L}^{(4)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_2$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{B}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_3$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{VB}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_4$	$\left[\overset{B}{\leftrightarrow},\overset{M}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$
$\overset{\leftrightarrow}{\Lambda}_5$	$\left[\overset{G}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$	$\left[\overset{B}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{G}{\leftrightarrow}\right]$	$\left[\overset{M}{\leftrightarrow},\overset{VG}{\leftrightarrow}\right]$

and 5, to five NSSPs $\overset{\leftrightarrow}{\Lambda}_\mu$ ($\mu = 1, 2, 3, 4, 5$).

$$\tilde{F} = \left\{ \begin{array}{l} \tilde{f}_{-3} = \text{extremely bad}(\overset{EB}{\leftrightarrow}), \tilde{f}_{-2} = \text{very bad}(\overset{VB}{\leftrightarrow}), \\ \tilde{f}_{-1} = \text{bad}(\overset{B}{\leftrightarrow}), v_0 = \text{medium}(\overset{M}{\leftrightarrow}), \tilde{f}_1 = \text{great}(\overset{G}{\leftrightarrow}) \\ \tilde{f}_2 = \text{very great}(\overset{VG}{\leftrightarrow}), \tilde{f}_3 = \text{extremely great}(\overset{EG}{\leftrightarrow}) \end{array} \right\},$$

The following clearly describes detail process of the application of PT-PULTS-EDAS about green credit risk assessment.

Table 5 The ULT matrix $\tilde{U}\tilde{L}^{(5)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_2$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_3$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} EB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_4$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_5$	$\begin{bmatrix} B & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$

Table 8 The standardized ULT matrix from $\tilde{U}\tilde{L}^{(3)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_2$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_3$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & EG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VG & EG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_4$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_5$	$\begin{bmatrix} B & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$

Table 6 The standardized ULT matrix from $\tilde{U}\tilde{L}^{(1)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_2$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_3$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_4$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_5$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$

Table 9 The standardized ULT matrix from $\tilde{U}\tilde{L}^{(4)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_2$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_3$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_4$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_5$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$

Table 7 The standardized ULT matrix from $\tilde{U}\tilde{L}^{(2)}$

	$\overset{\leftrightarrow}{\Upsilon}_1$	$\overset{\leftrightarrow}{\Upsilon}_2$	$\overset{\leftrightarrow}{\Upsilon}_3$	$\overset{\leftrightarrow}{\Upsilon}_4$
$\overset{\leftrightarrow}{\Lambda}_1$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_2$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VG & EG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_3$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_4$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$
$\overset{\leftrightarrow}{\Lambda}_5$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow & \leftrightarrow \end{bmatrix}$

Phase I: Preprocessing of basic information

Step 1   Judge whether one attribute is negative or not, and it is essential to transform the value of negative attribute $\left[\tilde{f}_a, \tilde{f}_b\right]$ into its corresponding form $\left[\tilde{f}_{-b}, \tilde{f}_{-a}\right]$. The results are shown in Tables 6, 7, 8, 9, and 10.

Step 2   According to the above information that has been processed for consistency, we are capable to establish the aggregated and adjusted PULTS matrix $\tilde{P}\tilde{U}\tilde{M} = \left(\Im_{\mu\gamma}(\tau)\right)_{\varsigma\times\chi} = \left(\left\{\left[\hbar_{\mu\gamma}^\iota, \varkappa_{\mu\gamma}^\iota\right]\left(\tau_{\mu\gamma}^\iota\right) \middle| \iota = 1, 2, \ldots, \#\Im_{\mu\gamma}(\tau)\right\}\right)_{5\times4}$ shown in Table 11.

Step 4   The CRITIC method is utilized (Eq. (10) – Eq. (13)) to extract the initial objective attribute weights $\overset{\leftrightarrow}{\text{Ioa}_\gamma}(\overset{\leftrightarrow}{\text{Ioa}_\gamma} \geq 0$ and $\sum_{\gamma=1}^{4} \overset{\leftrightarrow}{\text{Ioa}_\gamma} = 1)$ from known and aggregated PULTS matrix $\tilde{P}\tilde{U}\tilde{M}$.

$$\overset{\leftrightarrow}{\text{Ioa}_1} = 0.2076\ldots \overset{\leftrightarrow}{\text{Ioa}_2} = 0.2708\ldots \overset{\leftrightarrow}{\text{Ioa}_3} = 0.3196\ldots \overset{\leftrightarrow}{\text{Ioa}_4} = 0.2020$$

Adopt Eq. (14) to alter the initial objective attribute weights and further acquire the altered objective attribute weights $\tilde{A}\tilde{O}\tilde{A}_{\mu\gamma}$ ($\mu = 1, 2, 3, 4, 5; \gamma = 1, 2, 3, 4$) shown in Table 12. (Notes: the values of parameters $x = 0.61$ and $z = 0.69$ in Eq. (14) are derived from Lin et al. [41]'s the experimental proof).

Table 10 The standardized ULT matrix from $\tilde{U}\tilde{L}^{(5)}$

	$\overleftrightarrow{\Upsilon}_1$	$\overleftrightarrow{\Upsilon}_2$	$\overleftrightarrow{\Upsilon}_3$	$\overleftrightarrow{\Upsilon}_4$
$\overleftrightarrow{\Lambda}_1$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} VB & B \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$
$\overleftrightarrow{\Lambda}_2$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$
$\overleftrightarrow{\Lambda}_3$	$\begin{bmatrix} B & M \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & EG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$
$\overleftrightarrow{\Lambda}_4$	$\begin{bmatrix} VB & B \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} B & M \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$
$\overleftrightarrow{\Lambda}_5$	$\begin{bmatrix} B & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} M & G \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$	$\begin{bmatrix} G & VG \\ \leftrightarrow, & \leftrightarrow \end{bmatrix}$

Table 12 The altered objective attribute weights $\tilde{A}\tilde{O}\tilde{A}_{\mu\gamma}$

	$\overleftrightarrow{\Upsilon}_1$	$\overleftrightarrow{\Upsilon}_2$	$\overleftrightarrow{\Upsilon}_3$	$\overleftrightarrow{\Upsilon}_4$
$\overleftrightarrow{\Lambda}_1$	0.2655	0.3025	0.3288	0.2620
$\overleftrightarrow{\Lambda}_2$	0.2628	0.3079	0.3405	0.2585
$\overleftrightarrow{\Lambda}_3$	0.2628	0.3079	0.3405	0.2585
$\overleftrightarrow{\Lambda}_4$	0.2628	0.3025	0.3288	0.2620
$\overleftrightarrow{\Lambda}_5$	0.2628	0.3025	0.3288	0.2585

Phase II: Core operation of PT-PULTS-EDAS model

Step 5   Determine the mean value $\overline{\Im}_\gamma(\overline{\tau})$ ($\gamma = 1, 2, 3, 4$) of PULTS under each attribute as the reference point, just as Eq. (15).

$$\overline{\Im}_1(\overline{\tau}) = \left\{ [\tilde{f}_{-1}, \tilde{f}_0](0.16), [\tilde{f}_{-0.4}, \tilde{f}_{0.6}](0.4), [\tilde{f}_{0.6}, \tilde{f}_{1.6}](0.44) \right\}$$

$$\overline{\Im}_2(\overline{\tau}) = \left\{ [\tilde{f}_{-0.8}, \tilde{f}_{0.2}](0.22), [\tilde{f}_0, \tilde{f}_1](0.44), [\tilde{f}_1, \tilde{f}_2](0.34) \right\}$$

$$\overline{\Im}_3(\overline{\tau}) = \left\{ [\tilde{f}_{-1}, \tilde{f}_0](0.28), [\tilde{f}_{-0.2}, \tilde{f}_{0.8}](0.4), [\tilde{f}_{0.8}, \tilde{f}_{1.8}](0.32) \right\}$$

$$\overline{\Im}_4(\overline{\tau}) = \left\{ [\tilde{f}_{-0.6}, \tilde{f}_{0.4}](0.24), [\tilde{f}_0, \tilde{f}_1](0.36), [\tilde{f}_1, \tilde{f}_2](0.4) \right\}$$

Step 6   Just as Eqs. (16) and (17), anything greater than the average is counted as a gain in the positive distance $\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma}(\mu = 1, 2, 3, 4, 5; \gamma = 1, 2, 3, 4)$ gathered into matrix $\tilde{P}\tilde{D}\tilde{A}\tilde{M}$. At the same time, the part less than the average is regarded as a loss and included in the negative distance $\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma}(\mu = 1, 2, 3, 4, 5; \gamma = 1, 2, 3, 4)$ gathered into matrix $\tilde{N}\tilde{D}\tilde{A}\tilde{M}$. (Notes: the values of parameters $p = 0.88$, $q = 0.88$ and $\psi = 2.25$ in

Eq. (17) are derived from Lin et al. [41]'s the experimental proof.)

$$\tilde{P}\tilde{D}\tilde{A}\tilde{M} = \left(\tilde{P}\tilde{D}\tilde{A}_{\mu\gamma}\right)_{5\times4} = \begin{array}{cccc} \overleftrightarrow{\Upsilon}_1 & \overleftrightarrow{\Upsilon}_2 & \overleftrightarrow{\Upsilon}_3 & \overleftrightarrow{\Upsilon}_4 \end{array}$$

$$\begin{array}{c} \overleftrightarrow{\Lambda}_1 \\ \overleftrightarrow{\Lambda}_1 \\ \overleftrightarrow{\Lambda}_3 \\ \overleftrightarrow{\Lambda}_4 \\ \overleftrightarrow{\Lambda}_5 \end{array} \left\{ \begin{array}{cccc} 0 & 0 & 0 & 0 \\ 0.1790 & 0.2662 & 0.2672 & 0.1936 \\ 0.0447 & 0.4649 & 0.2210 & 0.2776 \\ 0 & 0 & 0 & 0 \\ 0.1045 & 0 & 0 & 0.3355 \end{array} \right\}$$

$$\tilde{N}\tilde{D}\tilde{A}\tilde{M} = \left(\tilde{N}\tilde{D}\tilde{A}_{\mu\gamma}\right)_{5\times4} = \begin{array}{cccc} \overleftrightarrow{\Upsilon}_1 & \overleftrightarrow{\Upsilon}_2 & \overleftrightarrow{\Upsilon}_3 & \overleftrightarrow{\Upsilon}_4 \end{array}$$

$$\begin{array}{c} \overleftrightarrow{\Lambda}_1 \\ \overleftrightarrow{\Lambda}_1 \\ \overleftrightarrow{\Lambda}_3 \\ \overleftrightarrow{\Lambda}_4 \\ \overleftrightarrow{\Lambda}_5 \end{array} \left\{ \begin{array}{cccc} 0.2906 & 0.5740 & 0.3657 & 0.5526 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.4515 & 0.3608 & 0.5230 & 0.2963 \\ 0 & 0.3608 & 0.2454 & 0 \end{array} \right\}$$

Step 7   Figure out the weighted positive distance $\tilde{S}\tilde{P}_\mu$ ($\mu = 1, 2, 3, 4, 5$) and the weighted negative

Table 11 The aggregated and adjusted PULTS matrix $\tilde{P}\tilde{U}\tilde{M}$

	$\overleftrightarrow{\Upsilon}_1$	$\overleftrightarrow{\Upsilon}_2$	$\overleftrightarrow{\Upsilon}_3$	$\overleftrightarrow{\Upsilon}_4$
$\overleftrightarrow{\Lambda}_1$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0), [\tilde{f}_{-1}, \tilde{f}_0](0.4) \\ , [\tilde{f}_0, \tilde{f}_1](0.6) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-2}, \tilde{f}_{-1}](0.6), [\tilde{f}_{-1}, \tilde{f}_0](0.2) \\ , [\tilde{f}_0, \tilde{f}_1](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-2}, \tilde{f}_{-1}](0.4), [\tilde{f}_{-1}, \tilde{f}_0](0.5) \\ , [\tilde{f}_0, \tilde{f}_1](0.1) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.4), [\tilde{f}_0, \tilde{f}_1](0.5) \\ , [\tilde{f}_1, \tilde{f}_2](0.1) \end{array} \right\}$
$\overleftrightarrow{\Lambda}_2$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0), [\tilde{f}_0, \tilde{f}_1](0.5) \\ , [\tilde{f}_1, \tilde{f}_2](0.5) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0.1), [\tilde{f}_1, \tilde{f}_2](0.7) \\ , [\tilde{f}_2, \tilde{f}_3](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0), [\tilde{f}_0, \tilde{f}_1](0.4) \\ , [\tilde{f}_1, \tilde{f}_2](0.6) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0), [\tilde{f}_0, \tilde{f}_1](0.5) \\ , [\tilde{f}_1, \tilde{f}_2](0.5) \end{array} \right\}$
$\overleftrightarrow{\Lambda}_3$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.2), [\tilde{f}_0, \tilde{f}_1](0.4) \\ , [\tilde{f}_1, \tilde{f}_2](0.4) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0), [\tilde{f}_0, \tilde{f}_1](0.1) \\ , [\tilde{f}_1, \tilde{f}_2](0.9) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0.2), [\tilde{f}_1, \tilde{f}_2](0.6) \\ , [\tilde{f}_2, \tilde{f}_3](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0.6), [\tilde{f}_1, \tilde{f}_2](0.2) \\ , [\tilde{f}_2, \tilde{f}_3](0.2) \end{array} \right\}$
$\overleftrightarrow{\Lambda}_4$	$\left\{ \begin{array}{l} [\tilde{f}_{-2}, \tilde{f}_{-1}](0.4), [\tilde{f}_{-1}, \tilde{f}_0](0.4) \\ , [\tilde{f}_0, \tilde{f}_1](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.2), [\tilde{f}_0, \tilde{f}_1](0.6) \\ , [\tilde{f}_1, \tilde{f}_2](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.6), [\tilde{f}_0, \tilde{f}_1](0.1) \\ , [\tilde{f}_1, \tilde{f}_2](0.3) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-2}, \tilde{f}_{-1}](0.2), [\tilde{f}_{-1}, \tilde{f}_0](0.4) \\ , [\tilde{f}_0, \tilde{f}_1](0.4) \end{array} \right\}$
$\overleftrightarrow{\Lambda}_5$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.2), [\tilde{f}_0, \tilde{f}_1](0.3) \\ , [\tilde{f}_1, \tilde{f}_2](0.5) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-1}, \tilde{f}_0](0.2), [\tilde{f}_0, \tilde{f}_1](0.6) \\ , [\tilde{f}_1, \tilde{f}_2](0.2) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_{-2}, \tilde{f}_{-1}](0.2), [\tilde{f}_{-1}, \tilde{f}_0](0.4) \\ , [\tilde{f}_0, \tilde{f}_1](0.4) \end{array} \right\}$	$\left\{ \begin{array}{l} [\tilde{f}_0, \tilde{f}_1](0), [\tilde{f}_0, \tilde{f}_1](0.2) \\ , [\tilde{f}_1, \tilde{f}_2](0.8) \end{array} \right\}$

Table 13 The weighted distance

	$\overleftrightarrow{\Lambda}_1$	$\overleftrightarrow{\Lambda}_2$	$\overleftrightarrow{\Lambda}_3$	$\overleftrightarrow{\Lambda}_4$	$\overleftrightarrow{\Lambda}_5$
$\tilde{S}\tilde{P}$	0	0.2700	0.3019	0	0.1142
$\tilde{S}\tilde{N}$	0.5158	0	0	0.4774	0.1898

distance $\tilde{S}\tilde{N}_\mu$ ($\mu = 1, 2, 3, 4, 5$) by utilizing Eqs. (20) and (21). And the corresponding outcomes are listed in Table 13

Step 8 Integrate $\tilde{S}\tilde{P}_\mu$ and $\tilde{S}\tilde{N}_\mu$ in accordance with Eq. (22) to obtain the overall score $\tilde{A}\tilde{S}_\mu$ ($\mu = 1, 2, 3, 4, 5$) of alternative $\overleftrightarrow{\Lambda}_\mu$.

$$\tilde{A}\tilde{S}_1 = 0...\tilde{A}\tilde{S}_2 = 0.9472...\tilde{A}\tilde{S}_3 = 1...\tilde{A}\tilde{S}_4$$
$$= 0.0372...\tilde{A}\tilde{S}_5 = 0.5052$$

$$\overleftrightarrow{\Lambda}_3 > \overleftrightarrow{\Lambda}_1 > \overleftrightarrow{\Lambda}_5 > \overleftrightarrow{\Lambda}_4 > \overleftrightarrow{\Lambda}_1$$

Undisputedly, the alternative $\overleftrightarrow{\Lambda}_3$ with the biggest overall score is affirmed as the best choice.

6 Comparative Analysis

This paper chooses two methods, traditional PULTS-EDAS [46] and PULTS-MABAC [49], to compare with the new method proposed in this paper. From the calculation results, as shown in Table 14, the three methods are consistent in the selection of the optimal alternative, which means that the PT-PULTS-EDAS method is reliable to some extent. However, compared with other methods, PT-PUTLS-EDAS presents certain advantages in terms of concept and calculation. On the one hand, the PT-PULTS-EDAS method is different from the traditional EDAS method, and it is an ideological improvement of the traditional method. The improved EDAS method, namely PT-PUTLS-EDAS, fully integrates the psychological state of decision-makers into the mathematical logic of the method, which is more suitable for the MAGDM problem in reality. Selecting the best option among a limited number of options based on the evaluation of multiple attributes relies on the cognition of decision-makers. The decision-maker obeys the biological attribute of human beings, and will inevitably produce emotional factors to affect the decision result. Therefore, one of the key issues in the MAGDM is how to truly depict the decision problem while reducing the executive judgment of some objective situations. Obviously, the newly proposed PT-PULTS-EDAS has solved these contradictions well. The PT-PULTS-EDAS method modifies the attribute weight and avoids the distortion of subjective judgment to the actual probability. Moreover, different parameters are introduced in this method to further deal with the part above and below the standard point respectively so that different types of decision-makers' attitudes towards gains and losses are taken into account. On the other hand, compared with other methods, the EDAS method simplifies the data processing steps as much as possible while ensuring the feasibility and rationality of the method, so it has the advantages of being simple and easy to understand.

7 Conclusions

MADM or MAGDM based on the evaluation of multiple attribute indicators to select the best alternative from limited alternatives is a very common research in the field of management decision-making, and it is also a decision problem often encountered in reality. In recent years, with the increasingly severe environmental problems, the voice of integrating the environmental protection concept of green development into the traditional financial industry is getting louder and louder. Green credit is a typical

Table 14 Comparison of different methods

	PULTS–MABAC	PULTS–EDAS	PT–PULTS–EDAS
$\overleftrightarrow{\Lambda}_1$	0.0962	0	0
$\overleftrightarrow{\Lambda}_2$	0.1869	0.9736	0.9472
$\overleftrightarrow{\Lambda}_3$	0.1906	1	1
$\overleftrightarrow{\Lambda}_4$	0.1213	0.2197	0.0372
$\overleftrightarrow{\Lambda}_5$	0.1466	0.4927	0.5052
The order	$\overleftrightarrow{\Lambda}_3 > \overleftrightarrow{\Lambda}_2 > \overleftrightarrow{\Lambda}_5 > \overleftrightarrow{\Lambda}_4 > \overleftrightarrow{\Lambda}_1$	$\overleftrightarrow{\Lambda}_3 > \overleftrightarrow{\Lambda}_2 > \overleftrightarrow{\Lambda}_5 > \overleftrightarrow{\Lambda}_4 > \overleftrightarrow{\Lambda}_1$	$\overleftrightarrow{\Lambda}_3 > \overleftrightarrow{\Lambda}_2 > \overleftrightarrow{\Lambda}_5 > \overleftrightarrow{\Lambda}_4 > \overleftrightarrow{\Lambda}_1$

MAGDM problem in green finance. Through a review of the literature, we found that many existing MAGDM models do not fully consider the impact of decision-makers' psychology on decision-making. However, MAGDM is an approach that relies on decision-makers' evaluation of the various options. The decision-maker obeys the biological attribute of human beings, and will inevitably produce emotional factors to affect the decision result. Therefore, this paper proposes a new EDAS model based on prospect theory and using probabilistic uncertain linguistic term set (PT-PULTS-EDAS model). The combination of PT and traditional EDAS makes the new model not only easy to calculate and understand, but also has the ability to integrate the decision-maker's psychological uncertainty into the data processing process, so that the calculation results are more in line with the practical problems. Moreover, the PT-PULTS-EDAS model uses CRITIC method to extract the initial objective attribute weights from the known information, and takes advantage of the weighting function to adjust the initial weights, so as to avoid the distortion of information caused by the decision-maker's subjective understanding as much as possible. More importantly, we successfully apply the method proposed in this paper to the field of green finance, and solve the MAGDM problem of the bank providing green credit to the appropriate enterprises. Finally, the comparison between the proposed method and the existing methods, PULTS-EDAS and PULTS-MABAC, also fully confirms the effectiveness and feasibility of the PT-PULTS-EDAS model in dealing with MAGDM in uncertain environment. In the near future, we will continue to explore the application of this method in more fields. At the same time, we will also focus on the related theories and methods around MADM or MAGDM.

Declarations

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