Research Article

New Framework for FCMs Using Dual Hesitant Fuzzy Sets with an Analysis of Risk Factors in Emergency Event

Zengwen Wang[1], Jian Wu[1], Xiaodi Liu[2,3,*], Harish Garg[4]

[1]*Researching Center of Social Security, Wuhan University, Hubei, 430072, China*

[2]*School of Mathematics and Physics, Anhui University of Technology, Ma'anshan, 243002, China*

[3]*Key Laboratory of Multidisciplinary Management and Control of Complex Systems of Anhui Higher Education Institutes, Anhui University of Technology, Ma'anshan, 243002, China*

[4]*School of Mathematics, Thapar Institute of Engineering and Technology, Deemed University, Patiala, 147004, India*

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ABSTRACT

As a kind of soft computing tool with strong knowledge representation and causal reasoning ability, fuzzy cognitive maps (FCMs) is a product of fuzzy logic and neural network. A limitation of the current FCMs method is its inability to model the uncertainty that is introduced into a complex system due to the hesitancy of people. Dual hesitant fuzzy sets (DHFSs), which considers the membership and nonmembership degrees by a set of possible values respectively, is an effective tool to model the hesitancy and epistemic uncertainty. Thus, a novel extension of FCMs model called dual hesitant fuzzy cognitive maps (DHFCMs) is proposed in this paper. Firstly, motivated by the idea of Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) method, a new similarity measure based on dual hesitant fuzzy distance measure is put forward, and its properties are also discussed. Then, detailed procedure and algorithm for DHFCMs are specified. Moreover, the application steps of the proposed method are provided. Finally, a case study on the huge explosion at Tianjin Port in China in 2015 is given to illustrate the rationality and effectiveness of the proposed method.

1. INTRODUCTION

When the emergency events happen, they usually can cause casualties, economic losses, ecological damage, and serious social hazards [1,2]. The researches on emergency response have become one of the hotspots and frontier issues in the field of emergency management in domestic and overseas, and the types of emergency events are diverse (See Figure 1).

Many different emergency decision-making methods have been put forward to select the optimal alternative in response to the emergency event under different fuzzy uncertainty environment. Levy and Taji [3] provided a group analytic network process method to deal with hazards planning and emergency management with incomplete information. For evaluating emergency management, Zhang *et al.* [4] proposed a way of extended fuzzy multi-criteria group decision-making. In order to improve the efficiency of decision-making process, Yan *et al.* [5] put forward the improved fuzzy analytic hierarchy process method for nuclear reactor accident emergency decision-making problem. Considering the dynamic characteristic of emergency response, Wu *et al.* [6] put forward a dynamic decision-making method with probabilistic hesitant fuzzy information based on grey system theory (GST) for

selecting the optimal emergency alternative. Based on regret theory, Liu *et al.* [7] proposed a new methodology for hesitant fuzzy emergency decision-making with unknown weight information. Existing researches mainly focus on emergency response and emergency management after emergency events. At the same time, cause analysis of emergency events is indispensable for emergency management: (1) it can clarify the risk factors of emergency events and provide theoretical reference for the prevention and early warning of similar emergencies in the future; (2) it can enhance the pertinence and effectiveness of relevant policies; (3) it can provide a theoretical basis for investigating the responsibility afterwards. In addition, through analyzing risk factors of emergency events, we can integrate social resources to provide effective early warning and improve the efficiency of emergency management. However, there are only a few pieces of literature on the cause analysis of emergency events. Stach *et al.* [21] pointed out that there are some difficulties in analyzing the causes of events by utilizing the Hidden Markov Model (HMM). The state transition probability sometimes is difficult to obtain because the HMM is only applicable to the systems with finite states. And the transition matrix between states is controlled by the probability set. On the basis of Bayesian method, Faubet and Oscar [9] provided a new model to identify the environmental factors that influence the recent migration. However, the Bayesian model must be constructed under an assumption that all attributes are mutually independent, and it is sensitive to the input
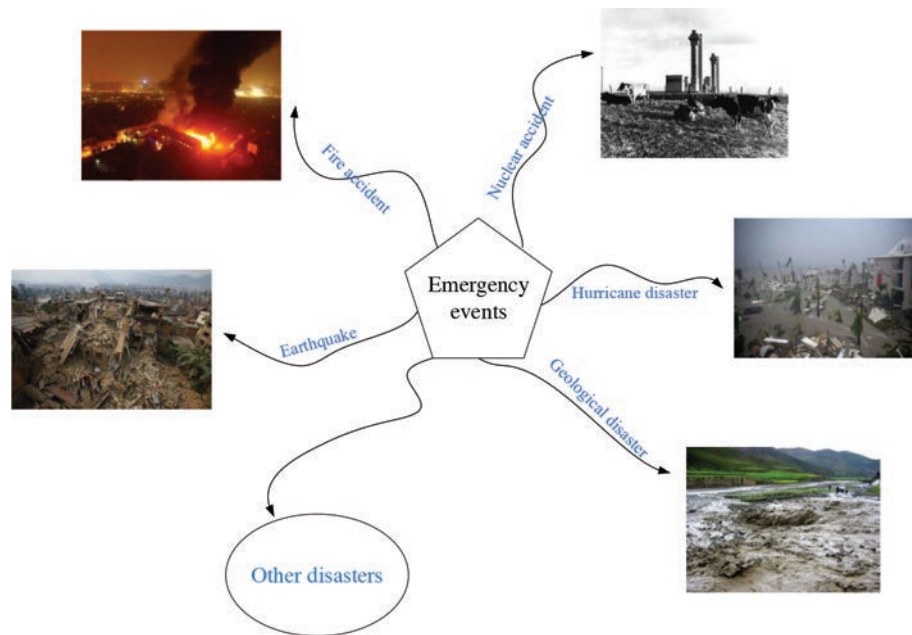
Figure 1 | Emergency events.

data. Decision-Making Trial and Evaluation Laboratory (DEMA-TEL) method is a useful tool to identify the risk factors of events as well. Zhou *et al.* [10] proposed a DEMATEL method to analyze the risk factors in emergency management. Li *et al.* [11] put forward an evidential DEMATEL method to identify the cause factors in emergency management. But there are some drawbacks in DEMATEL method. For example, the hesitancy of experts is ignored and the criteria states are required to be linearly interactive. In order to overcome the shortcomings mentioned above, it is necessary to propose a new method to analyze the risk factors of emergency events.

As a useful soft computing tool to model complex systems, fuzzy cognitive maps (FCMs) integrates fuzzy logic and neural networks [12,13]. Since FCMs is proposed by Kosko [12], scholars have paid much attention to it, and it has been applied to various fields, such as decision-making [14–16], prediction of time series [8,17], risk management [18,19], medical diagnosis [20], simulation and prediction [21], and other fields [22–24]. At the same time, there are many theoretical studies on FCMs. On the one hand, some evolutionary models for FCMs have also been proposed. Miao *et al.* [25] proposed dynamic causal networks to quantify the concepts and the strength of causality between concepts in FCMs. Zhou *et al.* [26] presented fuzzy causal networks on the basis of the convergent features of FCMs. On the other hand, practical constraints of the real world hamper the widespread use of crisp values [16]. In the decision-making process, there are different sources of uncertainty [8,26]. To deal with the uncertainty, many different uncertain theories are proposed, such as fuzzy sets (FSs) [27,28], intuitionistic fuzzy sets (IFSs) [29,30], hesitant fuzzy sets (HFSs) [25,31,32], DHFSs [33], GST [34], hesitant fuzzy linguistic term sets [35,36], etc. [37,38]. Furthermore, several extensions of FCMs based on different uncertain theories have been presented for modeling complex systems. Iakovidis and Papageorgiou [13,39] proposed intuitionistic fuzzy cognitive maps (IFCMs), which combines IFSs and FCMs. Salmeron [40] proposed fuzzy grey cognitive maps (FGCMs) based on grey systems theory. Çoban and Onar [41] put

forward an approach to FCMs under hesitant fuzzy linguistic environment called hesitant fuzzy linguistic cognitive maps (HFLCMs). Ghaderi *et al.* [42] and Liu *et al.* [43] proposed new FCMs called hesitant fuzzy cognitive maps (HFCMs), respectively. Although these extensions provide better modeling of uncertainty in knowledge representation, a certain source of uncertainty, i.e., the experts' hesitancy, is ignored. The HFCMs considers the experts' hesitancy, but it fails to reflect the nonmembership degrees of the concept, which is common in uncertain systems. To overcome the drawbacks mentioned above, a novel FCMs model under DHFSs environment, which integrates the advantages of IFCMs and HFCMs, is proposed in this paper. The reasons for choosing DHFSs theory are in the following: (1) DHFSs, whose membership and nonmembership degrees are represented by a set of possible values in [0, 1] respectively, is considered as a powerful tool to express uncertain information in the process of multi-attribute group decision-making [44]. (2) It can integrate the advantages of IFSs and HFSs to describe fuzzy uncertainty more accurately. (3) It can retain more decision-making information from a group of experts. Hence, DHFSs is used to represent the values of the initial state and the connection weight between concepts, and then a new FCMs model with dual hesitant fuzzy information is constructed in this paper.

In addition, the original operation rules for DHFSs will lead to an increase in the computational dimensions [32]. To overcome this drawback, this paper presents some novel operation rules for DHFSs. Then a novel approach to FCMs under DHFSs environment is presented. Besides, motivated by the idea of TOPSIS, a new similarity measure between two DHFSs A and B is proposed. In summary, the novelties of our work are as follows:

1. Similarity measure is one of the most useful tools to measure the similarity and correlation between two sets. The similarity measure proposed in this paper takes into account not only the distance between sets A and B but also the distance between sets A and B^C (the complementary set of B).

2. As a novel extension of FCMs model, DHFCMs integrates the advantages of DHFSs and FCMs to deal with hesitancy and uncertainty during the evaluation process. Compared with the classical FCMs model, DHFCMs can handle the uncertainty in the human reasoning process more flexibly.

3. The proposed method allows us to deal with the hesitancy of experts in the assessment of the initial concept values and the causal relationship between concepts. It is also the first time that the DHFCMs and similarity measure between DHFSs are combined to analyze the risk factors in emergency events.

The remainder of this paper is organized as follows: In Section 2, some basic concepts related to DHFSs and FCMs are introduced. The DHFCMs model is constructed and its specific reasoning process is shown in Section 3. In Section 4, a case study on the huge explosion at Tianjin Port in China in 2015 and the comparative analysis with IFCMs are conducted. Section 5 ends the paper with some conclusions.

2. PRELIMINARIES

In this section, we review some basic concepts related to DHFSs and FCMs, and then introduce some preliminaries used throughout the paper.

2.1. Dual Hesitant Fuzzy Sets

Definition 1. [32] Let X be a fixed set, then a DHFSs D on X is described as

$$D = \{\langle x, h(x) \rangle, g(x), x \in X\} \tag{1}$$

in which $h(x)$ and $g(x)$ are two sets of some values in [0, 1], denoting the possible membership degrees and nonmembership degrees of the element $x \in X$ to the set D, respectively, with the conditions:

$$0 \leq \gamma, \eta \leq 1, 0 \leq \gamma^+ + \eta^+ \leq 1 \tag{2}$$

where $\gamma \in h(x)$, $\eta \in g(x)$. $\gamma^+ \in h^+(x) = \cup_{\gamma \in h(x)} \max\{\gamma\}$, $\eta^+ \in g^+(x) = \cup_{\eta \in g(x)} \max\{\eta\}$ for all $x \in X$. For convenience, the pair $d(x) = (h(x), g(x))$ is called a DHFE denoted by $d = (h, g)$, with the conditions: $\gamma \in h$, $\eta \in g$. $\gamma^+ \in h^+ = \cup_{\gamma \in h} \max\{\gamma\}$, $\eta^+ \in g^+ = \cup_{\eta \in g} \max\{\eta\}$, and $0 \leq \gamma, \eta \leq 1, 0 \leq \gamma^+ + \eta^+ \leq 1$.

Definition 2. [32] Let X be a fixed set, $d = \{h_d, g_d\}$, $d_1 = \{h_{d_1}, g_{d_1}\}$, $d_2 = \{h_{d_2}, g_{d_2}\}$ are three DHFEs, then the following operations are valid:

1. $d_1 \oplus d_2 = \{h_{d_1} \oplus h_{d_2}, g_{d_1} \otimes g_{d_2}\}$

   $= \cup_{\gamma_{d_1} \in h_{d_1}, \gamma_{d_2} \in h_{d_2}, \eta_{d_1} \in g_{d_1}, \eta_{d_2} \in g_{d_2}}$

   $\{\{\gamma_{d_1} + \gamma_{d_2} - \gamma_{d_1}\gamma_{d_2}\}, \{\eta_{d_1}\eta_{d_2}\}\};$

2. $d_1 \otimes d_2 = \{h_{d_1} \otimes h_{d_2}, g_{d_1} \oplus g_{d_2}\}$

   $= \cup_{\gamma_{d_1} \in h_{d_1}, \gamma_{d_2} \in h_{d_2}, \eta_{d_1} \in g_{d_1}, \eta_{d_2} \in g_{d_2}}$

   $\{\{\gamma_{d_1}\gamma_{d_2}\}, \{\eta_{d_1} + \eta_{d_2} - \eta_{d_1}\eta_{d_2}\}\};$

3. $nd = \cup_{\gamma_d \in h_d, \eta_d \in g_d} \{\{1 - (1 - \gamma_d)^n\}, \{(\eta_d)^n\}\};$

4. $d^n = \cup_{\gamma_d \in h_d, \eta_d \in g_d} \{\{(\gamma_d)^n\}, \{1 - (1 - \eta_d)^n\}\};$

5. $d^c = \{g_d, h_d\}.$

For a DHFS $A = \{\langle x, h_A(x), g_A(x) \rangle | x \in X\}$, let $\sigma : (1, 2, \cdots, n) \to (1, 2, \cdots, n)$ be a permutation satisfying $h_A^{\sigma(s)}(x) \geq h_A^{\sigma(s+1)}(x)$ for $s = 1, 2, \cdots, n - 1$, and $h_A^{\sigma(s)}(x)$ be the sth largest value in $h_A(x)$; let $\sigma : (1, 2, \cdots, m) \to (1, 2, \cdots, m)$ be a permutation satisfying $g_A^{\sigma(t)}(x) \geq g_A^{\sigma(t+1)}(x)$ for $t = 1, 2, \cdots, m - 1$, and $g_A^{\sigma(t)}(x)$ be the tth largest value in $g_A(x)$ [45].

Definition 3. [46] For a reference set X, let $A = \{\langle x_i, d_A(x_i) \rangle | x_i \in X\}$ be a DHFSs on X with $d_A(x_i) = \{\{\gamma_{A_{i_1}}, \gamma_{A_{i_2}}, \cdots, \gamma_{A_{i_n}}\}, \{\eta_{A_{i_1}}, \eta_{A_{i_2}}, \cdots, \eta_{A_{i_m}}\}\}$, $i = 1, 2, \cdots, k$. Then the ordered DHFE is defined as follows:

$$d_A^\sigma(x_i) = \{\{\gamma_{A_{i_1}}^{\sigma(1)}, \gamma_{A_{i_2}}^{\sigma(2)}, \cdots, \gamma_{A_{i_n}}^{\sigma(n)}\}, \{\eta_{A_{i_1}}^{\sigma(1)}, \eta_{A_{i_2}}^{\sigma(2)}, \cdots, \eta_{A_{i_m}}^{\sigma(m)}\}\} \tag{3}$$

The number of values in different DHFEs might be different. Assume $\#h = max\{l(h_A(x_i)), l(h_B(x_i))\}$ and $\#g = max\{l(g_A(x_i)), l(g_B(x_i))\}$ for each $x_i \in X$, where $l(h)$ and $l(g)$ are the number of the elements in h and g, respectively. For two DHFSs A and B, if $l(h_A(x_i)) \neq l(h_B(x_i))$ and $l(g_A(x_i)) \neq l(g_B(x_i))$, we can extend the shorter DHFE by adding any values to make the number of elements in two DHFEs equal. In terms of the pessimistic principle, the minimum value in it will be added while in the opposite case, the maximum value in it will be added [47]. In this paper, we add the minimum value into the shorter DHFE until it has the same length as the longer DHFE.

Distance measure is an important tool for indicating the proximity between two DHFSs [48,49]. For the convenience of calculation, Hamming distance between two DHFSs is defined as follows:

Definition 4. [48,49] Let A and B be two DHFSs on $X = \{x_1, x_2, \cdots, x_k\}$. The Hamming distance $d(A, B)$ between A and B is defined as follows:

$$d_{D-HFS}(A, B) = \frac{1}{2k} \sum_{i=1}^{k}$$

$$\left(\frac{1}{\#h} \sum_{s=1}^{\#h} |h_A^{\sigma(s)}(x_i) - h_B^{\sigma(s)}(x_i)| + \frac{1}{\#g} \sum_{t=1}^{\#g} |g_A^{\sigma(t)}(x_i) - g_B^{\sigma(t)}(x_i)| \right),$$

$$s = 1, 2, \cdots, \#h; t = 1, 2, \cdots, \#g. \tag{4}$$

Proposition 1. [48,49] Let A and B be two DHFSs on $X = \{x_1, x_2, \cdots, x_k\}$. $d(A, B)$ is defined as the distance between A and B, if $d(A, B)$ satisfies the following properties:

1. $0 \leq d(A, B) \leq 1;$

2. $d(A, B) = 0$ if and only if $A = B$;

3. $d(A, B) = d(B, A);$

4. Let C be a DHFSs, if $A \subseteq B \subseteq C$, then $d(A, B) \leq d(A, C)$ and $d(B, C) \leq d(A, C)$.

2.2. Fuzzy Cognitive Maps

The FCMs is a fuzzy directed map consisting of directed edges and nodes called concepts. These nodes in FCMs can represent different concepts, such as characteristics, causes, variables, states, outputs, events of the system, etc. For instance, in risk factors analysis of emergency events, nodes can represent the risk factors and result of emergency events. A directed edge represents a causal relationship between two risk factors in emergency events. The causal relationship describes the effect of one variable over another. So, it takes shape the causal reasoning model for representing complex systems in graphical form. FCMs utilizes nodes and directed edges to represent the concepts of entities in the system and the casual relationship between nodes, respectively. And it can simulate the interaction between entities well. FCMs can indicate the dynamic behavior of the entire complex system and complete the prediction. It is widely used in practice due to its strong explanatory power, simple reasoning and the ability of handling feedback.

Definition 5. FCMs is a four-tuple structure $G = (C, E, X, f)$, where $C = \{C_1, C_2, \cdots, C_n\}$ is a set of nodes, n is the number of nodes, $E : (C_i, C_j) \to \omega_{ij}$ is a mapping, which is a reflection of the casual relationship between concepts, and $X : V_i \to x_i$ is a mapping. Here, $x_i(t)$ represents the state value of node V_i at time t. $X(t) = [x_1(t), \cdots, x_n(t)]$ represents the state of FCMs G at time t. $f(x)$ is the threshold function, which ensures that the nodes values in each iteration are in the interval [0, 1].

Definition 6 (Concept node). The nodes in the FCMs are called concept nodes, which can represent some concepts in the system such as entities, action, behaviors, causes, results, trends, etc. They are denoted as $C_i (i = 1, 2, \cdots, n)$, which represents the ith concept node in G.

Definition 7 (Weight). In FCMs, a value denoted as $\omega_{ij} (\omega_{ij} \in E)$ in the interval [0, 1] is utilized to describe the degree of influence of C_i on C_j when the direct causal relationship between C_i and C_j exists.

In general, for a FCMs with n nodes, in order to ensure that the nodes values of each iteration are within the interval of [0, 1], a threshold function $f(x)$ is required for mapping, and the value of each node at time $t + 1$ is calculated by the following formula:

$$x_i(t+1) = f\left(\sum_{j=1, i \neq j}^{n} x_i(t) \cdot \omega_{ij} + x_i(t)\right) \quad (5)$$

The initial state of the FCMs is determined by the experts. Then through the iteration by Eq. (5), the system can be stabilized to a fixed point or limit cycle, thereby the iteration and the reasoning process should be stopped. Moreover, complex FCMs may also end up with a chaotic attractor [26].

3. AN APPROACH TO ANALYZE THE CAUSES FACTORS OF EMERGENCY EVENTS BASED ON DHFCMs

In this section, a novel similarity measure of DHFSs is proposed. Then, the DHFCMs model is constructed, and the specific decision process is given.

3.1. The Novel Operation Rules and Similarity Measure of DHFSs

At the beginning of this part, since original operation rules for DHFSs will lead to an increase in the computational dimensions, some new operation rules are proposed. Motivated by the idea of Ref. [51], we adjust the operation rules for DHFEs as follows:

Definition 8. Let X be a fixed set. $d_1 = \{h_{d_1}, g_{d_1}\} = \{\{\gamma_{d_1}^{\sigma(1)}, \gamma_{d_1}^{\sigma(2)}, \cdots, \gamma_{d_1}^{\sigma(\#h)}\}, \{\eta_{d_1}^{\sigma(1)}, \eta_{d_1}^{\sigma(2)}, \cdots, \eta_{d_1}^{\sigma(\#g)}\}\}$ and $d_2 = \{h_{d_2}, g_{d_2}\} = \{\{\gamma_{d_2}^{\sigma(1)}, \gamma_{d_2}^{\sigma(2)}, \cdots, \gamma_{d_2}^{\sigma(\#h)}\}, \{\eta_{d_2}^{\sigma(1)}, \eta_{d_2}^{\sigma(2)}, \cdots, \eta_{d_2}^{\sigma(\#g)}\}\}$ are two DHFEs on X, where $\gamma_{d_i}^{\sigma(j)}$ and $\eta_{d_i}^{\sigma(j)}$ $(i = 1, 2; j = 1, 2, \cdots, \#h \text{ or } \#g)$ represent the jth largest values of membership and non-membership degree, respectively. The basic operation rules for DHFEs is defined as below:

1. $d_1 \oplus d_2 = \cup_{\gamma_{d_1} \in h_{d_1}, \gamma_{d_2} \in h_{d_2}, \eta_{d_1} \in g_{d_1}, \eta_{d_2} \in g_{d_2}}$

$$\left\{\left\{\gamma_{d_1}^{\sigma(i)} + \gamma_{d_2}^{\sigma(i)} - \gamma_{d_1}^{\sigma(i)}\gamma_{d_2}^{\sigma(i)}\right\}, \left\{\eta_{d_1}^{\sigma(j)}\eta_{d_2}^{\sigma(j)}\right\}\right\},$$

$$i = 1, 2, \cdots, \#h; j = 1, 2, \cdots, \#g;$$

2. $d_1 \otimes d_2 = \cup_{\gamma_{d_1} \in h_{d_1}, \gamma_{d_2} \in h_{d_2}, \eta_{d_1} \in g_{d_1}, \eta_{d_2} \in g_{d_2}}$

$$\left\{\left\{\gamma_{d_1}^{\sigma(i)}\gamma_{d_2}^{\sigma(i)}\right\}, \left\{\eta_{d_1}^{\sigma(j)} + \eta_{d_2}^{\sigma(j)} - \eta_{d_1}^{\sigma(j)}\eta_{d_2}^{\sigma(j)}\right\}\right\},$$

$$i = 1, 2, \cdots, \#h; j = 1, 2, \cdots, \#g;$$

Therefore, we can find that the dimensions of the derived DHFEs have not been increased, thus it calls for less calculation effort.

In Section 2.1, the Hamming distance measure of DHFSs is introduced. And motivated by the idea of TOPSIS method [48], the similarity measure based on Eq. (4) is defined as follows:

Definition 9. Let X be a fixed set, and $A = \{\langle x_i, d_A(x_i)\rangle | x_i \in X\}$ and $B = \{\langle x_i, d_B(x_i)\rangle | x_i \in X\}$ are two DHFSs, where $d_A(x_i) = \{\{\gamma_{A_{i_1}}^{\sigma(1)}, \gamma_{A_{i_2}}^{\sigma(2)}, \cdots, \gamma_{A_{i_n}}^{\sigma(\#h)}\}, \{\eta_{A_{i_1}}^{\sigma(1)}, \eta_{A_{i_2}}^{\sigma(2)}, \cdots, \eta_{A_{i_m}}^{\sigma(\#g)}\}\}$ and

$d_B(x_i) = \{\{\gamma_{B_{i_1}}^{\sigma(1)}, \gamma_{B_{i_2}}^{\sigma(2)}, \cdots, \gamma_{B_{i_n}}^{\sigma(\#h)}\}, \{\eta_{B_{i_1}}^{\sigma(1)}, \eta_{B_{i_2}}^{\sigma(2)}, \cdots, \eta_{B_{i_m}}^{\sigma(\#g)}\}\}$

represent the DHFEs in A and B, respectively, then the similarity measure between A and B is defined as

$$s(A, B) = \frac{d_{D-HFS}(A, B^C)}{d_{D-HFS}(A, B) + d_{D-HFS}(A, B^C)} \quad (6)$$

Here, B^C denotes the complementary set of B, and $B^C = \{\langle x_i, \{\eta_{B_{i_1}}^{\sigma(1)}, \eta_{B_{i_2}}^{\sigma(2)}, \cdots, \eta_{B_{i_m}}^{\sigma(\#g)}\}, \{\gamma_{B_{i_1}}^{\sigma(1)}, \gamma_{B_{i_2}}^{\sigma(2)}, \cdots, \gamma_{B_{i_n}}^{\sigma(\#h)}\}\rangle | x_i \in X\}$.

Example 1. Let $A = \{\{0.6, 0.3, 0.2\}, \{0.3, 0.2, 0.1\}\}$, $B = \{\{0.5, 0.4, 0.2\}, \{0.4, 0.3, 0.2\}\}$ and $C = \{\{0.4, 0.3, 0.1\}, \{0.5, 0.2, 0.1\}\}$ be three DHFEs, according to Eq. (4), we have

$$\begin{aligned} d(A, B) &= \frac{1}{2}\left(\frac{1}{3}\left(|0.6 - 0.5| + |0.3 - 0.4| + |0.2 - 0.2|\right)\right. \\ &\quad \left. + \frac{1}{3}\left(|0.3 - 0.4| + |0.2 - 0.3| + |0.1 - 0.2|\right)\right) \\ &= \frac{1}{12} \end{aligned}$$

Similarly, the distance between A and C is $d(A, C) = 1/12$.

It's found that $d(A, B) = d(A, C)$, which implies that we cannot determine whether B or C is more similar to A. Therefore, there is an urgent need to propose a new similarity measure to distinguish the difference between two DHFSs. By the proposed method, we obtain $B^C = \{\{0.4, 0.3, 0.2\}, \{0.5, 0.4, 0.2\}\}$ and $C^C = \{\{0.5, 0.2, 0.1\}, \{0.4, 0.3, 0.1\}\}$. Then, according to Eq. (4), we derive $d(A, B^C) = 7/60$ and $d(A, C^C) = 1/12$. Thus, according to Eq. (6), we derive that $s(A, B) = 7/12$ and $s(A, C) = 1/2$. Then

$$s(A, B) > s(A, C)$$

Thus, A is more similar to B than to C. The similarity measure proposed in this paper takes both the distance between A and B and the distance between A and B^C into account, which has high degree of distinction.

Proposition 2. *The similarity degree between $A = \{\langle x_i, d_A(x_i)\rangle | x_i \in X\}$ and $B = \{\langle x_i, d_B(x_i)\rangle | x_i \in X\}$ is defined as $s(A, B)$, which satisfies the following properties:*

1. $0 \leq s(A, B) \leq 1$, where $s(A, B) = 0$ if and only if $A = B^C$;

2. $s(A, B) = 1$ if and only if $A = B$;

3. $s(A, B) = s(B, A)$;

4. If $A \subseteq B \subseteq C, A, B, C \in X$, then $s(A, C) \leq s(A, B)$ and $s(A, C) \leq s(B, C)$.

Proof:

1. Since $d_{D-HFS}(A, B^C) \geq 0$ and $d_{D-HFS}(A, B) \geq 0$, we then obtain $0 \leq s(A, B) \leq 1$. If $s(A, B) = 0$, then $d_{D-HFS}(A, B^C) = 0$, i.e., $B = A^C$, and vice versa.

2. $s(A, B) = 1$ is equivalent to $d_{D-HFS}(A, B) = 0$, i.e., $A = B$;

3. Since $B = \{\langle x_i, d_B(x_i)\rangle | x_i \in X\} = \left\{\left\{\gamma_{B_{i_1}}, \gamma_{B_{i_2}}, \cdots, \gamma_{B_{i_n}}\right\}, \left\{\eta_{B_{i_1}}, \eta_{B_{i_2}}, \cdots, \eta_{B_{i_m}}\right\}\right\}$, we derive $B^C = \left\{\left\{\eta_{B_{i_1}}, \eta_{B_{i_2}}, \cdots, \eta_{B_{i_m}}\right\}, \left\{\gamma_{B_{i_1}}, \gamma_{B_{i_2}}, \cdots, \gamma_{B_{i_n}}\right\}\right\}$. According to the operational laws mentioned above,

$$d_{D-HFS}(A, B^C)$$
$$= \frac{1}{2n} \sum_{i=1}^{n} \left(\frac{1}{n} \sum_{s=1}^{n} |h_{A\sigma(s)}(x_i) - g_{B\sigma(s)}(x_i)| \right.$$
$$\left. + \frac{1}{n} \sum_{s=1}^{n} |g_{A\sigma(s)}(x_i) - h_{B\sigma(s)}(x_i)| \right)$$
$$= \frac{1}{2n} \sum_{i=1}^{n} \left(\frac{1}{n} \sum_{s=1}^{n} |h_{B\sigma(s)}(x_i) - g_{A\sigma(s)}(x_i)| \right.$$
$$\left. + \frac{1}{n} \sum_{s=1}^{n} |g_{B\sigma(s)}(x_i) - h_{A\sigma(s)}(x_i)| \right)$$
$$= d_{D-HFS}(B, A^C).$$

Then, $s(A, B) = \frac{d_{D-HFS}(A, B^C)}{d_{D-HFS}(A, B) + d_{D-HFS}(A, B^C)} = \frac{d_{D-HFS}(B, A^C)}{d_{D-HFS}(B, A) + d_{D-HFS}(B, A^C)} = s(B, A)$; Since $A \subseteq B \subseteq C$, we obtain $d_{D-HFS}(A, B) \leq d_{D-HFS}(A, C)$ and $d_{D-HFS}(A, B^C) \geq$

$d_{D-HFS}(A, C^C)$. Since $f(x) = \frac{x}{1+x}$ is a monotonically increasing function with respect to x, we derive

$$s(A, C) = \frac{d_{D-HFS}(A, C^C)}{d_{D-HFS}(A, C) + d_{D-HFS}(A, C^C)}$$
$$\leq \frac{d_{D-HFS}(A, B^C)}{d_{D-HFS}(A, C) + d_{D-HFS}(A, B^C)}$$
$$\leq \frac{d_{D-HFS}(A, B^C)}{d_{D-HFS}(A, B) + d_{D-HFS}(A, B^C)}$$
$$= s(A, B).$$

Similarly, $s(A, C) \leq s(B, C)$, which completes the proof.

3.2. The Construction of DHFCMs and the Inference Process

In this section, a new extended model called DHFCMs, which combines the advantages of the FCMs and DHFSs, is proposed.

Definition 10. DHFCMs is a four-tuple structure $G = (C, E, X, f)$, where $C = \{C_1, C_2, \cdots, C_n\}$ is a set of nodes, $C_i = \left(c^h, c^g\right)_i$ is a DHFE, n is the number of nodes, and $E : (C_i, C_j) \rightarrow \omega_{ij}$ is a mapping, where $\omega_{ij} = \left(\omega^h, \omega^g\right)_{ij}$ is a DHFE and denotes the casual relationship between two concepts. $X : V_i \rightarrow x_i$ is a mapping. $X(t) = [x_1(t), \cdots, x_n(t)]$ represents the state of FCMs G at time t where $x_i(t)$ represents the state of node V_i at time t. $f(x)$ is the threshold function, which ensures that the node values in each iteration are in [0, 1].

Definition 11 (Concept node). The node in the DHFCMs is called a concept node, which can represent entities, actions, behaviors, causes, results, trends, and indicators in the system. It is denoted as $C_i \left(C_i = \left(c^h, c^g\right)_i\right)$, which represents the ith concept node in G.

Definition 12 (Weight). In DHFCMs, C_i and C_j are two different concept nodes in C, a DHFE $\omega_{ij} \left(\omega_{ij} = \left(\omega^h, \omega^g\right)_{ij} \in E\right)$ is used to describe the influence degree of C_i on C_j when a direct causal relationship between them exists. Here, $\omega_{ij} \left(\omega_{ij} = \left(\omega^h, \omega^g\right)_{ij} \in E\right)$ represents the weight between the concept nodes C_i and C_j.

A simple DHFCMs consisting of five nodes is illustrated in Figure 2. In DHFCMs, each node C_k is expressed in the context of DHFE $C_k = \left(c^h, c^g\right)_k$. And, the edge linking two nodes C_i and C_j represents the causalities, and the connection weight ω_{ij} taking the form of DHFEs $\omega_{ij} = \left(\omega^h, \omega^g\right)_{ij}$ represents the influence degree of C_i on C_j.

Generally, for a DHFCMs model containing n nodes, in order to ensure that the node values in each iteration are in [0, 1], a threshold function $f(\cdot)$ is required for mapping. The nodes value at time $t + 1$ is calculated as $x_i(t+1) = f\left(x_i(t) \oplus \sum_{j=1, i\neq j}^{n} \left(x_i(t) \otimes \omega_{ij}\right)\right)$. Then the iteration formula of DHFCMs can be obtained as follows:

$$\left(c^h, c^g\right)_i^{t+1} = f\left(\left(c^h, c^g\right)_i^t \oplus \sum_{\substack{i\neq j \\ j\in S}} \left(\left(c^h, c^g\right)_i^t \otimes \left(\omega^h, \omega^g\right)_{ij}\right)\right) \quad (7)$$
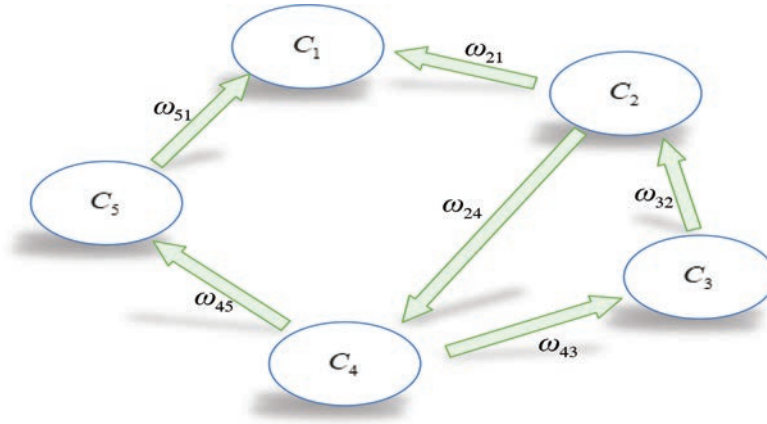
Figure 2 | A simple dual hesitant fuzzy cognitive maps (DHFCMs).

The threshold function $f(\cdot)$ plays a role in forcing the uncertain system to converge to a steady state. Sometimes, the iteration is also stopped when the difference between two iterations is less than or equal to the given threshold. In this paper, we choose the threshold function as follows [39]:

$$f(x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}, \lambda > 0 \qquad (8)$$

To illustrate that the mapping results by $f(\cdot)$ are still DHFEs, we have the following proposition:

Proposition 3. *In DHFCMs, let* $\left(c^h, c^g\right)_i^t = \left(\left\{c^{h(1)}, c^{h(2)}, \cdots, c^{h(n)}\right\},\right.$ $\left.\left\{c^{g(1)}, c^{g(2)}, \cdots, c^{g(n)}\right\}\right)_i^t$ *and* $\left(c^h, c^g\right)_j^t = \left(\left\{c^{h(1)}, c^{h(2)}, \cdots, c^{h(n)}\right\},\right.$ $\left.\left\{c^{g(1)}, c^{g(2)}, \cdots, c^{g(n)}\right\}\right)_j^t$ *be the state vectors of concept* C_i *and* C_j *at time t, respectively, and* ω_{ij} *represents the influence degree of* C_i *on* C_j, *then the new state vector* $\left(c^h, c^g\right)_i^{t+1}$ *of DHFCMs at time t + 1 can be expressed as a DHFE, and*

$$\left(c^h, c^g\right)_i^{t+1} = f\left(\left(\left(c_i^{h\sigma(k)}\right)^t + \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^{h\sigma(k)} \cdot \omega_{ji}^{h\sigma(k)}\right)^t\right)\right.\right.$$
$$\left. - \left(c_i^{h\sigma(k)}\right)^t \cdot \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^{h\sigma(k)} \cdot \omega_{ji}^{h\sigma(k)}\right)^t\right),\right.$$
$$\left. \left(c_i^{g\sigma(k)}\right)^t \cdot \prod_{\substack{i\neq j \\ j\in S}} \left(c_i^{g\sigma(k)} + \omega_{ji}^{g\sigma(k)} - c_i^{g\sigma(k)} \cdot \omega_{ji}^{g\sigma(k)}\right)^t\right),$$
$$k = 1, 2, \cdots, n.$$
$$(9)$$

Proof: By Definition 5, we obtain

$$\left(c^h, c^g\right)_i^{t+1}$$
$$= f\left(\left(c^h, c^g\right)_i^t \oplus \prod_{\substack{i\neq j \\ j\in S}} \left(c^h, c^g\right)_i^t \otimes \left(\omega^h, \omega^g\right)_{ij}\right)$$

$$= f\left(\left(c^h, c^g\right)_i^t \oplus \sum_{\substack{i\neq j \\ j\in S}} \left(c_i^h \cdot \omega_{ji}^h, c_i^g + \omega_{ji}^g - c_i^g \cdot \omega_{ji}^g\right)^t\right)$$
$$= f\left(\left(c^h, c^g\right)_i^t \oplus \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^h \cdot \omega_{ji}^h\right)^t,\right.\right.$$
$$\left.\left. \prod_{\substack{i\neq j \\ j\in S}} \left(c_i^g + \omega_{ji}^g - c_i^g \cdot \omega_{ji}^g\right)^t\right)\right)$$
$$= f\left(\left(c_i^h\right)^t + \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^h \cdot \omega_{ji}^h\right)^t\right),\right.$$
$$\left. - \left(c_i^h\right)^t \cdot \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^h \cdot \omega_{ji}^h\right)^t\right)\right.$$
$$\left(c_i^g\right)^t \cdot \prod_{\substack{i\neq j \\ j\in S}} \left(c_i^g + \omega_{ji}^g - c_i^g \cdot \omega_{ji}^g\right)^t\right) [12pt]$$
$$= f\left(\left(\left(c_i^{h\sigma(k)}\right)^t + \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^{h\sigma(k)} \cdot \omega_{ji}^{h\sigma(k)}\right)^t\right)\right)\right.$$
$$\left. - \left(c_i^{h\sigma(k)}\right)^t \cdot \left(1 - \prod_{\substack{i\neq j \\ j\in S}} \left(1 - c_i^{h\sigma(k)} \cdot \omega_{ji}^{h\sigma(k)}\right)^t\right),\right.$$
$$\left. \left(\left(c_i^{g\sigma(k)}\right)^t \cdot \prod_{\substack{i\neq j \\ j\in S}} \left(c_i^{g\sigma(k)} + \omega_{ji}^{g\sigma(k)} - c_i^{g\sigma(k)} \cdot \omega_{ji}^{g\sigma(k)}\right)^t\right),\right.$$
$$k = 1, 2, \cdots, n. [12pt]$$

Since $f(x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}, \lambda > 0$, we obtain that the membership and nonmembership degrees of DHFE $\left(c^h, c^g\right)_i^{t+1}$ belong to the interval [0, 1], respectively. Therefore, $\left(c^h, c^g\right)_i^{t+1}$ is still a DHFE, which completes the proof of Proposition 3.

The reasoning process of DHFCMs stops when the steady state is reached or the iteration value reaches the threshold. The final dual hesitant fuzzy vector shows the effect of the change in the value of each concept. After several iterations, the DHFCMs will reach one of the following states: (1) It converges to a fixed point of concept value, which is described as the dual hesitant fuzzy fixed-point attractor. (2) The state continues cycling between several fixed

states, which is known as a dual hesitant fuzzy limit cycle. (3) A chaotic state may occur, which will be uninformative.

3.3. The Decision Steps of the Proposed Approach

In this section, the application process of the proposed method is presented. Firstly, the domain experts are invited to determine the number and kind of nodes, which forms the DHFCMs model. Moreover, the influence of one node on another is determined in the light of experts' knowledge and experience, and the strength of influence is expressed as a DHFE. Therefore, a connection matrix, in which the elements represent the casual relationship or the strength of influence between concepts, is determined. The initial state with $n + 1$ nodes, which denotes the initial value of each concept node, can be expressed as follows:

$$C^0 = \{C_1, C_2, \cdots, C_n, R\}^0 \qquad (10)$$

Here, C_i^0 $(i = 1, 2, \cdots, n)$ and R^0 represent the initial value of concepts and final result respectively. There are only two states, i.e., "activation" and "inactivation," which can be expressed as DHFEs $\{\{1\}, \{0\}\}$, and $\{\{0\}, \{1\}\}$, respectively. Then, the novel concept values are obtained by Eq. (7). In this section, we extend FCMs to accommodate dual hesitant fuzzy environment, and integrate DHFCMs and dual hesitant fuzzy similarity measure to analyze the impact of risk factors on emergency events. Based on above analysis, a novel approach based on DHFCMs for modeling uncertainty of the emergency management system is presented as follows and the flowchart of DHFCMs is shown in Figure 3.

Step 1. Form a committee of domain experts to evaluate the risk factors of the emergency event. And the number and kind of nodes are determined through literature reviews and consultation of experts.

Step 2. The causal relationships between nodes are determined on the basis of the domain experts' knowledge and experience. Then, a connection matrix is obtained and the graph-based DHFCMs is constructed.

Step 3. Simulation scenario is designed. Then analyze the risk factors resulting in the emergency events.

Step 4. According to Eqs. (4) and (6), the similarity measure between the steady values of the cause factors and the final results is calculated, and the risk factors are ranked.

Step 5. End.

By handling hesitancy in the experts' evaluation of the causal relationships among initial concepts, DHFCMs can be used to derive the system's steady states and model the dynamic systems involving feedback. Based on DHFSs theory, the nodes can reflect the hesitancy of experts. And the connection weights between them expressed as DHFEs describes the effect of change in one node on another node. It's found that DHFCMs is more flexible tool in simulating the reality and has superiority over the existing ones. It's an extension of FCMs, IFCMs, and HFCMs. Moreover, it can represent the hesitancy of experts and deal with the uncertainty more flexibly than the FCMs, IFCMs, and HFCMs, and thus has potential for wider application.

4. A NUMERICAL EXAMPLE AND COMPARATIVE ANALYSIS

In this section, an illustrative example on the analysis of risk factors in the huge explosion at Tianjin Port is presented to demonstrate the application of the proposed approach. And the comparative analysis is conducted to illustrate the feasibility and superiority of the proposed method.

4.1. An Illustrative Example

At 22:51 on August 12, 2015, a fire breaks out in the dangerous goods warehouse of Ruihai Company (Hereinafter referred to as "RH") in the Binhai New Area of Tianjin, China, which then causes two violent explosions. The impact of the emergency event is huge and extensive (See Figure 4). It causes 165 deaths, 8 missing, 58 seriously injured, and 740 slightly injured. The direct economic loss is 6.866 billion yuan, and the surrounding air, water, and soil are all polluted to varying degrees.

To investigate responsibility and prevent similar emergency events occurring, the emergency management department needs to analyze the risk factors of the emergency events. We extract risk factors from the documents released by the Chinese government (hereinafter referred to as "DCG")[1] and other papers [52–57]. The risk factors influencing emergency events are analyzed. Through experts' interviews, literature reviews and DCG, the risk factors are derived and shown in Table 1.

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[1] http://www.gov.cn/foot/2016-02/05/5039788/files/460731d8cb4c4488be3bb0c218f8b527.pdf
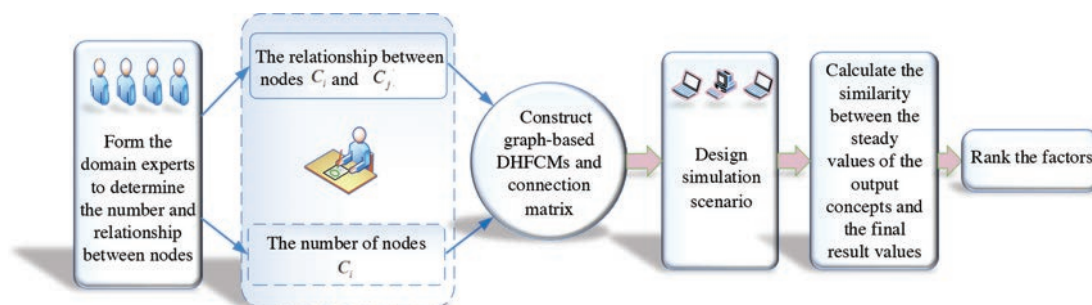

Figure 3 | The flowchart of the proposed method.

Figure 4 | Impact of the huge explosion at Tianjin Port.

Table 1 | The risk factors of the huge explosion at Tianjin Port.

Factors	Sub-factors	Sources
Human factor	Personal professional ability factor C_1	[52,53]
	Limitations of personal cognitive ability C_2	[52,54]
	Personnel's neglect of danger C_3	[54,56,57]
Environment	Natural factors such as high temperature and dryness C_4	DCG
	Other uncertain environmental factors C_5	[52]
Technology	Ability to issue specific early warning procedures for potential hazards C_6	DCG
	Unsatisfactory storage of dangerous goods and overloading operation C_7	DCG
	Safety of rescue assistance during distribution and transportation C_8	DCG
Maintenance management	Statistics and feedback on loss information and lack of information sharing mechanisms C_9	DCG [55]
	Clear reporting and procedures for submitting information C_{10}	DCG
	Lack of unified planning in factory C_{11}	[56,58]
	Lack of reasonable organizational structure and a clear sense of responsibility C_{12}	[56,58]
	Lack of factory emergency preparations C_{13}	[52,54,57]
Final result	Emergency event R (i.e., the end result)	

According to the above analysis, the risk factors of the emergency event are determined by the proposed method. The specific process is shown as follows:

Step 1. Form a committee of domain experts and identify the risk factors represented by the nodes in DHFCMs. And the risk factors are shown in Table 1.

Step 2. Graph-based DHFCM model is constructed (See Figure 5).

Step 3. The causal relationship between nodes are identified based on the domain experts' knowledge and experience, and the connection matrix W is represented in the following:

$$W = \left(\omega_{ij} \right)_{14 \times 14} \qquad (11)$$

Table 2 | Initial state vector C^0 with 14 nodes.

Nodes	Initial State Vector
C_1	{{1}, {0}}
C_2	{{1}, {0}}
C_3	{{1}, {0}}
C_4	{{0}, {1}}
C_5	{{1}, {0}}
C_6	{{0}, {1}}
C_7	{{1}, {0}}
C_8	{{0}, {1}}
C_9	{{0}, {1}}
C_{10}	{{1}, {0}}
C_{11}	{{0}, {1}}
C_{12}	{{1}, {0}}
C_{13}	{{0}, {1}}
R	{{1}, {0}}

where W is shown in Table 1 in the **Appendix**.

Step 4. Simulation scenario is designed. The initial state vector with 14 nodes are defined and shown in Table 2. Here, {{0},{1}} denoted as a DHFE indicates that the risk factor is not activated, whereas {{1},{0}} indicates that the risk factor is activated. For convenience, we set the parameter $\lambda = 1$, and the threshold of the iteration result is 1×10^{-6}. Then the stable values are reached and shown in Tables 3 and 4.

Step 5. Thus, according to Eqs. (4) and (6), the similarity between the steady values of risk factors and final result is calculated as follows:

$s(C_1, R) = 0.6497$; $s(C_2, R) = 0.5629$; $s(C_3, R) = 0.6892$; $s(C_4, R) = 0.6193$; $s(C_5, R) = 0.6914$; $s(C_6, R) = 0.7729$; $s(C_7, R) = 0.8692$; $s(C_8, R) = 0.8434$; $s(C_9, R) = 0.7314$; $s(C_{10}, R) = 0.7709$; $s(C_{11}, R) = 0.7856$; $s(C_{12}, R) = 0.7609$; $s(C_{13}, R) = 0.7555$;

Therefore,

$s(C_7, R) > s(C_8, R) > s(C_{11}, R) > s(C_6, R) > s(C_{10}, R) > s(C_{12}, R) > s(C_{13}, R) > s(C_9, R) > s(C_5, R) > s(C_3, R) > s(C_1, R) > s(C_4, R) > s(C_2, R)$.
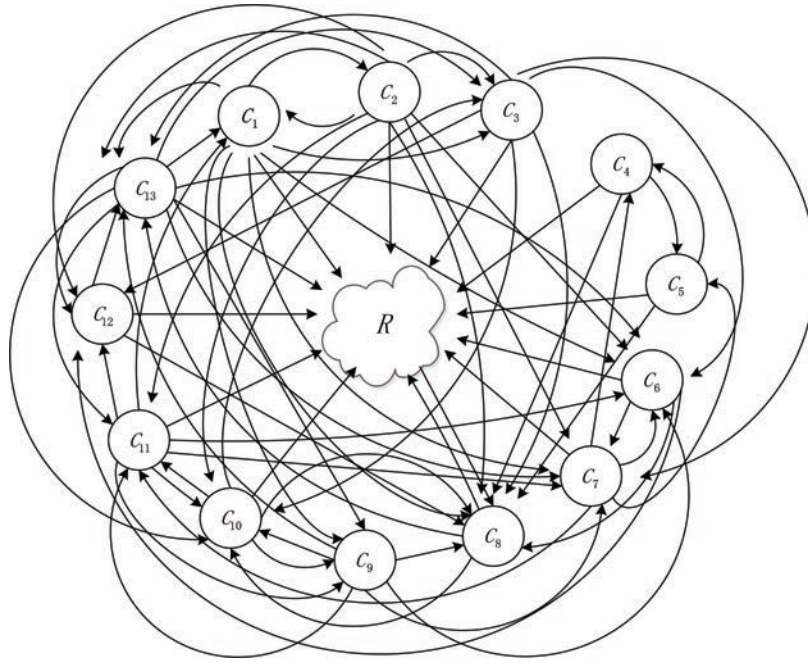
Figure 5 | Dual hesitant fuzzy cognitive maps (DHFCMs) for modeling risk factors in emergency events.

Table 3 | The obtained membership's values (threshold is 1×10^{-6}).

Iterations k	$k=1$	$k=2$		Steady Values
C_1	[0.4621, 0.4621, 0.4621]	[0.2612, 0.2757, 0.3059]	$\cdots$	[0.0346, 0.0816, 0.1752]
C_2	[0.4621, 0.4621, 0.4621]	[0.2621, 0.2736, 0.2851]	$\cdots$	[0.0106, 0.0317, 0.0802]
C_3	[0.4621, 0.4621, 0.4621]	[0.2938, 0.3106, 0.3493]	$\cdots$	[0.0464, 0.1054, 0.2164]
C_4	[0.1586, 0.1781, 0.2496]	[0.1437, 0.1601, 0.2181]	$\cdots$	[0.0261, 0.0661, 0.1399]
C_5	[0.4621, 0.4621, 0.4621]	[0.2800, 0.2952, 0.3141]	$\cdots$	[0.0481, 0.1200, 0.2044]
C_6	[0.2666, 0.3574, 0.4333]	[0.2544, 0.3340, 0.4050]	$\cdots$	[0.0550, 0.1579, 0.3184]
C_7	[0.4621, 0.4621, 0.4621]	[0.3640, 0.4026, 0.4293]	$\cdots$	[0.1111, 0.2399, 0.3677]
C_8	[0.3882, 0.4103, 0.4481]	[0.3485, 0.3705, 0.4126]	$\cdots$	[0.1140, 0.2130, 0.3416]
C_9	[0.1391, 0.1829, 0.2260]	[0.1770, 0.2297, 0.2848]	$\cdots$	[0.0657, 0.1407, 0.2441]
C_{10}	[0.4621, 0.4621, 0.4621]	[0.3024, 0.3189, 0.3584]	$\cdots$	[0.0783, 0.1585, 0.2906]
C_{11}	[0.2724, 0.2950, 0.3575]	[0.2687, 0.2954, 0.3532]	$\cdots$	[0.1223, 0.1804, 0.2891]
C_{12}	[0.4621, 0.4621, 0.4621]	[0.3340, 0.3611, 0.3931]	$\cdots$	[0.0640, 0.1584, 0.2854]
C_{13}	[0.2054, 0.2898, 0.3936]	[0.2345, 0.2956, 0.3706]	$\cdots$	[0.0755, 0.1506, 0.2714]
R	[0.4621, 0.4621, 0.4621]	[0.4355, 0.4473, 0.4585]	$\cdots$	[0.2001, 0.3373, 0.4360]

Table 4 | The obtained non-membership's values (threshold is 1×10^{-6}).

Iterations k	$k=1$	$k=2$		Steady Values
C_1	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_2	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_3	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_4	[0.0997, 0.1489, 0.2402]	[0.0100, 0.0223, 0.0588]	$\cdots$	[0, 0, 0]
C_5	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_6	[0.0015, 0.0025, 0.0225]	[6.1e-8, 3.8e-7, 9.6e-5]	$\cdots$	[0, 0, 0]
C_7	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_8	[9.6e-05, 0.0003, 0.0073]	[8.2e-10, 9.3e-9, 1.4e-5]	$\cdots$	[0, 0, 0]
C_9	[0.0350, 0.0350, 0.1194]	[2.8e-5, 5.6e-5, 0.0021]	$\cdots$	[0, 0, 0]
C_{10}	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_{11}	[0.0150, 0.0300, 0.0898]	[1.9e-5, 9.6e-5, 0.0019]	$\cdots$	[0, 0, 0]
C_{12}	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]
C_{13}	[0.0045, 0.00675, 0.0350]	[2.6e-6, 7.7e-6, 0.0004]	$\cdots$	[0, 0, 0]
R	[0, 0, 0]	[0, 0, 0]	$\cdots$	[0, 0, 0]

Step 6. End.

The results show that the main risk factors of the emergency event are unsatisfactory storage of dangerous goods and overloading operation, safety of rescue assistance during distribution and transportation, lack of unified planning in factory, etc. And the most pivotal cause factor of the huge explosion at Tianjin Port is C_7 (unsatisfactory storage of dangerous goods and overloading operation). In this case, RH seriously violates the *Tianjin City Master Planning* and the *Binhai New Area Controlled Detailed Planning*, and does not meet the construction requirements of the dangerous goods yard yet. The other critical risk factors are C_8 (safety of rescue assistance during distribution and transportation) and C_{11} (lack of unified planning in factory) in this emergency event. The safety management of transportation and loading and unloading operation is seriously insufficient. In the process of packing and handling nitrocellulose or other inflammable and explosive dangerous goods, there exists barbaric loading and unloading behaviors. The results obtained by our proposed method are consistent with that reported by the government. The report released by the government clearly points out that the main cause factors of the huge explosion at Tianjin Port are unqualified storage of dangerous goods, management confusion, personnel's negligence, lack of professional employees,

emergency plans and sense of responsibility, etc.[2] Through above analysis, the following suggestions are given：

1. Enterprises should clarify the safety management requirements of hazardous chemicals, raise the level of safety supervision, and enhance the applicability and uniformity of safety management standards.

2. Enterprises need to carry out reasonable layout, vigorously strengthen the construction of emergency production teams for safety production, and establish full-time or part-time emergency rescue teams in high-risk. And thus, it can eventually improve the level of emergency command information management.

3. Enterprises need to strengthen the improvement of safety measures, update processes and equipment, and improve the stability and scientificity of the overall plan.

4.2. Comparative Analysis

As an extension of FCMs, the HFCMs model has been applied to investigate student accommodation problems [42]. However, it ignores the nonmembership degree in the decision-making process, while the proposed method takes the membership degree and nonmembership degree into account simultaneously in this paper. In such case, the HFCMs can be considered as a special case of the DHFCMs. And the comparison with HFCMs is omitted here. Moreover, Papageorgiou and Iakovidis [39] have compared the IFCMs model with the FCMs. Considering that the calculation rule for elements in DHFCMs is similar to that in IFCM-II model [39], this paper performs a comparison analysis between DHFCMs and IFCM-II model. In order to illustrate the difference between DHFCMs and IFCM, we use the same example of the huge explosion at Tianjin Port. The DHFCM model degrades to an IFCM model if both the membership degree and nonmembership degree are represented by a value, respectively. And the computational steps and results are shown as follows:

Step 1. In order to facilitate comparison, the DHFEs is transformed into an intuitionistic fuzzy number by separately calculating the average values of the membership degrees and the nonmembership degrees, and the results are shown in Table 2 in the Appendix.

Step 2. The iterative results by IFCM-II are shown in Table 5.

Step 3. According to Eqs. (4) and (6), the similarity measure between the steady values of risk factors and final result are calculated as follows:

$s(C_1, R) = 0.6344$; $s(C_2, R) = 0.5517$; $s(C_3, R) = 0.6737$; $s(C_4, R) = 0.6079$; $s(C_5, R) = 0.6792$; $s(C_6, R) = 0.7594$; $s(C_7, R) = 0.8613$; $s(C_8, R) = 0.8341$; $s(C_9, R) = 0.7184$; $s(C_{10}, R) = 0.7597$; $s(C_{11}, R) = 0.7763$; $s(C_{12}, R) = 0.7462$; $s(C_{13}, R) = 0.7415$;

Therefore,

Table 5 | The steady values of membership degree and nonmembership degree.

States	Initial Value	Steady Values of Membership Degree	Steady Values of Nonmembership Degree
C_1	$\langle 1, 0 \rangle$	0.0987	0
C_2	$\langle 1, 0 \rangle$	0.0380	0
C_3	$\langle 1, 0 \rangle$	0.1276	0
C_4	$\langle 0, 1 \rangle$	0.0792	0
C_5	$\langle 1, 0 \rangle$	0.1316	0
C_6	$\langle 0, 1 \rangle$	0.1905	0
C_7	$\langle 1, 0 \rangle$	0.2653	0
C_8	$\langle 0, 1 \rangle$	0.2453	0
C_9	$\langle 0, 1 \rangle$	0.1604	0
C_{10}	$\langle 1, 0 \rangle$	0.1907	0
C_{11}	$\langle 0, 1 \rangle$	0.2029	0
C_{12}	$\langle 1, 0 \rangle$	0.1808	0
C_{13}	$\langle 0, 1 \rangle$	0.1774	0
R	$\langle 1, 0 \rangle$	0.3672	0

$s(C_7, R) > s(C_8, R) > s(C_{11}, R) > s(C_{10}, R) > s(C_6, R) > s(C_{12}, R) > s(C_{13}, R) > s(C_9, R) > s(C_5, R) > s(C_3, R) > s(C_1, R) > s(C_4, R) > s(C_2, R)$;

Step 4. End.

Through the comparison analysis, we can find that the most pivotal risk factors derived by these two methods are consistent, which illustrates the effectiveness and reliability of DHFCMs. However, the ranking order between risk factors C_6 and C_{10} are different. Due to the limitations of the experts' knowledge and experience, it is often difficult to reach an agreement in the group decision-making process. DHFSs, which is an extension of IFSs, has more advantages in the expression of uncertainty. It can effectively deal with the hesitancy of experts and reflect different opinions of groups well. Thus, DHFCMs is better than IFCM-II in modeling the complex system and the decision results derived by the proposed method is more reasonable and reliable.

5. CONCLUSION

Aiming at the risk factors analysis of the emergency event, a novel decision-making analysis method based on DHFCMs, which combines the advantages of DHFSs and FCMs, is presented in this paper. In addition, motivated by the idea of TOPSIS, a new similarity measure, which is utilized to measure the correlation between risk factors and final results, is proposed. And the most pivotal risk factor affecting the final results is identified. It is worth mentioning that the results obtained are highly consistent with the findings in the Chinese government report about the emergency event of RH in the Binhai New Area of Tianjin, China. Meanwhile, a comparative analysis with IFCMs method is carried out to illustrate the rationality and superiority of the proposed approach.

However, as for the dual hesitant fuzzy distance measure, the decision-making result may be affected when some values are added into the shorter DHFE to make the length of the compared DHFEs equal. We will continue to study the distance measure under dual hesitant fuzzy environment in future research. Then, motivated by the social network analysis theory [36,59], we will study the fusion process of multi-FCMs based on trust relationship among

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[2] http://www.gov.cn/foot/2016-02/05/5039788/files/460731d8cb4c4488be3bb0c218f8b527.pdf

decision-makers. In addition, linguistic assessment model is a useful tool for assessing fuzzy uncertainty information [60], and the FCMs based on linguistic assessment model will be discussed in the future. The consensus process in the group decision-making is very important [61,62], and the consensus reaching process based on FCMs would be investigated. Meanwhile, the proposed method will be used in other fields, such as medical diagnosis, risk prediction in the enterprise development, etc.

CONFLICTS OF INTEREST

The authors declared that they have no conflicts of interest to this work.

AUTHORS' CONTRIBUTIONS

Zengwen Wang designed the study, Jian Wu contributed to the study design, analyzed the data and took the lead in the manuscript writing. Xiaodi Liu supervised the study design and helped in the writing of the final draft of the manuscript. Harish Garg made critical revisions of the final manuscript. All authors read and approved the final manuscript.

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