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Published online: 04 Feb 2021.

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Dynamic reference point method with probabilistic linguistic information based on the regret theory for public health emergency decision-making

Wenting Xue[a], Zeshui Xu[a,b], Xiaomei Mi[b] and Zhiliang Ren[c]

[a]School of Economics and Management, Southeast University, Nanjing, Jiangsu, China; [b]Business School, Sichuan University, Chengdu, Sichuan, China; [c]School of Management Science and Engineering, Shandong Technology and Business University, Yantai, Shandong, China

ABSTRACT

Group emergency decision-making is an uncertain and dynamic process, in which the decision makers may be bounded rational and have a risk appetite. To depict the vague qualitative assessments, the probabilistic linguistic term sets are employed to express the perceptions of decision makers. First, considering the regret-aversion of the decision makers' psychological characteristic, the value function and the regret-rejoice function in the regret theory are modified to adapt the probabilistic linguistic information. Second, the definition and aggregation operators of the probabilistic linguistic time variable are proposed to describe and aggregate the dynamic decision information. Third, the probabilistic linguistic models based on the dynamic reference point method and the regret theory are studied to maximise the expectation-levels of alternatives at the relative time point. The proposed method is applied to select the optimal response strategy for the outbreak of COVID-19 in China. Finally, the comparative analysis is designed to verify the applicability and reasonability of the proposed method.

1. Introduction

In recent years, various emergencies have caused huge economic losses and casualties to human society, such as September 11 terrorist attacks in 2001, severe acute respiratory syndrome (SARS) in 2003, Wenchuan earthquake in 2008, Japan's nuclear leakage event caused by earthquake in 2011. As of May 18, 2020, there have been more than 4.5 million confirmed cases of COVID-19 and 300,000 deaths worldwide (World Health Organization, 2020). When the emergency occurs, decision makers should make some effective emergency measures to reduce casualties and economic loss as much as possible. In the decision-making process, it is of great significance to adjust

strategies as emergency situations evolve (Jiang et al., 2011). In the early stage of emergency, since the collected assessment information is usually incomplete and inaccurate, the decision makers need to estimate the seriousness of emergency by combining the objective information with their own subjective experience and implement response measures immediately (Ge et al., 2010; Mendonca et al., 2001). At the beginning of the emergency, it is essential to collect the relevant information and adopt response measures within a very short time to ensure the safety of life and minimise the economic loss. Due to the uncertainty in the development and evolution process, the emergency probably presents a variety of complex situations. Therefore, the strategy selection of uncertain emergency is a risky decision-making problem (Peng & Li, 2019). When the emergency plan is executed, the development trend of the emergency gradually becomes clear and the situation of emergency may change over time. The initial measures may be inappropriate to response the emergency of next stage and therefore policymakers need to constantly adjust previous strategy according to the updated decision information (Altay & Green, 2006).

In conclusion, in the emergency decision-making (EDM), the decision makers may encounter the following issues: (1) Express the uncertain and incomplete assessment information in a limited time; (2) Consider decision maker's psychological behaviour characterised by bounded rationality; (3) Establish a dynamic decision-making model to respond to the changing circumstances of an emergency.

Considering that human thought and characteristic of evaluation index are fuzzy (Wang et al., 2018), the real numbers are difficult to describe the uncertain quantitative assessments. For example, the risk levels of COVID-19 for some provinces in China are usually expressed by 'High-risk', 'General-risk', 'Low-risk', etc. In some cases, since decision makers are more likely to evaluate some criteria by qualitative estimation rather than quantitative data, the linguistic term is in alignment with the human expressive habits (He et al., 2016; Wang et al., 2018; Zadeh, 1975). However, the single linguistic term has limitations in expressing the increasing uncertainties due to the complexity of uncontrolled factors, such as the limited time and knowledge in the professional field (He et al., 2019). To tackle these problems, the probabilistic linguistic term sets (PLTSs) (Pang et al., 2016) were introduced to depict the uncertain linguistic information. The PLTSs not only can express several linguistic terms, but also reflect the probability of each linguistic term, such as '30% sure very low-risk and 70% sure low-risk'.

Owning to the effectiveness and flexibility of describing uncertain linguistic information, the PLTSs have aroused increasing attention (Liao et al., 2020; Liu et al., 2019; Zhang et al., 2017) and many ranking methods based on the probabilistic linguistic information were proposed to solve the decision-making problems (Lei et al., 2020; Wei et al., 2019, 2020). In the process of the EDM, due to the complexity, strong destructiveness and uncertainty of the incident, the incomplete decision-making information increases the difficulty for decision makers to formulate strategy. It is impossible for all the decision makers to have comprehensive understanding of the changing emergency circumstances due to the limitations of personal cognition and the urgency of time. When decision makers are under enormous social stress, they are characterised by bounded rationality, loss sensitivity and susceptible to the

emergency (Ding et al., 2019). Therefore, decision makers usually do not satisfy the conditions of totally rationality in the dynamic EDM.

Recently, regret theory (Bell, 1982; Loomes & Sugden, 1982) has attracted a lot attention of scholars and applied to many domains (Chorus, 2012; Gong et al., 2019; Wang et al., 2020). Regret theory considers the comparison between the selected strategy and other unselected strategies. If the decision makers find that the benefit of selected strategy is greater than others, they rejoice, otherwise they regret. The key to regret theory is to avoid selecting the strategy that makes the decision makers regret, that is, the decision makers are regret-aversion.

Given that the dynamic feature of emergency events, some dynamic reference point methods (Gao et al., 2017; Wang et al., 2015) are proposed to adjust the response measures of emergency. Based on the TOPSIS method and the proposed probability density function, a prospect theory-based dynamic reference point method is presented under the interval values circumstance (Wang et al., 2015). A dynamic decision-making method is developed to handle the hesitant probabilistic fuzzy information by the dynamic reference point method (Gao et al., 2017). Inspired by Gao et al. (2017), we propose a dynamic reference point method with probabilistic linguistic information combining the modified regret theory.

There are three challenges when we extend the dynamic reference point method to the probabilistic linguistic environment considering the regret-aversion feature of decision makers. (1) The classical utility function of regret theory cannot be applied directly to the probabilistic linguistic environment, because the results may exceed the scale of linguistic term set and change the essential feature of regret theory. We propose the modified utility function and regret-rejoice function to bridge the gap combining with original characteristic of regret theory. (2) A concept should be proposed to express the decision matrix represented by PLTSs with time variable. In the paper, we define the probabilistic linguistic time variable (PLTV) to describe the dynamic probabilistic linguistic decision matrix. The operations of PLTVs with the weight vector of time variable are presented according to the weighted averaging and geometric operators. (3) The dynamic model should be established to maximise the expectation-levels of alternatives at the corresponding time point. First, we define the deviation degree of PLTSs and the probabilistic linguistic positive and negative ideal solutions. Then the expectation-levels of alternatives are proposed with unknown weight vector inspired by the TOPSIS method. Combining with the modified perceived utility function of regret theory, the dynamic nonlinear programming models at any time point are constructed. Finally, according to the calculated weights of decision makers by solving the models and the aggregating operator, the optimal alternatives of each stage can be obtained for the dynamic emergency. The main contributions of the paper are summarised as follows:

1. The paper proposes the modified perceived utility function of regret theory which includes the revised utility and regret-rejoice functions under the probabilistic linguistic circumstance. The modified regret theory inherits the essential characteristic of classic regret theory and reflects the decision make's risk appetite effectively.

2. The definition and aggregation methods of PLTVs are developed to describe the dynamic probabilistic linguistic decision matrix with the time variable.
3. Combining with the modified regret theory, the probabilistic linguistic dynamic reference point (PLDRP) method is proposed to handle the optimal alternative selection of dynamic EDM problems at different time points. The nonlinear programming model whose objective function maximises the expectation-levels of alternatives is built to obtain decision makes' unknown weight values.
4. The PLDRP method is applied to the dynamic optimal alternative selection of the outbreak of COVID-19 in China. The comparative analysis with other probabilistic linguistic decision-making methods illustrates the applicability and effectiveness of the proposed method.

The remainder of the paper is organised as follows: In Section 2, the literature review about the current EDM and probabilistic linguistic decision-making methods is presented. Section 3 introduces some related definitions about PLTSs and regret theory. In Section 4, based on the modified regret theory for PLTSs and the proposed PLTV, the PLDRP method is presented to find the optimal alternatives at different time points. In Section 5, the procedure of the PLDRP method is introduced. In Section 6, the PLDRP method is applied to a numerical example about the selection of dynamic optimal alternatives and its superiority is illustrated by the comparative analysis. Conclusions and future directions are drawn in Section 7.

2. Literature review

In the EDM, how to select the appropriate response strategy in the limited time is a crucial issue when the decision makers encounter uncertain decision-making information. The multiple criteria decision making (MCDM) methods have been applied widely to respond and resolve the emergency events (Ding & Liu, 2019a). A dynamic case-based reasoning group decision making approach is proposed for a gas explosion by choosing the most suitable case from a set of similar cases after case retrieval (Zheng et al., 2020). To describe decision makers' psychological characteristics, a dynamic EDM method based on the prospect theory and interval-valued Pythagorean fuzzy linguistic variables is developed to determine the optimal solution dynamically under different emergency status (Ding et al., 2019). According to the constructed prospect decision matrix, an extended VIKOR approach is proposed to handle the EDM problems with 2-dimension uncertain linguistic information (Ding & Liu, 2019b). To avoid information loss and keep the form of PLTS, the probabilistic linguistic weighted averaging operator combining Dempster-Shafer evidence theory is applied to a serious mine accident (Li & Wei, 2019). An EDM model under the Z-uncertain probabilistic linguistic circumstance is developed using the information credibility and the maximising deviation method (Chai et al., 2021). To select the best alternative in the multi-stage group decision-making problems, type alpha and type gamma consensus are constructed combining the mining consensus sequences (Tang et al., 2020). Based on the decision makers' preference transfer and cumulative prospect theory, a large group risk dynamic EDM method is presented to select the optimal scheme in the emergency incident (Xu et al., 2018). Zhou et al. (2018) provided an overview of

the EDM for natural disasters and illustrated the construction of emergency decision support system in detail.

The aim of multiple criteria group decision making (MCGDM) is to support decision makers when they choose the best solution among alternatives considering multiple criteria (Tian et al., 2017, 2018), which can be applied to the strategy selection problems in the EDM. As for the decision matrix represented by the probabilistic linguistic information, many decision-making methods have been developed to copy with the MCDM problems (Wei et al., 2020). The aggregation operators (Liu & Teng, 2018; Pang et al., 2016) calculate each alternative's overall utility value based on the specific operation laws of PLTSs, then rank the alternatives. The probabilistic linguistic MULTIMOORA method derives three subordinate utility values and adopts the improved Borda rule to obtain the ranking results (Wu et al., 2018). The main purpose of the reference point-based methods is to select a reference point which is closest to the positive ideal solution. The TOPSIS method (Pang et al., 2016) and the VIKOR method (Zhang & Xing, 2017) are two classical reference point-based methods which are widely applied to solve the decision-making problems. Pan et al. (2018) extended the ELECTRE II method to probabilistic linguistic environment to deal with the therapeutic schedule evaluation problem. Based on the proposed differential evolution algorithm, the probabilistic linguistic PROMETHEE method is developed to evaluate the meteorological disaster risk (Yu et al., 2019). Feng et al. (2019) defined some concordance and discordance indexes according to the proposed possibility degrees of PLTSs and then presented a probabilistic linguistic QUALIFLEX method. Most MCGDM methods are based on the expected utility theory which assumes that decision makers are totally rational. Considering the psychological factors of decision makers, the probabilistic linguistic TODIM method is proposed and applied to the evaluation of water security (Zhang et al., 2019).

Although various of MCGDM theories and methods have been introduced to handle the strategy selection in the uncertain EDM. However, the existing literature rarely considers the regret theory which combines decision makers' regret-aversion characteristic under the probabilistic linguistic circumstance. Besides, the research of dynamic reference point method with probabilistic linguistic information to deal with the emergencies has not found from the existing literature. To bridge these research gaps, we propose a PLDRP method considering the regret theory and the dynamic evolutionary process of public health EDM. With the proposed dynamic EDM method, the local government can accurately and quickly select the optimal response strategy for the outbreak of COVID-19.

3. Preliminaries

In this section, we recall some basic concepts and the comparison rules about PLTSs and regret theory.

3.1. PLTSs

To express the cognitive uncertain information, Pang et al. (2016) proposed the PLTSs by assigning corresponding probability to each linguistic term.

Definition 1 (Pang et al., 2016). Let $x_i \in X$ be fixed and $S = \{s_{-\tau}, \ldots, s_{-1}, s_0, s_1, \ldots, s_\tau\}$ be a linguistic term set, a PLTS on S is $H_S(p) = \{< x_i, h_S^i(p) > | x_i \in X\}$ with

$$h_S^i(p) = \left\{ s^{i(l)}(p^{(l)}) | s^{i(l)} \in S, p^{(l)} \geq 0, l = 1, 2, \ldots, L, \sum_{l=1}^{L} p^{(l)} \leq 1 \right\} \quad (1)$$

where $s^{i(l)}(p^{(l)})$ is the l th linguistic term $s^{i(l)}$ with the probability $p^{(l)}$. The linguistic terms $s^{i(l)}$ are arranged in ascending order. $h_S^i(p)$ is the probabilistic linguistic element and L is the number of different $s^{i(l)}$ in $h_S^i(p)$.

When the judgement information is missing or incomplete, that is $\sum_{l=1}^{L} p^{(l)} < 1$, some methods (Pang et al., 2016; Wu et al., 2018) are proposed to distribute the missing probability. The missing probability could be distributed to the linguistic terms which appear in $s^{i(l)}$. Let $\dot{p}^{(l)} = p^{(l)} / \sum_{l=1}^{L} p^{(l)}$, $l = 1, 2, \ldots, L$, then $\sum_{l=1}^{L} \dot{p}^{i(l)} = 1$ (Pang et al., 2016). The distribution proportion of unknown probability to each linguistic term in $s^{i(l)}$ is equal in this paper.

Furthermore, since the number of PLTSs may be different, it is difficult to directly operate the PLTSs. To make the PLTSs with different numbers of linguistic terms computable and comparable, an extension method (Pang et al., 2016) is developed as follows: for any two PLTSs $h_S^1(p)$ and $h_S^2(p)$, if $L_1 > L_2$, then add $L_1 - L_2$ linguistic terms to $h_S^2(p)$, where the corresponding probabilities of added linguistic terms are equal to zero. The extension method is proposed without changing any previous information of the PLTSs. Then we get the normalised PLTS (NPLTS): $\dot{h}_S^i(p) = \left\{ \dot{s}^{i(l)}(\dot{p}^{(l)}) | l = 1, 2, \ldots, L \right\}$.

The comparison rules and the deviation degree of PLTSs are introduced as follows:

Definition 2 (Pang et al., 2016). Let $h_S(p) = \{s^{(l)}(p^{(l)}) | l = 1, 2, \ldots, L\}$ be a PLTS, and $r^{(l)}$ be the subscript of linguistic $s^{(l)}$. The score function of $h_S(p)$ is:

$$E(h_S(p)) = s_{\bar{r}} \quad (2)$$

where $\bar{r} = \sum_{l=1}^{L} r^{(l)} p^{(l)} / \sum_{l=1}^{L} p^{(l)}$.

The deviation function of $h_S(p)$ is defined as:

$$\sigma(h_S(p)) = \sqrt{\sum_{l=1}^{L} \left(p^{(l)}(r^{(l)} - \bar{r}) \right)^2 / \sum_{l=1}^{L} p^{(l)}} \quad (3)$$

The comparison method of any two PLTSs $h_S^1(p)$ and $h_S^2(p)$ is given as follows:

1. if $E(\dot{h}_S^1(p)) > E(\dot{h}_S^2(p))$, then $h_S^1(p) \succ h_S^2(p)$;
2. if $E(\dot{h}_S^1(p)) < E(\dot{h}_S^2(p))$, then $h_S^1(p) \prec h_S^2(p)$;
3. if $E(\dot{h}_S^1(p)) = E(\dot{h}_S^2(p))$, then we need to make further comparison:

   a. if $\sigma(\dot{h}_S^1(p)) > \sigma(\dot{h}_S^2(p))$, then $h_S^1(p) \prec h_S^2(p)$;

b.   if $\sigma(\dot{h}_S^1(p)) < \sigma(\dot{h}_S^2(p))$, then $h_S^1(p) \succ h_S^2(p)$;

c.   if $\sigma(\dot{h}_S^1(p)) = \sigma(\dot{h}_S^2(p))$, then $h_S^1(p) \sim h_S^2(p)$

where $\dot{h}_S^1(p)$ and $\dot{h}_S^2(p)$ are NPLTSs of $h_S^1(p)$ and $h_S^2(p)$, respectively.

Definition 3 (Pang et al., 2016). Let $h_S^1(p) = \left\{ s^{1(l)}(p_1^{(l)}) | l = 1, 2, \ldots, L_1 \right\}, h_S^2(p) = \left\{ s^{2(l)}(p_2^{(l)}) | l = 1, 2, \ldots, L_2 \right\}$ be two PLTSs with $L_1 = L_2$. Then the deviation degree between $h_S^1(p)$ and $h_S^2(p)$ can be defined as:

$$d\left(h_S^1(p), h_S^2(p)\right) = \sqrt{\sum_{l=1}^{L_1} \left(p_1^{(l)} r_1^{(l)} - p_2^{(l)} r_2^{(l)} \right)^2 / L_1} \tag{4}$$

where $r_1^{(l)}$ and $r_2^{(l)}$ are the subscripts of linguistic term $s^{1(l)}$ and $s^{2(l)}$, respectively.

3.2. Regret theory

Regret theory is an important behavioural decision theory proposed by Bell (1982) and Loomes and Sugden (1982) which depicts the regret-aversion characteristic of decision makers. In the regret theory, the policymakers not only concern the obtained results, but also focus on the results if they select other solutions in the decision-making process. The perceived utility of the regret theory consists of two parts: the current results of the utility function and regret-rejoice function compared with other results.

Definition 4 (Zhang et al., 2016). Let x be the attribute value, then the utility function $v(x)$ can be defined as follows:

$$v(x) = x^\alpha, 0 < \alpha < 1 \tag{5}$$

where the first derivative satisfies $v'(x) > 0$ and the second derivative satisfies $v''(x) < 0$, and α is the risk aversion coefficient of the decision maker.

Definition 5 (Zhang et al., 2016). The regret-rejoice function $R(\Delta v)$ can be defined as follows:

$$R(\Delta v) = 1 - e^{-\delta \Delta v}, \delta > 0 \tag{6}$$

where Δv denotes the utility difference of two alternatives, and $R(\Delta v)$ represents the regret-rejoice function of Δv. Similar to $v(x)$, the first and second derivatives of $R(\Delta v)$ satisfy $R'(\Delta v) > 0$ and $R''(\Delta v) < 0$, and δ is the regret aversion coefficient of the decision maker. If $R(\Delta v) > 0$, $R(\Delta v)$ is the rejoice value; otherwise, $R(\Delta v)$ is the regret value.

Definition 6 (Zhang et al., 2016). Let x and y denote the evaluation values of the alternatives A and B, respectively. The perceived utility value of A is obtained by the utility function and regret-rejoice function as follows:

$$U(A) = v(x) + R(\Delta v) = x^\alpha + 1 - e^{-\delta \Delta v}, \Delta v = v(x) - v(y) \tag{7}$$

4. The PLDRP method

In this section, the modified regret theory under the probabilistic linguistic circumstance and the PLTV are proposed, which build a basic framework for the PLDRP method.

4.1. The modified regret theory for PLTSs

The classical utility function of regret theory cannot be applied directly to the EDM with probabilistic linguistic information, because the results may exceed the scale of linguistic term set and change the essential feature of the utility function and regret-rejoice function.

The NPLTSs $\dot{h}_S(p) = \left\{ \dot{s}^{(l)}(\dot{p}^{(l)}) | l = 1, 2, \ldots, L \right\}$ are composed of two parts: the linguistic term $\dot{s}^{(l)}$ and its probability $\dot{p}^{(l)}$. In the modified regret theory for PLTSs, we only revise the value and regret-rejoice functions for the linguistic term $\dot{s}^{(l)}$. The probability $\dot{p}^{(l)}$ associated with $\dot{s}^{(l)}$ remains unchanged.

Definition 7. Let $\dot{h}_S(p) = \left\{ \dot{s}^{(l)}(\dot{p}^{(l)}) | l = 1, 2, \ldots, L \right\}$ denote the evaluation value of the alternative A expressed by the NPLTS. The modified value function of A under the probabilistic linguistic circumstance is as follows:

$$\bar{v}(r^{(l)}) = \tau \cdot \left[\left(\frac{r^{(l)}}{\tau} + 1 \right)^{\alpha} - 1 \right], \tag{8}$$

$$\bar{v}(h_S(p)) = \left\{ s_{\bar{v}(r^{(l)})}(\dot{p}^{(l)}) | l = 1, 2, \ldots, L \right\}, \tag{9}$$

where $r^{(l)}$ is the subscript of the linguistic term $\dot{s}^{(l)}$. The modified value function $\bar{v}(r^{(l)})$ with respect to different α is shown in Figure 1.

Since the range of $r^{(l)}$ is $[-\tau, \tau]$, the domain of utility function $\bar{v}(r^{(l)})$ for PLTSs should be $[-\tau, \tau]$ which satisfies the range of $\bar{v}(r^{(l)})$ within the virtual linguistic term sets. First, we translate $v(x) = x^{\alpha}$ in Equation (5) into $\bar{v}(r^{(l)}) = (r^{(l)} + 1)^{\alpha} - 1$ to hold $\bar{v}(0) = 0$. Then, we zoom $\bar{v}(r^{(l)})$ to $\bar{v}(r^{(l)}) = \left(\frac{r^{(l)}}{\tau} + 1 \right)^{\alpha} - 1$. Considering that individuals are much more sensitive to loss than gain, we multiply $\bar{v}(r^{(l)})$ by k_1 to hold $\bar{v}(-\tau) = -\tau$, then obtain $k_1 = \tau$. Hence, the value function of regret theory is transferred to Equation (8). When $r^{(l)} = -\tau$, the value function is $\bar{v}(-\tau) = -\tau$; When $r^{(l)} = 0$, the value function is $\bar{v}(0) = 0$; When $r^{(l)} = 2\tau$, the value function is $\bar{v}(\tau) = \tau(2^{\alpha} - 1) < \tau$. The modified $\bar{v}(r^{(l)})$ is a function obtained by translating and zooming in and out the classical value function of regret theory. When $\alpha = 0.88$, the outcomes obtained by experiments are in accordance with the original data (Tversky & Kahneman, 1992).

Definition 8. Let $\dot{h}_S^1(p) = \left\{ \dot{s}^{1(l)}(\dot{p}_1^{(l)}) | l = 1, 2, \ldots, L \right\}$ and $\dot{h}_S^2(p) = \left\{ \dot{s}^{2(l)}(\dot{p}_2^{(l)}) | l = 1, 2, \ldots, L \right\}$ denote the evaluation value of the alternatives A and B expressed by NPLTSs, respectively. The modified regret-rejoice function of A compared with B under the probabilistic linguistic circumstance is as follows:
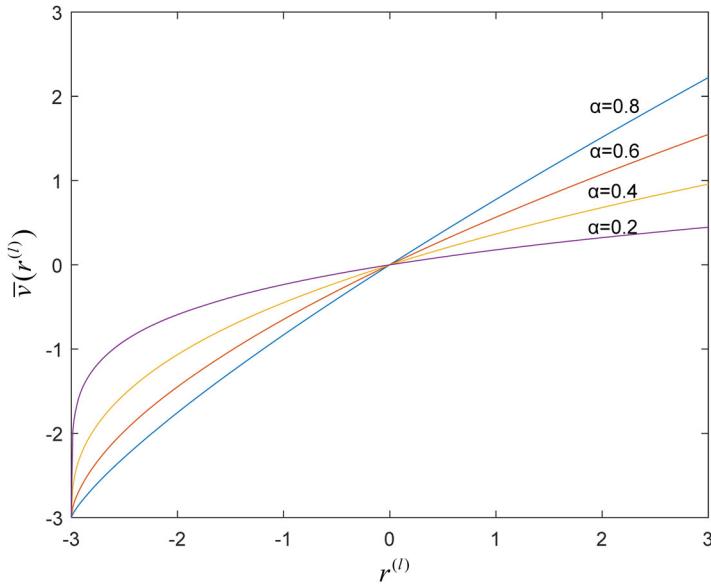
Figure 1. The modified value function $\bar{v}(r^{(l)})$ when $\tau = 3$.
Source: Authors' calculation.

$$R(\Delta H) = \frac{\tau}{e^{2\delta\tau} - 1} \cdot (1 - e^{-\delta\triangle H}), \Delta H = \bar{v}(r_1^{(l)}) - \bar{v}(r_2^{(l)}), \tag{10}$$

$$R\left(\dot{h}_S^1(p)\right) = \left\{s_{R(\Delta H)}(\dot{p}_1^{(l)})|l = 1, 2, \ldots, L\right\}, \tag{11}$$

where $r_1^{(l)}$ and $r_2^{(l)}$ are the subscripts of the linguistic terms $\dot{s}^{1(l)}$ and $\dot{s}^{2(l)}$, respectively.

Since the range of ΔH is $[-2\tau, 2\tau]$, the domain of regret-rejoice function $R(\Delta H)$ for PLTSs should be $[-\tau, \tau]$ to satisfy that the range of $R(\Delta H)$ within the virtual linguistic term sets. Considering that individuals are much more sensitive to loss than gain, we multiply $R(\Delta H)$ by k_2 to hold $R(-2\tau) = -\tau$, then we obtain $k_2 = \frac{\tau}{e^{2\delta\tau}-1}$. Hence, the regret-rejoice value of regret theory is converted to Equation (10). When $\Delta H = -2\tau$, the regret-rejoice value is $R(-2\tau) = -\tau$; When $\Delta H = 0$, the regret-rejoice value is $R(0) = 0$; When $\Delta H = 2\tau$, the regret-rejoice value is $R(2\tau) = \frac{\tau}{e^{\delta \cdot 2\tau}} < \tau$. The modified regret-rejoice function with respect to different values of δ is shown in Figure 2. It is a function that zooms in and out the classical regret-rejoice function of regret theory. Figure 2 shows that the decision maker is more sensitive to $\Delta H < 0$ than $\Delta H > 0$, which indicates that the decision maker is more regret aversive. We adopt $\delta = 0.3$ in this paper which is recommended in Wang et al. (2020).

Definition 9. Let $\dot{h}_S^1(p) = \left\{\dot{s}^{1(l)}(\dot{p}_1^{(l)})|l = 1, 2, \ldots, L\right\}$ and $\dot{h}_S^2(p) = \left\{\dot{s}^{2(l)}(\dot{p}_2^{(l)})|l = 1, 2, \ldots, L\right\}$ denote the evaluation value of the alternatives A and B expressed by NPLTSs, respectively. The perceived utility value of A compared with B can be obtained by the modified utility function and regret-rejoice function as follows:
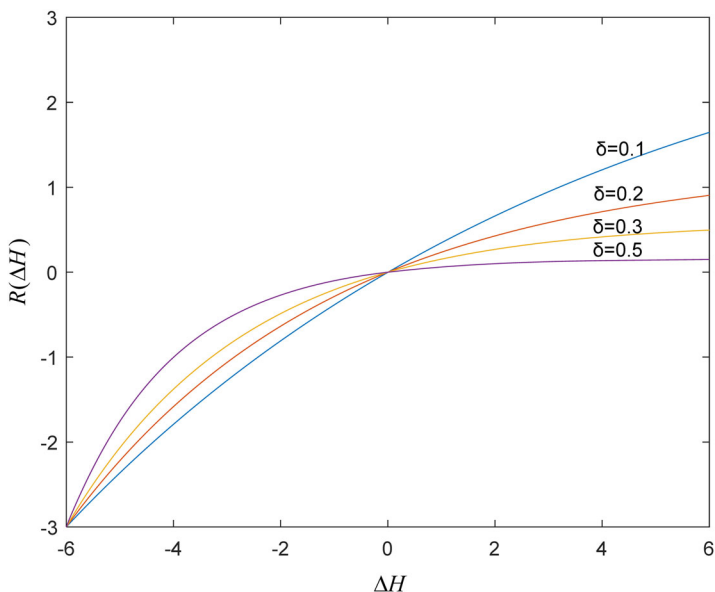
Figure 2. The modified regret-rejoice function $R(\Delta H)$ when $\tau = 3$.
Source: Authors' calculation.

$$U(A) = \lambda \bar{v}(r_1^{(l)}) + (1-\lambda)R(\Delta H)$$

$$= \lambda \tau \cdot \left[\left(\frac{r_1^{(l)}}{\tau} + 1 \right)^{\alpha} - 1 \right] + (1-\lambda) \frac{\tau}{e^{2\delta\tau} - 1} \cdot (1 - e^{-\delta\Delta H}), \tag{12}$$

$$U\left(\dot{h}_S^1(p)\right) = \left\{ s_{\lambda\bar{v}(r_1^{(l)})+(1-\lambda)R(\Delta H)}(\dot{p}_1^{(l)}) | l = 1, 2, \ldots, L \right\}, \tag{13}$$

where $r_1^{(l)}$ and $r_2^{(l)}$ are the subscript of the linguistic term $\dot{s}^{1(l)}$ and $\dot{s}^{2(l)}$, and $\Delta H = \bar{v}(r_1^{(l)}) - \bar{v}(r_2^{(l)})$. $\lambda \in [0, 1]$ is a parameter to adjust the importance degree of the utility function and regret-rejoice function. Referring to the classical regret theory, we assume $\lambda = 0.5$ in the following part of the paper.

4.2. The PLTV

When the emergency occurs, decision-making environment will change over time due to human intervention and the evolution of emergency. The decision matrix should be updated to response the changing emergency in the multi-stage process. In order to describe the multi-stage probabilistic linguistic information, we propose the definition of PLTV.

Definition 10. Let $x_i \in X$ be fixed and t be a time variable, then the PLTV at time t on a linguistic term set S is $H_S(p) = \{< x_i, h_S^i(p) | t > | x_i \in X\}$ with

$$h_S^i(p) | t = \left\{ s^{i(l)}(p^{(l)}) | t \middle| s^{i(l)} \in S, p^{(l)} \geq 0, l = 1, 2, \ldots, L, \sum_{l=1}^{L} p^{(l)} \leq 1 \right\} \tag{14}$$

where $s^{i(l)}(p^{(l)})|t$ is the l th linguistic term $s^{i(l)}$ with the probability $p^{(l)}$ at time t in $h_S^i(p)|t$. The linguistic terms $s^{i(l)}$, $l = 1, 2, \ldots, L$ are arranged in ascending order. $h_S^i(p)|t$ is called the probabilistic linguistic time element (PLTE).

If $t = (t_1, t_2, \ldots, t_K)^T$, then $s^{i(l)}(p^{(l)})|t_1, s^{i(l)}(p^{(l)})|t_2, \ldots, s^{i(l)}(p^{(l)})|t_K$ indicate K PLTEs of the element $x_i \in X$ collected at K different stages. In other words, the values of a PLTV are PLTEs. The PLTV can record the changes of decision makers' evaluation information over time. The operations of PLTEs with the time weight vector $\varpi(t_k)(k = 1, 2, \ldots, K)$ are as follows:

Definition 11. Let $h_S(p)|t_k = \{s^{(l)}(p^{(l)})|t_k|l = 1, 2, \ldots, L\}$ $(k = 1, 2, \ldots, K)$ be K PLTEs, where $s^{(l)}|t_k$ and $p^{(l)}|t_k$ are the k th linguistic term and corresponding probability in $h_S(p)|t_k$. The probabilistic linguistic time weighted averaging (PLTWA) operator can be defined as:

$$PLTWA\big(h_S(p)|t_1, h_S(p)|t_2, \ldots, h_S(p)|t_K\big) = \varpi_1\big(h_S(p)|t_1\big) \oplus \varpi_2\big(h_S(p)|t_2\big) \oplus \cdots \oplus \varpi_K\big(h_S(p)|t_K\big)$$
$$= \cup_{s^{(l)}|t_1 \in h_S(p)|t_1}\big\{\varpi_1 s^{(l)} p^{(l)}|t_1\big\} \oplus \cup_{s^{(l)}|t_2 \in h_S(p)|t_2}\big\{\varpi_2 s^{(l)} p^{(l)}|t_2\big\} \oplus \cdots \oplus \cup_{s^{(l)}|t_K \in h_S(p)|t_K}\big\{\varpi_K s^{(l)} p^{(l)}|t_K\big\}$$

where $\oplus$ represents the sum symbol of PLTEs, $\varpi = (\varpi_1, \varpi_2, \ldots, \varpi_K)^T$ is the time weight vector of $h_S(p)|t_k$, $\varpi_k \geq 0, k = 1, 2, \ldots, K$, and $\sum_{k=1}^{K} \varpi_k = 1$.

If $\varpi = (\frac{1}{K}, \frac{1}{K}, \ldots, \frac{1}{K})^T$, then the PLTWA operator is reduced to the probabilistic linguistic time averaging operator.

Definition 12. Let $h_S(p)|t_k = \{s^{(l)}(p^{(l)})|t_k|l = 1, 2, \ldots, L\}$ $(k = 1, 2, \ldots, K)$ be K PLTEs, where $s^{(l)}|t_k$ and $p^{(l)}|t_k$ are the k th linguistic term and corresponding probability in $h_S(p)|t_k$. The probabilistic linguistic time weighted geometric (PLTWG) operator can be defined as:

$$PLTWG\big(h_S(p)|t_1, h_S(p)|t_2, \ldots, h_S(p)|t_K\big) = \big(h_S(p)|t_1\big)^{\varpi_1} \oplus \big(h_S(p)|t_2\big)^{\varpi_2} \oplus \cdots \oplus \big(h_S(p)|t_K\big)^{\varpi_K}$$
$$= \cup_{s^{(l)}|t_1 \in h_S(p)|t_1}\big\{\big(s^{(l)}\big)^{\varpi_1 p^{(l)}}|t_1\big\} \oplus \cup_{s^{(l)}|t_2 \in h_S(p)|t_2}\big\{\big(s^{(l)}\big)^{\varpi_2 p^{(l)}}|t_2\big\} \oplus \cdots \oplus \cup_{s^{(l)}|t_K \in h_S(p)|t_K}\big\{\big(s^{(l)}\big)^{\varpi_K p^{(l)}}|t_K\big\}$$

where $\oplus$ represents the sum symbol of PLTEs, $\varpi = (\varpi_1, \varpi_2, \ldots, \varpi_K)^T$ is the time weight vector of $h_S(p)|t_k$, $\varpi_k \geq 0, k = 1, 2, \ldots, K$, and $\sum_{k=1}^{K} \varpi_k = 1$.

If $\varpi = (\frac{1}{K}, \frac{1}{K}, \ldots, \frac{1}{K})^T$, then the PLTWG operator is reduced to the probabilistic linguistic time geometric operator.

4.3. The PLDRP model

The emergency event is a dynamic development and evolution process considering that most decision information is uncertain and incomplete in the initial period. With more decision information being collected, the emergency response should be adjusted timely as the reference point changes. In this part, based on the proposed positive ideal solution and negative ideal solution for PLTSs, the expectation-levels of alternatives are proposed. Then the nonlinear programming models are established to maximise the reference point of emergency response. Combining with the modified

regret theory with the probabilistic linguistic information, the PLDRP model is presented to obtain optimal alternative for the EDM.

Definition 13. Let $(h_S^{ij}(p))_{m \times n}$ be a probabilistic linguistic decision matrix with $h_S^{ij}(p) = \left\{ s^{ij(l)}(p_{ij}^{(l)}) | l = 1, 2, \ldots, L_{ij} \right\}$. Then $h_S^{ij}(p)^+ = \left\{ s_{\max r_{ij}^{(l)}}(1) \right\}$ is called the probabilistic linguistic positive ideal solution (PLPIS), where $r_{ij}^{(l)}$ is the subscript of the linguistic term $s^{ij(l)}$.

Definition 14. Let $(h_S^{ij}(p))_{m \times n}$ be a probabilistic linguistic decision matrix with $h_S^{ij}(p) = \left\{ s^{ij(l)}(p_{ij}^{(l)}) | l = 1, 2, \ldots, L_{ij} \right\}$. Then $h_S^{ij}(p)^- = \left\{ s_{\min r_{ij}^{(l)}}(1) \right\}$ is called the probabilistic linguistic negative ideal solution (PLNIS), where $r_{ij}^{(l)}$ be the subscript of the linguistic term $s^{ij(l)}$.

We first calculate the deviation degree between $h_S^{ij}(p)$ for the alternative A_j of the decision maker d_i and the PLPIS.

$$d\left(h_S^{ij}(p), h_S^{ij}(p)^+ \right) = \sqrt{ \sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} - \frac{\max r_{ij}^{(l)}}{L} \right)^2 / L }$$

Then we compute the deviation degree between $h_S^{ij}(p)$ for the alternative A_j of the decision maker d_i and the PLNIS.

$$d\left(h_S^{ij}(p), h_S^{ij}(p)^- \right) = \sqrt{ \sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} - \frac{\min r_{ij}^{(l)}}{L} \right)^2 / L }$$

Motivated by the TOPSIS method, the expectation-levels of alternatives are as follows:

Definition 15. The expectation-levels of the alternatives A_j $(j = 1, 2, \ldots, N)$ with the weight vector $w^{t_k} = (w_1^{t_k}, w_2^{t_k}, \ldots, w_M^{t_k})^T$, where $0 \le w_i^{t_k} \le 1$ and $\sum_{i=1}^{M} w_i^{t_k} = 1$ at the time point $t_k (k = 1, 2, \ldots, K)$ are defined as:

$$
\begin{aligned}
E\left(A_j^{t_k} \right) &= \frac{ (1-\theta) \cdot \sum_{i=1}^{M} \left[d\left(h_S^{ij}(p)|t_k, h_S^{ij}(p)^-|t_k \right) \cdot w_i^{t_k} \right] }{ \theta \cdot \sum_{i=1}^{M} \left[d\left(h_S^{ij}(p)|t_k, h_S^{ij}(p)^+|t_k \right) \cdot w_i^{t_k} \right] + (1-\theta) \cdot \sum_{i=1}^{M} \left[d\left(h_S^{ij}(p)|t_k, h_S^{ij}(p)^-|t_k \right) \cdot w_i^{t_k} \right] } \\[2mm]
&= \frac{ (1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{ \sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} | t_k - \min r_{ij}^{(l)} | t_k \right)^2 / L } \cdot w_i^{t_k} \right] }{ \theta \cdot \sum_{i=1}^{M} \left[\sqrt{ \sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} | t_k - \max r_{ij}^{(l)} | t_k \right)^2 / L } \cdot w_i^{t_k} \right] + (1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{ \sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} | t_k - \min r_{ij}^{(l)} | t_k \right)^2 / L } \cdot w_i^{t_k} \right] }
\end{aligned}
\tag{15}
$$

where the parameter θ denotes the risk appetite of the decision maker: $\theta > 0.5$ means the decision maker is a general risk seeker; $\theta < 0.5$ means the opposite.

The aim of the PLDRP model is to maximise the reference point $\xi_j^{t_k}$ of emergency response at the time point t_k based on the proposed expectation-levels of alternatives.

To obtain the reference point and form the weight vector $w^{t_k} = (w_1^{t_k}, w_2^{t_k}, \ldots, w_M^{t_k})^T$ at the time point t_k, the nonlinear model is built as follows:

Model 1

$$\max \sum_{j=1}^{N} \xi_j^{t_k}$$

$$s.t. \begin{cases} E\left(A_j^{t_k}\right) \geq \xi_j^{t_k} & (j = 1, 2, \ldots, N) \\ 0 \leq w_i^{t_k} \leq 1 & (i = 1, 2, \ldots, M) \\ \sum_{i=1}^{M} w_i^{t_k} = 1 \end{cases}$$

Combining Equation (15), Model 1 is translated to Model 2 as follows:

Model 2

$$\max \sum_{j=1}^{N} \xi_j^{t_k}$$

$$s.t. \begin{cases} \dfrac{(1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} |t_k - \min r_{ij}^{(l)} |t_k\right)^2 / L} \cdot w_i^{t_k} \right]}{\theta \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} |t_k - \max r_{ij}^{(l)} |t_k\right)^2 / L} \cdot w_i^{t_k} \right] + (1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} r_{ij}^{(l)} |t_k - \min r_{ij}^{(l)} |t_k\right)^2 / L} \cdot w_i^{t_k} \right]} \geq \xi_j^{t_k} (j = 1, 2, \ldots, N) \\ \qquad\qquad 0 \leq w_i^{t_k} \leq 1 \qquad\qquad (i = 1, 2, \ldots, M) \\ \qquad\qquad\qquad \sum_{i=1}^{M} w_i^{t_k} = 1 \end{cases}$$

Solving Model 2, the optimal weight vector $w^{*t_k} = (w_1^{*t_k}, w_2^{*t_k}, \ldots, w_M^{*t_k})^T$ and the optimal reference point $\xi_j^{*t_k}$ of the alternatives A_j $(j = 1, 2, \ldots, N)$ can be calculated at the time point t_k. We obtain the initial reference point $\xi_j^{*t_k}$ by solving Model 2, then the optimal alternative can be selected by the probabilistic linguistic weighted averaging (PLWA) operator or the probabilistic linguistic weighted geometric (PLWG) operator (Zhang et al., 2017). In the next stage, that is, at the time point t_{k+1}, the programming model is developed as follows:

Model 3

$$\max \sum_{j=1}^{N} \xi_j^{t_{k+1}}$$

$$s.t. \begin{cases} E\left(A_j^{t_{k+1}}\right) \geq \xi_j^{t_{k+1}} & (j = 1, 2, \ldots, N) \\ \xi_j^{t_{k+1}} \geq \xi_j^{*t_k} \\ 0 \leq w_i^{t_{k+1}} \leq 1 & (i = 1, 2, \ldots, M) \\ \sum_{i=1}^{M} w_i^{t_{k+1}} = 1 \end{cases}$$

Combining Equation (15), Model 3 can be converted to Model 4:

Model 4

$$\max \sum_{j=1}^{N} \xi_j^{t_{k+1}}$$

$$s.t. \begin{cases} \dfrac{(1-\theta)\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}r_{ij}^{(l)}|t_{k+1}-\min r_{ij}^{(l)}|t_{k+1}\right)^2/L}\cdot w_i^{t_{k+1}}\right]}{\theta\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}r_{ij}^{(l)}|t_{k+1}-\max r_{ij}^{(l)}|t_{k+1}\right)^2/L}\cdot w_i^{t_{k+1}}\right]+(1-\theta)\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}r_{ij}^{(l)}|t_{k+1}-\min r_{ij}^{(l)}|t_{k+1}\right)^2/L}\cdot w_i^{t_{k+1}}\right]} \geq \xi_j^{t_{k+1}} \\ \quad \xi_j^{t_{k+1}} \geq \xi_j^{*t_k} \qquad\qquad (j=1,2,\ldots,N) \\ \quad 0 \leq w_i^{t_{k+1}} \leq 1 \qquad (i=1,2,\ldots,M) \\ \sum_{i=1}^{M} w_i^{t_{k+1}} = 1 \end{cases}$$

Solving Model 4, if there is no optimal solution, then the reference point $\xi_j^{*t_k}$ isn't consistent with the time point t_{k+1}. Hence, we need to reset the optimal reference point by Model 2 and rank the alternatives by the recomputed $\xi_j^{*t_{k+1}}$ and $w^{*t_{k+1}}$.

In the process of the EDM, due to the urgency and complexity of the incident, it is difficult for decision makers to collect the uncertain and incomplete decision-making information by crisp values. When the decision makers are under enormous social stress, they are characterised by bounded rationality and regret-aversion in the process of risk decision. Therefore, in order to meet the actual requirement of the EDM, regret theory is introduced to the dynamic reference point method under the probabilistic linguistic circumstance. The models of the PLDRP method with regret theory are as follows:

Model 5

$$\max \sum_{j=1}^{N} \bar{\xi}_j^{t_k}$$

$$s.t. \begin{cases} \dfrac{(1-\theta)\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}\bar{r}_{ij}^{(l)}|t_k-\min\bar{r}_{ij}^{(l)}|t_k\right)^2/L}\cdot\bar{w}_i^{t_k}\right]}{\theta\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}\bar{r}_{ij}^{(l)}|t_k-\max\bar{r}_{ij}^{(l)}|t_k\right)^2/L}\cdot\bar{w}_i^{t_k}\right]+(1-\theta)\cdot\sum_{i=1}^{M}\left[\sqrt{\sum_{l=1}^{L}\left(p_{ij}^{(l)}\bar{r}_{ij}^{(l)}|t_k-\min\bar{r}_{ij}^{(l)}|t_k\right)^2/L}\cdot\bar{w}_i^{t_k}\right]} \geq \bar{\xi}_j^{t_k}\,(j=1,2,\ldots,N) \\ \qquad\qquad 0 \leq \bar{w}_i^{t_k} \leq 1 \qquad\qquad (i=1,2,\ldots,M) \\ \sum_{i=1}^{M} \bar{w}_i^{t_k} = 1 \end{cases}$$

where $\bar{r}_{ij}^{(l)}|t_k$ and $\max\bar{r}_{ij}^{(l)}|t_k$ are the perceived utility value of $r_{ij}^{(l)}|t_k$ and $\max r_{ij}^{(l)}|t_k$, respectively. $\bar{r}_{ij}^{(l)} = \lambda\bar{v}(r_{ij}^{(l)}) + (1-\lambda)R(\bar{v}(r_{ij}^{(l)}) - \bar{v}(\bar{r}_i))$, where $\bar{r}_i = \sum_{j=1}^{N}\sum_{l=1}^{L} p_{ij}^{(l)} r_{ij}^{(l)}/N$.

By solving Model 5 we obtain the optimal weight vector $\bar{w}^{*t_k} = (\bar{w}_1^{*t_k}, \bar{w}_2^{*t_k}, \ldots, \bar{w}_M^{*t_k})^T$ and the optimal reference point $\bar{\xi}_j^{*t_k}$ of the alternatives A_j ($j = 1, 2, \ldots, N$). The PLWA or PLWG operator (Zhang et al., 2017) is utilised to aggregate the decision information of the alternatives $A_j(j = 1, 2, \ldots, N)$ according to $\bar{w}^{*t_k}$ and $\bar{H}_{t_k}$, then choose the best alternative.

For $t = t_{k+1}$, we solve the optimal programming of Model 6 based on the reference point $\bar{\xi}_j^{*t_k}$ and $\bar{E}(A_j^{t_{k+1}})$. If Model 6 does not exist an optimal solution, then return to solve Model 5 to obtain a new optimal reference point and adjust the emergency response strategy according to $\bar{w}^{*t_{k+1}} = (\bar{w}_1^{*t_{k+1}}, \bar{w}_2^{*t_{k+1}}, \ldots, \bar{w}_M^{*t_{k+1}})^T$ and $\bar{\xi}_j^{*t_{k+1}}$.

When $t = t_K$, we select the optimal alternatives of each stage t_k $(k = 1, 2, \ldots, K)$ that form the optimal alternative chain of the EDM.

Model 6

$$\max \sum_{j=1}^{N} \bar{\xi}_j^{t_{k+1}}$$

$$s.t. \begin{cases} \dfrac{(1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} \bar{r}_{ij}^{(l)} |t_{k+1} - \min \bar{r}_{ij}^{(l)} |t_{k+1} \right)^2 / L} \cdot \bar{w}_i^{t_{k+1}} \right]}{\theta \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} \bar{r}_{ij}^{(l)} |t_{k+1} - \max \bar{r}_{ij}^{(l)} |t_{k+1} \right)^2 / L} \cdot \bar{w}_i^{t_{k+1}} \right] + (1-\theta) \cdot \sum_{i=1}^{M} \left[\sqrt{\sum_{l=1}^{L} \left(p_{ij}^{(l)} \bar{r}_{ij}^{(l)} |t_{k+1} - \min \bar{r}_{ij}^{(l)} |t_{k+1} \right)^2 / L} \cdot \bar{w}_i^{t_{k+1}} \right]} \geq \bar{\xi}_j^{t_{k+1}} \\ \bar{\xi}_j^{t_{k+1}} \geq \bar{\xi}_j^{*t_k} \qquad (j = 1, 2, \ldots, N) \\ 0 \leq \bar{w}_i^{t_{k+1}} \leq 1 \qquad (i = 1, 2, \ldots, M) \\ \sum_{i=1}^{M} \bar{w}_i^{t_{k+1}} = 1 \end{cases}$$

where $\bar{r}_{ij}^{(l)} |t_{k+1}$ and $\max \bar{r}_{ij}^{(l)} |t_{k+1}$ are the perceived utility value of $r_{ij}^{(l)} |t_{k+1}$ and $\max r_{ij}^{(l)} |t_{k+1}$, respectively. $\bar{r}_{ij}^{(l)} = \lambda \bar{v}(r_{ij}^{(l)}) + (1-\lambda) R(\bar{v}(r_{ij}^{(l)}) - \bar{v}(\bar{r}_i))$, where $\bar{r}_i = \sum_{j=1}^{N} \sum_{l=1}^{L} p_{ij}^{(l)} r_{ij}^{(l)} / N$.

5. The procedure of the PLDRP method

The following steps can be used to build the PLDRP method for emergency response under the probabilistic linguistic environment:

Step 1. Identify the alternatives A_j $(j = 1, 2, \ldots, N)$ and the decision makers d_i $(i = 1, 2, \ldots, M)$ and then construct the PLTV decision matrices $H_{t_k} = (h_S^{ij}(p)|t_k)_{M \times N}$ about the emergency at different time points t_k $(k = 1, 2, \ldots, K)$.

Step 2. Calculate the modified perceived utility values for all probabilistic linguistic elements in H_{t_k} $(k = 1, 2, \ldots, K)$ according to Equation (12), denoted by $\bar{H}_{t_k} = (\bar{h}_S^{ij}(p)|t_k)_{M \times N}$ $(i = 1, 2, \ldots, M; j = 1, 2, \ldots, N)$.

Step 3. Compute the deviation degrees $d(\bar{h}_S^{ij}(p)|t_k, \bar{h}_S^{ij}(p)^+|t_k)$ and $d(\bar{h}_S^{ij}(p)|t_k, \bar{h}_S^{ij}(p)^-|t_k)$ $(k = 1, 2, \ldots, K)$ and then obtain the expectation-levels of the alternative $\bar{E}(A_j^{t_k})$ with the weight vector $\bar{w}^{t_k} = (\bar{w}_1^{t_k}, \bar{w}_2^{t_k}, \ldots, \bar{w}_M^{t_k})^T$ at different time points t_k $(k = 1, 2, \ldots, K)$.

Step 4. Solve Model 5 to obtain the optimal weight vector $\bar{w}^{*t_k} = (\bar{w}_1^{*t_k}, \bar{w}_2^{*t_k}, \ldots, \bar{w}_M^{*t_k})^T$ and the optimal reference point $\bar{\xi}_j^{*t_k}$ of the alternatives A_j $(j = 1, 2, \ldots, N)$.

Step 5. Utilise the PLWA or PLWG operator (Zhang et al., 2017) to aggregate the decision information of the alternatives $A_j (j = 1, 2, \ldots, N)$ according to $\bar{w}^{*t_k}$ and $\bar{H}_{t_k}$ and then choose the best alternative.

Step 6. For $t = t_{k+1}$, solve the optimal programming of Model 6 based on the reference point $\bar{\xi}_j^{*t_k}$ and $\bar{E}(A_j^{t_{k+1}})$. If Model 6 does not exist an optimal solution, then return to Step 4 to obtain a new optimal reference point and adjust the emergency response strategy according to $\bar{w}^{*t_{k+1}} = (\bar{w}_1^{*t_{k+1}}, \bar{w}_2^{*t_{k+1}}, \ldots, \bar{w}_M^{*t_{k+1}})^T$ and $\bar{\xi}_j^{*t_{k+1}}$.

Step 7. When $t = t_K$, end the algorithm.

Step 8. Select the optimal alternatives of each stage t_k $(k = 1, 2, \ldots, K)$ that form the optimal alternative chain of the EDM.

The procedure of the PLDPR method is manifested by Figure 3.
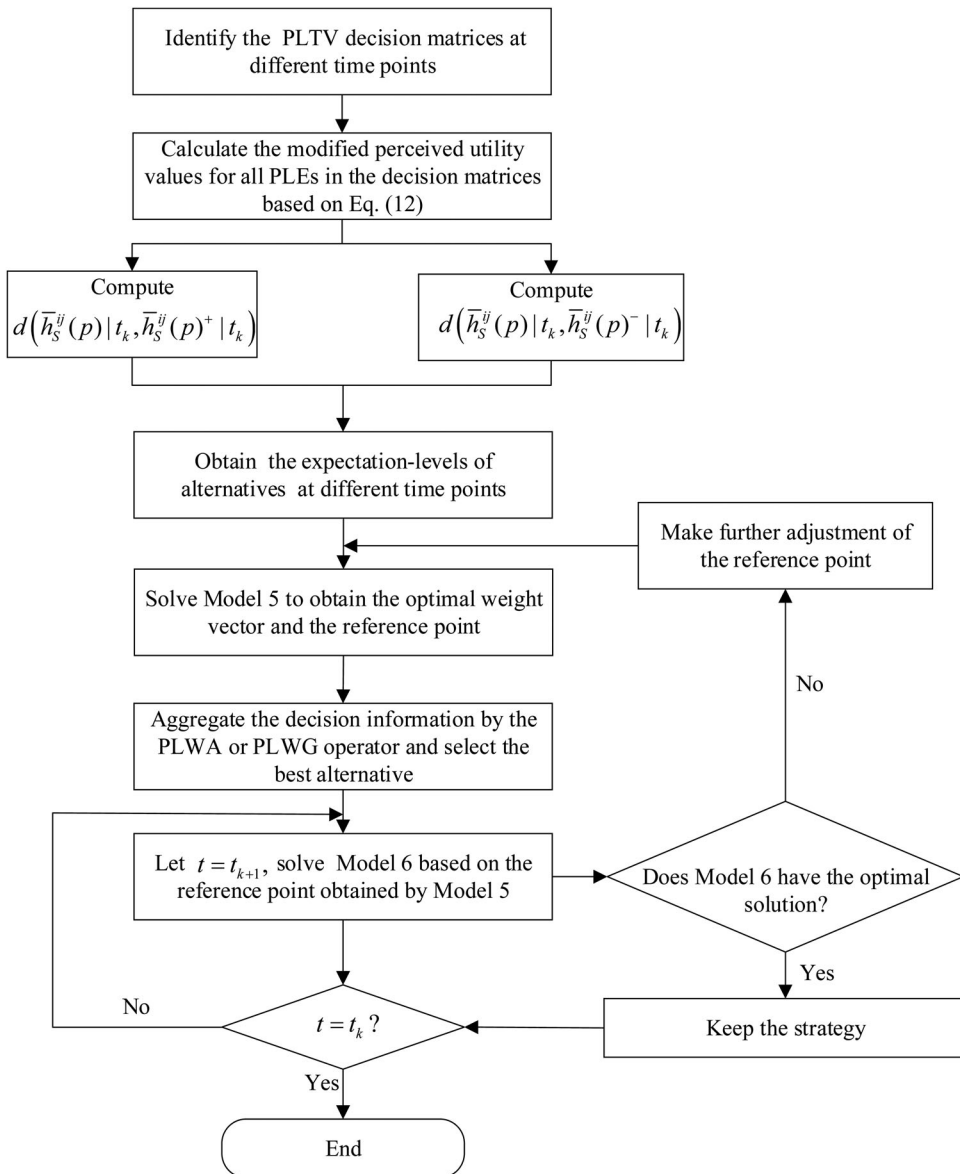
Figure 3. A framework of the PLDPR method.
Source: Authors' calculation.

6. A numerical example: strategy selection in the EDM

6.1. Case description: the application in the public health EDM

In December 2019, some cases of pneumonia with unknown cause suffered from the symptoms, such as fever, cough and fatigue were reported in Wuhan, China. The epidemic disease is proven to be COVID-19, which have not been found before (The 2019-nCoV Outbreak Joint Field Epidemiology Investigation Team & Li, 2020). The current research indicates that the novel coronavirus has strong affinity to a human respiratory receptor and can be spread by droplets and close contact (Li et al., 2020).

Afterwards, the existence of human-to-human transmission is confirmed, then the lockdown of 11 million people in Wuhan from January 23, 2020 is implemented, which is rare in human public health history. The highway traffic is strictly controlled and the public-transport system is temporarily suspended over the whole country. The holidays of Chinese New Year are extended and people are forbidden to go out except some special situations. The cross-provincial traffic is limited and some retail stores and restaurants are closed to reduce gathering and cross-infection as low as possible. A total of 74,185 confirmed cases and 2004 cases of death have been reported on February 18, 2020 (Health.people.com.cn, 2020). As the number of confirmed cases continues to increase in China, on January 30, 2020 World Health Organization (WHO) declared the outbreak of COVID-19 as a Public Health Emergency of International Concern (World Health Organization, 2020).

Since the outbreak of COVID-19, China has been recognised and praised by WHO for its rapid and efficient prevention and control measures. On March 13, 2020, the number of new confirmed cases dropped to 11 cases in China mainland and the number of new confirmed cases dropped for 15 consecutive days outside Hubei province. The strict control measures have proven to be effective in the early days of outbreak, such as banning all public gatherings, closing entertainment venues and suspending public transport. More than 38,000 medical staffs, among which the intensive care medical professionals have nearly 10% of the nation, were sent to Hubei province. Adequate medical treatment and epidemic prevention materials have made a significant contribution to reducing mortality of COVID-19 and containing outbreaks.

The sudden outbreak of COVID-19 has unprecedented negative influences on China's economic and social development. According to the report of National Bureau of Statistics of China, the national economy shrinks 6.8% in the first quarter of 2020 (National Bureau of Statistics of China, 2020). The growth rate over the same period last year of Wholesale and Retail Trades, Accommodation and Restaurants, Manufacturing and Construction are −17.8%, −35.3%, −10.2% and −17.5%, respectively. Chinese people have made great sacrifices to contain the outbreak of novel coronavirus. Along with the normalisation of COVID-19, it is of great significance to arouse public consumption in combination with efforts to improve the public service system. At present, China's epidemic prevention and control situation is further consolidated, but the international epidemic continues to spread. When and how to resume work and reboot economy in an orderly manner are severe questions and challenges for the government. The measures of epidemic response should keep up with the changing epidemic situation and flexibly adjust.

The PLDRP method can be applied to deal with the optimal alternative selection for the response of COVID-19. Through interviews and survey, four alternatives are selected as follows: A_1 : Adopt public epidemic prevention measures, A_2 : Reopen school, A_3 : Lockdown and A_4 : Resumption of work. The time points are determined as: t_1 : January 23, 2020, t_2 : February 18, 2020 and t_3 : March 13, 2020. Five experts $D_i(i = 1, 2, \ldots, 5)$ are invited to make evaluation towards the alternative A_j at different time points t_k. D_1 is a member of National Health Commission who organises the specific work of emergency response to COVID-19 and medical relief. D_2 is

member of National Health Commission who is responsible for guiding and supervising the implementation of epidemic prevention. D_3 and D_4 are members of the government's leadership group on the epidemic prevention and control. D_5 is an expert of clinical medical research on the respiratory diseases. Suppose that S is a linguistic term set, whose linguistic terms are s_{-3} : extremely poor, s_{-2} : poor, s_{-1} : slightly poor, s_0 : fair, s_1 : slightly good, s_2 : good and s_3 : extremely good.

6.2. Case solution

The specific steps of selecting the optimal alternatives of each stage t_k $(k = 1, 2, 3)$ are as follows:

Step 1. The PLTV decision matrices $H_{t_k} = (h_S^{ij}(p)|t_k)_{5 \times 4}$ about the emergency at different time points t_k $(k = 1, 2, 3)$ are collected as Tables 1–3.

Step 2. Calculate the modified perceived utility values for all probabilistic linguistic elements in H_{t_k} $(k = 1, 2, 3)$ according to Equation (12) and then compute the deviation degrees $d(\bar{h}_S^{ij}(p)|t_k, \bar{h}_S^{ij}(p)^+|t_k)$ and $d(\bar{h}_S^{ij}(p)|t_k, \bar{h}_S^{ij}(p)^-|t_k)(k = 1, 2, 3)$ as Tables 4–9.

Step 3. Set $\theta = 0.5$, and solve Model 5 based on the deviation degrees in Tables 4 and 5 as follows:

$$
\max\left(\bar{\xi}_1^{t_1} + \bar{\xi}_2^{t_1} + \bar{\xi}_3^{t_1} + \bar{\xi}_4^{t_1}\right)
$$

$$
s.t. \begin{cases}
\dfrac{0.5 \cdot (0.6828\bar{w}_1^{t_1} + 0.4492\bar{w}_2^{t_1} + 0.5219\bar{w}_3^{t_1} + 0.3770\bar{w}_4^{t_1} + 0.5799\bar{w}_5^{t_1})}{0.5 \cdot (0.7975\bar{w}_1^{t_1} + 0.9167\bar{w}_2^{t_1} + 0.8410\bar{w}_3^{t_1} + 0.9648\bar{w}_4^{t_1} + 0.8025\bar{w}_5^{t_1}) + 0.5 \cdot (0.6828\bar{w}_1^{t_1} + 0.4492\bar{w}_2^{t_1} + 0.5219\bar{w}_3^{t_1} + 0.3770\bar{w}_4^{t_1} + 0.5799\bar{w}_5^{t_1})} \geq \bar{\xi}_1^{t_1} \\[4pt]
\dfrac{0.5 \cdot (0.2844\bar{w}_1^{t_1} + 0.5747\bar{w}_2^{t_1} + 0.3160\bar{w}_3^{t_1} + 0.2681\bar{w}_4^{t_1} + 0.5305\bar{w}_5^{t_1})}{0.5 \cdot (1.0600\bar{w}_1^{t_1} + 0.8007\bar{w}_2^{t_1} + 1.0188\bar{w}_3^{t_1} + 1.1286\bar{w}_4^{t_1} + 0.8308\bar{w}_5^{t_1}) + 0.5 \cdot (0.2844\bar{w}_1^{t_1} + 0.5747\bar{w}_2^{t_1} + 0.3160\bar{w}_3^{t_1} + 0.2681\bar{w}_4^{t_1} + 0.5305\bar{w}_5^{t_1})} \geq \bar{\xi}_2^{t_1} \\[4pt]
\dfrac{0.5 \cdot (0.4181\bar{w}_1^{t_1} + 0.3879\bar{w}_2^{t_1} + 0.6054\bar{w}_3^{t_1} + 1.0929\bar{w}_4^{t_1} + 0.7297\bar{w}_5^{t_1})}{0.5 \cdot (0.9358\bar{w}_1^{t_1} + 0.9564\bar{w}_2^{t_1} + 0.7996\bar{w}_3^{t_1} + 0.4655\bar{w}_4^{t_1} + 0.6938\bar{w}_5^{t_1}) + 0.5 \cdot (0.4181\bar{w}_1^{t_1} + 0.3879\bar{w}_2^{t_1} + 0.6054\bar{w}_3^{t_1} + 1.0929\bar{w}_4^{t_1} + 0.7297\bar{w}_5^{t_1})} \geq \bar{\xi}_3^{t_1} \\[4pt]
\dfrac{0.5 \cdot (0.3979\bar{w}_1^{t_1} + 0.4137\bar{w}_2^{t_1} + 0.7502\bar{w}_3^{t_1} + 0.5246\bar{w}_4^{t_1} + 0.2642\bar{w}_5^{t_1})}{0.5 \cdot (0.9493\bar{w}_1^{t_1} + 1.0296\bar{w}_2^{t_1} + 0.6912\bar{w}_3^{t_1} + 0.8545\bar{w}_4^{t_1} + 1.1160\bar{w}_5^{t_1}) + 0.5 \cdot (0.3979\bar{w}_1^{t_1} + 0.4137\bar{w}_2^{t_1} + 0.7502\bar{w}_3^{t_1} + 0.5246\bar{w}_4^{t_1} + 0.2642\bar{w}_5^{t_1})} \geq \bar{\xi}_4^{t_1} \\[4pt]
0.1 \leq \bar{w}_i^{t_1} \leq 1 \qquad (i = 1, 2, \ldots, 5) \\[4pt]
\sum_{i=1}^{5} \bar{w}_i^{t_1} = 1
\end{cases}
$$

We obtain the initial weight vector $\bar{w}^{*t_1} = (0.15, 0.15, 0.3246, 0.2254, 0.15)^T$ and the initial optimal reference point $\bar{\bar{\xi}}_j^{*t_1} = (0.3707, 0.2731, 0.4722, 0.3725)^T$.

Table 1. Evaluation information of H_{t_1}.

	A_1	A_2	A_3	A_4
d_1	$\{s_1(0.2), s_2(0.8)\}$	$\{s_{-1}(0.3), s_0(0.7)\}$	$\{s_0(0.5), s_1(0.5)\}$	$\{s_0(0.6), s_1(0.4)\}$
d_2	$\{s_0(0.3), s_1(0.6)\}$	$\{s_1(0.5), s_2(0.4)\}$	$\{s_0(0.6), s_1(0.3)\}$	$\{s_{-1}(0.3), s_0(0.4), s_1(0.3)\}$
d_3	$\{s_1(0.8), s_2(0.2)\}$	$\{s_0(0.9)\}$	$\{s_1(0.4), s_2(0.6)\}$	$\{s_2(0.5), s_3(0.5)\}$
d_4	$\{s_0(0.7), s_1(0.3)\}$	$\{s_{-1}(0.6), s_0(0.3)\}$	$\{s_1(0.2), s_2(0.5), s_3(0.3)\}$	$\{s_1(0.9), s_2(0.1)\}$
d_5	$\{s_1(0.5), s_2(0.5)\}$	$\{s_1(0.7), s_2(0.2)\}$	$\{s_2(0.6), s_3(0.4)\}$	$\{s_{-1}(0.5), s_0(0.4)\}$

Source: Authors' calculation.

Table 2. Evaluation information of H_{t_2}.

	A_1	A_2	A_3	A_4
d_1	$\{s_2(0.3), s_3(0.7)\}$	$\{s_{-2}(0.4), s_{-1}(0.6)\}$	$\{s_0(0.5), s_1(0.5)\}$	$\{s_{-1}(0.5), s_0(0.4)\}$
d_2	$\{s_0(0.6), s_1(0.4)\}$	$\{s_1(0.3), s_2(0.7)\}$	$\{s_1(0.4), s_2(0.6)\}$	$\{s_0(0.4), s_1(0.5)\}$
d_3	$\{s_1(0.6), s_2(0.4)\}$	$\{s_3(0.9)\}$	$\{s_1(0.3), s_2(0.7)\}$	$\{s_2(0.2), s_3(0.8)\}$
d_4	$\{s_{-1}(0.5), s_0(0.5)\}$	$\{s_{-1}(0.7), s_0(0.2)\}$	$\{s_1(0.5), s_2(0.5)\}$	$\{s_1(0.5), s_2(0.4)\}$
d_5	$\{s_1(0.4), s_2(0.5)\}$	$\{s_2(0.4), s_3(0.5)\}$	$\{s_1(0.5), s_2(0.4)\}$	$\{s_0(0.4), s_1(0.6)\}$

Source: Authors' calculation.

Table 3. Evaluation information of H_{t_3}.

	A_1	A_2	A_3	A_4
d_1	$\{s_2(0.6), s_3(0.4)\}$	$\{s_0(0.6), s_1(0.4)\}$	$\{s_0(0.5), s_1(0.5)\}$	$\{s_1(0.5), s_2(0.4)\}$
d_2	$\{s_0(0.6), s_1(0.4)\}$	$\{s_1(0.3), s_2(0.7)\}$	$\{s_{-1}(0.6), s_0(0.4)\}$	$\{s_1(0.4), s_2(0.5)\}$
d_3	$\{s_1(0.6), s_2(0.4)\}$	$\{s_1(0.2), s_2(0.8)\}$	$\{s_0(0.3), s_1(0.7)\}$	$\{s_0(0.2), s_1(0.8)\}$
d_4	$\{s_0(0.7), s_1(0.2)\}$	$\{s_1(0.7), s_2(0.2)\}$	$\{s_0(0.5), s_1(0.5)\}$	$\{s_1(0.5), s_2(0.4)\}$
d_5	$\{s_1(0.4), s_2(0.5)\}$	$\{s_1(0.4), s_2(0.5)\}$	$\{s_0(0.5), s_1(0.4)\}$	$\{s_2(0.2), s_3(0.8)\}$

Source: Authors' calculation.

Table 4. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_1, \bar{h}_S^{ij}(p)^+|t_1)$.

	A_1	A_2	A_3	A_4
d_1	0.7975	1.0600	0.9358	0.9493
d_2	0.9167	0.8007	0.9564	1.0296
d_3	0.8410	1.0188	0.7996	0.6912
d_4	0.9648	1.1286	0.4655	0.8545
d_5	0.8025	0.8308	0.6938	1.1160

Source: Authors' calculation.

Table 5. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_1, \bar{h}_S^{ij}(p)^-|t_1)$.

	A_1	A_2	A_3	A_4
d_1	0.6828	0.2844	0.4181	0.3979
d_2	0.4492	0.5747	0.3879	0.4137
d_3	0.5219	0.3160	0.6054	0.7502
d_4	0.3770	0.2681	1.0929	0.5246
d_5	0.5799	0.5305	0.7297	0.2642

Source: Authors' calculation.

Table 6. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_2, \bar{h}_S^{ij}(p)^+|t_2)$.

	A_1	A_2	A_3	A_4
d_1	0.7649	2.2023	1.2748	1.7962
d_2	1.3153	0.8515	0.8062	1.2555
d_3	0.8062	1.0713	0.8515	1.0050
d_4	1.7678	1.9121	0.7906	0.7945
d_5	0.7945	0.4373	0.7945	1.2369

Source: Authors' calculation.

Table 7. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_2, \bar{h}_S^{ij}(p)^-|t_2)$.

	A_1	A_2	A_3	A_4
d_1	2.4668	0.3162	1.2748	0.7754
d_2	1.2166	1.9300	1.8439	1.3043
d_3	1.7029	1.7653	1.9300	2.6000
d_4	0.7906	0.7289	1.7678	1.7339
d_5	1.8045	2.3057	1.7339	1.3342

Source: Authors' calculation.

Table 8. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_3, \bar{h}_S^{ij}(p)^+|t_3)$.

	A_1	A_2	A_3	A_4
d_1	0.3000	1.3153	1.2748	0.7945
d_2	1.3153	0.8515	1.8248	0.7945
d_3	0.8062	0.9220	1.2021	1.1705
d_4	1.3807	0.8839	1.2748	0.7945
d_5	0.7945	0.7945	1.2947	1.0050

Source: Authors' calculation.

Table 9. The deviation degrees $d(\bar{h}_S^{ij}(p)|t_3, \bar{h}_S^{ij}(p)^-|t_3)$.

	A_1	A_2	A_3	A_4
d_1	1.7000	0.7280	0.7906	1.2374
d_2	0.7280	1.4577	0.3606	1.3158
d_3	1.2042	1.5652	0.9192	0.9849
d_4	0.6374	1.1319	0.7906	1.2374
d_5	1.3158	1.3158	0.7591	2.1471

Source: Authors' calculation.

Step 4. According to $\bar{w}^{*t_1}$ and $\bar{H}_{t_1}$, we utilise the PLWA operator (Zhang et al., 2017) to aggregate the decision information of the alternatives and obtain corresponding score functions:

$$E(PLWA(A_1|t_1)) = E\left(\overset{5}{\underset{i=1}{\oplus}} \bar{w}_i^{*t_1}\left(\sum_{l=1}^{L} p_{i1}^{(l)} \bar{r}_{i1}^{(l)}|t_1\right)\right) = s_{0.4529}, E(PLWA(A_2|t_1))$$

$$= E\left(\overset{5}{\underset{i=1}{\oplus}} \bar{w}_i^{*t_1}\left(\sum_{l=1}^{L} p_{i2}^{(l)} \bar{r}_{i2}^{(l)}|t_1\right)\right) = s_{0.0552}$$

$$E(PLWA(A_3|t_1)) = E\left(\overset{5}{\underset{i=1}{\oplus}} \bar{w}_i^{*t_1}\left(\sum_{l=1}^{L} p_{i3}^{(l)} \bar{r}_{i3}^{(l)}|t_1\right)\right) = s_{0.9097}, E(PLWA(A_4|t_1))$$

$$= E\left(\overset{5}{\underset{i=1}{\oplus}} \bar{w}_i^{*t_1}\left(\sum_{l=1}^{L} p_{i4}^{(l)} \bar{r}_{i4}^{(l)}|t_1\right)\right) = s_{0.4420}$$

Then we choose the best alternative A_3 and the ranking order of alternatives is $A_3 \succ A_1 \succ A_4 \succ A_2$.

Step 5. For $t = t_2$, we solve the nonlinear programming of Model 6 based on the reference point $\bar{\bar{\xi}}_j^{*t_1} = (0.3707, 0.2731, 0.4722, 0.3725)^T$ obtained in Model 5. Model 6 converts to the following nonlinear programming problem:

$$\max\left(\bar{\bar{\xi}}_1^{t_2} + \bar{\bar{\xi}}_2^{t_2} + \bar{\bar{\xi}}_3^{t_2} + \bar{\bar{\xi}}_4^{t_2}\right)$$

$$s.t. \begin{cases} \dfrac{0.5 \cdot (2.4668\bar{w}_1^{t_2} + 1.2166\bar{w}_2^{t_2} + 1.7029\bar{w}_3^{t_2} + 0.7906\bar{w}_4^{t_2} + 1.8045\bar{w}_5^{t_2})}{0.5 \cdot (0.7649\bar{w}_1^{t_2} + 1.3153\bar{w}_2^{t_2} + 0.8062\bar{w}_3^{t_2} + 1.7678\bar{w}_4^{t_2} + 0.7945\bar{w}_5^{t_2}) + 0.5 \cdot (2.4668\bar{w}_1^{t_2} + 1.2166\bar{w}_2^{t_2} + 1.7029\bar{w}_3^{t_2} + 0.7906\bar{w}_4^{t_2} + 1.8045\bar{w}_5^{t_2})} \geq \bar{\bar{\xi}}_1^{t_2} \\[6pt] \dfrac{0.5 \cdot (0.3162\bar{w}_1^{t_2} + 1.9300\bar{w}_2^{t_2} + 1.7653\bar{w}_3^{t_2} + 0.7289\bar{w}_4^{t_2} + 2.3057\bar{w}_5^{t_2})}{0.5 \cdot (2.2023\bar{w}_1^{t_2} + 0.8515\bar{w}_2^{t_2} + 1.0713\bar{w}_3^{t_2} + 1.9121\bar{w}_4^{t_2} + 0.4373\bar{w}_5^{t_2}) + 0.5 \cdot (0.3162\bar{w}_1^{t_2} + 1.9300\bar{w}_2^{t_2} + 1.7653\bar{w}_3^{t_2} + 0.7289\bar{w}_4^{t_2} + 2.3057\bar{w}_5^{t_2})} \geq \bar{\bar{\xi}}_2^{t_2} \\[6pt] \dfrac{0.5 \cdot (1.2748\bar{w}_1^{t_2} + 1.8439\bar{w}_2^{t_2} + 1.9300\bar{w}_3^{t_2} + 1.7678\bar{w}_4^{t_2} + 1.7339\bar{w}_5^{t_2})}{0.5 \cdot (1.2748\bar{w}_1^{t_1} + 0.8062\bar{w}_2^{t_2} + 0.8515\bar{w}_3^{t_2} + 0.7906\bar{w}_4^{t_2} + 0.7945\bar{w}_5^{t_2}) + 0.5 \cdot (1.2748\bar{w}_1^{t_1} + 1.8439\bar{w}_2^{t_2} + 1.9300\bar{w}_3^{t_2} + 1.7678\bar{w}_4^{t_2} + 1.7339\bar{w}_5^{t_2})} \geq \bar{\bar{\xi}}_3^{t_2} \\[6pt] \dfrac{0.5 \cdot (0.7754\bar{w}_1^{t_2} + 1.3043\bar{w}_2^{t_2} + 2.6000\bar{w}_3^{t_2} + 1.7339\bar{w}_4^{t_2} + 1.3342\bar{w}_5^{t_2})}{0.5 \cdot (1.7962\bar{w}_1^{t_2} + 1.2555\bar{w}_2^{t_2} + 1.0050\bar{w}_3^{t_2} + 0.7945\bar{w}_4^{t_2} + 1.2369\bar{w}_5^{t_2}) + 0.5 \cdot (0.7754\bar{w}_1^{t_2} + 1.3043\bar{w}_2^{t_2} + 2.6000\bar{w}_3^{t_2} + 1.7339\bar{w}_4^{t_2} + 1.3342\bar{w}_5^{t_2})} \geq \bar{\bar{\xi}}_4^{t_2} \\[6pt] \bar{\bar{\xi}}_1^{t_2} \geq 0.3707, \bar{\bar{\xi}}_2^{t_2} \geq 0.2731, \bar{\bar{\xi}}_3^{t_2} \geq 0.4722, \bar{\bar{\xi}}_4^{t_2} \geq 0.3725 \\ 0.15 \leq \bar{w}_i^{t_2} \leq 1 \qquad (i = 1, 2, \ldots, 5) \\[6pt] \sum_{i=1}^{5} \bar{w}_i^{t_2} = 1 \end{cases}$$

By solving the model, we obtain the weight vector $\bar{w}^{*t_2} = (0.15, 0.15, 0.3341, 0.15, 0.2159)^T$ and the optimal reference point $\bar{\bar{\xi}}_j^{*t_2} = (0.6155, \ 0.5616, 0.6640, 0.5944)^T$.

According to $\bar{w}^{*t_2}$ and $\bar{H}_{t_2}$, we aggregate the decision information of the alternatives and obtain corresponding score functions:

$$E(PLWA(A_1|t_2)) = E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_2}\left(\sum_{l=1}^{L}p_{i1}^{(l)}\bar{r}_{i1}^{(l)}|t_2\right)\right) = s_{1.1924}, E(PLWA(A_2|t_2))$$

$$= E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_2}\left(\sum_{l=1}^{L}p_{i2}^{(l)}\bar{r}_{i2}^{(l)}|t_2\right)\right) = s_{0.9132}$$

$$E(PLWA(A_3|t_2)) = E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_2}\left(\sum_{l=1}^{L}p_{i3}^{(l)}\bar{r}_{i3}^{(l)}|t_2\right)\right) = s_{1.4210}, E(PLWA(A_4|t_2))$$

$$= E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_2}\left(\sum_{l=1}^{L}p_{i4}^{(l)}\bar{r}_{i4}^{(l)}|t_2\right)\right) = s_{1.2825}$$

Then we choose the best alternative A_3 and the ranking of alternatives is $A_3 \succ A_4 \succ A_1 \succ A_2$.

Step 6. For $t = t_3$, we solve nonlinear programming of Model 6 based on the obtained reference point $\bar{\xi}_j^{*t_2}$. Model 6 is converted to the nonlinear programming problem as follows:

$$\max\left(\bar{\xi}_1^{t_3} + \bar{\xi}_2^{t_3} + \bar{\xi}_3^{t_3} + \bar{\xi}_4^{t_3}\right)$$

$$s.t.\begin{cases}
\dfrac{0.5 \cdot \left(1.7000\bar{w}_1^{t_3} + 0.7280\bar{w}_2^{t_3} + 1.2042\bar{w}_3^{t_3} + 0.6374\bar{w}_4^{t_3} + 1.3158\bar{w}_5^{t_3}\right)}{0.5 \cdot \left(0.3000\bar{w}_1^{t_3} + 1.3153\bar{w}_2^{t_3} + 0.8062\bar{w}_3^{t_3} + 1.3807\bar{w}_4^{t_3} + 0.7945\bar{w}_5^{t_3}\right) + 0.5 \cdot \left(1.7000\bar{w}_1^{t_3} + 0.7280\bar{w}_2^{t_3} + 1.2042\bar{w}_3^{t_3} + 0.6374\bar{w}_4^{t_3} + 1.3158\bar{w}_5^{t_3}\right)} \geq \bar{\xi}_1^{t_3} \\
\dfrac{0.5 \cdot \left(0.7280\bar{w}_1^{t_3} + 1.4577\bar{w}_2^{t_3} + 1.5652\bar{w}_3^{t_3} + 1.1319\bar{w}_4^{t_3} + 1.3158\bar{w}_5^{t_3}\right)}{0.5 \cdot \left(1.3153\bar{w}_1^{t_3} + 0.8515\bar{w}_2^{t_3} + 0.9220\bar{w}_3^{t_3} + 0.8839\bar{w}_4^{t_3} + 0.7945\bar{w}_5^{t_3}\right) + 0.5 \cdot \left(0.7280\bar{w}_1^{t_3} + 1.4577\bar{w}_2^{t_3} + 1.5652\bar{w}_3^{t_3} + 1.1319\bar{w}_4^{t_3} + 1.3158\bar{w}_5^{t_3}\right)} \geq \bar{\xi}_2^{t_3} \\
\dfrac{0.5 \cdot \left(0.7906\bar{w}_1^{t_3} + 0.3606\bar{w}_2^{t_3} + 0.9192\bar{w}_3^{t_3} + 0.7906\bar{w}_4^{t_3} + 0.7591\bar{w}_5^{t_3}\right)}{0.5 \cdot \left(1.2748\bar{w}_1^{t_3} + 1.8248\bar{w}_2^{t_3} + 1.2021\bar{w}_3^{t_3} + 1.2748\bar{w}_4^{t_3} + 1.2947\bar{w}_5^{t_3}\right) + 0.5 \cdot \left(0.7906\bar{w}_1^{t_3} + 0.3606\bar{w}_2^{t_3} + 0.9192\bar{w}_3^{t_3} + 0.7906\bar{w}_4^{t_3} + 0.7591\bar{w}_5^{t_3}\right)} \geq \bar{\xi}_3^{t_3} \\
\dfrac{0.5 \cdot \left(1.2374\bar{w}_1^{t_3} + 1.3158\bar{w}_2^{t_3} + 0.9849\bar{w}_3^{t_3} + 1.2374\bar{w}_4^{t_3} + 2.1471\bar{w}_5^{t_3}\right)}{0.5 \cdot \left(0.7945\bar{w}_1^{t_3} + 0.7945\bar{w}_2^{t_3} + 1.1745\bar{w}_3^{t_3} + 0.7945\bar{w}_4^{t_3} + 1.0050\bar{w}_5^{t_3}\right) + 0.5 \cdot \left(1.2374\bar{w}_1^{t_3} + 1.3158\bar{w}_2^{t_3} + 0.9849\bar{w}_3^{t_3} + 1.2374\bar{w}_4^{t_3} + 2.1471\bar{w}_5^{t_3}\right)} \geq \bar{\xi}_4^{t_3} \\
\bar{\xi}_1^{t_3} \geq 0.6155, \bar{\xi}_2^{t_3} \geq 0.5616, \bar{\xi}_3^{t_3} \geq 0.6640, \bar{\xi}_4^{t_3} \geq 0.5944 \\
0.15 \leq \bar{w}_i^{t_3} \leq 1 \qquad (i = 1, 2, \ldots, 5) \\
\sum_{i=1}^{5}\bar{w}_i^{t_3} = 1
\end{cases}$$

By solving the model, we obtain the weight vector $\bar{w}^{*t_3} = (0.2281, 0.15, 0.2624, 0.15, 0.2095)^T$ and the optimal reference point $\bar{\xi}_j^{*t_3} = (0.6155, 0.5616, 0.6640, 0.5944)^T$.

According to $\bar{w}^{*t_3}$ and $\bar{H}_{t_3}$, we aggregate the decision information of the alternatives and obtain corresponding score functions:

$$E(PLWA(A_1|t_3)) = E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_3}\left(\sum_{l=1}^{L}p_{i1}^{(l)}\bar{r}_{i1}^{(l)}|t_3\right)\right) = s_{1.3314}, E(PLWA(A_2|t_3))$$

$$= E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_3}\left(\sum_{l=1}^{L}p_{i2}^{(l)}\bar{r}_{i2}^{(l)}|t_3\right)\right) = s_{1.3252}$$

$$E(PLWA(A_3|t_3)) = E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_3}\left(\sum_{l=1}^{L}p_{i3}^{(l)}\bar{r}_{i3}^{(l)}|t_3\right)\right) = s_{0.3754}, E(PLWA(A_4|t_3))$$

$$= E\left(\bigoplus_{i=1}^{5}\bar{w}_i^{*t_3}\left(\sum_{l=1}^{L}p_{i4}^{(l)}\bar{r}_{i4}^{(l)}|t_3\right)\right) = s_{1.5672}$$

Table 10. The results of comparison.

	t_1	t_2	t_3
The PLDRP method	$A_3 \succ A_1 \succ A_4 \succ A_2$	$A_3 \succ A_4 \succ A_1 \succ A_2$	$A_4 \succ A_1 \succ A_2 \succ A_3$
The PLDRP method without regret theory	$A_3 \succ A_4 \succ A_1 \succ A_2$	$A_3 \succ A_4 \succ A_2 \succ A_1$	$A_4 \succ A_2 \succ A_1 \succ A_3$
The PLWA operator	$A_3 \succ A_1 \succ A_4 \succ A_2$	$A_3 \succ A_1 \succ A_2 \succ A_4$	$A_4 \succ A_2 \succ A_1 \succ A_3$

Source: Authors' calculation.

Then we choose the best alternative A_4 and the ranking of alternatives is $A_4 \succ A_1 \succ A_2 \succ A_3$.

Based on the above results obtained by the proposed PLDRP method at the time points t_1, t_2, t_3, we get the optimal decision chain: $A_3 \rightarrow A_3 \rightarrow A_4$. The results indicate that: at the time point t_1, the government should enforce a strict lockdown policy, that is the alternative A_3, since t_1 is the early days of the outbreak. Besides, it is quite necessary to implement some public epidemic prevention measures to curb the spread of the epidemic, that is the alternative A_1. At the time point t_2, the optimal alternative is still A_3. Although the spread of COVID-19 is still serious, the production of society can be properly resumed, that is the alternative A_4 which is followed the optimal alternative A_3. At the time point t_3, the optimal alternative is A_4. Resumption of work and economic development are urgent, while the government should adopt some public epidemic prevention measures to contain the spread of COVID-19.

6.3. Comparative analysis

In this part, first, we compare the PLDRP method with the PLDRP method without regret theory to discuss the influence of regret theory on the PLDRP method. Next, the PLWA operator (Zhang et al., 2017) is employed to compare the decision-making results by the example in Section 6.2 with the PLDRP method. Note that the decision makers are endowed with same weight in the aggregating process of the PLWA operator. The concrete results of comparison are shown in Table 10.

1. Although the ranking results of the PLDRP method and the PLDRP method without regret theory are roughly consistent, there are still some small difference between them. For example, at the time point t_1, the result of PLDRP method indicates that the alternative A_1 works better than the alternative A_4, but the result of the PLDRP method without regret theory is the opposite. The reason for this is because the participation of regret theory considers the bounded rationality and regret-aversion feature of decision makers. The comparison results of the two methods show the importance of regret theory which can directly affect the ranking of alternatives, especially in the decision-making problems which exist little difference among various alternatives.

2. The optimal alternatives at the time points $t_k(k = 1, 2, 3)$ are the same as those obtained by the PLDRP method and the PLWA operator, but the concrete ranking orders vary. For example, at the time point t_2, the ranking of alternatives is $A_3 \succ A_4 \succ A_1 \succ A_2$ by the PLDRP method and the ranking is $A_3 \succ A_1 \succ A_2 \succ A_4$ by the PLWA operator. The reason lies in that the PLDRP method is dynamic

process that the last stage will affect the next stage. In other words, the result of the time point t_k will influence the decision-making process of the time point t_{k+1} in the PLDRP method.

The rankings of the PLDRP method, which consider both the vague decision information and the decision maker's bounded rationality, are different from the rankings obtained by the PLDRP method without regret theory and the PLWA operator. In most EDM situations, the decision-making problems are uncertain, risk and dynamic process. It is unreasonable to assume that the decision makers are perfectly rational and different decision stages are unconnected. The proposed PLDRP method which considers the decision maker's characteristic of bounded rationality and the interconnected relationship of different stages in the EDM process is much more effective and reliable to resolve the EDM problems.

7. Conclusions

In the paper, we propose a PLDRP method to select the optimal alternative considering the decision maker's psychological behaviour. The proposed method not only fills the theoretical gap of the reference point method with the probabilistic linguistic information, but also has significant practical value from the prospective of the dynamic evolutionary process of the EDM. The utility and regret-rejoice functions of regret theory are modified to adapt the probabilistic linguistic information. Then the concept and related operations of PLTV are presented to lay a foundation for the PLDRP model. Based on the expectation-levels of alternatives and dynamic reference points, the PLDRP model is established to maximise the reference point of emergency response. We apply the proposed method to select the optimal response strategy for the outbreak of COVID-19 in China. Furthermore, the comparative analysis is conducted to compare the ranking results obtained by the PLDRP method and other two probabilistic linguistic decision-making methods, which indicates the effectiveness of the proposed method.

The limitations of the proposed method are list as follows: (1) The PLDRP method should be generalised to the large-scale group decision-making combining different decision makers' characteristics; (2) The heterogeneous information need to be considered in the decision matrix, since different decision makers may differ in their preferences and habits when they express their assessments; (3) The time variable and PLTE are discrete in the proposed method, the continuous PLDRP method should be extended in the further research. In other words, it is necessary to extend the multi-stage decision-making process into continuous process. In the future, the time series analysis with probabilistic linguistic information can be further explored in the EDM process. The PLDRP model can be applied into the prevention phase of diseases.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Xiaomei Mi 🔟 http://orcid.org/0000-0001-8651-0033

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