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A Dynamic Emergency Decision-Making Method Based on Group Decision Making with Uncertainty Information

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Accepted: 8 September 2020 / Published online: 8 October 2020
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Abstract In emergency decision making (EDM), it is necessary to generate an effective alternative quickly. Case-based reasoning (CBR) has been applied to EDM; however, choosing the most suitable case from a set of similar cases after case retrieval remains challenging. This study proposes a dynamic method based on case retrieval and group decision making (GDM), called dynamic case-based reasoning group decision making (CBRGDM), for emergency alternative generation. In the proposed method, first, similar historical cases are identified through case similarity measurement. Then, evaluation information provided by group decision makers for similar cases is aggregated based on regret theory, and comprehensive perceived utilities for the similar cases are obtained. Finally, the most suitable historical case is obtained from the case similarities and the comprehensive perceived utilities for similar historical cases. The method is then applied to an example of a gas explosion in a coal company in China. The results show that the proposed method is feasible and effective in EDM. The advantages of the

proposed method are verified based on comparisons with existing methods. In particular, dynamic CBRGDM can adjust the emergency alternative according to changing emergencies. The results of application of dynamic CBRGDM to a gas explosion and comparison with existing methods verify its feasibility and practicability.

Keywords Case-based reasoning · Dynamic emergency decision making · Group decision making · Interval-valued Pythagorean fuzzy linguistic variable (IVPFLV) · Regret theory

1 Introduction

In recent years, several major emergency events have occurred, including the Indian Ocean Tsunami in 2004, the 12 May Wenchuan Earthquake in China in 2008, the missing Malaysian Airlines MH370 in 2014, and the fire in Rio de Janeiro, Brazil, in 2018. These disasters not only disrupted daily life, but also caused huge loss of property and lives. Moreover, the environment is affected, and secondary derivative hazards arise. Consequently, emergency decision making (EDM) has been garnering increasing attention from both national governments and scholars (Ding et al. 2019; Li and Cao 2019; Zheng et al. 2019). To reduce or eliminate all types of losses due to emergency events, an effective emergency alternative needs to be formulated in a short period (Peng and Garg 2018). However, because by nature emergency events occur suddenly and decision information contains uncertainty, emergency plans may fail, and it is difficult to deal with such events using conventional decision-making methods.

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To overcome the issues identified above, case-based reasoning (CBR), which is an artificial intelligence method, is widely applied in emergency response. For example, Yu et al. (2018) applied CBR to risk response for an urban water supply network, Fan et al. (2015) used CBR to generate project risk response strategies, and Liao et al. (2012) applied CBR to design an environmental emergency preparedness system. These methods employ the alternative of the most similar historical case as the alternative of the target case. However, in scenarios where the most similar historical case is not the most appropriate for the target case, the decision-making result is affected negatively. Therefore, it is necessary to develop a method by which the most suitable historical case can be selected from a similar case set.

Selection problems in EDM are often solved using group decision making (GDM). For example, Xu et al. (2019) proposed a large-group emergency risk decision method based on data mining of public attribute preference, to select the most suitable alternative from three alternatives. Ding and Liu (2019a) developed an integrated approach based on prospect theory and VIKOR (Vise Kriterijumska Optimizacija i Kompromisno Resenje) to solve EDM problems. Ding and Liu (2019b) presented a novel combined approach by extending the zero-sum game using the best–worst method and Pythagorean fuzzy uncertain linguistic variables. Yu et al. (2011) proposed a distance-based GDM method to select the most suitable alternative from five alternatives, to manage a chemical spill emergency. Wang et al. (2017) developed a GDM based on prospect theory to select the most suitable alternative from four alternatives for a barrier lake emergency. Ding et al. (2020) presented an EDM approach based on picture fuzzy sets and axiomatic design technique, to determine an optimal rescue plan. The above studies used crisp numbers, interval numbers, and linguistic variables to express the evaluation information. In EDM, the decision situation is uncertain, and the decision information is inaccurate; however, effectively expressing the information is important (Wan et al. 2017).

Due to the dynamic and uncertain characteristics of emergencies, scholars often adopt fuzzy theory when studying EDM (Jiang et al. 2008; Fan et al. 2014; Wang et al. 2018; Ding et al. 2019; Ding and Liu 2019a; Ding and Liu 2019b; Gao et al. 2019; Zheng et al. 2019). In particular, linguistic variables and Pythagorean fuzzy sets have been widely used in the expression of the opinions of decision makers (Zadeh et al. 1975; Wu et al. 2018; Wang and Li 2020). Recently, Du et al. (2017) proposed a new linguistic variable called interval-valued Pythagorean fuzzy linguistic variable (IVPFLV), which combines Pythagorean uncertain linguistic sets and interval-valued Pythagorean fuzzy sets. The membership degree and non-

membership degree of an IVPFLV is an interval value in the range $[0, 1]$. They can describe the evaluation of decision makers more accurately, when expressing the opinions of decision makers as precise numbers is difficult. Furthermore, several studies (Ding et al. 2019; Liu et al. 2019) have applied IVPFLVs to handle information given by decision makers in EDM with some success. Hence, IVPFLVs are suitable for situations wherein information is given by decision makers.

The purpose of GDM is to make the best decision based on the opinions of several experts. Most GDM methods assume that decision makers are completely rational. In realistic situations, decision makers often exhibit bounded rationality under risk and uncertainty. The prospect theory has been used to describe the psychological behavior of a decision maker (Ren et al. 2017; Wang et al. 2017; Dou et al. 2018; Zhang et al. 2018; Gao et al. 2019). However, there are certain limitations for instance, the aspiration levels of the attributes are required, which is difficult because they must be determined in advance. To avoid this problem, the regret theory has been used to express the psychological behavior of decision makers. The regret theory, introduced by Bell (1982) and Loomes and Sugden (1982), is an alternative behavioral decision theory that can be used to quantify the psychological behavior of regret aversion of decision makers in the decision-making process. It has been used in some studies to solve decision-making problems considering the psychological behavior of decision makers. Zhang et al. (2016) used regret theory for the decision making with an air-fighter selection problem. Peng and Yang (2017) applied regret theory and prospect theory in the decision process to solve stochastic multi-criteria decision-making problem. Therefore, GDM based on IVPFLVs and regret theory can be used to select the most suitable historical case.

In the real world, when an emergency event escalates into different stages and more information is collected over time, the emergency decision should be modified dynamically to improve the emergency response. Few studies have considered the dynamics of emergencies (Ren et al. 2017; Wang et al. 2018; Zhang et al. 2018). Therefore, it is necessary to consider the dynamic evolution of emergencies in EDM. Against this background, considering the advantages of CBR and GDM, a dynamic method based on case retrieval and GDM, called dynamic case-based reasoning group decision making (CBRGDM), is proposed to generate a suitable alternative in EDM.

The novelties of the developed approach include the following aspects: (1) Because of the dynamic nature of emergencies, our proposed method of generating emergency alternatives takes into account the adjustment of emergency alternatives. Thus, we can better deal with emergencies according to the evolution of emergencies. (2)

We use an improved GDM method to select the most feasible historical case, in which we apply IVPFLVs to represent fuzzy information and regret theory to express the decision makers' psychological behavior. (3) This method not only considers the similarity between the historical cases and the target case but also the evaluation of the decision makers. Therefore, the results are more consistent with the actual decision-making process.

The remainder of this article is organized as follows. Section 2 reviews related concepts and definitions. Section 3 describes the proposed dynamic CBRGDM method for solving EDM problems. Section 4 provides an empirical case study and a comparison analysis that illustrate the efficacy and practicability of the proposed method. Section 5 presents the conclusion and future research directions.

2 Preliminaries

In this section, the steps of case retrieval are introduced. Then, the concept of IVPFLVs and regret theory are reviewed.

2.1 Case Retrieval

Case retrieval is an important step in CBR. Its central issue is to identify similar historical cases through similarity measurement. The following are the steps involved in case retrieval:

Step 1 Calculate the attribute distance/similarity

Attribute distance is often calculated using either Manhattan distance or Euclidian distance. However, these attribute distance functions can be applied only to linear numeric attributes. To overcome this drawback, Li and Sun (2009) proposed a Gaussian distance formula. Furthermore, attribute distance formulas—that is, attribute similarity functions without the distance value—have been used frequently. Examples of these are the inverse exponential function (Fan et al. 2014) and gray correlation degree (Li and Sun 2009). The above methods are for numerical data. However, given the complexity of the data type, fuzzy attribute distance/similarity functions have also been proposed (Fan et al. 2014; Zheng et al. 2019).

Step 2 Calculate the case similarities

First, attribute weights should be determined. Attribute weights can be determined using three methods. The first is the subjective method, such as the analytic hierarchy process (Park and Han 2002). The second is the objective method, mainly statistical methods and machine learning methods, such as optimization models (Zhao and Yu 2011),

functions based on gray correlation degree (Han and Cao 2015), membrane computing (Yan et al. 2014), and neural network (Biswas et al. 2017). The third is a mixture of the two. Then, we can aggregate the attribute distance/similarity and attribute weight to obtain the case similarities. The most common method is linear weighting.

Step 3 Identify the similar historical case set

When the case similarities have been determined, the threshold of case similarity needs to be determined. In general, the decision makers make decisions based on their own experience and knowledge. Once the similarity threshold is determined, the similar case set can be obtained.

2.2 Interval-Valued Pythagorean Fuzzy Linguistic Variables

Definition 1 (Du et al. 2017) Let Ψ be a finite universe of discourse, and S be a continuous linguistic term set; then, an interval-valued Pythagorean fuzzy linguistic set (IVPFLS) in Ψ can be proposed as follows:

$$\tilde{D} = \left\{ \left\langle x, [s_{\theta}(x), [u_D^-(x), u_D^+(x)], [v_D^-(x), v_D^+(x)]] \right\rangle \mid x \in \Psi \right\} \quad (1)$$

Here, for $s_{\theta}(x) \in S$, $[u_D^-(x), u_D^+(x)]$ and $[v_D^-(x), v_D^+(x)]$ are two interval values and indicate the membership degree and non-membership degree of the element $x \in \Psi$, respectively, $[u_D^-(x), u_D^+(x)] \in [0, 1]$, $[v_D^-(x), v_D^+(x)] \in [0, 1]$, and for each $\gamma \in [u_D^-(x), u_D^+(x)]$ and $\eta \in [v_D^-(x), v_D^+(x)]$,

they satisfy $\gamma^2 + \eta^2 \leq 1$. For simplicity, the expression $\tilde{d} = \left\{ \left\langle [s_{\theta}(x), [u_D^-(x), u_D^+(x)], [v_D^-(x), v_D^+(x)]] \right\rangle \right\}$ is called an interval-valued Pythagorean fuzzy linguistic number (IVPFLN).

Definition 2 (Ding et al. 2019) Let $\tilde{d} = \left\{ \left\langle [s_{\theta}(x), [u_D^-(x), u_D^+(x)], [v_D^-(x), v_D^+(x)]] \right\rangle \right\}$ be an IVPFLN; it can be transformed into an interval-valued variable, which is shown as:

$$A(\tilde{d}) = \left[\frac{\theta}{2} (1 + (u_D^-(x))^2 - (u_D^+(x))^2), \frac{\theta}{2} (1 + (v_D^-(x))^2 - (v_D^+(x))^2) \right] \quad (2)$$

Definition 3 (Du et al. 2017) Let $\tilde{D} = \{\tilde{d}_1, \tilde{d}_2, \dots, \tilde{d}_j, \dots, \tilde{d}_n\}$ be a vector of IVPFLNs, where

$\tilde{d}_j = \left\{ \left\langle [s_{\theta_j}(x), [u_{d_j}^-(x), u_{d_j}^+(x)], [v_{d_j}^-(x), v_{d_j}^+(x)]] \right\rangle \right\}$; then, the interval-valued Pythagorean fuzzy linguistic weighted averaging (IVPFLWA) operator is defined as follows:

$$\begin{aligned} & IVPFLWA(\tilde{d}_1, \tilde{d}_2, \dots, \tilde{d}_n) \\ &= \left\{ \left\langle S_{\sum_{j=1}^n w_j \theta_j}, \left[\sqrt{1 - \prod_{j=1}^n (1 - u_{d_j}^2)^{w_j}}, \right. \right. \right. \\ & \quad \left. \left. \times \sqrt{1 - \prod_{j=1}^n (1 - u_{d_j}^2)^{w_j}} \right] \left[\prod_{j=1}^n v_{d_j}^{-w_j}, \prod_{j=1}^n v_{d_j}^{+w_j} \right] \right\rangle \right\} \end{aligned} \quad (3)$$

Here, w_j is the weight of $\tilde{d}_j$, satisfying $0 \leq w_j \leq 1$ ($j = 1, 2, \dots, n$) and $\sum_{j=1}^n w_j = 1$.

2.3 Regret Theory

Decision makers' psychological behaviors are expressed by regret theory (Laciana and Weber 2008) in this study. Regret theory holds that the decision maker not only pays attention to the results obtained by the selected alternative but also pays attention to the possible results if other alternatives are chosen (Bell et al. 1982; Loomes et al. 1982). Therefore, the perceived utility of decision makers consists of two parts: the utility function of the current result and the regret-rejoice function in comparison with other results.

The decision maker's perceived utility value of alternative A_i ($i \in \{1, 2, \dots, m\}$), proposed by Quiggin et al. (1997), is defined as follows:

$$u_i = v(x_i) + R(v(x_i) - v(x^*)) \quad (4)$$

where x_i represents the result of alternative A_i , $x^* = \max\{x_i | i \in \{1, 2, \dots, m\}\}$, $v(x_i)$ represents the utility value of x_i , and $R(v(x_i) - v(x^*))$ represents the regret-rejoice function. When $R(v(x_i) - v(x^*)) > 0$, $R(v(x_i) - v(x^*))$ denotes the rejoice value. When $R(v(x_i) - v(x^*)) < 0$, $R(v(x_i) - v(x^*))$ denotes the regret value.

According to Chorus (2012), the utility function $v(x_i)$ can be defined as follows:

$$v(x_i) = (x_i)^\alpha \quad (5)$$

Here, α is the risk aversion coefficient of a decision maker, $0 < \alpha < 1$. The greater the value of α , the greater the degree of risk aversion of a decision maker.

According to Zhang et al. (2016), the regret-rejoice function $R(v(x_i) - v(x^*))$ can be defined as follows:

$$R(v(x_i) - v(x^*)) = 1 - \exp(-\delta(v(x_i) - v(x^*))) \quad (6)$$

Here, δ is the risk aversion coefficient of a decision maker. The greater the value of δ , the greater the degree of

risk aversion of a decision maker. Figure 1 shows the effect of δ on the regret-rejoice function $R(v(x_i) - v(x^*))$.

3 A Dynamic Emergency Decision-Making Method

In this section, a dynamic CBR method is presented for generating alternatives in a GDM environment. Assuming $Z = \{z_1, z_2, \dots, z_h\}$ is the state set, where z_t represents the t th state, namely, when the emergency develops into z_t , the alternative should be considered to adjust, $t \in \{1, 2, \dots, h\}$. Figure 2 shows the basic procedure of the proposed method. First, the similar historical cases are identified by searching the historical case base. Second, the evaluated values of the similar historical cases are obtained by aggregating the evaluations of the decision makers with the assistance of the regret theory. Third, the alternative of the target case for state z_t is obtained from the case similarities between the target case in state z_t and the similar historical cases and the comprehensive utilities of the similar historical cases. Furthermore, when the emergency develops into the state z_{t+1} , we should consider the adjustment of alternative according to the similarity between the most suitable historical case in state z_t and the target case in state z_{t+1} .

3.1 Identifying Similar Historical Cases

This section describes a method to identify the similar historical cases according to the target case and the historical case base.

There are two types of cases in the case base: historical cases and the target case. Let c_j denote the j th historical case, $j \in \{1, 2, \dots, n\}$, and $c_0^{(t)}$ denote the target case in state z_t . Let p_i denote the i th problem attribute, $i \in \{1, 2, \dots, m\}$. Let x_{ji} denote the problem attribute value with regard to the historical case c_j . Let $x_{0i}^{(t)}$ denote the problem attribute value with regard to the target case $c_0^{(t)}$. Let w_i^P denote the weight of attribute p_i , such that $\sum_{i=1}^m w_i^P = 1$, and $0 \leq w_i^P \leq 1$.

In the real case base, the type of case attribute is diverse. Fan et al. (2014) and Zheng et al. (2019) proposed hybrid similarity measurement. Fan et al. (2014) considered five formats of attribute values: crisp symbols, crisp numbers, interval numbers, fuzzy linguistic variables, and random variables. Zheng et al. (2019) considered four formats of attribute values: crisp numbers, interval numbers, multi-granularity linguistic variables, and intuitionistic fuzzy numbers. In this study, we considered the following formats of attribute values: crisp numbers, interval numbers,

Fig. 1 Regret-rejoice function
 $R(v(x_i) - v(x^*))$

and fuzzy linguistic variables. On this basis, the case similarity measurement can be defined as follows.

Step 1 Calculate the attribute distances

When attributes x_{ji} and $x_{0i}^{(t)}$ are crisp numbers, the attribute distance $\Delta(x_{0i}^{(t)}, x_{ji})$ is given as follows:

$$\Delta(x_{0i}^{(t)}, x_{ji}) = \frac{\sqrt{(x_{0i}^{(t)} - x_{ji})^2}}{\Delta_i^{(t)\max}} \quad (7)$$

Here, $\Delta_i^{(t)\max} = \max\{\sqrt{(x_{0i}^{(t)} - x_{ji})^2} | j \in \{1, 2, \dots, n\}\}$.

When attributes x_{ji} and $x_{0i}^{(t)}$ are interval numbers, that is, $x_{ji} = [x_{ji}^-, x_{ji}^+]$ and $x_{0i}^{(t)} = [x_{0i}^{(t)-}, x_{0i}^{(t)+}]$, the attribute distance $\Delta(x_{0i}^{(t)}, x_{ji})$ is given as follows:

$$\Delta(x_{0i}^{(t)}, x_{ji}) = \frac{\sqrt{(x_{0i}^{(t)-} - x_{ji}^-)^2 + (x_{0i}^{(t)+} - x_{ji}^+)^2}}{\Delta_i^{(t)\max}} \quad (8)$$

Here, $\Delta_i^{(t)\max} = \max\{\sqrt{(x_{0i}^{(t)-} - x_{ji}^-)^2 + (x_{0i}^{(t)+} - x_{ji}^+)^2} | j \in \{1, 2, \dots, n\}\}$

When attributes x_{ji} and $x_{0i}^{(t)}$ are fuzzy linguistic variables, they can be transformed into triangular fuzzy numbers. According to Jiang et al. (2008), a linguistic variable $\tilde{y}_k$ ($0 \leq k \leq T-1$) can be represented using the triangular fuzzy number $\tilde{y}_k = (y_k^a, y_k^b, y_k^c)$, that is,

$$\tilde{y}_k = (y_k^a, y_k^b, y_k^c) = (\max((k-1)/T, 0), k/T, \min((k+1)/T, 1)) \quad (9)$$

Here, y_k^a , y_k^b , and y_k^c are real numbers, $0 \leq y_k^a \leq y_k^b \leq y_k^c$. T is the number of linguistic variables.

Thus, the attribute distance $\Delta(x_{0i}^{(t)}, x_{ji})$ is given as follows:

$$\Delta(x_{0i}^{(t)}, x_{ji}) = \frac{\sqrt{(x_{0i}^{(t)a} - x_{ji}^a)^2 + (x_{0i}^{(t)b} - x_{ji}^b)^2 + (x_{0i}^{(t)c} - x_{ji}^c)^2}}{\Delta_i^{(t)\max}} \quad (10)$$

Here, $\Delta_i^{(t)\max} =$

$$\max\{\sqrt{(x_{0i}^{(t)a} - x_{ji}^a)^2 + (x_{0i}^{(t)b} - x_{ji}^b)^2 + (x_{0i}^{(t)c} - x_{ji}^c)^2} | j \in \{1, 2, \dots, n\}\}.$$

Fig. 2 Flowchart of the proposed dynamic emergency decision-making method

Step 2 Calculate the case similarities $\text{Sim}(c_0^{(t)}, c_j)$

Based on the attribute distance $\Delta(x_{0i}^{(t)}, x_{ji})$, the case similarity $\text{Sim}(c_0^{(t)}, c_j)$ can be obtained as follows:

$$\text{Sim}(c_0^{(t)}, c_j) = 1 - \sum_{i=1}^m w_i^p \Delta(x_{0i}^{(t)}, x_{ji}) \quad (11)$$

Here, w_i^p is given by the decision maker according to his/her experience. Clearly, $\text{Sim}(c_0^{(t)}, c_j) \in [0, 1]$. The greater the value of $\text{Sim}(c_0^{(t)}, c_j)$, the more similar the historical case c_j is to the target case $c_0^{(t)}$.

Step 3 Identify the similar historical case set $C^{(t)\text{Sim}}$

Decision makers select the top λ ($0 \leq \lambda \leq n$) historical cases according to their experience. If $\text{Sim}(c_0^{(t)}, c_j)$ ranks the top λ , the corresponding historical case c_j will be regarded as the similar historical case. On this basis, the similar historical case set $C^{(t)\text{Sim}}$ in state z_t is formed, where $C^{(t)\text{Sim}} = \{G_a^t | a \in \{1, 2, \dots, \lambda\}\}$, where $G_a^t \in \{c_j\}$.

3.2 Determine the Evaluated Value of the Similar Historical Cases

Several decision makers evaluate the alternatives of the similar historical cases for applicability to the target case $c_0^{(t)}$.

Let e_r denote the r th decision maker, $r \in \{1, 2, \dots, M\}$. Their corresponding weight vector is

$W = \{w_1^e, w_2^e, \dots, w_M^e\}$, such that $\sum_{r=1}^M w_r^e = 1$, and $0 \leq w_r^e \leq 1$. Let R_l denote the l th evaluation attribute, $l \in \{1, 2, \dots, L\}$. Let $W^{v(t)} = \{w_1^{v(t)}, w_2^{v(t)}, \dots, w_L^{v(t)}\}$ be the evaluation attribute weight vector in state z_t , such that $\sum_{l=1}^L w_l^{v(t)} = 1$, and $0 \leq w_l^{v(t)} \leq 1$. Let $q_{al}^{r(t)}$ denote the evaluation attribute value of the r th expert with regard to the similar historical case $G_{al}^{(t)}$ in state z_t , and $q_{al}^{r(t)}$ is an IVPFLV, that is, $q_{al}^{r(t)} = \{<[s_{\theta al}^{r(t)}, [u_{al}^{r(t)-}, u_{al}^{r(t)+}], [v_{al}^{r(t)-}, v_{al}^{r(t)+}]]>\}$.

Step 1 Aggregate the evaluation attribute value of decision makers $q_{al}^{r(t)}$ into group evaluation $p_{al}^{(t)}$

According to the IVPFLWA operator, the group evaluation $p_{al}^{(t)}$ is gained as

$$\begin{aligned} p_{al}^{(t)} &= \{S_{\beta}, [\mu_{al}^{(t)-}, \mu_{al}^{(t)+}], [v_{al}^{(t)-}, v_{al}^{(t)+}]\} \\ &= \text{IVPFLWA}(q_{al}^{1(t)}, q_{al}^{2(t)}, \dots, q_{al}^{M(t)}) \\ &= \left\{ \left\langle S_{\sum_{r=1}^M w_r^e \theta_{al}}, \left[\sqrt{1 - \prod_{r=1}^M (1 - (u_{al}^{r(t)-})^2)^{w_r^e}}, \right. \right. \right. \\ &\quad \left. \left. \sqrt{1 - \prod_{r=1}^M (1 - (u_{al}^{r(t)+})^2)^{w_r^e}}, \left[\prod_{r=1}^M (v_{al}^{r(t)-})^{w_r^e}, \prod_{r=1}^M (v_{al}^{r(t)+})^{w_r^e} \right] \right] \right\rangle \right\} \end{aligned} \quad (12)$$

Step 2 Calculate the attribute utilities

Step 2.1 Transform $p_{al}^{(t)}$ into an interval value $p_{al}^{(t)} = [p_{al}^{(t)-}, p_{al}^{(t)+}]$

According to the transformation method proposed by Ding et al. (2019) and the group evaluation $p_{al}^{(t)}$, the interval-valued evaluation information is obtained as follows:

$$\begin{aligned} p_{al}^{(t)} &= [p_{al}^{(t)-}, p_{al}^{(t)+}] \\ &= \left[\frac{\beta}{2} (1 + (u_{al}^{(t)-})^2 - (u_{al}^{(t)+})^2), \frac{\beta}{2} (1 + (v_{al}^{(t)-})^2 - (v_{al}^{(t)+})^2) \right] \end{aligned} \quad (13)$$

Step 2.2 Normalize the interval value $\bar{p}_{al}^{(t)} = [\bar{p}_{al}^{(t)-}, \bar{p}_{al}^{(t)+}]$

Based on the interval value $p_{al}^{(t)} = [p_{al}^{(t)-}, p_{al}^{(t)+}]$, the normalized interval value $\bar{p}_{al}^{(t)} = [\bar{p}_{al}^{(t)-}, \bar{p}_{al}^{(t)+}]$ is derived as follows:

$$\bar{p}_{al}^{(t)-} = \begin{cases} (p_{al}^{(t)-} - g_l^{(t)}) / (q_l^{(t)} - g_l^{(t)}), & p_{al}^{(t)} \in N_b \\ (q_l^{(t)} - p_{al}^{(t)-}) / (q_l^{(t)} - g_l^{(t)}), & p_{al}^{(t)} \in N_c \end{cases} \quad (14)$$

$$\bar{p}_{al}^{(t)+} = \begin{cases} (p_{al}^{(t)+} - g_l^{(t)}) / (q_l^{(t)} - g_l^{(t)}), & p_{al}^{(t)} \in N_b \\ (q_l^{(t)} - p_{al}^{(t)+}) / (q_l^{(t)} - g_l^{(t)}), & p_{al}^{(t)} \in N_c \end{cases} \quad (15)$$

Here, $g_l^{(t)} = \min\{p_{al}^{(t)-} | a \in \{1, 2, \dots, \lambda\}\}$,

$q_l^{(t)} = \max\{p_{al}^{(t)+} | a \in \{1, 2, \dots, \lambda\}\}$, N_b represents the benefit attribute, and N_c represents the cost attribute.

Step 2.3 Calculate the attribute utility $\varphi_{al}^{(t)}$

As the interval number comes from the calculation of random sampling, the attribute value π is considered a random value in the interval $[\bar{p}_{al}^{(t)-}, \bar{p}_{al}^{(t)+}]$ and obeys a certain distribution. Based on this, the utility $\varphi_{al}^{(t)}$ is derived as follows:

$$\varphi_{al}^{(t)} = \int_{\bar{p}_{al}^{(t)-}}^{\bar{p}_{al}^{(t)+}} v(\pi) f_{al}^{(t)}(\pi) d\pi \quad (16)$$

Here, $v(\pi)$ is the utility function. As the decision maker is risk-averse in EDM, it is more appropriate to use a concave function with a monotonically increasing trend. Therefore, the power function is employed as the utility function in this study, that is, $v(\pi) = \pi^\alpha$. $f_{al}^{(t)}(\pi)$ is the probability distribution function, and it usually obeys uniform and normal distributions. In this study, we considered that $f_{al}^{(t)}(\pi)$ obeys a uniform distribution, that is, $f_{al}^{(t)}(\pi) = \frac{1}{\bar{p}_{al}^{(t)+} - \bar{p}_{al}^{(t)-}}$.

Step 3 Calculate the regret-rejoice value $h_{al}^{(t)}$ of every attribute

According to Eq. 6, the regret-rejoice value $h_{al}^{(t)}$ is obtained as follows:

$$h_{al}^{(t)} = 1 - \exp[-\delta(\varphi_{al}^{(t)} - \varphi_l^{(t)*})] \quad (17)$$

Here, $\varphi_l^{(t)*} = \max\{\varphi_{al}^{(t)} | a \in \{1, 2, \dots, \lambda\}\}$.

Step 4 Calculate the perceived utilities $Q_{al}^{(t)}$

According to Eq. 4, the perceived utility can be expressed as follows:

$$Q_{al}^{(t)} = \varphi_{al}^{(t)} + h_{al}^{(t)} \quad (18)$$

Step 5 Calculate the comprehensive perceived utilities

Step 5.1 Determine the evaluation attribute weights $w_l^{v(t)}$

The distance-based method (Yu et al. 2011) can be used to determine the weights of the attributes in accordance with the distance between the attribute value and the extreme value. According to the distance-based weighting method, the greater the positive distance, the more important is the attribute. Therefore, a higher weight value should be assigned to the attribute. The distance-based weighting method can be described as follows:

$$d_l^{(t)+} = \sqrt{\sum_{a=1}^{\lambda} (Q_{al}^{(t)} - Q_l^{(t)\max})^2} \quad (19)$$

$$d_l^{(t)-} = \sqrt{\sum_{a=1}^{\lambda} (Q_{al}^{(t)} - Q_l^{(t)\min})^2} \quad (20)$$

$$\chi_l^{(t)} = \frac{d_l^{(t)+}}{d_l^{(t)+} + d_l^{(t)-}} \quad (21)$$

$$w_l^{v(t)} = \frac{\chi_l^{(t)}}{\sum_{l=1}^L \chi_l^{(t)}} \quad (22)$$

where $Q_l^{(t)\max} = \max_{1 \leq a \leq \lambda} \{Q_{al}^{(t)}\}$, $Q_l^{(t)\min} = \min_{1 \leq a \leq \lambda} \{Q_{al}^{(t)}\}$.

Step 5.2 Determine the comprehensive perceived utility

$$V_a^{(t)} = \sum_{l=1}^L w_l^{v(t)} Q_{al}^{(t)} \quad (23)$$

Clearly, a higher value of $V_a^{(t)}$ corresponds to a better alternative.

3.3 Generate the Alternative

Step 1 Calculate the overall utilities of the similar historical cases

Once the case similarity with regard to similar historical cases in state z_t $Sim(c_0^{(t)}, c_a)$ and the comprehensive perceived utility in state z_t $V_a^{(t)}$ are obtained, the overall utilities of each similar historical case in state z_t $U_a^{(t)}$ can be calculated using the simple additive method, as follows:

$$U_a^{(t)} = Sim(c_0^{(t)}, c_a) * V_a^{(t)} \quad (24)$$

The greater the value of $U_a^{(t)}$, the better the alternative of historical case c_j in state z_t .

Step 2 Obtain the most similar historical case

Based on the value of $U_a^{(t)}$, the ranking of the similar historical cases can be obtained. According to the ranking of the similar historical cases, the most similar historical case $c^{(t)*}$ can be gain. Then, the decision makers can select or adjust the alternative of the best similar historical case $c^{(t)*}$ to cope with the emergency.

3.4 Alternative Dynamic Adjustment

Let $t = t + 1$, that is, the target case develops into $c_0^{(t+1)}$. Then we should consider the adjustment of alternative. If $Sim(c_0^{(t+1)}, c^{(t)*}) \geq \xi$, the alternative generated at state z_t continues to be used, where ξ is the state case similarity threshold and is given by decision maker(s). Otherwise, the alternative generated at state z_t should be adjusted by repeating the above steps to generate a new alternative.

4 Illustrative Example

In this section, the emergency alternative for a gas explosion is generated as an example to demonstrate the applicability and practicability of the proposed dynamic CBRGDM method.

4.1 Implementation and Results

Company A is a coal company in area B of China. To better deal with gas explosions, company A collected 10 historical cases $(c_1, c_2, \dots, c_{10})$. A gas explosion that occurred recently is considered the target case $c_0^{(t)}$. The emergency response to gas explosion is divided into two states: one is gold rescue within 72 h, and the other is urgent rescue within 4–10 days. Five attributes are considered for every case: the number of underground personnel (p_1 , unit: person), gas concentration (p_2 , unit: %), CO concentration (p_3 , unit: %), ventilation (p_4), and O₂ concentration (p_5 , unit: %). The attribute weight vector provided by the decision makers is $w^P = \{0.2, 0.2, 0.2, 0.2, 0.2\}$. Among them, p_1 is a crisp number, p_2 , p_3 , and p_5 are interval numbers, and p_4 is a linguistic variable, whose linguistic assessment set is $S^1 = \{DB : \text{definitely bad}, VB : \text{very bad}, B : \text{bad}, M : \text{medium}, G : \text{good}, VG : \text{very good}, DG : \text{definitely good}\}$. Table 1 lists the attribute values of the historical cases and the target case. The decision makers determine the value of λ as four. Three decision makers $\{e_1, e_2, e_3\}$ were invited to make decision for the emergency alternative. They preferred four criteria, including the casualty reduction rate (R_1), property loss rate (R_2), response timeliness (R_3), and control effect (R_4). For each state, the linguistic evaluations given by the three decision makers for the similar case set

Table 1 Problem attributes for the historical cases and the target case

	p_1	p_2	p_3	p_4	p_5
c_1	230	[0.13, 0.21]	[0.40, 0.53]	M	[0.03, 0.07]
c_2	128	[0.14, 0.29]	[0.22, 0.35]	DG	[0.09, 0.13]
c_3	116	[0.12, 0.22]	[0.13, 0.31]	DG	[0.04, 0.06]
c_4	185	[0.12, 0.23]	[0.46, 0.67]	G	[0.04, 0.06]
c_5	147	[0.07, 0.13]	[0.12, 0.32]	VG	[0.06, 0.07]
c_6	184	[0.15, 0.21]	[0.45, 0.63]	M	[0.08, 0.10]
c_7	132	[0.06, 0.14]	[0.17, 0.26]	G	[0.04, 0.05]
c_8	178	[0.12, 0.18]	[0.32, 0.47]	B	[0.03, 0.06]
c_9	165	[0.15, 0.23]	[0.28, 0.37]	G	[0.05, 0.08]
c_{10}	218	[0.08, 0.17]	[0.42, 0.65]	VG	[0.03, 0.06]
$c_0^{(1)}$	152	[0.12, 0.22]	[0.53, 0.63]	G	[0.05, 0.07]

are represented by IVPFLNs based on the following linguistic term set:

$$S^2 = \{s_0 = \text{very poor}, s_1 = \text{poor}, s_2 = \text{slightly poor}, s_3 = \text{fair}, s_4 = \text{slightly good}, s_5 = \text{good}, s_6 = \text{very good}\}.$$

Owing to space limitations, we only list the first state z_1 evaluation information, as listed in Table 2. The state case similarity threshold ξ is given as 0.8 by the decision makers.

The decision process and results of the proposed CBRGDM method for generating the most suitable alternative in two states are summarized as follows.

First, we introduce the steps of generating the alternative in state z_1 .

Stage 1 Identify the similar historical cases

Step 1 Calculate the attribute distances

For crisp attributes, the attribute distance $\Delta(x_{0i}^{(1)}, x_{ji})$ is calculated by Eq. 7; for interval number attributes, the attribute distance $\Delta(x_{0i}^{(1)}, x_{ji})$ is calculated by Eq. 8; for fuzzy linguistic variable attributes, the attribute distance $\Delta(x_{0i}^{(1)}, x_{ji})$ is calculated by Eqs. 9–10, and the computation results can be found in Table 3.

Step 2 Calculate the case similarities

Using Eq. 11, we can determine the case similarity $\text{Sim}(c_0^{(1)}, c_j)(j = 1, 2, \dots, n)$, that is, $\text{Sim}(c_0^{(1)}, c_1) = 0.6689$, $\text{Sim}(c_0^{(1)}, c_2) = 0.2620$, $\text{Sim}(c_0^{(1)}, c_3) = 0.4968$, $\text{Sim}(c_0^{(1)}, c_4) = 0.7101$, $\text{Sim}(c_0^{(1)}, c_5) = 0.4603$, $\text{Sim}(c_0^{(1)}, c_6) = 0.6079$, $\text{Sim}(c_0^{(1)}, c_7) = 0.4924$, $\text{Sim}(c_0^{(1)}, c_8) = 0.4913$, $\text{Sim}(c_0^{(1)}, c_9) = 0.7378$, $\text{Sim}(c_0^{(1)}, c_{10}) = 0.5011$.

Step 3 Identify the similar historical case set

Decision makers select the top four historical cases according to their experience. Hence, a similar case set is determined as $G^{(1)\text{Sim}} = \{G_1^{(1)}, G_2^{(1)}, G_3^{(1)}, G_4^{(1)}\} = \{c_1, c_4, c_6, c_9\}$.

Stage 2 Determine the evaluated value of the similar historical cases

Step 1 To avoid loss of generality, we assume equal weight w_r^e for all experts. Using Eq. 12, we aggregate the IVPFLN evaluations of the three decision makers $q_{al}^{r(1)}$ into the group evaluation $p_{al}^{(1)}$. The results are shown in Table 4.

Step 2 Using Eq. 13, the group IVPFLN evaluations $p_{al}^{(1)}$ are transformed into the interval value $p_{al}^{(1)} = [p_{al}^{(1)-}, p_{al}^{(1)+}]$. The interval values $p_{al}^{(1)}$ are normalized as $\bar{p}_{al}^{(1)} = [\bar{p}_{al}^{(1)-}, \bar{p}_{al}^{(1)+}]$ using Eqs. 14 and 15. Table 5 lists the results. The utility value $\varphi_{al}^{(1)}$ is calculated using Eq. 16.

Step 3 The regret-rejoice value $h_{al}^{(1)}$ is calculated using Eq. 17.

Step 4 The perceived utility $Q_{al}^{(1)}$ is obtained using Eq. 18. Table 6 lists the results.

Step 5 According to Eqs. 19–22, the evaluation attribute weights $w_l^{v(1)}$ are obtained as $w_1^{v(1)} = 0.2321$, $w_2^{v(1)} = 0.2230$, $w_3^{v(1)} = 0.2615$, and $w_4^{v(1)} = 0.2835$. According to Eq. 23, the comprehensive perceived utility $V_a^{(1)}$ is calculated as $V_1^{(1)} = 0.5822$, $V_2^{(1)} = 0.6640$, $V_3^{(1)} = 0.1023$, and $V_4^{(1)} = 0.6385$.

Stage 3 Generate the alternative

Step 1 According to Eq. 24, the overall utilities of each similar historical case $U_a^{(1)}$ is obtained as follows: $U_1^{(1)} = 0.3539$, $U_2^{(1)} = 0.4715$, $U_3^{(1)} = 0.0671$, and $U_4^{(1)} = 0.4711$.

Step 2 Clearly, the greater the overall utility, the more suitable is the alternative of the similar historical case. Consequently, according to the obtained overall utilities, $U_2^{(1)}$ is the maximum and the historical case c_4 can be selected as the most suitable historical case $c^{(1)*}$.

Stage 4 Alternative dynamic adjustment

In the second state z_2 , the target case is $c_0^{(2)} = \{100, [0.08, 0.10], [0.2, 0.3], VG, [0.01, 0.02]\}$. According to Eqs. 7–11, the case similarity $\text{Sim}(c_0^{(2)}, c^{(1)*}) = 0.8139$. As $\text{Sim}(c_0^{(2)}, c^{(1)*}) > \xi$, the decision makers determine that the alternative in state z_1 is continued to be used.

It is indicated from the computation results, obtained by using the proposed dynamic CBRGDM, that the retrieved historical case c_4 has the most resemblance to the target case in state z_1 , and no adjustment is required in state z_2 . Thus, the alternative for the historical case c_4 can be considered as that for Company A.

4.2 Comparative Analysis and Advantages of the Proposed Approach

In this subsection, we compare some existing methods with the proposed approach and summarize some advantages of the proposed approach.

4.2.1 Comparative Analysis

In this subsection, to verify the effectiveness and practicability of the proposed CBRGDM approach, we compare it with four existing EDM methods, including the EDM based on the CBR method (Fan et al. 2014), called CBR-F; the method based on the CBR and IVPFLWA operator (Du et al. 2017), called CBR-IVPFLWA; the GDM method

based on the prospect theory (Wang et al. 2015), called CBR-GDMPT; and the GDM method based on IVPFLV and prospect theory (Ding et al. 2019), called CBR-IVPFLVPT. The most similar historical cases based on the five approaches for the above case study are shown in Table 7. Some of the observations made from Table 7 are as follows:

1. CBR-F obtains the most similar historical case as a reference for the target case only by case retrieval. The result obtained using the CBR-F method is c_9 . This is because the CBR-F does not consider the opinions of decision makers on similar historical case sets. However, in reality, the most similar historical case is not the most suitable for the target case (Zheng et al. 2018). Therefore, choosing the most appropriate historical case based on the evaluation of similar
2. The calculated result using the method CBR-IVPFLWA is $c_9 > c_4 > c_1 > c_6$. This is different from that obtained using the proposed method. This is because CBR-IVPFLWA does not consider the psychological behavior of decision makers. In a real decision-making process, decision makers have their own preferences and psychological behavior; therefore, considering the psychological behavior is more reasonable.
3. The calculated result obtained using the method based on CBR-GDMPT is $c_4 > c_1 > c_9 > c_6$. The most suitable case is c_4 , which is the same as that obtained using the proposed method. However, the prospect theory requires determination of the reference point in advance. Furthermore, there are several parameters

Table 2 Evaluation information of the similar historical cases in state z_1

	R_1	R_2	R_3	R_4
e_1	$G_1^{(1)}$	$\langle s_6, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_4, [0.6, 0.7], [0.3, 0.4] \rangle$	$\langle s_3, [0.7, 0.8], [0.2, 0.3] \rangle$
	$G_2^{(1)}$	$\langle s_5, [0.5, 0.6], [0.3, 0.4] \rangle$	$\langle s_6, [0.5, 0.7], [0.3, 0.4] \rangle$	$\langle s_4, [0.7, 0.9], [0.1, 0.2] \rangle$
	$G_3^{(1)}$	$\langle s_4, [0.6, 0.7], [0.3, 0.4] \rangle$	$\langle s_4, [0.5, 0.6], [0.4, 0.5] \rangle$	$\langle s_6, [0.6, 0.7], [0.3, 0.4] \rangle$
	$G_4^{(1)}$	$\langle s_7, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_6, [0.5, 0.6], [0.4, 0.5] \rangle$
e_2	$G_1^{(1)}$	$\langle s_7, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$
	$G_2^{(1)}$	$\langle s_5, [0.4, 0.6], [0.4, 0.5] \rangle$	$\langle s_6, [0.8, 0.9], [0.1, 0.2] \rangle$	$\langle s_4, [0.8, 0.9], [0.1, 0.2] \rangle$
	$G_3^{(1)}$	$\langle s_4, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_4, [0.6, 0.7], [0.3, 0.4] \rangle$	$\langle s_6, [0.7, 0.8], [0.1, 0.3] \rangle$
	$G_4^{(1)}$	$\langle s_7, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.9], [0.1, 0.2] \rangle$	$\langle s_6, [0.6, 0.7], [0.2, 0.4] \rangle$
e_3	$G_1^{(1)}$	$\langle s_7, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.8, 0.9], [0.1, 0.2] \rangle$	$\langle s_6, [0.7, 0.8], [0.2, 0.3] \rangle$
	$G_2^{(1)}$	$\langle s_5, [0.8, 0.9], [0.1, 0.2] \rangle$	$\langle s_6, [0.8, 0.9], [0.1, 0.2] \rangle$	$\langle s_7, [0.7, 0.9], [0.1, 0.2] \rangle$
	$G_3^{(1)}$	$\langle s_6, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_8, [0.5, 0.7], [0.3, 0.4] \rangle$
	$G_4^{(1)}$	$\langle s_7, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_6, [0.6, 0.7], [0.3, 0.4] \rangle$

Table 3 The computation results of attribute distance between historical cases and the target case

Historical cases	$\Delta(x_{01}^{(1)}, x_{j1})$	$\Delta(x_{02}^{(1)}, x_{j2})$	$\Delta(x_{03}^{(1)}, x_{j3})$	$\Delta(x_{04}^{(1)}, x_{j4})$	$\Delta(x_{04}^{(1)}, x_{j4})$
c_1	0.4231	0.1374	0.3177	0.5000	0.2774
c_2	0.3077	0.7071	0.8092	0.8660	1.0000
c_3	0.4615	0.0000	0.9923	0.8660	0.1961
c_4	1.0000	0.0971	0.1562	0.0000	0.1961
c_5	0.0641	1.0000	0.9957	0.5000	0.1387
c_6	0.4103	0.3071	0.1550	0.5000	0.5883
c_7	0.2564	0.9713	1.0000	0.0000	0.3101
c_8	0.3333	0.3885	0.5114	1.0000	0.3101
c_9	0.1667	0.3071	0.6987	0.0000	0.1387
c_{10}	0.8462	0.6219	0.2166	0.5000	0.3101

Table 4 The results of group evaluation $p_{al}^{(1)}$

	$p_{a1}^{(1)}$	$p_{a2}^{(1)}$	$p_{a3}^{(1)}$	$p_{a4}^{(1)}$
$G_1^{(1)}$	$\langle s_7, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_6, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_6, [0.6, 0.7], [0.3, 0.4] \rangle$
$G_2^{(1)}$	$\langle s_6, [0.6, 0.8], [0.3, 0.4] \rangle$	$\langle s_6, [0.7, 0.9], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.9], [0.1, 0.2] \rangle$	$\langle s_7, [0.6, 0.8], [0.2, 0.3] \rangle$
$G_3^{(1)}$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_4, [0.6, 0.7], [0.3, 0.4] \rangle$	$\langle s_7, [0.6, 0.7], [0.3, 0.4] \rangle$	$\langle s_5, [0.5, 0.7], [0.3, 0.4] \rangle$
$G_4^{(1)}$	$\langle s_7, [0.6, 0.8], [0.2, 0.3] \rangle$	$\langle s_5, [0.7, 0.8], [0.2, 0.3] \rangle$	$\langle s_6, [0.6, 0.7], [0.2, 0.4] \rangle$	$\langle s_5, [0.8, 0.9], [0.1, 0.2] \rangle$

Table 5 Normalized interval-valued evaluation information

	R_1	R_2	R_3	R_4
$G_1^{(1)}$	[0.7279, 0.8812]	[0.4947, 0.6693]	[0.7037, 1.0000]	[0.2144, 0.2784]
$G_2^{(1)}$	[0.2912, 0.5713]	[0.8029, 1.0000]	[0.0000, 0.5477]	[0.7467, 1.0000]
$G_3^{(1)}$	[0.0000, 0.0953]	[0.0000, 0.1069]	[0.4942, 0.8007]	[0.0000, 0.1636]
$G_4^{(1)}$	[0.6299, 1.0000]	[0.4301, 0.6206]	[0.1959, 0.3613]	[0.4963, 0.6370]

Table 6 Perceived utility $Q_{al}^{(1)}$

	$Q_{a1}^{(1)}$	$Q_{a2}^{(1)}$	$Q_{a3}^{(1)}$	$Q_{a4}^{(1)}$
$G_1^{(1)}$	0.8231	0.7247	0.8407	0.0344
$G_2^{(1)}$	0.3028	0.9235	0.5214	0.8873
$G_3^{(1)}$	-0.1916	-0.1867	0.8890	-0.1552
$G_4^{(1)}$	0.8344	0.6258	0.6057	0.5186

that need to be determined during the calculation process, and different parameters lead to different results. In regret theory, the reference point need not be determined, and fewer parameters are involved in the calculation process. In addition, CBR-GDMPT adopts the form of interval number to evaluate decision makers' opinion. The proposed method adopts the form of IVPFLV, which is a better representation of uncertainty.

4. The calculated result obtained using the method based on CBR-IVPFLVPT is $c_4 > c_1 > c_9 > c_6$. The most suitable case is c_4 , which is the same as that obtained using the proposed method. However, as discussed above, the computation process of the prospect theory is a little more complicated than the regret theory.

In addition, the proposed method considers the dynamic nature of an emergency and generates different alternatives according to changes in emergencies, whereas the other

methods generate an alternative based on the situation when the emergency occurs. Emergencies constantly evolve and are often accompanied by secondary disasters. Therefore, by continuously modifying the emergency alternatives, we can better respond to emergencies.

4.2.2 Advantages of the Proposed Approach

From the comparison with the existing EDM methods, we summarize the following advantages of the proposed dynamic CBRGDM approach: (1) The existing EDM based on the CBR does not consider the evolution of the emergency, and the alternative generated is constant throughout the emergency process. The proposed method considers the changes in an emergency and generates an alternative according to these changes. It can therefore better respond to emergencies. (2) In the case selection, using IVPFLVs can better represent the fuzziness and uncertainty in the evaluation information given by decision makers. This is particularly useful for EDM problems characterized by time limitations, partial or incomplete information, and limited expertise. (3) With the regret theory, the proposed method can consider the psychological behaviors of decision makers under emergency situations. As a result, a more accurate ranking of the similar historical cases can be derived in the EDM.

Table 7 Comparisons with different approaches

Approach	The most suitable case
CBR-F (case-based reasoning proposed by Fan et al. 2014)	c_9
CBR-IVPFLWA (case-based reasoning based on interval-valued Pythagorean fuzzy linguistic weighted averaging)	c_9
CBR-GDMPT (case-based reasoning based on group decision making and prospect theory)	c_4
CBR-IVPFLVPT(case-based reasoning based on interval-valued Pythagorean fuzzy linguistic variable and prospect theory)	c_4
CBRGDM (case-based reasoning group decision making)	c_4

5 Conclusion

To generate a suitable emergency alternative, this article proposed a dynamic EDM method based on CBR and GDM, called dynamic CBRGDM. Compared with existing EDM methods, the proposed method has the following three characteristics: (1) To quickly generate an emergency alternative, the CBR method is applied to generate a similar historical case set. The alternative of the target emergency is generated based on the similar historical case set. (2) GDM is used to select the most suitable and similar historical case. In this process, IVPFLVs are used to express any vague information. Furthermore, regret theory is applied to determine the most suitable historical case considering the bounded rationality of decision makers. (3) To better deal with emergencies, the proposed method adjusts the alternative according to the different stages of an emergency.

In the future, two following issues need to be addressed: (1) extension of the case retrieval method in the context of big data; (2) development of a new method for evaluation information. Further, in the EDM, in addition to the opinions of decision makers, public opinions also need to be considered. Considering the uncertainty of the emergency, public opinions will be expressed as uncertain using interval-valued Pythagorean fuzzy set, soft set, and other uncertain and fuzzy environments.

Acknowledgements This work was partly supported by the National Natural Science Foundation of China under the Grant Nos. 71371053 and 71902034; Humanities and Social Sciences Foundation of Chinese Ministry of Education, No. 20YJC630229; Humanities and Social Science Foundation of Fujian Province, No. FJ2019B079; and Science and Technology Development Center of Chinese Ministry of Education, No. 2018A01019.

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