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Dependence assessment in human reliability analysis under uncertain and dynamic situations

Xianghao Gao, Xiaoyan Su*, Hong Qian, Xiaolei Pan

School of Automation Engineering, Shanghai University of Electric Power, Shanghai, 200090, China

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ABSTRACT

Since reliability and security of man-machine system increasingly depend on reliability of human, human reliability analysis (HRA) has attracted a lot of attention in many fields especially in nuclear engineering. Dependence assessment among human tasks is a important part in HRA which contributes to an appropriate evaluation result. Most of methods in HRA are based on experts' opinions which are subjective and uncertain. Also, the dependence influencing factors are usually considered to be constant, which is unrealistic. In this paper, a new model based on Dempster–Shafer evidence theory (DSET) and fuzzy number is proposed to handle the dependence between two tasks in HRA under uncertain and dynamic situations. First, the dependence influencing factors are identified and the judgments on the factors are represented as basic belief assignments (BBAs). Second, the BBAs of the factors that varying with time are reconstructed based on the correction BBA derived from time value. Then, BBAs of all factors are combined to gain the fused BBA. Finally, conditional human error probability (CHEP) is derived based on the fused BBA. The proposed method can deal with uncertainties in the judgments and dynamics of the dependence influencing factors. A case study is illustrated to show the effectiveness and the flexibility of the proposed method.

1. Introduction

Human reliability analysis (HRA), a significant input in the probabilistic safety assessment (PSA), pays much attention to the risk assessment and management of a large-scale complicated system, such as nuclear power plant operations [1,2]. One of the principal objective of HRA is to determine and evaluate the operator's effect to reliability of system by predicting human error probability and evaluating man-machine systems failure probability due to human errors [3]. Various kinds of methods have been proposed to solve the problems of HRA [4–7].

Dependence analysis in HRA aims to address two main problems: (1) how to evaluate the dependence degree among human tasks; (2) what is the effect of the dependence on the failure probability of the following human tasks. Normally, the more dependence exists between two sequent tasks, the higher failure probability will be for the following task when the preceding task fails. The conditional human error probability (CHEP) of a task given failure on the preceding task is the result of dependence assessment in HRA [8]. Fully assessing the dependence among tasks is a necessary prerequisite to obtain reasonable results in risk analysis [9].

So far, there has been a lot of researches on dependence assessment between Human Failure Events (HEFs). In the early 1980s, Swain A. and Guttmann H. in HRA field completed a research report "Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications" [10]. Technique for Human Error Rate Prediction (THERP), one of the most commonly used method in HRA including dependence assessment, was proposed in this report. THERP is a method of qualitative analysis that provides guidelines for evaluating dependence among HFEs. One contribution of the method is that it suggests five dependence levels (see Table 1) and five main dependence influential factors: space, time, function, stress, and similarities among performers [11]. Another contribution of THERP is that it provides a formula to calculate the CHEP based on the dependence level which can be shown in Eq. (1).

Assume that there are two sequent tasks: T_A is the preceding task, its failure event is denoted as A; T_B is the following task, its failure event is denoted as B. P_A and P_B are the basic failure probabilities of T_A and T_B, respectively. The CHEP is calculated as follows [10]:

* Corresponding author.
E-mail address: suxiaoyan@shiep.edu.cn (X. Su).

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Table 1
Five dependence levels.

Dependence (similarity) level	Acronym
Zero Dependence	ZD
Low Dependence	LD
Moderate Dependence	MD
High Dependence	HD
Complete Dependence	CD

$$P_{XD}(B|A) = (1 + K \cdot P_B)/(K+1) \quad (1)$$

where $K = 0, 1, 6, 19, \infty$, for dependence levels CD, HD, MD, LD, and ZD, where XD = CD, HD, MD, LD, and ZD, respectively.

Although THERP is widely used in HRA, it still falls short in some aspects. On the one hand, it depends heavily on expert's judgment which is made referring to vague outlines, and thus is highly subjective; on the other hand, the result obtained by this method may lack traceability and repeatability.

To solve this problem, decision trees (DTs) have been installed to solve the problems of dependence level analysis in HRA, such as the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) [12], the Institute Jožef Stefan human reliability analysis (IJS-HRA) [13,14], the Central Research Institute of Electric Power Industry (CRIEPI-HRA) [15], the DEPEND-HRA method [16] and so on. It can reduce the subjectivity because the central idea of DTs is to provide standard guidelines of the judgment on the input factors. However, DTs are generally limited by extreme conditions and thus are inflexible in representing analysts' judgements [11]. Moreover, the more judgment options, the more branch there are in the DTs, which increases the difficulty for analysts to make judgments.

To solve above problems, a fuzzy expert system (FES) has been developed by Podofillini, Zio et al. [8,11]. It allows analysts to give judgements in the form of accurate points, intervals or linguistic labels. Then the input judgements are converted into fuzzy numbers and handled by fuzzy logic rules that suggested by experts to identify the relationships between the input factor and output final dependence level [17]. However, the process of getting fuzzy rules requires expert's guidance which is also subjective. Moreover, information is either added or lost during the process of fuzzification and defuzzification [18].

Nevertheless, the above three methods cannot represent the ignorance or confidence of the analyst that generally exist in practical application. Dempster-Shafer Evidence Theory (DSET), which is also known as D-S evidence theory or belief function theory was first proposed by Dempster in 1967 [19], and further developed by Shafer in 1976 [20]. DSET is a generalization of classical probability theory. It broadens the frame of discernment in probability theory into a power set of basic events, and allows for representation of uncertainty, imprecision and ignorance [21]. Due to its flexibility in dealing with uncertain and imprecise information, DSET is widely applied in many fields [22–27]. Its mathematical properties and generalizations are also the hot topic and investigated by many researchers [28–32].

Therefore Chen et al. proposed an improved method based on DSET and the analytic hierarchy process (AHP) to deal with dependence assessment in HRA [18]. DSET is used to express uncertainty in analyst' s judgements and fuse different judgments. The AHP is used for obtaining weights that measures degrees of importance of the dependence influencing factors. The DSET-AHP method represents the analyst's judgments more flexibly by considering the ambiguity and confidence of the judgments [18].

In Chen et al.'s method, the uncertainty in the analyst's judgment is fully concerned, however the uncertainty in expert's knowledge about the relationship between input factors is not well addressed [33]. To overcome this problem, Deng et al. proposed an improved evidence network model. Jiang et al. applied a novel Z-network model in dependence assessment [34]. These two methods have shown their advantages in representing experts' knowledge of the relationships between different input factors. However, both of these methods involve solving nonlinear programming problems, and the calculation processes are complicated. Therefore, Zhang et al. proposed a method based on belief rules and evidential reasoning (ER) which can simplify the calculation process [3].

However, in all the above methods, the factor "Time" is regarded as a static and independent factor which is elicited directly from experts' judgment, and the influence of time on other factors is not considered. To address this problem, Guo et al. proposed an interesting method using Evidence Credibility Decay Model (ECDM) to deal with time related factors for dependence assessment in HRA [17]. It proposed the dynamic credibility α in ECDM to discount the Basic Belief Assignments (BBAs) of time related factor. Zheng et al. proposed an improved method based on ECDM and Induced Ordered Weighted Averaging (IOWA) operator to extent the scope of application [35]. However, the use of ECDM in handling the influence of time on the factors and dependence level is questionable. For one thing, the discount rate derived from Credibility Decay Model changes too fast with time, which is impractical in practice. For example, when interval time between two tasks changes from 5min to 14min, the discount rate changes from 0.6065 to 0.2466, and this discount rate may approach 0 when the interval time is 30min (in real circumstances, interval time between two tasks may longer than 30min). For the other, the assignment of the unreliable part (after discounting) to the vacuous BBA will increase the uncertainty of BBA and may lead to counter-intuitive results under some conditions. For example, the CHEP will be increasing when the interval time between two tasks becomes larger (see Table 10 for more details).

In this paper, we propose a new method to deal with uncertain and dynamic situations for dependence assessment in HRA. DSET is applied to model the uncertainty of judgement given by experts or analysts and to fuse the evaluations. The influence of time on the factors is considered by introducing the correction BBA which is constructed based on the fuzzy set panel of time value. The BBAs of time related factors (dynamic factors) are reconstructed by the correction BBA. Finally, a computing method for deriving CHEP is provided based on the fused BBA.

The remainder of this paper is organized as follows. In Section 2, basic concepts of the DSET and fuzzy number are introduced. In Section 3, the process of this method is introduced in detail. In Section 4, case studies are used to illustrate the effectiveness and practicability of the proposed method. In Section 5, some discussions are provided. Section 6 concludes the paper.

2. Preliminaries

2.1. Dempster-Shafer evidence theory

Definition 1. *(BBA). [20] (BBA) Let $\Theta = \{H_1, H_2, \ldots, H_N\}$ be a finite nonempty set of N pairwise mutually exclusive elements, then Θ is called as frame of discernment. The basic belief assignment (BBA) function is defined as a mapping of the power set $P(\Theta)$ to a number between 0 and 1, i.e. $m: P(\Theta) \rightarrow [0,1]$, and which satisfies the following conditions:*

$$m(\emptyset) = 0, \quad \sum_{A \subseteq P(\Theta)} m(A) = 1 \tag{2}$$

The mass $m(A)$ represents the degree which evidence supports A. The mass $m(\Theta)$ represents uncertainty of evidence.

Definition 2. [17] Given a BBA m and a discounting coefficient $\alpha \in [0, 1]$, the discounted BBA m' *on Θ is defined as*:

$$\begin{cases} m'(A) = \alpha m(A), & \forall A \subset \Theta, A \neq \Theta \\ m'(\Theta) = 1 - \alpha + \alpha m(\Theta) \end{cases} \tag{3}$$

where $m(\Theta)$ represents the completely uncertain BBA. α is used to express the credibility of the evidence source S.

Definition 3. (***Dempster's rule of combination***) [35] *Two bodies of evidence X and Y of Θ can be fused by a set of formula to obtained a new evidence C and the mass function after combination is*

$$m(C) = m_i(X) \oplus m_{i'}(Y) = \begin{cases} 0, & \text{If } X \cap Y = \emptyset, \\ \dfrac{\sum\limits_{X \cap Y = C, \forall X, Y \subseteq \Theta} m_i(X) \times m_{i'}(Y)}{1 - K}, & \text{If } X \cap Y \neq \emptyset. \end{cases} \tag{4}$$

where K is a normalization factor (see Eq. (5)), which represents the conflict degree between two BBAs.

$$K = \sum_{X \cap Y = \emptyset, \forall X, Y \subseteq \Theta} m_i(X) \times m_{i'}(Y) \tag{5}$$

Definition 4. ***(Evidence distance)*** [36] *Let m_1 and m_2 be two BBAs on the same frame of discernment Θ, containing N mutually exclusive and exhaustive hypotheses. The distance between m_1* and *m_2* is:

$$d(m_1, m_2) = \sqrt{\frac{1}{2}(\vec{m}_1 - \vec{m}_2)^T \underline{\underline{D}}(\vec{m}_1 - \vec{m}_2)} \tag{6}$$

where m_1 and m_2 are the BBAs and $\underline{\underline{D}}$ is an $2^N \times 2^N$ matrix whose elements are $D(A, B) = \frac{|A \cap B|}{|A \cup B|}$. $A, B \in P(\Theta)$. The distance represents conflict level between two BBAs, and the conflict degree increases with distance.

Definition 5. (***Pignistic probability function***) [37] *Let m be a BBA on Θ. Its associated pignistic probability function $BetP_m$: $\Theta \rightarrow [0, 1]$ is defined as*

$$BetP_m(w) = \sum_{A \subseteq \Theta, w \in A} \frac{1}{|A|} \frac{m(A)}{1 - m(\emptyset)}, \quad m(\emptyset) \neq 1, \tag{7}$$

where $|A|$ is the cardinality of subset A.

2.2. Fuzzy number

Fuzzy number was first proposed by Zadeh in 1965. It is a method of describing ambiguity and is widely used in decision-making fields [38].

Definition 6. (***Fuzzy number***) [39] *Let $\mu_{\widetilde{M}}(x)$ be a continuous mapping from R to the closed interval [0,1].A fuzzy number is defined as*

$$\widetilde{M} = \{(x), \mu_{\widetilde{M}}(x), x \in R\} \tag{8}$$

Definition 7. (***Trapezoidal fuzzy numbers***) [39] *Let n_1, n_2, n_3, $n_4 \in R$ and $n_1 < n_2 \leq n_3 < n_4$. A trapezoidal fuzzy number is defined as a four tuple $\widetilde{A} = (n_1, n_2, n_3, n_4)$, and its membership function is defined as*

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x - n_1}{n_2 - n_1}, & x \in [n_1, n_2] \\ 1, & x \in [n_2, n_3] \\ \dfrac{n_4 - x}{n_4 - n_3}, & x \in [n_3, n_4] \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

3. Proposed approach to model dependence in HRA

The framework of proposed method, which divided into 11 steps is shown as below (see Fig. 1).

Step 1. *Determine influencing factors and their relationships*: First is to identify the influential factors provided by the experts that affect the dependence of human actions such as five main factors referred in THERP which have been discussed in Section 1. It is noted that different influencing factors are selected in different situations. Fig. 2 shows an example of relationships between the input factors and output dependence level [11]. The influencing factors include Similarity of Cues (SC), Similarity of Goals (SG), Closeness in Time (CT), Task Relatedness (TR), and Similarity of Performers (SP).

Step 2. *Suggest anchor points and linguistic judgement for each factor*: Anchor points and linguistic judgments are provided by domain experts to instruct analysts to make their judgments of the input factors more easily and less subjectively. For example, anchor points and linguistic judgments for the influencing factor “Similarity of performers” is presented in Table 2, with the associated dependence (similarity) level of performers. For example, if the tasks are operated by performers from different teams, the dependence level between tasks will be judged as “LD”, which means a low dependence level of performers similarity exists between certain tasks.

Step 3. *Determine the dependence level and the confidence of the judgement for each factor*: According to the anchor points and linguistic judgments obtained in *Step 2*, analysts can judge the dependence level of each influencing factor. Analysts' judgments may be uncertain, for example, the analyst may not give judgement on just one dependence level. In addition, analysts are requested to rate how confident they are in their judgments on a scale from 0 to 1. “0” means analyst has no confidence in his/her judgement at all and “1” represents that the analyst is completely confident (see more details in Table 3).

Examples of analyst's judgments are shown in Table 4. In Case 1, the judgement shows that the dependence level belongs to HD or

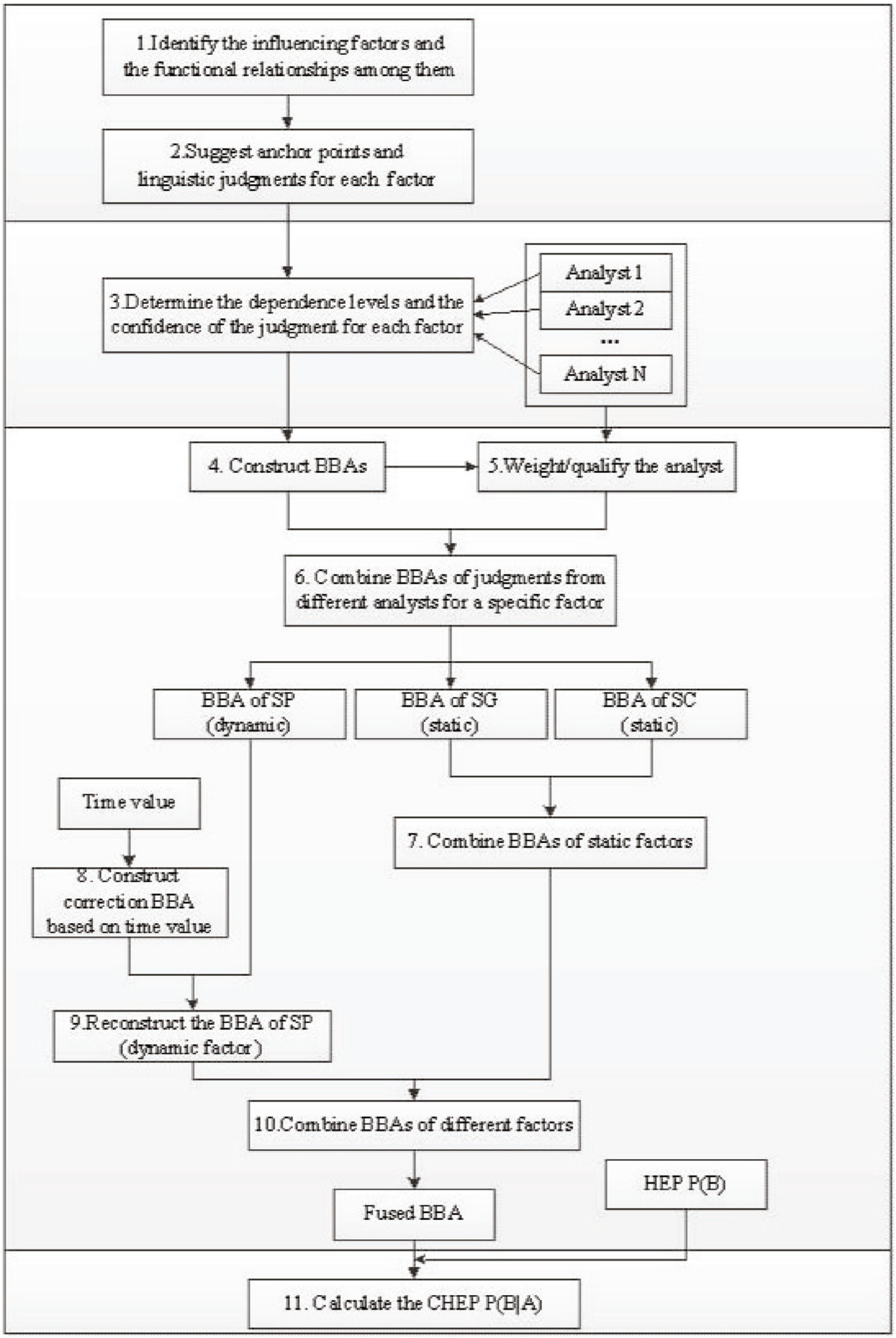

Fig. 1. Framework of the proposed approach.

MD with the same rate and the confidence of judgement is 0.8. In case 2, the analyst has low confidence that the dependence level falls in between HD and MD, but couldn't determine the rate. In Case 3, the analyst judges that the dependence level is probably belong to HD or MD, and the proportional for their probabilities is 3:1 and the confidence of judgement is 0.8. Case 4 means that the analyst has no idea how to judge.

Step 4. *Construct basic belief assignments (BBAs)*: The BBA is constructed as follow:

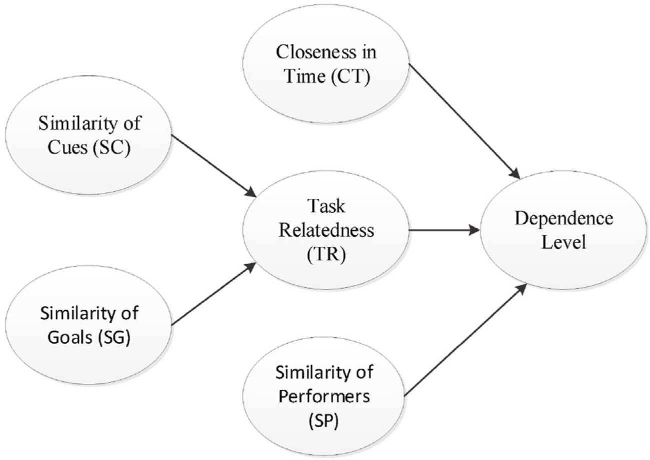

Fig. 2. Functional relationships among the input factors [11].

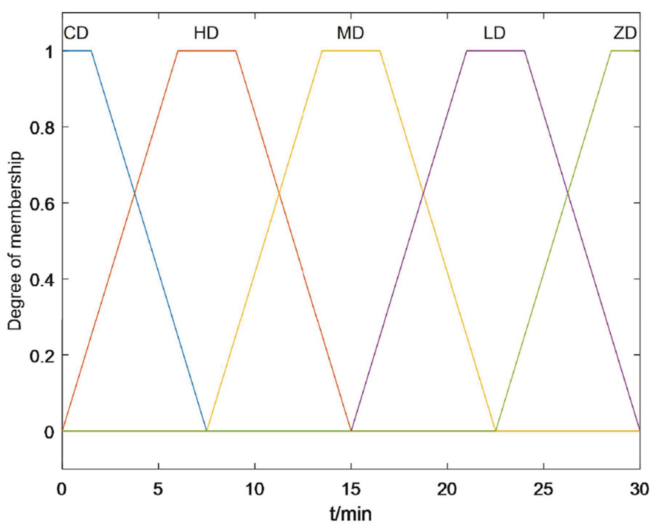

Fig. 3. Membership function of trapezoidal fuzzy number.

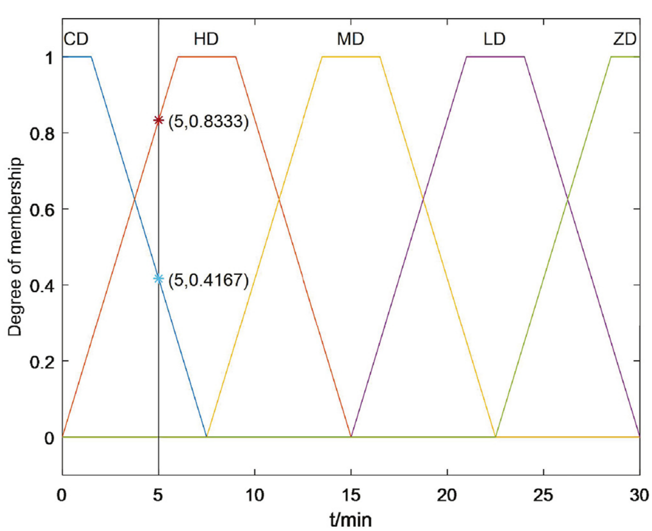

Fig. 4. The corresponding value of “5 min” on the membership function of each dependence level.

$$m(S_i) = \alpha \cdot \frac{r_i}{\sum_{j=1}^{31} r_j}, \quad m(\Theta) = 1 - \alpha \tag{10}$$

where $S_1, S_2, \cdots, S_{31}$ are elements of the power set of Θ excluding the empty set, α is analyst's confidence, and $0 \le \alpha \le 1$. The possibility ratios of the sets S_1: S_2: $\cdots$: $S_{31} = r_1$: r_2: $\cdots$: r_{31}.

For example, in Case 3, the BBA is constructed as follow:

$$m(\{\mathrm{HD}\}) = \alpha \cdot \frac{r_i}{\sum\limits_{j=1}^{31} r_j} = 0.8 \times \frac{3}{3+1} = 0.6;$$

$$m(\{\mathrm{MD}\}) = \alpha \cdot \frac{r_i}{\sum\limits_{j=1}^{31} r_j} = 0.8 \times \frac{1}{3+1} = 0.2; m(\Theta) = 1 - 0.8 = 0.2$$

The results of BBAs constructed based on the judgments in Table 4 are listed in Table 5.

Step 5. *Weight/qualify the analyst*: The judgements of different analysts may not be consistent, thus it is necessary to integrate the judgments of different analysts. This requires weighing the credibility of different analysts' judgments. The process in Ref. [40] is adopted to weigh the analysts, which is shown as follow:

(1) Calculate evidence distance $d(m_i, m_j)$ between every two BBAs by Eq. (6) respectively.

(2) Obtain similarity measure matrix (SMM):

The similarity degree $Sim(m_i, m_j)$ between two BBAs is defined as:

$$Sim(m_i, m_j) = 1 - d(m_i, m_j). \tag{11}$$

Once all the degrees of similarity between the BBAs are obtained, SMM can be constructed by Eq. (12):

$$SMM = \begin{bmatrix} 1 & S_{12} & \cdots & S_{1n} \\ S_{21} & 1 & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & 1 \end{bmatrix}, \tag{12}$$

where $S_{ij} = Sim(m_i, m_j)$.

(3) Calculate the support degree of the BBA m_i by using Eq. (13):

$$Sup(m_i) = \sum_{\substack{j=1 \\ j \ne i}}^{n} Sim(m_i, m_j). \tag{13}$$

(4) The credibility degree Crd_i of the BBA m_i is defined as:

$$Crd_i = \frac{Sup(m_i)}{\sum_{i=1}^{n} Sup(m_i)}. \tag{14}$$

(5) The relative weight ω_i of the BBA m_i derived from the corresponding analyst is defined as:

$$\omega_i = \frac{Crd_i}{Crd_{\max}} \tag{15}$$

Step 6. *Combine BBAs given from different analysts*: Once the relative weight of an analyst is obtained, the BBA judged by him/her is discounted by Eq. (3). The comprehensive evaluation (the

Table 2
Anchor points for input factor "Similarity of performers" [8].

"Performers" anchor points	Linguistic judgment	Dependence (similarity) levels
TSC vs control shift room	No similarity of performers is present between tasks	ZD
Different team	A low level of performer similarity exist	LD
Different individuals with same qualification	The level of performer similarity is medium	MD
Same team	High level of performer similarity is present between tasks	HD
Same person	The tasks are accomplished by the same individual	CD

Table 3
Value of the confidence level [18].

Specification of the confidence level	Value
Complete confident	1
Very high confident	0.8
High confident	0.6
Low confident	0.4
Very low confident	0.2
Zero confident	0

Table 4
Examples of analyst's judgments for a specific factor.

Case	Dependence (similarity) level	Confidence
Case 1	{HD}:{MD} = 1:1	0.8
Case 2	{HD, MD}	0.4
Case 3	{HD}:{MD} = 3:1	0.8
Case 4	{ZD, LD, MD, HD, CD}	1

Table 5
Constructed BBAs of analyst's judgments in Table 4.

Case	BBA
Case 1	$m(\{\mathrm{HD}\}) = 0.4$, $m(\{\mathrm{MD}\}) = 0.4$, $m(\Theta) = 0.2$
Case 2	$m(\{\mathrm{HD, MD}\}) = 0.4$, $m(\Theta) = 0.6$
Case 3	$m(\{\mathrm{HD}\}) = 0.6$, $m(\{\mathrm{MD}\}) = 0.2$, $m(\Theta) = 0.2$
Case 4	$m(\Theta) = 1$

fused BBA) of a specific factor is then obtained by combining these BBAs (pretreated by discounting operation) from different analysts by using Dempster's combination rule referred in Definition. 2.3.

Step 7. *Combine BBAs of static factors*: In this paper, we divide the dependence influencing factors into two categories, one is called static factors such as Similarity of Goals (SG), Similarity of Cues (SC) and Task Relatedness (TR), and the other is called dynamic factors (Similarity of Performers (SP)) influenced by time. In this step static factors (SG, SC) are combined as TR according to an averaging rule rather than Dempster's combination rule (Definition. 3). The reasons are: on the one hand, Dempster's combination rule cannot combine BBAs which exist highly conflict; on the other hand, Dempster's combination rule may make results converge too quickly.

Step 8. *Construct correction BBA based on time value*: In this step, the correction BBA is constructed by using trapezoidal fuzzy sets (see Fig. 3) based on time value. The correction BBA satisfies the condition that as the time goes on, the dependence level gradually decreases from CD to ZD. For example, when the time value is 5 min, corresponding correction BBA can obtained as follow:

(1) Find the corresponding value of the membership function on each dependence level to this time point (see Fig. 4). The degrees of membership are shown as follow:

$$\mu_{HD}(5) = 0.8333, \mu_{CD}(5) = 0.4167$$

Where $\mu_{HD}(5)$ is the membership degree of high dependence (HD) when the time interval is 5 min $\mu_{CD}(5)$ is the membership degree of complete dependence (CD) when the time interval is 5 min.

(2) Obtain the correction BBA of "5 min" by normalizing the degrees of membership obtained above.

The correction BBA of 5 min is:

$$m(\{HD\}) = \frac{\mu_{HD}(5)}{\mu_{HD}(5) + \mu_{CD}(5)} = 0.6666, \quad m(\{CD\}) = \frac{\mu_{CD}(5)}{\mu_{HD}(5) + \mu_{CD}(5)} = 0.3334.$$

Step 9. *Reconstruct the BBA of SP (dynamic factor)*: Once the correction BBA is obtained, it could be applied to reconstruct the BBA of SP (dynamic factor). In this part, an averaging method is used for reconstructing BBA of SP by calculating average value of original BBA of SP and correction BBA. For example, assume that the original BBA of SP is:

$$m(\{\mathrm{ZD}\}) = 0.8,\ m(\{\mathrm{LD}\}) = 0.1,\ m(\{\mathrm{MD}\}) = 0.1$$

The correction BBA corresponding to 5 min is the same as calculated above, then the reconstructed BBA of SP at time 5 min is:

$$m(\{\mathrm{ZD}\}) = \frac{0.8+0}{2} = 0.4,\quad m(\{\mathrm{LD}\}) = \frac{0.1+0}{2} = 0.05,\quad m(\{\mathrm{MD}\}) = \frac{0.1+0}{2} = 0.05,\quad m(\{\mathrm{HD}\}) = \frac{0+0.6666}{2} = 0.3333,\quad m(\{\mathrm{CD}\}) = \frac{0+0.3334}{2} = 0.1667$$

Step 10. *Combine BBAs of different factors*: In this step, BBAs of dynamic factor and static factor are combined to gain a fused BBA. The combination method is based on an averaging rule referred in *Step 7.*

Step 11. *Calculate the CHEP $P(B|A)$*: First, the confidence of the final result α_f can be directly calculated as:

$$\alpha_f = 1 - m(\Theta) \tag{16}$$

In order to calculate the CHEP, it is necessary to derive associated *BetP* of the fused BBA. Furthermore, due to the focal element $m(\Theta)$ of the BBA is applied for representing the uncertainty of the judgment, it is also necessary to eliminate its influence during the pignistic probability transformation process. The *BetP* is modified as:

$$BetP(XD) = \sum_{A \subset \Theta, XD \in A} \frac{1}{|A|} \frac{m(A)}{1 - m(\emptyset) - m(\Theta)}, \quad m(\emptyset) + m(\Theta) \neq 1 \tag{17}$$

where XD = CD, HD, MD, LD, and ZD.

The CHEP $P(B|A)$ is calculated as

$$P\left(B|A\right) = \sum_{XD} BetP(XD)\cdot P_{XD}(B|A\right) \tag{18}$$

where $P_{XD}(B|A)$ is the modification formula obtained by Eq. (1).

4. Case study

4.1. The process of proposed method

In order to further explain the process of this method and demonstrate its effectiveness, the case study on postinitiator human failure events of a nuclear power plant adopted from Zio et al. [8] is used.

Step 1. *Determine the influencing factors and their relationships*: In the working condition mentioned in this section, the relevant input factors and their functional relationships are shown in Fig. 2. According to Fig. 2, SP and TR directly affect the overall dependence level. TR is further influenced by SG and SC. It is noted that SP is classified as a dynamic factor in this method which means that it varies with time. Therefore, CT is no longer a direct influencing factor, but indirectly affects the dependence level by affecting SP.

Step 2. *Suggest anchor points and linguistic judgement for each factor*: As described above, the anchor points and linguistic judgments for input factors SP SC and SG should be provided by experts. The example of anchor points and linguistic judgement is shown in Table 2.

Step 3. *Determine the dependence level and the confidence of the judgement for each other*: The dependence level of each influencing factor and confidence of their judgements determined by different analysts are shown in Table 6.

Step 4. *Construct basic belief assignments (BBAs)*: The BBAs of each analyst (see Table 7) are constructed by using Eq. (10).

Step 5. *Weight/qualify the analyst*: After BBAs of each analyst are constructed, the relative weights of the analysts are derived based on the credibility degree of their judgments. For example, for the analysts' judgments on SC, the distance between every two BBAs can be calculated by Eq. (6) as follows:

$$d(m_1, m_2) = 0.2550,\ d(m_1, m_3) = 0.1768,\ d(m_2, m_3) = 0.4138,$$

The SMM, which measures the support level between the BBAs, can be constructed based on Eqs. (6) and (12) as:

$$SMM = \begin{bmatrix} 1 & 0.7450 & 0.8232 \\ 0.7450 & 1 & 0.5862 \\ 0.8232 & 0.5862 & 1 \end{bmatrix}.$$

The support degree of each of the BBAs can be obtained according to Eq. (13) as:

$$Sup(m_1) = 2.5682,\ Sup(m_2) = 2.3312,\ Sup(m_3) = 2.4094.$$

Then, the credibility degree of each of the BBAs can be obtained according to Eq. (14) as:

$$Crd_1 = 0.3514,\ Crd_2 = 0.3190,\ Crd_3 = 0.3296.$$

The relative weights can be obtained according to Eq. (15) as:

$$\omega_1 = 1,\ \omega_2 = 0.9,\ \omega_3 = 0.94.$$

Step 6. *Combine BBAs given from different analysts*: The fused BBA of SC based on an overall consideration of three different analysts' judgments are obtained by using Eq. (3) in Definition 2.2 first and then the Dempster's combination rule in Definition 2.3. The combined BBA is:

$m(\{\mathrm{LD}\}) = 0.0314$, $m(\{\mathrm{LD, MD}\}) = 0.1115$, $m(\{\mathrm{MD}\}) = 0.8571$.
All fused BBAs are shown in Table 8.

Step 7. *Combine BBAs of static factors*: The BBAs of factors SC and SG are combined by an averaging combination rule to get the BBA of factor TR. The combined BBA is:

$m_T(\{\mathrm{LD}\}) = 0.04555$, $m_T(\{\mathrm{LD, MD}\}) = 0.1053$, $m_T(\{\mathrm{MD}\}) = 0.84765$, $m_T(\{\Theta\}) = 0.0015$.

Step 8. *Construct correction BBA based on time value*: We can get the correction BBA of each time nodes between 0 min and 30 min in this step. For example the correction BBA of 5 min is:

$m(\{\mathrm{HD}\}) = 0.6666$, $m(\{\mathrm{CD}\}) = 0.3334$.
It is noted that we only consider the range of time from 0 to 30min in this paper for better comparison with Guo et al.'s method [17]. In real application, the range of time can be redefined according to specific situations.

Step 9. *Reconstruct the BBA of SP (dynamic factor)*: We can reconstruct the BBA of SP by the correction BBA using the averaging method. The initial BBA of SP is:

$m_P(\{\mathrm{LD}\}) = 0.0241$, $m_P(\{\mathrm{LD, MD}\}) = 0.0872$, $m_P(\{\mathrm{MD}\}) = 0.8887$.
Assume that the time interval between two tasks is 5 min, the reconstructed BBA is:
$m_P(\{\mathrm{LD}\}) = 0.0121$, $m_P(\{\mathrm{LD, MD}\}) = 0.0436$, $m_P(\{\mathrm{MD}\}) = 0.4444$, $m_P(\{\mathrm{HD}\}) = 0.3333$, $m_P(\{\mathrm{CD}\}) = 0.16667$.

Step 10. *Combine BBAs of different factors*: Then the BBA of TR and reconstructed BBA of SP are combined by the averaging method to get the final fused BBA:

$m(\{\mathrm{LD}\}) = 0.0288$, $m(\{\mathrm{LD, MD}\}) = 0.0745$, $m(\{\mathrm{MD}\}) = 0.6460$, $m(\{\mathrm{HD}\}) = 0.1667$, $m(\{\mathrm{CD}\}) = 0.0833$, $m(\{\Theta\}) = 0.0007$.

Step 11. *Calculate the CHEP $P(B|A)$*: In this step, first, the confidence of the final result α_f can be directly calculated by Eq. (16):

Table 6
Analysts' judgments on the input factors.

Factor	Analyst	Dependence (similarity) level	confidence
SC	Analyst 1	$\{LD, MD\}$: $\{MD\} = 1:1$	1
	Analyst 2	$\{MD\}$: $\{LD, MD\}$: $\{MD\} = 1:3:1$	1
	Analyst 3	$\{LD, MD\}$: $\{MD\} = 1:3$	1
SG	Analyst 1	$\{LD, MD\}$: $\{MD\} = 1:1$	0.8
	Analyst 2	$\{MD\}$: $\{LD, MD\}$: $\{MD\} = 2:3:5$	1
	Analyst 3	$\{LD, MD\}$: $\{MD\} = 1:4$	0.7
SP	Analyst 1	$\{LD, MD\}$: $\{MD\} = 1:4$	1
	Analyst 2	$\{LD, MD\}$: $\{MD\} = 2:3$	0.9
	Analyst 3	$\{MD\}$: $\{LD, MD\}$: $\{MD\} = 1:3:1$	1

Table 7
Constructed BBAs based on analysts' judgments for input factors.

Factor	Analyst	BBA
SC	Analyst 1	$m_{C_1}(\{LD, MD\}) = 0.5$, $m_{C_1}(\{MD\}) = 0.5$
	Analyst 2	$m_{C_2}(\{LD\}) = 0.2$, $m_{C_2}(\{LD, MD\}) = 0.6$, $m_{C_2}(\{MD\}) = 0.2$
	Analyst 3	$m_{C_3}(\{LD, MD\}) = 0.25$, $m_{C_3}(\{MD\}) = 0.75$
SG	Analyst 1	$m_{G_1}(\{LD, MD\}) = 0.4$, $m_{G_1}(\{MD\}) = 0.4$, $m_{G_1}(\{\Theta\}) = 0.2$
	Analyst 2	$m_{G_2}(\{LD\}) = 0.2$, $m_{G_2}(\{LD, MD\}) = 0.3$, $m_{G_2}(\{MD\}) = 0.5$
	Analyst 3	$m_{G_3}(\{LD, MD\}) = 0.14$, $m_{G_3}(\{MD\}) = 0.56$, $m_{G_3}(\{\Theta\}) = 0.3$
SP	Analyst 1	$m_{P_1}(\{LD, MD\}) = 0.2$, $m_{P_1}(\{MD\}) = 0.8$
	Analyst 2	$m_{P_2}(\{LD, MD\}) = 0.36$, $m_{P_2}(\{MD\}) = 0.54$, $m_{P_2}(\{\Theta\}) = 0.1$
	Analyst 3	$m_{P_3}(\{LD\}) = 0.2$, $m_{P_3}(\{LD, MD\}) = 0.6$, $m_{P_3}(\{MD\}) = 0.2$

Table 8
Fused BBAs for input factors.

Factor	Fused BBA
SC	$m_C(\{LD\}) = 0.0314$ $m_C(\{LD, MD\}) = 0.1115$, $m_C(\{MD\}) = 0.8571$
SG	$m_G(\{LD\}) = 0.00597$ $m_G(\{LD, MD\}) = 0.0991$, $m_G(\{MD\}) = 0.8382$, $m_G(\{\Theta\}) = 0.003$
SP	$m_P(\{LD\}) = 0.0241$ $m_P(\{LD, MD\}) = 0.0872$, $m_P(\{MD\}) = 0.8887$

$\alpha_f = 1 - m(\Theta) = 1 - 0.0007 = 0.9993$.

The associated $BetP$ of the fused BBA m is calculated by Eq. (7).
$BetP(LD) = 0.066$, $BetP(MD) = 0.683$, $BetP(HD) = 0.167$,
$BetP(CD) = 0.083$.

Assume that the basic human error probability of the subsequent task T_B is $P(B) = 0.01$, then CHEP $P(B|A)$ is calculated using Eq. (18)

$$P\left(B|A\right) = \sum_{XD} BetP(XD) \cdot P_{XD}(B|A) = BetP(LD) \cdot P_{LD}(B|A) + BetP(MD) \cdot P_{MD}(B|A) + BetP(HD) \cdot P_{HD}(B|A) \quad + BetP(CD) \cdot P_{CD}(B|A)$$
$$= 0.066 \times \frac{1 + 19 \times 0.01}{20} + 0.683 \times \frac{1 + 6 \times 0.01}{7} + 0.167 \times \frac{1 + 1 \times 0.01}{2} + 0.083 \times 1 = 0.2749$$

4.2. Additional cases

4.2.1. Static case

In this section, we investigate how the factor SP effects on the dependence level to show the effectiveness of this model under static situations. In other words, when the time interval between two tasks remains unchanged, how the factor SP effects CHEP. For a more rigorous study of the influence of SP, we assume that the BBA of TR is unchanged. For simplicity, BBAs of factor TR and SP are given directly as follows.

Assume that the BBA of TR is: $m_T(\{MD\}) = 0.5$, $m_T(\{HD\}) = 0.3$, $m_T(\{CD\}) = 0.2$, which remains unchanged. The dependence (similarity) level of SP decrease gradually, from: $m_P(\{CD\}) = 1$ to $m_P(\{MD\}) = 0.5$, $m_P(\{HD\}) = 0.3$ $m_P(\{CD\}) = 0.2$. The time interval is 5 min and the basic human error probability of the subsequent task T_B is $P(B) = 0.01$. Final results are shown in Table 9.

As shown in Table 9, when the time interval and the BBA of TR are kept constant, it is obvious that the CHEP is decreasing with the dependence (similarity) level of SP is decreasing. The result is reasonable since it is conformed to the expectation that the higher the dependence level exists between two tasks, the more influence of the failure of one task on the failure probabilities of subsequent tasks (higher CHEP). The result is also consistent with Guo et al.'s method [17] and Zio et al.'s method [8], indicating that the proposed method is effective.

4.2.2. Dynamic case

In this section, an experiment is designed to show the effectiveness and advantage of this model under dynamic situations. Under normal conditions, the CHEP and the dependence level will decrease when the time interval between two tasks increase. For simplicity, BBAs of factors SP and TR are given directly. Assume that the BBA of TR is: $m_T(\{ZD\}) = 0.1$, $m_T(\{LD\}) = 0.1$, $m_T(\{MD\}) = 0.8$. The BBA of SP is: $m_P(\{ZD\}) = 0.8$, $m_P(\{LD\}) = 0.1$, $m_P(\{MD\}) = 0.1$. The basic human error probability of the subsequent task T_B is $P(B) = 0.01$.

The comparative results are shown in Tables 10 and 11.

As shown in Tables 10 and 11, CHEP is increasing with the time interval between two tasks getting larger in Guo et al.'s method which is counter-intuitive. In the proposed method, CHEP is decreasing with the time interval getting larger (less dependent). Thus, the result of this method is more consistent with the actual situation. The reasons are discussed in the next section.

5. Discussion

5.1. Reconstruction of BBA

In Guo et al.'s method, discounting process in Definition 2 is used for discounting the BBA of SP. The discounting coefficient is calculated by using ECDM which considers the effect of time. This will results in a considerable increasing value of focal element $m(\theta)$ of the reconstructed BBA (see the second column of Tables 10 and 11). It may be the case that the BBA of SP changes from a BBA that originally support "ZD" to a completely ignorant one with time increase, which is unreasonable. The method proposed in this paper designed the correction BBA based on the trapezoidal fuzzy sets to model the effect of time on dynamic factors, which fits the

Table 9
An example of influence of SP on CHEP.

time node	Correction BBA	BBA of TR	BBAs of SP	Reconstructed BBA of SP	Fused BBA	CHEP
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0 m(HD) = 0 m(CD) = 1	m(MD) = 0 m(HD) = 0.33332 m(CD) = 0.66668	m(MD) = 0.25 m(HD) = 0.31666 m(CD) = 0.43334	0.63111
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0 m(HD) = 0.2 m(CD) = 0.8	m(MD) = 0 m(HD) = 0.43332 m(CD) = 0.56668	m(MD) = 0.25 m(HD) = 0.36666 m(CD) = 0.38334	0.60636
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0 m(HD) = 0.4 m(CD) = 0.6	m(MD) = 0 m(HD) = 0.53332 m(CD) = 0.46668	m(MD) = 0.25 m(HD) = 0.41666 m(CD) = 0.33334	0.58161
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0.1 m(HD) = 0.5 m(CD) = 0.4	m(MD) = 0.1 m(HD) = 0.58332 m(CD) = 0.36668	m(MD) = 0.3 m(HD) = 0.44166 m(CD) = 0.28334	0.551807
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0.3 m(HD) = 0.4 m(CD) = 0.3	m(MD) = 0.3 m(HD) = 0.53332 m(CD) = 0.31668	m(MD) = 0.4 m(HD) = 0.41666 m(CD) = 0.25834	0.529325
5min	m(HD) = 0.66664 m(CD) = 0.33336	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0.5 m(HD) = 0.3 m(CD) = 0.2	m(MD) = 0.5 m(HD) = 0.48332 m(CD) = 0.26668	m(MD) = 0.5 m(HD) = 0.39166 m(CD) = 0.23334	0.506843

Table 10
CHEP Results of Guo et al.'s method and the proposed method.

Time nodes	Results in Guo's method			Results in proposed method		
	Reconstructed BBA of SP	Fused BBA	CHEP	Reconstructed BBA of SP	Fused BBA	CHEP
5min	m(ZD) = 0.4852 m(LD) = 0.0607 m(MD) = 0.0607 $m(\theta)$ = 0.3935	m(ZD) = 0.1769 m(LD) = 0.0915 m(MD) = 0.7316	0.11623	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.05 m(HD) = 0.3333 m(CD) = 0.1667	m(ZD) = 0.25 m(LD) = 0.075 m(MD) = 0.4250 m(HD) = 0.1667 m(CD) = 0.0833	0.2363
6min	m(ZD) = 0.4390 m(LD) = 0.0549 m(MD) = 0.0549 $m(\theta)$ = 0.4512	m(ZD) = 0.1635 m(LD) = 0.0929 m(MD) = 0.7436	0.11813	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.05 m(HD) = 0.4 m(CD) = 0.1	m(ZD) = 0.25 m(LD) = 0.075 m(MD) = 0.4250 m(HD) = 0.2 m(CD) = 0.05	0.2198
7min	m(ZD) = 0.3973 m(LD) = 0.0497 m(MD) = 0.0497 $m(\theta)$ = 0.5034	m(ZD) = 0.1532 m(LD) = 0.0941 m(MD) = 0.7527	0.11958	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.05 m(HD) = 0.4616 m(CD) = 0.0384	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.4250 m(HD) = 0.2380 m(CD) = 0.0192	0.2046
8min	m(ZD) = 0.3594 m(LD) = 0.0449 m(MD) = 0.0449 $m(\theta)$ = 0.5507	m(ZD) = 0.1451 m(LD) = 0.095 m(MD) = 0.7599	0.12072	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.0884 m(HD) = 0.4616 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.0442 m(HD) = 0.2308 m(CD) = 0	0.1883
9min	m(ZD) = 0.3253 m(LD) = 0.0407 m(MD) = 0.0407 $m(\theta)$ = 0.5934	m(ZD) = 0.1387 m(LD) = 0.0957 m(MD) = 0.7656	0.12163	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.15 m(HD) = 0.4 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.4750 m(HD) = 0.2 m(CD) = 0	0.1774
10min	m(ZD) = 0.2943 m(LD) = 0.0368 m(MD) = 0.0368 $m(\theta)$ = 0.6321	m(ZD) = 0.1334 m(LD) = 0.0963 m(MD) = 0.7703	0.12238	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.2167 m(HD) = 0.3333 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.5083 m(HD) = 0.1667 m(CD) = 0	0.1656
11min	m(ZD) = 0.2663 m(LD) = 0.0333 m(MD) = 0.0333 $m(\theta)$ = 0.6671	m(ZD) = 0.129 m(LD) = 0.0968 m(MD) = 0.7742	0.12300	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.2833 m(HD) = 0.2667 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.5417 m(HD) = 0.1333 m(CD) = 0	0.1538
12min	m(ZD) = 0.2410 m(LD) = 0.0301 m(MD) = 0.0301 $m(\theta)$ = 0.6988	m(ZD) = 0.1253 m(LD) = 0.0972 m(MD) = 0.7775	0.12352	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.35 m(HD) = 0.2 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.5750 m(HD) = 0.1 m(CD) = 0	0.1420

recognition that dependence level among two tasks decreases with time.

Another advantage of the method presented in this paper is that it can flexibly express the effects of different time ranges. As shown in Tables 10 and 11, the value of $m(\theta)$ get changes fast with time and is getting close to 1 after 30 min in Guo et al.'s method and the value of CHEP is almost a constant after 30 min. In other word, Guo et al.'s method may only be effective in treating time intervals

Table 11
CHEP Results of Guo et al.'s method and the proposed method (continued).

Time nodes	Results in Guo's method			Results in proposed method		
	Reconstructed BBA of SP	Fused BBA	CHEP	Reconstructed BBA of SP	Fused BBA	CHEP
13min	m(ZD) = 0.2180 m(LD) = 0.0273 m(MD) = 0.0273 m(θ) = 0.7275	m(ZD) = 0.1222 m(LD) = 0.0975 m(MD) = 0.7803	0.12396	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.4167 m(HD) = 0.1333 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.6083 m(HD) = 0.0667 m(CD) = 0	0.1302
14min	m(ZD) = 0.1973 m(LD) = 0.0247 m(MD) = 0.0247 m(θ) = 0.7534	m(ZD) = 0.1195 m(LD) = 0.0978 m(MD) = 0.7862	0.12433	m(ZD) = 0.4 m(LD) = 0.05 m(MD) = 0.4786 m(HD) = 0.0714 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.0750 m(MD) = 0.6393 m(HD) = 0.0357 m(CD) = 0	0.1193
20min	m(ZD) = 0.1082 m(LD) = 0.0135 m(MD) = 0.0135 m(θ) = 0.8647	m(ZD) = 0.1096 m(LD) = 0.0989 m(MD) = 0.7915	0.12574	m(ZD) = 0.4 m(LD) = 0.3833 m(MD) = 0.2167 m(HD) = 0 m(CD) = 0	m(ZD) = 0.25 m(LD) = 0.2417 m(MD) = 0.5083 m(HD) = 0 m(CD) = 0	0.0914
25min	m(ZD) = 0.0657 m(LD) = 0.0082 m(MD) = 0.0082 m(θ) = 0.9179	m(ZD) = 0.1056 m(LD) = 0.0994 m(MD) = 0.7951	0.12632	m(ZD) = 0.5667 m(LD) = 0.3833 m(MD) = 0.05 m(HD) = 0 m(CD) = 0	m(ZD) = 0.3333 m(LD) = 0.2417 m(MD) = 0.4250 m(HD) = 0 m(CD) = 0	0.0787
30min	m(ZD) = 0.0398 m(LD) = 0.0050 m(MD) = 0.0050 m(θ) = 0.9502	m(ZD) = 0.1003 m(LD) = 0.0996 m(MD) = 0.7971	0.12663	m(ZD) = 0.9 m(LD) = 0.05 m(MD) = 0.05 m(HD) = 0 m(CD) = 0	m(ZD) = 0.5 m(LD) = 0.0750 m(MD) = 0.4250 m(HD) = 0 m(CD) = 0	0.0688

between two tasks from 0 to 30 min. In the proposed method, the influence of time on dynamic factors can be represented more flexibly. When larger time intervals are considered, such as 0–24 h, an enlargement of time scale from 0-30min to 0–24 h is applicable.

5.2. The value of using confidence level

In our paper, we consider the necessity of confidence levels, including the input confidence level of analyst's judgment "α" and the output confidence level of final result "α_f". The main purpose of providing confidence level of analyst's judgment"α" is to fully express the uncertainty during the process of judgement. In the expert elicitation stage, experts are required to define the functional relationships among the dependence influencing factors, and select proper anchor points and linguistic judgments corresponding to five dependence (similarity) levels for each factor. This process helps the analysts to give their judgments more easily and also decreases the subjectivity in the judgments. However, even based on the guidance from expert, the analysts may not be complete confident to give their judgments especially when the conditions are complex. For example, it is sometimes hard to judge the "same qualification" of operators in the anchor point "different individuals with same qualification" in Table 2. Thus, it is necessary to use confidence level "α" to express analysts' judgements. The higher their confidence level, the more credible their judgement. For "α_f", it is used to express the credibility of the final result.

6. Conclusion

In this paper, a new computing model for dependence assessment in HRA under uncertain and dynamic situations is proposed. First, this method requires the participation of experts in related fields, who are supposed to determine the input factors and their functional relationships and select anchor points and linguistic judgements. Second, analysts make judgements and provide their confidence degree according to real situation and guidance provided by experts. Third, DSET is applied to represent the uncertainty of analysts' judgements on the dependence level for each influencing factor. It is also applied to fuse different analysts' judgements to obtain fused BBAs of different factors. Fourth, a new evidence discounting method based on fuzzy sets is proposed to reconstruct BBA of dynamic factor (SP). Fifth, the BBAs of static factors (SC and SG) are combined into a BBA of TR, and then the BBA of TR and the reconstructed BBA of SP are combined to get final fused BBA. Finally, CHEP and its confidence are calculated according to the final fused BBA.

The advantages of the proposed method are as follows: First, the proposed method can improve the flexibility of expressing uncertainty and reduce subjectivity in dependence assessment among human tasks in HRA. The proposed method can express and handle different types of uncertain judgements from analysts and take analysts' confidence into consideration. Thus, flexibility is improved. The reason for the decrease in subjectivity is that the output results are obtained from a computational model. Second, it takes the time dimension into account, explains how time influence the dynamic factor on its dependence level between two tasks and avoids counter-intuitive results.

However, there are some potential limitations to the use of the proposed method. First, membership functions of trapezoidal fuzzy numbers that corresponding to time intervals fuzzy numbers are used to construct "Correction BBA" to modify the BBA of time-related factor (dynamic factor). However, this is only one possible influence model, more complex influences of "time" on the dynamic factors may exist in practical applications. Moreover, average combination method is a relatively simple fusion method, more fusion methods should be investigated in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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