Research on The Emergency Decision-making Method Based on Case-based Reasoning under Triangle Fuzzy Preference

Liyuan Zhang, Chunlei Liang and Ziyu Yang

Abstract—**For emergency decision-making (EDM), it is necessary to generate an optimal alternative quickly. Case-based reasoning (CBR) is one of the best techniques to assist EDM. However, there are still some problems in the existing research of EDM with CBR. On the one hand, the method for case representation in CBR is rarely studied. On the other hand, previous studies only refer to a most similar historical case to solve the new problem, which is not suitable for complex EDM. In order to solve the first problem, we study the the case representation method for an emergency with the regional disaster systems theory and the common knowledge element model. On this basis, we develop a similarity measurement method to case retrieval. For the second problem, we generate a set of alternatives by referring to several similar historical cases, and develop a fuzzy multi-attribute group decision making (FMAGDM) approach to select the optimal alternative. In conclusion, this paper presents an EDM method combining CBR and FMAGDM, and a case of floods proves the effectiveness and feasibility of this method.**

Index Terms—**Emergency decision making, case-based reasoning, fuzzy multiple attribute group decision making, knowledge element.**

I. Introduction

In recent years, a series of emergencies have broken out, such as the SARS in 2003, the H1N1 in 2009, and the COVID-19 outbreak in 2019. These disasters have caused great losses to human society. For reducing the impact caused by emergencies, it is important to generate an emergency plan efficiently. However, due to the complexity of emergencies, it is difficult for decision makers to make decisions quickly. As a result, there has been an increasing interest in the EDM method based on the artificial intelligence technology [1]–[3]. Case-based Reasoning (CBR) is a mature technology in the field of artificial intelligence, whose idea is to solve new problems by referring to historical cases. Nowadays, CBR has been widely used in EDM in various fields, such as medical diagnosis [4], [5], industrial production [6], [7], and natural disaster reduction [8], [9]. Therefore, the application of CBR in EDM is considered to be highly suitable.

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The working process of the CBR system consists of four steps: case retrieval, case reuse, case revision, and case retention. Among them, case retrieval is the most critical step. If the retrieved cases are not relevant to the new problem, and then it has made no use in solving the new problem. The most commonly used case retrieval method is to retrieve by the similarity between cases. There are many similarity measurement methods, which take into account the decision-maker's bounded rationality [10], [11], the diversity of attribute values [12], and the spatiotemporal characteristics of the emergencies [13]. The above similarity measurement methods provide important insights into this paper. But these methods do not consider the case representation in CBR. Case representation is the basis of case retrieval, and the content and formalism of case representation directly affect the method of similarity measurement. Consequently, it is more reasonable to introduce the similarity measurement method after the introduction of a case representation method [14]. To tackle the above problem, we analyze the content and formalism of emergency representation, and then develop a similarity measurement method for case retrieval. Based on which, a CBR-based method for generating the alternatives is proposed.

After generating a set of alternatives, the selection process for the optimal option is also critical. Multi-attribute decision-making (MADM) is an effective way to select a suitable option from multiple alternatives based on the evaluation of alternatives with multi-attribute [15]–[17]. Due to the time urgency of EDM and the ambiguity of human thinking, it is hard to evaluate alternatives with precise numerical values. Moreover, it is necessary to invite several experts to evaluate the alternatives. Considering the above problems, a fuzzy multi-attribute group decision-making (FMAGDM) method is proposed to select the optimal alternative. In this method, experts evaluate the alternatives with linguistic variables and then convert the linguistic variables into triangular fuzzy numbers (TFNs) [18], [19]. Furthermore, the similarity between the alternative and the ideal solution is defined to rank the alternatives.

The remaining part of this paper proceeds as follows. Section 2 gives the common knowledge element model and the case representation method for an emergency, and defines the similarity between two TFNs. Section 3 presents the generation process of the alternative set. Section 4 proposes the FMAGDM method, compares it with another method, and then gives the flowchart of EDM method. Section 5 concludes this study.

II. Preliminaries

This section first introduces the common knowledge element model, then analyzes the content and formalism of emergency representation, and finally gives the definition of the TFNs and the similarity between two TFNs.

A. The common knowledge element model

For any knowledge m of an object in knowledge domain M, it can be represented by three models: the object knowledge element model K_m, the attribute knowledge element model K_a, and the knowledge element model of attribute relationship K_r [20].

$$\begin{cases} K_m = (N_m, A_m, R_m) & ; \\ K_a = (p_a, d_a, f_a) & a \in A_m; \\ K_r = (p_r, A_r^I, A_r^O, f_r) & r \in R_m. \end{cases} \tag{1}$$

Where, N_m is the concept of the object m, and N_m includes the name of m and attributes names of m; A_m is the corresponding attribute state set; R_m is the attribute relation set, which describes the change of attribute state and the interaction relationship of attributes. For attribute $a \in A_m$, p_a describes the measurable characteristics, d_a represents the corresponding measure dimension set, and f_a describes the change rule of measurable attributes. The relationship $r \in R_m$ between attributes can be described by the attributes relationship knowledge element K_r, where p_r describes the mapping attributes of the relationship (such as membership function, linear function, random function, etc.), A_r^I and A_r^O are the input and output attributes of the relationship respectively, and $f_r : A_r^O = f_r(A_r^I)$ is the mapping function.

B. The case representation method for an emergency

For case representation in CBR, two issues need to be considered: the content to be stored in a case and the formalism to represent a case. A case is mainly consists of the problem part and solution part. In addition, a case can be of two types: the target case which contains the description of a new problem, and the historical case which contains the problem part and its solution. This paper discusses the case representation of an emergency as the target case.

According to the regional disaster system theory, a disaster is the result caused by the joint action of hazard factors, hazard-effected bodies, and hazard-formative environments. Hazard factors are the necessary condition for the occurrence of a disaster. Hazard-effected bodies are the necessary condition for scaling up or reducing the disaster. Hazard-formative environments are the conditions for breeding hazard factors. Therefore, the content of case representation for an emergency should consist of three components: hazard factors, hazard-effected bodies, and hazard-formative environments.

Let P represents the content of case representation for an emergency, K_1 represents the knowledge of hazard factors, K_2 represents the knowledge of hazard-effected bodies, and K_3 represents the knowledge of hazard-formative environments. By the common knowledge element model, the formalism of case representation for an emergency can be represented as below.

$$\begin{aligned} &P = \{K_1, K_2, K_3\} \\ &K_i = (N_i, A_i, R_i)(i = 1, 2, 3) \end{aligned} \tag{2}$$

where, $N_i(i = 1, 2, 3)$ is the concept of the hazard factors, hazard-effected bodies, and hazard-formative environments. A_i and $R_i(i = 1, 2, 3)$ respectively represent the corresponding attribute state set and the attribute relationship set, which are represented by the attribute knowledge element model K_a and the attributes relationship knowledge element model K_r of formula (1).

Formula (2) is an abstract knowledge element model, which can be transformed into concrete knowledge element instances by assigning values to attributes.

C. TFNs and the similarity between two TFNs

Definition 1. *[21] If $\alpha = (a_1, a_2, a_3)$, $0 \leqslant a_1 \leqslant a_2 \leqslant a_3$, then α is a triangular fuzzy number. The membership function $\mu_\alpha(x)$ is as follows:*

$$\mu_\alpha(x) = \begin{cases} 0, & x < a_1, \\ \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2, \\ \frac{x-a_3}{a_2-a_3}, & a_2 \leq x \leq a_3, \\ 0, & a_3 < x. \end{cases}$$

If the triangular fuzzy number $\alpha = (a_1, a_2, a_3)$ is regarded as a three-dimensional vector, its three parameters $a_i\,(i = 1, 2, 3)$ can be regarded as the three components of the vector. By the similarity of vector space, the similarity between two TFNs is defined. See definition 2 for details.

Definition 2. *let $\alpha = (a_1, a_2, a_3)$ and $\beta = (b_1, b_2, b_3)$ be any two TFNs, the similarity between α and β is defined as follows:*

$$\begin{aligned} S(\alpha, \beta) =& \frac{1}{2} \frac{\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2 - \sum_{i=1}^3 a_i b_i} \\ &+ \frac{1}{2} \frac{2\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2}. \end{aligned} \tag{3}$$

Theorem 1. *Formula (3) is the similarity between two TFNs and satisfies the following properties:*

$(P1)$ $0 \leq S(\alpha, \beta) \leq 1$;
$(P2)$ $S(\alpha, \beta) = S(\beta, \alpha)$;
$(P3)$ $if\ \alpha = \beta, S(\alpha, \beta) = 1$.

Proof:

(P1) It is obvious that $S(\alpha, \beta) \geq 0$. So we just have to prove $S(\alpha, \beta) \leq 1$.

On the basis of the basic mathematical inequality: $2a_ib_i \leqslant a_i^2 + b_i^2$, we get:

$$\frac{\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2 - \sum_{i=1}^3 a_i b_i} \leq 1, \tag{4}$$

$$\frac{2\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2} \leq 1. \tag{5}$$

Taking the Eqs. (4) and (5) into (3), we get:

$$\begin{aligned} S(\alpha, \beta) =& \frac{1}{2} \frac{\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2 - \sum_{i=1}^3 a_i b_i} \\ &+ \frac{1}{2} \frac{2\sum_{i=1}^3 a_i b_i}{\sum_{i=1}^3 a_i^2 + \sum_{i=1}^3 b_i^2} \\ &\leq \frac{1}{2} + \frac{1}{2} \leq 1. \end{aligned} \tag{6}$$

One can see that (P2) and (P3) are clearly true. ∎

III. Generation of emergency alternatives based on CBR

This section presents the method for emergency alternatives generation.

Step 1 Represent an emergency

According to the collected information, the attributes in the corresponding knowledge element model are assigned, and some knowledge element instances are obtained to represent the emergency p.

$$\begin{aligned} p = \{&k_{11}, k_{12}, ..., k_{1n}, k_{21}, \\ &k_{22}, ..., k_{2m}, k_{31}, k_{32}, ..., k_{3r}\} \end{aligned} \tag{7}$$

where, $k_{11}, k_{12}, ..., k_{1n}$ are knowledge element instances representing hazard factors, $k_{21}, k_{22}, ..., k_{2m}$ are knowledge element instances representing hazard-effected bodies, and $k_{31}, k_{32}, ..., k_{3r}$ are knowledge element instances representing hazard-formative environments.

Step 2 Retrieve similar historical cases

The decision maker sets a similarity threshold. Through similarity measurement, the historical case whose similarity with the target emergency is greater than the threshold are retrieved. The method for similarity measurement between the target emergency and the historical case is as below.

(1)The similarity measurement between the target emergency and the historical case

According to the content of case representation for an emergency, the similarity between the target emergency and the historical case consists of three parts: the similarity of the hazard factors, the similarity of the hazard-effected bodies, and the similarity of the hazard-formative environments. The three parts have different effects on the similarity between cases. If the similarity of the hazard factors or the similarity of the hazard-effected bodies between the target emergency and the historical case is 0, and then the historical case has made no use in solving the new problem. In this case, the similarity between the target emergency and the historical case is 0. Based on the above analysis, the calculation process of the similarity measurement between cases is shown in Figure 1. The calculation method of the similarity measurement is shown in Eq. (8), where $s(t^i, h^i)(i = 1, 2, 3)$ respectively represent the similarity of hazard factors, hazard-effected bodies and hazard-formative environments between the target emergency and historical case.

$$s(t, h) = \begin{cases} 0, s(t^1, h^1) \times s(t^2, h^2) = 0; \\ \sum_{i=1}^{3} w_i s(t^i, h^i), s(t^1, h^1) \times s(t^2, h^2) \neq 0. \end{cases} \tag{8}$$

$$s(t^i, h^i) = \frac{1}{f} \sum_{j=1}^{f} sim(k_{ij}^t, k_{ij}^h) \tag{9}$$

where $w_i(i = 1, 2, 3)$ are the weights of $s(t^i, h^i)(i = 1, 2, 3)$, $sim(k_{ij}^t, k_{ij}^h)$ is the similarity of the j-*th* knowledge element instance contained in three parts between target emergency and historical case. The method for similarity measurement between knowledge element instances is as below.

(2)The similarity measurement between knowledge element instances

A knowledge element instance consists of three parts: concept, attribute values, and the relationship between attributes. The first two parts are used for similarity calculation. Let k_1 and k_2 are any knowledge element instances in target case t and historical case h, and the similarity between k_1 and k_2 is calculated as follows:

$$sim(k_1, k_2) = sim(N_1, N_2) \times sim(A_1, A_2) \tag{10}$$

where $sim(N_1, N_2)$ represents the concept similarity between k_1 and k_2, and $sim(A_1, A_2)$ represents the attribute similarity. The concept of knowledge element instance, includes the name of the knowledge element instance and the name of its attribute. If the names of two knowledge element instances are different, their concept similarity is 0; Otherwise, their concept similarity is the ratio of the number of their common attributes to the total number of attributes contained in one of them. The calculation of concept similarity is shown in Formula (11).

$$sim\left(N_1, N_2\right) = \begin{cases} 0, & n_1 \neq n_2, \\ \frac{|N_{1A} \bigcap N_{2A}|}{|N_{1A}|}, & n_1 = n_2. \end{cases} \tag{11}$$

where n_1 and n_2 represents the name of k_1 and k_2, N_{1A} and N_{2A} represents the set of attribute names in k_1 and k_2 , $|N_{1A} \bigcap N_{2A}|$ represents the number of common attribute names in k_1 and k_2, and $|N_{1A}|$ represents the number of attribute names in k_1.

Attributes similarity $sim(A_1, A_2)$ is the weighted sum of the similarity of each attribute value contained in k_1 and k_2,as shown in Formula (12). The attribute values can be of multiple data types, such as crisp number, symbol, language value, interval number, and so on. In this paper, we use the method proposed in [12] to calculate the attribute values similarity with a variety of data types.

$$sim(A_1, A_2) = w_{ai} sim(a_i^1, a_i^2) \tag{12}$$

Step 3 Generate a set of alternatives

The decision maker refers to the solutions of the retrieved historical cases to generate a set of alternatives for the emergency.

IV. The FMAGDM approach and the flowchart of the EDM method

This section proposes an FMAGDM approach to select the optimal alternative. Then, the FMAGDM approach is compared with another approach to demonstrate its effectiveness. Finally, the flowchart of the EDM method is given.

A. The FMAGDM approach

After alternatives generation process, suppose the alternatives set be $A_l(l = 1, 2, ..., m)$. Let the experts set be $G_i(i = 1, 2, ..., p)$, and the decision attribute set be $C = \{C_1, C_2, ..., C_n\}$. The steps to select the optimal alternative by the FMAGDM approach are as follows:

Step 1 Evaluate alternatives

The expert evaluates each alternative with all attributes using linguistic variables, and convert the linguistic variables into TFNs by Table 1. Set the *ith* expert's preference vector of the *lth* alternative as:

$$\begin{aligned} v_l^i =&\{\langle C_1, (a_{11}^i, a_{12}^i, a_{13}^i)\rangle, \langle C_2, (a_{21}^i, a_{22}^i, a_{23}^i)\rangle, \\ &..., \langle C_n, (a_{n1}^i, a_{n2}^i, a_{n3}^i)\rangle\} \end{aligned}$$

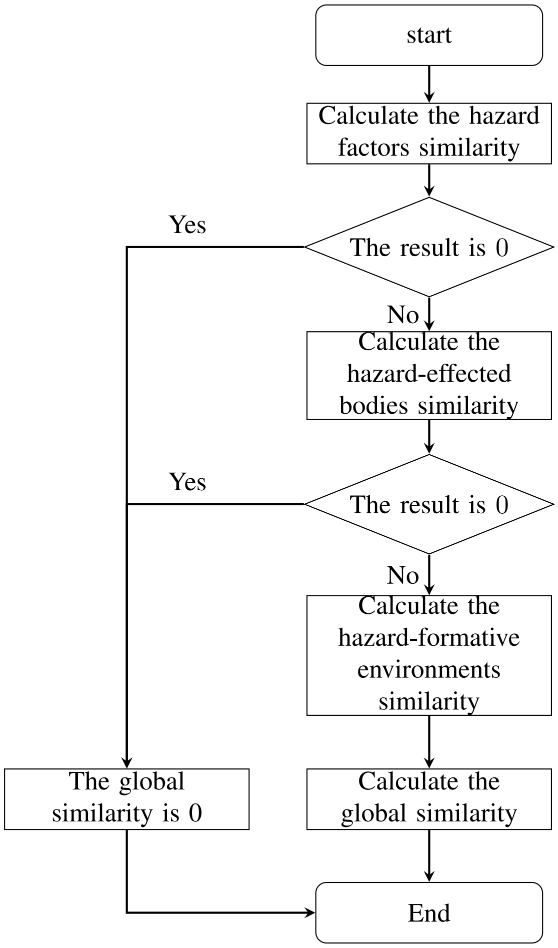

Fig. 1: The calculation process of similarity between the target case and historical case

TABLE I: The relations between linguistic variables and TFNs

Linguistic variables	Triangular fuzzy numbers
Absolutely bad	$(0.0, 0, 0, 0.1)$
Very poor	$(0.1, 0.2, 0.3)$
Poor	$(0.2, 0.3, 0.4)$
Medium poor	$(0.3, 0.4, 0.5)$
Medium	$(0.4, 0.5, 0.6)$
Medium good	$(0.5, 0.6, 0.7)$
Good	$(0.6, 0.7, 0.8)$
Very good	$(0.7, 0.8, 0.9)$
Absolutely good	$(0.8, 0, 9, 1.0)$

Step 2 Calculate the group preference vector of alternatives

Suppose the weight vector of p experts is $\lambda = (\lambda_1, \lambda_2, ..., \lambda_p)$, and the group preference vector of alternative A_l is calculated as follows:

$$V_l = \sum_{i=1}^{p} \lambda_i v_l^i \tag{13}$$

Step 3 Calculate the standardized attributes weight

Set the weight of attribute $C_j (j = 1, 2, ..., n)$ as $w_j = (w_{j1}, w_{j2}, w_{j3})$. The expected weight value is calculated by Eq. (14), and then the standardized weight value is obtained by Eq. (15).

$$EV\left(w_j\right) = \frac{w_{j1} + w_{j1} + w_{j1}}{3} \tag{14}$$

$$W_j = \frac{EV\left(w_j\right)}{\sum_{j=1}^{n} EV\left(w_j\right)} \tag{15}$$

Step 4 Calculate the similarity between the alternatives and the ideal alternative

The decision maker gives the preference vector of the ideal alternative with TFNs. The similarity between the alternative A_l and the ideal alternative A^* is calculated as follows:

$$\begin{aligned} WS(A_l, A^*) &= sim(V_l, V_*) = \sum_{j=1}^{n} W_j sim(c_j^l, c_j^*) \\ &= \frac{1}{2} \sum_{j=1}^{n} W_j \\ &\frac{\sum_{k=1}^{3} a_{jk}^l a_{jk}^*}{\sum_{k=1}^{3} (a_{jk}^l)^2 + \sum_{k=1}^{3} (a_{jk}^*)^2 - \sum_{k=1}^{3} a_{jk}^l a_{jk}^*} \\ &+ \frac{1}{2} \sum_{j=1}^{n} W_j \frac{2 \sum_{k=1}^{3} a_{jk}^l a_{jk}^*}{\sum_{k=1}^{3} (a_{jk}^l)^2 + \sum_{k=1}^{3} (a_{jk}^*)^2} \end{aligned} \tag{16}$$

where V_l is the group preference vector of A_l, and V_* is the preference vector of A^*. $c_j^l = (a_{j1}^l, a_{j2}^l, a_{j3}^l)$ is the jth attribute in V_l, and $c_j^* = (a_{j1}^*, a_{j2}^*, a_{j3}^*)$ is the jth attribute in V_*. $sim(c_j^l, c_j^*)$ represents the similarity between A_l and A^* in attribute C_j.

Step 5 Rank the alternatives and select the optimal one

The alternatives are ranked by comparing their similarity to the ideal alternative, and the optimal one is selected.

B. Comparative analysis

This section applies the FMAGDM method to the case in literature [22]. The case is as follows:

An investment company is ready to invest in a business. There are five alternatives: A_1 is an automobile company; A_2 is a food company; A_3 is a computer company; A_4 is an arms company; A_5 is a television company. Three experts evaluate the five alternatives $A_i (i = 1, 2, 3, 4, 5)$ according to the following four attributes: C_1 is the risk analysis; C_2 is the growth analysis; C_3 is the social and political impact analysis; C_4 is the environmental impact analysis. The weighting vector of experts is $v = (0.2, 0.5, 0.3)^T$, and the weighting vector of attributes is $\omega = (0.2, 0.1, 0.3.0.4)^T$. The decision-making steps with the FMAGDM method are as follows:

Step 1 The expert preference vector for each alternative are $\tilde{R}_k = (\tilde{r}_{ij}^{(k)})_{5\times 4} (k = 1, 2, 3)$ in literature [22].

Step 2 The group preference vector for each alternative are calculated by Eq. (13), and the results are as follows:

$$\begin{aligned} V_1 = \{&\langle C_1, (0.61, 0.66, 0.71)\rangle, \langle C_2, (0.53, 0.57, 0.61)\rangle, \\ &\langle C_3, (0.72, 0.74, 0.77)\rangle, \langle C_4, (0.43, 0.46, 0.49)\rangle\}; \\ V_2 = \{&\langle C_1, (0.69, 0.71, 0.74)\rangle, \langle C_2, (0.48, 0.58, 0.64)\rangle, \\ &\langle C_3, (0.40, 0.51, 0.49)\rangle, \langle C_4, (0.50, 0.53, 0.56)\rangle\}; \\ V_3 = \{&\langle C_1, (0.76, 0.78, 0.79)\rangle, \langle C_2, (0.71, 0.74, 0.76)\rangle, \\ &\langle C_3, (0.58, 0.60, 0.63)\rangle, \langle C_4, (0.74, 0.76, 0.77)\rangle\}; \\ V_4 = \{&\langle C_1, (0.63, 0.66, 0.69)\rangle, \langle C_2, (0.78, 0.79, 0.81)\rangle, \\ &\langle C_3, (0.79, 0.80, 0.81)\rangle, \langle C_4, (0.78, 0.80, 0.81)\rangle\}; \\ V_5 = \{&\langle C_1, (0.59, 0.60, 0.62)\rangle, \langle C_2, (0.59, 0.60, 0.59)\rangle, \\ &\langle C_3, (0.64, 0.66, 0.71)\rangle, \langle C_4, (0.75, 0.78, 0.78)\rangle\}. \end{aligned}$$

Step 3 The decision maker gives the preference vector of the ideal alternative.

$$V_* = \{\langle C_1, (0.44, 0.47, 0.50)\rangle, \langle C_2, (0.79, 0.82, 0.80)\rangle, \langle C_3, (0.97, 0.98, 1.00)\rangle, \langle C_4, (0.83, 0.85, 0.88)\rangle\}$$

Step 4 The similarity between each alternative and the ideal alternative is calculated by Eq. (16). The decision results are shown in Table 2.

From Table 2, we can see that the ranking results are consistent with those in the literature [22], which shows that the proposed FMAGDM approach is effective. Moreover, the calculation process of the FMAGDM approach in this paper is simpler than the method in literature [22].

C. The flowchart of the EDM method

In the EDM method, first, a set of alternatives are generated with CBR, then, the optimal solution is selected by the FMAGDM method. Figure 2 shows the flowchart of the EDM method.

V. Case Application

A city is located in the lower reaches of the Yangtze River, with a low and flat terrain, dense river network, and topographic elevation between $5.0m$ and $8.0m$, which is vulnerable to typhoons, heavy rain, and other weather factors. On September $6, 2014$, due to the influence of the typhoon, heavy rainfall occurred, water could not be discharged in time, resulting in floods, which seriously affected the lives of people in the affected areas. According to preliminary statistics, the flood situation is as follows: the average precipitation is $169mm$, and the maximum daily precipitation is 211mm. The impact on the hazard-effected bodies are as follows: 96,957 people were affected, and 1259 people were transferred; 60 houses were destroyed, 111 were seriously damaged and 311 were generally damaged; the affected area of crops is 6010 hectares, the inundated area is 519 hectares, and the lost crop area is 464.1 hectares.

The decision making process for the above emergency by the EDM method is as follows:

Stage 1: Multiple alternatives are generated by the CBR technique.

Step 1.1 Represent the emergency

According to the collected information, the decision maker assigns values for the attributes in the corresponding knowledge element model, and thus some knowledge element instances are obtained to represent the emergency. Among these knowledge element instances, the flood belongs to the hazard factors, while people, buildings, and crops belong to the hazard-effected bodies. The attribute information of the knowledge element instances is shown in Table 3.

Step 1.2 Retrieve similar historical cases

The similarity threshold is set to 0.7, and the historical cases whose similarity to the emergency is greater than 0.7 are retrieved. In order to illustrate the similarity calculation process, the similarity measurement between the emergency t and the historical case $h1$ is given below. Table 4 shows the attribute values of t and $h1$ and the attribute value similarities between t and $h1$. We assume that the attribute weights of each knowledge element instance are equal.

First, the hazard factors similarity between t and $h1$ is calculated by Eqs. (9)-(12), and the similarity result is as follows:

$$s(t^1, h1^1) = sim(k_{11}^t, k_{11}^{h1}) = 1 \times (\frac{1}{4}0.7929 + \frac{1}{4}0.8436) = 0.4091$$

The hazard factors similarity between t and $h1$ is greater than 0. Then, the hazard-effected bodies similarity between t and $h1$ is calculated by Eqs. (9)-(12), and the result is as follows:

$$s(t^2, h1^2) = \frac{1}{3}\sum_{f=1}^{3} sim(k_{2f}^t, k_{2f}^{h1}) = (1 \times (\frac{1}{2} \times 0.7128 + \frac{1}{2} \times 0.4988) + \frac{2}{3} \times (\frac{1}{3} \times 0.6333 + \frac{1}{3} \times 0.8939) + 1 \times (\frac{1}{3} \times 0.8807 + \frac{1}{3} \times 0.6339 + \frac{1}{3} \times 0.8446)) \div 3 = 0.5772$$

The hazard-effected bodies similarity between t and $h1$ is greater than 0, and then the hazard-formative environments similarity between t and $h1$ is calculated by Eqs. (9)-(12). The result is as follows:

$$s(t^3, h1^3) = sim(k_{31}^t, k_{31}^{h1}) = 1 \times (\frac{1}{2} \times 0.4444) = 0.2222$$

Finally, the similarity between t and $h1$ is calculated by Eq. (8). Let $w_i(i = 1, 2, 3) = (0.6, 0.3, 0.1)$ be the weight of the hazard factor similarity, the hazard-effected bodies similarity, and the hazard-formative environments similarity. The similarity between t and $h1$ is as follows:

$$s(t, h1) = \sum_{i=1}^{3} w_i s(t^i, h1^i) = 0.6 \times 0.4091 + 0.3 \times 0.5772 + 0.1 \times 0.2222 = 0.4408$$

Step 1.3 Generate a set of alternatives

The decision maker refers to the solutions of the retrieved historical cases to generate an alternative set of the emergency. The results are as follows.

A_1: 600 police officers, 100 firefighters, 100 medical rescue personnel, 800,000 RMB of rescue and relief funds, 2 ships, and 2 rescue vehicles;

A_2: 500 police officers, 90 firefighters, 80 medical rescue personnel, 600,000 RMB of rescue and relief funds, 1 ships, and 2 rescue vehicles;

A_3: 700 police officers, 110 firefighters, 120 medical rescue personnel, 800,000 RMB of rescue and relief funds, 4 ships, and 4 rescue vehicles.

Stage 2: The optimal alternative selection process with FMAGDM approach

The decision maker invites 5 experts to evaluate the alternatives. The decision attributes are: human casualties (C_1), economic losses (C_2), environmental change control effect (C_3) and social impact (C_4). The optimal alternative selection process is as below.

Step 2.1 The experts evaluate each alternative with all attributes using linguistic variables, and convert the linguistic

TABLE II: Decision results of different methods

	The results by the proposed FMAGDM method	The results by the method in literature [22]
A_1	0.8723	1.3310
A_2	0.8232	0.6690
A_3	0.9177	2.5000
A_4	0.9733	4.5000
A_5	0.9534	3.5000
Ranking of alternatives	$A_4 > A_5 > A_3 > A_1 > A_2$	$A_4 > A_5 > A_3 > A_1 > A_2$
The optimal solution	A_4	A_4

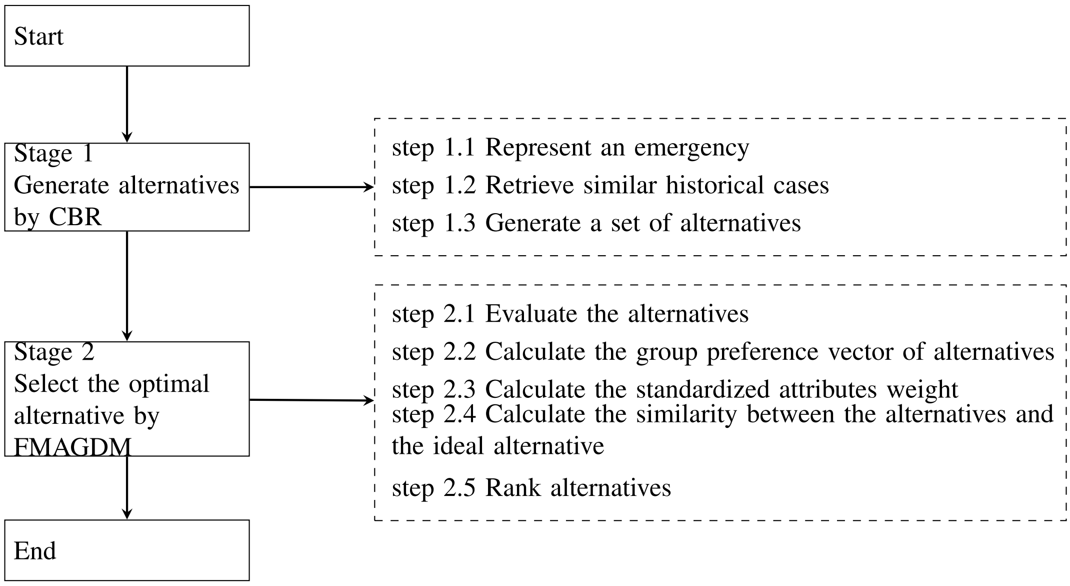

Fig. 2: The flowchart of the EDM method

TABLE III: The attribute information of the knowledge element instances

The name of the knowledge elements	Attribute names	Unit	Attribute values type
Floods k_{11}	Time c_1	$-$	Crisp number
	Place c_2	$-$	Crisp symbol
	The average precipitation c_3	mm	Crisp number
	The maximum daily precipitation c_4	mm	Crisp number
People k_{21}	The number of injured c_5	$-$	Crisp number
	The number of emergency evacueesc_6	$-$	Crisp number
Building k_{22}	The number of collapsed houses c_7	$-$	Crisp number
	Slightly damaged houses c_8	$-$	Crisp number
	Severely damaged housesc_9	$-$	Crisp number
Crops k_{23}	The affected area c_{10}	hectares	Crisp number
	Inundated area c_{11}	hectares	Crisp number
	The lost crop area c_{12}	hectares	Crisp number
Hazard-formative environments k_{31}	The terrain elevation c_{13}	m	Interval number
	The density of river network c_{14}	$-$	Crisp symbol

TABLE IV: The attribute values of t and $h1$ and the attribute value similarities

Attributes	Attribute values of t	Attribute values of $h1$	Attribute value similarities
c_1	2014.9.6	2013.8.9	0
c_2	A city	Wei Fang	0
c_3	169	134	0.7929
c_4	211	178	0.8436
c_5	96757	69112	0.7128
c_6	1295	628	0.4988
c_7	60	38	0.6333
c_8	111	$-$	$-$
c_9	311	278	0.8939
c_{10}	6010	5293	0.8807
c_{11}	519	329	0.6339
c_{12}	464.1	392	0.8446
c_{13}	[5 8]	[4 7]	0.4444
c_{14}	High	Medium	0

TABLE V: The expert's preference vector for each alternative

A	G	C_1	C_2	C_3	C_4
A_1	1	$(0.4, 0.5, 0.6)$	$(0.3, 0.4, 0.5)$	$(0.3, 0.4, 0.5)$	$(0.6, 0.7, 0.8)$
	2	$(0.4, 0.5, 0.6)$	$(0.3, 0.4, 0.5)$	$(0.3, 0.4, 0.5)$	$(0.6, 0.7, 0.8)$
	3	$(0.3, 0.4, 0.5)$	$(0.3, 0.4, 0.5)$	$(0.3, 0.4, 0.5)$	$(0.6, 0.7, 0.8)$
	4	$(0.5, 0.6, 0.7)$	$(0.4, 0.5, 0.6)$	$(0.4, 0.5, 0.6)$	$(0.6, 0.7, 0.8)$
	5	$(0.4, 0.5, 0.6)$	$(0.3, 0.4, 0.5)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$
A_2	1	$(0.4, 0.5, 0.6)$	$(0.5, 0.6, 0.7)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$
	2	$(0.3, 0.4, 0.5)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$	$(0.6, 0.7, 0.8)$
	3	$(0.4, 0.5, 0.6)$	$(0.6, 0.7, 0.8)$	$(0.4, 0.5, 0.6)$	$(0.5, 0.6, 0.7)$
	4	$(0.2, 0.3, 0.4)$	$(0.6, 0.7, 0.8)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$
	5	$(0.4, 0.5, 0.6)$	$(0.5, 0.6, 0.7)$	$(0.5, 0.6, 0.7)$	$(0.5, 0.6, 0.7)$
A_3	1	$(0.6, 0.7, 0.8)$	$(0.2, 0.3, 0.4)$	$(0.6, 0.7, 0.8)$	$(0.5, 0.6, 0.7)$
	2	$(0.5, 0.6, 0.7)$	$(0.1, 0.2, 0.3)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$
	3	$(0.7, 0.8, 0.9)$	$(0.1, 0.2, 0.3)$	$(0.5, 0.6, 0.7)$	$(0.6, 0.7, 0.8)$
	4	$(0.6, 0.7, 0.8)$	$(0.2, 0.3, 0.4)$	$(0.5, 0.6, 0.7)$	$(0.7, 0.8, 0.9)$
	5	$(0.5, 0.6, 0.7)$	$(0.3, 0.4, 0.5)$	$(0.4, 0.5, 0.6)$	$(0.5, 0.6, 0.7)$

variables into TFNs by Table 1. Table 5 shows the expert's preference vector for each alternative.

Step 2.2 The experts weight vector is $\lambda = (0.1, 0.1, 0.2, 0.3, 0.3)$. The group preference vector for each alternative are calculated by Eq (13), and the results are as follows:

$$\begin{aligned}
V_1 = \{&C_1, (0.42, 0.52, 0.62), C_2, (0.33, 0.43, 0.53),\\
&C_3, (0.40, 0.50, 0.60), C_4, (0.59, 0.69, 0.79)\};\\
V_2 = \{&C_1, (0.33, 0.43, 0.53), C_2, (0.55, 0.65, 0.75),\\
&C_3, (0.49, 0.59, 0.69), C_4, (0.55, 0.65, 0.75)\};\\
V_3 = \{&C_1, (0.58, 0.68, 0.78), C_2, (0.20, 0.30, 0.40),\\
&C_3, (0.48, 0.58, 0.68), C_4, (0.59, 0.69, 0.79)\}.
\end{aligned}$$

Step 2.3 The attribute weights are as follows:

$$\begin{aligned}
w_1 &= (0.80, 0.90, 1.00),\\
w_2 &= (0.40, 0.50, 0.60),\\
w_3 &= (0.70, 0.80, 0.90),\\
w_4 &= (0.70, 0.80, 0.90).
\end{aligned}$$

The normalized attribute weight calculated by Eqs. (14) and (15) are: $W = (0.3, 0.1667, 0.2667, 0.2667)$.

Step 2.4 The decision maker gives the preference vector of the ideal alternative.

$$\begin{aligned}
V_* =\{&\langle C_1, (0.8, 0.9, 1.0)\rangle, \langle C_2, (0.4, 0.5, 0.6)\rangle,\\
&\langle C_3, (0.5, 0.6, 0.7)\rangle, \langle C_4, (0.6, 0.7, 0.8)\rangle\}
\end{aligned}$$

The similarity between alternative $A_l(l = 1, 2, 3)$ and the ideal alternative A^* are calculated by Eq. (16), and the results are as follows: $WS(A_1, A^*)$=0.9143,$WS(A_2, A^*)$=0.9042, $WS(A_3, A^*)$=0.9569.

Step 2.5 According to the similarity between alternative $A_l(l = 1, 2, 3)$ and the ideal alternative A^*, the alternatives are ranked as: $A_3 > A_1 > A_2$, and thus A_3 is the optimal emergency alternative.

VI. CONCLUSIONS

Based on CBR and FMAGDM approach, an EDM method is presented in this paper, which includes two processes: alternatives generation and selection. In summary, three important contributions of the EDM method are made: (1) To ensure the integrity and structuredness of emergency representation, the content of emergency representation is studied with the regional disaster system theory , and is represented by common knowledge element model; (2) A similarity measurement method is proposed to case retrieval. The calculation of this method is hierarchical, and hence improving the efficiency of case retrieval; (3) To select the optimal alternative, an FMAGDM approach is put forward.

The EDM method integrates the advantage of the CBR with FMAGDM, and the reasonable and practicability of this method is demonstrated by a case application of floods. In the future, two issues need to be addressed: (1) The method for revising the solutions of the historical cases; (2) Determination of common attributes in the case representation method for an emergency.

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