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Dependence Assessment in Human Reliability Analysis Based on the Interval Evidential Reasoning Algorithm Under Interval Uncertainty

WENHAO BI[1,2], **(Member, IEEE), FEI GAO**[1], **AN ZHANG**[1,2], **(Member, IEEE), AND MI YANG**[1]

[1]School of Aeronautics, Northwestern Polytechnical University, Xi'an 710072, China
[2]CETC Key Laboratory of Data Link Technology, Xi'an 710068, China

Corresponding author: Wenhao Bi (biwenhao@nwpu.edu.cn)

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ABSTRACT Dependence assessment, which is to assess the influence of the operator's failure of a task on the failure probability of subsequent tasks, is an important part in Human reliability analysis (HRA). The technique for human error rate prediction (THERP) has been widely applied to assess the dependence in HRA. However, due to the complexity of the real world, various kinds of uncertainty could occur in dependence assessment problem, and how to properly express and deal with uncertainty especially interval uncertainty remains a pressing issue. In this article, a novel method based on the interval evidential reasoning (IER) algorithm is proposed to assess dependence in HRA under interval uncertainty. First, dependence influential factors are identified and their functional relationship is determined. Then, judgments on these factors provided by the analysts are represented using interval belief distributions. Next, the interval evidential reasoning algorithm is employed to aggregate interval belief distributions of different factors according to their functional relationship while considering the credibility of the interval belief distribution. Finally, the conditional human error probability (CHEP) is calculated based on the fused interval belief distribution, where the upper and lower values are determined by assigning belief degree to the highest and lowest grade of the corresponding grade interval, respectively. Two numerical examples demonstrate that the proposed method not only properly deals with interval uncertainty using interval belief distribution and IER algorithm, but also provides a novel and effective way for dependence assessment in HRA.

INDEX TERMS Dependence assessment, human reliability analysis, interval evidential reasoning, interval uncertainty.

I. INTRODUCTION

Aims to quantify human's contribution to the system risk for a given task and provide recommendations in improving the reliability of the task, human reliability analysis (HRA) is a crucial part of the probability safety assessment (PSA) of large-scale complex systems as the human error has attracted increasing attention in the design and risk assessment of complex systems. Generally, HRA includes the evaluation of human's performance and the corresponding impact on structures, systems, and components of a complex facility [1]–[3], and many methods have been developed for HRA [4]–[7].

Dependence assessment, which refers to the assessment of the influence of the operator's failure to perform a task on the failure probability of subsequent tasks, is an important part of HRA [8]–[10]. When there is dependence between two tasks, the failure probability of the subsequent task would be higher

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if the operator fails the preceding task [11]–[13], hence, it is important to properly assess the dependence among tasks to avoid underestimation of the risk. Normally, the result of dependence assessment is the conditional human error probability (CHEP), given the failure of the preceding task.

Various methods have been developed regarding the assessment of dependence between human failure events (HFEs) in HRA, including technique for human error rate prediction (THERP) [4], [14], [15], cognitive reliability and error analysis method (CREAM) [16]–[18], and standardized plant analysis risk-human reliability analysis method (SPAR-H) [19]–[22]. Among these methods, THERP has been the most commonly used one for its contributions including (1) It suggests five dependence levels and provides guidelines for assigning the level of dependence between two tasks based on several factors, (2) It provides a modification formula for each dependence level to calculate the CHEP.

Despite these advantages, there are still some limitations, and the most significant one is that the obtained result may lack traceability and repeatability due to the absence of specific guidance [10]. To overcome these limitations, many methods have been extended for the THERP model, including decision tree (DT) [19], [23], fuzzy expert system (FES) [10], [12], [24], [25], and evidence theory [26]–[31]. However, the flexibility of DT is limited since the analyst's judgments are typically constrained to extreme situations [1], which could impact its applicability. The FES relies heavily on the rules by the experts, but subjectivity and inconsistency could be found in some cases, and the number of rules would also increase exponentially when the number of input factors increases, thus limit its usage in the dependence assessment problem [26], [27]. The evidence theory, on the other hand, has shown to be effective in dependence assessment problems for its ability to model and fuse information under uncertainty, and there have been various applications [15], [28], [32]. However, several challenges are not well-addressed, and the most significant one is the interval uncertainty problem [24]. In the dependence assessment process, the analysts may not always be confident enough to provide judgments on a certain grade, but at times wish to provide judgment on a group of them, and such interval uncertainty would have an impact on the assessment result, and the CHEP could be an interval value as well. However, current researches mainly use the pignistic probability function to evenly distribute the belief on the grade intervals to separate grades and the obtained CHEP is a precise value, which in some way ignores the interval uncertainty and could impact the reliability and accuracy of the result.

To this end, a novel dependence assessment based on the interval evidential reasoning (IER) algorithm, which is developed by [33] and has been used in several decision-making problems under interval uncertainty [26], [34]–[36], is proposed to deal with interval uncertainty in this article. Firstly, the interval belief distribution is used to represent the analysts' judgments on the input factors under both probabilistic and interval uncertainty. Next, the IER algorithm is applied to aggregate interval belief distributions of different factors, while the weight of the interval belief distributions are determined based on their credibility. Then, the CHEP is calculated using the final interval belief distribution, where the upper and lower values are calculated by assigning the belief degree to the highest and lowest grade of the grade interval, respectively. Finally, two examples are studied to demonstrate the effectiveness and efficiency of the proposed method, where the results are compared with other methods. By using the IER algorithm, the proposed method could represent the analysts' judgments more flexibly and reliably as the interval belief distribution is applied, furthermore, since the obtained CHEP is in the form of interval value, the proposed method could more accurately reflect the actual result without the loss of any information.

The remainder of this article is organized as follows. Section 2 briefly reviews the basics of evidence theory, interval belief distribution, and interval evidential reasoning algorithm. In Section 3, the proposed IER-based dependence assessment is introduced. Two numerical examples are introduced in Section 4 to demonstrate the effectiveness of the proposed method, and Section 5 concludes the paper.

II. PRELIMINARIES

A. EVIDENCE THEORY

Evidence theory is an effective tool to deal with uncertainty, and has been widely used in problems such as decision making [37], [38], classification [39], [40], clustering [41] and many others [42]–[46]. In evidence theory, one of the basic concepts is the frame of discernment, which is a set of mutually exclusive and collective exhaustive events denoted by $\Theta = \{\theta_1, \theta_2, \ldots, \theta_N\}$. The power set of Θ consists of 2^N subsets, denoted by 2^Θ, as follows:

$$2^\Theta = \{\varnothing, \{\theta_1\}, \ldots, \{\theta_n\}, \{\theta_1, \theta_2\}, \ldots, \{\theta_1, \ldots, \theta_{N-1}\}, \Theta\} \tag{1}$$

Definition 1 (Basic Probability Assignment): A basic probability assignment (BPA) that is assigned to a proposition is defined as $m(\theta)$, and the BPA assigned to 2^Θ is called the degree of global ignorance and the BPA assigned to a smaller subset of Θ except for any singleton proposition or Θ is referred to as the degree of local ignorance, i.e., interval uncertainty, and is defined as follows:

$$m(\varnothing) = 0 \text{ and } \sum_{A \subseteq \Theta} m(A) = 1 \tag{2}$$

When $m(A) > 0$, A is called a focal element, and the set of all focal elements is called the core of a BPA.

In evidence theory, $m(A)$ measures how strongly the evidence supports A, while the belief measure *Bel* and plausibility measure *Pl* express the lower bound and upper bound of the degree of support for each proposition. *Bel* and *Pl* are defined as follows:

$$Bel(A) = \sum_{B \subseteq A} m(B)$$
$$Pl(A) = 1 - Bel(\bar{A}) = \sum_{B \cap A \neq \varnothing} m(B) \tag{3}$$

where $\bar{A} = \Theta - A$, and $Pl(A) \geq Bel(A)$ for all $A \subseteq \Theta$. $[Bel(A), Pl(A)]$ is defined as the belief interval of A.

Two independent BPAs m_1, m_2 can be combined by Dempster's rule of combination as:

$$m_1 \oplus m_2(A) = \begin{cases} \dfrac{1}{1-k} \displaystyle\sum_{B \cap C = A} m_1(B)m_2(C), & A \neq \varnothing \\ 0, & A = \varnothing \end{cases} \tag{4}$$

with

$$k = \sum_{B \cap C = \varnothing} m_1(B)m_2(C) \tag{5}$$

where k is the conflicting factor.

Definition 2 (Evidence Distance): Let m_1 and m_2 be two independent BPAs on the same frame of discernment with N 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 $\vec{m}_1$ and $\vec{m}_2$ are the vectors of m_1 and m_2, and $\underline{\underline{D}} = \frac{|A \cap B|}{|A \cup B|}$ is the similarity matrix between the focal elements with $2^N \times 2^N$ elements. This distance represents the conflict between two BPAs, the larger the distance between two BPAs, the more conflict exists between these two BPAs.

Assume that there are n BPAs for combination, these BPAs may be of different credibility, thus different weight when being combined, and the credibility of different BPAs can be defined as follows [28].

Definition 3 (Evidence Similarity): Suppose the distance between two BPAs m_i and m_j is $d(m_i, m_j)$, then the similarity degree between these two BPAs is:

$$Sim(m_i, m_j) = 1 - d(m_i, m_j) \tag{7}$$

and the similarity matrix can be obtained as:

$$SMM = \begin{bmatrix} S_{11} & \cdots & S_{1j} & \cdots & S_{1M} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{i1} & \ldots & S_{ij} & \ldots & S_{iM} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{M1} & \ldots & S_{Mj} & \ldots & S_{MM} \end{bmatrix} \tag{8}$$

Definition 4 (Evidence Credibility): The credibility degree of the BPA m_i is defined as:

$$Crd_i = \frac{Sup(m_i)}{\sum_{j=1}^{M} Sup(m_j)}, \quad i = 1, 2, \ldots, M \tag{9}$$

where $Sup(m_i)$ is the support degree of m_i, and is defined as:

$$Sup(m_i) = \sum_{j=1, j \neq i}^{M} S_{ij} \tag{10}$$

B. INTERVAL BELIEF DISTRIBUTION

Though Dempster's rule of combination has been effective in many scenarios, it falls short when there is high conflict between two BPAs. To this end, [47] proposed the evidential reasoning (ER) algorithm, which uses a new evidence combination rule to deal with highly conflicted evidences. On the basis of that, [33] further extended the evidential reasoning algorithm by considering interval uncertainty, and proposed the interval evidential reasoning (IER) algorithm. Based on the evidence theory, the IER algorithm can effectively combine conflicting evidences under various kinds of uncertainties, such as probability uncertainty, cognitive uncertainty, and interval uncertainty, by taking both local ignorance and global ignorance of the frame of discernment into consideration. In the IER algorithm, based on the concept of BPA, the interval distribution is introduced under the frame of discernment to represent how strongly the evidence supports a given proposition.

1) INTERVAL BELIEF DISTRIBUTION

Definition 5 (Interval Belief Distribution): The interval belief distribution is used to measure the extents to which the evidence supports each hypothesis and the propositions, which is also known as a piece of evidence. A piece of evidence e_p can be represented by an interval belief distribution on the power set of the frame of discernment Θ as follows:

$$e_p = \{(\theta_{ij}, \beta_{ij,p}) | \, i = 1, \ldots, N; \; j = i, \ldots, N\}, \tag{11}$$

where θ_{ij} denotes the grade interval from θ_i to θ_j, i.e. $\theta_{ij} = \{\theta_i, \theta_{i+1}, \ldots, \theta_j\}$, and β_{ij} is the corresponding belief degree which represents how strongly the evidence supports this proposition. $(\theta_{ij}, \beta_{ij})$ is a focal element of e_p and represents that the evidence supports proposition θ_{ij} to a degree of β_{ij}. Both global ignorance and local ignorance are taken into account in the definition of interval belief distribution, and $\sum_{i=1}^{n} \sum_{j=i}^{n} \beta_{ij,p} = 1$.

It should be noted that in the interval belief distribution, all the subsets of Θ are regarded as referential grades with $\theta_i \prec \theta_j$, $i < j$ for all $i, j \in \{1, \ldots, N\}$, and the proposition θ_{ij} is regarded as the grade interval from θ_i to θ_j. Therefore, the complete set of all grades intervals of an evidence can be represented as follows [26]:

$$A = \left\{ \begin{matrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1(N-1)} & \theta_{1N} \\ & \theta_{22} & \cdots & \theta_{2(N-1)} & \theta_{2N} \\ & & \ddots & \vdots & \vdots \\ & & & \theta_{(N-1)(N-1)} & \theta_{(N-1)N} \\ & & & & \theta_{NN} \end{matrix} \right\} \tag{12}$$

where there are N singleton grades and $N(N-1)/2$ grade intervals, i.e. $N(N+1)/2$ elements in total.

Unlike the power set of Θ, the interval belief distribution only considers grade intervals between neighboring propositions, and subsets such as $\{\theta_1, \theta_N\}$ are ignored. That's because that all the singletons of Θ are assumed to be referential grades, hence, only assessments on grade intervals between neighboring grades would exist in the real world.

The IER algorithm also extends evidence theory by introducing evidence weight to reflect the relative importance of different evidences. A piece of evidence e_p is characterized by two elements including the interval belief distribution $(\theta_{ij}, \beta_{ij})$ and weight ω_p in the framework of the IER algorithm. A weighted interval belief distribution is defined as follows:

$$m_p = \{(\theta_{ij}, m_{ij,p})|\ i = 1, \ldots, N;\ j = i, \ldots, N;\ (\Theta, m_{\Theta,p})\} \tag{13}$$

where $m_{ij,p}$ represents the degree of support for θ_{ij} from evidence e_p while taking the weight ω_p into consideration, and is defined as:

$$m_{ij,p} = \omega_p \beta_{ij,p} \tag{14}$$

It should be noted that $m_{\Theta,p}$ is the degree of residual support that reflects the uncertainty of evidence e_p, and it satisfies $m_{\Theta,p} = 1 - \sum_{i=1}^{N} \sum_{j=i}^{N} m_{ij,p}$. Normally, it can be divided into two parts: $\bar{m}_{\Theta,p}$ and $\tilde{m}_{\Theta,p}$, where $\bar{m}_{\Theta,p} = 1 - \omega_p$ is caused by the relative importance of the evidence e_p and $\tilde{m}_{\Theta,p} = \omega_p(1 - \sum_{\theta \subseteq \Theta} m_{\theta,p})$ is caused by the cognitive uncertainty in the information on e_p, i.e. global ignorance and local ignorance. It should be noted that since global ignorance and local ignorance can be expressed using grade intervals, the cognitive uncertainty would eliminate to zero, i.e., $\tilde{m}_{\Theta,p} = \omega_p(1 - \sum_{i=1}^{N} \sum_{j=i}^{N} m_{ij,p}) = 0$.

2) INTERVAL EVIDENTIAL REASONING (IER) ALGORITHM

Proposed by [33], the IER algorithm is effective in dealing with interval belief distributions. Suppose two interval belief distributions are defined as:

$$m_1 = \{(\theta_{ij}, \beta_{1,ij})\}, \quad m_2 = \{(\theta_{ij}, \beta_{2,ij})\} \tag{15}$$

where $\beta_{1,ij}$, $\beta_{2,ij}$ are the belief degrees associated with the grade interval θ_{ij}.

Suppose ω_1 and ω_2 are the weights of two interval belief distributions, then the weighted BPAs of two interval belief distributions are calculated as:

$$\begin{aligned} m_{ij}^1 &= \omega_1 \beta_{1,ij} \\ m_{\Theta}^1 &= 1 - \sum_{i=1}^{N} \sum_{j=i}^{N} \omega_1 \beta_{1,ij} = 1 - \omega_1 \\ m_{ij}^2 &= \omega_n \beta_{2,ij} \\ m_{\Theta}^2 &= 1 - \sum_{i=1}^{N} \sum_{j=i}^{N} \omega_n \beta_{2,ij} = 1 - \omega_2 \end{aligned} \tag{16}$$

By aggregating two interval belief distributions, the combined BPA assigned to each grade interval θ_{ij}, denoted by C_{ij}, can be calculated as follows:

$$C_{ij} = \frac{1}{1-k} \Bigg[-m_{ij}^1 m_{ij}^2 + \sum_{t=1}^{i} \sum_{l=j}^{N} (m_{tl}^1 m_{ij}^2 + m_{ij}^1 m_{tl}^2) + \sum_{t=1}^{i-1} \sum_{l=j+1}^{N} (m_{ij}^1 m_{il}^2 + m_{il}^1 m_{ij}^2) + m_{\Theta}^1 m_{ij}^2 + m_{ij}^1 m_{\Theta}^2 \Bigg] \tag{17}$$

and the BPA at large in Θ is defined as:

$$C_{\Theta} = \frac{m_{\Theta}^1 m_{\Theta}^2}{1-k} \tag{18}$$

where

$$k = \sum_{i=1}^{N} \sum_{j=i}^{N} \sum_{t=1}^{i-1} \sum_{l=t}^{i-1} (m_{tl}^1 m_{ij}^2 + m_{ij}^1 m_{tl}^2) \tag{19}$$

Hence, the overall combined belief degree β_{ij} on grade interval θ_{ij} can be obtained as:

$$\beta_{ij} = \frac{C_{ij}}{1 - C_{\Theta}} \tag{20}$$

For ranking purposes, the expected utilities can be calculated. Suppose $u(\theta_{ii})$ is the value of grade θ_{ii} with $u(\theta_{i+1,i+1}) > u(\theta_{ii})$ as it is assumed that the grade $\theta_{i+1,i+1}$ is preferred to θ_{ii}. Due to the interval uncertainty, the maximum, minimum and average utilities should be calculated. As the belief degree β_{ij} could be assigned to the best grade θ_{jj} in the grade interval θ_{ij}, the maximum expected utility could be calculated as:

$$u_{max} = \sum_{i=1}^{N} \sum_{j=i}^{N} \beta_{ij} u(\theta_{jj}) \tag{21}$$

Similarly, if the belief degree β_{ij} is assessed to the worst grade θ_{ii} in the grade interval θ_{ij}, the minimum expected utility can be obtained as:

$$u_{min} = \sum_{i=1}^{N} \sum_{j=i}^{N} \beta_{ij} u(\theta_{ii}) \tag{22}$$

The average expected utility is given by:

$$u_{avg} = \frac{u_{max} + u_{min}}{2} \tag{23}$$

III. METHODOLOGY

In this section, an IER-based dependence assessment method is developed for assessing the dependence among human errors in HRA, and the proposed method consists of four parts: (1) identify the influential factors and their anchor points; (2) evaluate each input factor using interval belief distributions; (3) combine the analysts' judgments using the IER algorithm; (4) calculate the overall dependence levels error among human operations. The detailed process of the proposed method is illustrated in Fig 1.

Step 1: Identify the influential factors and the functional relationship among them

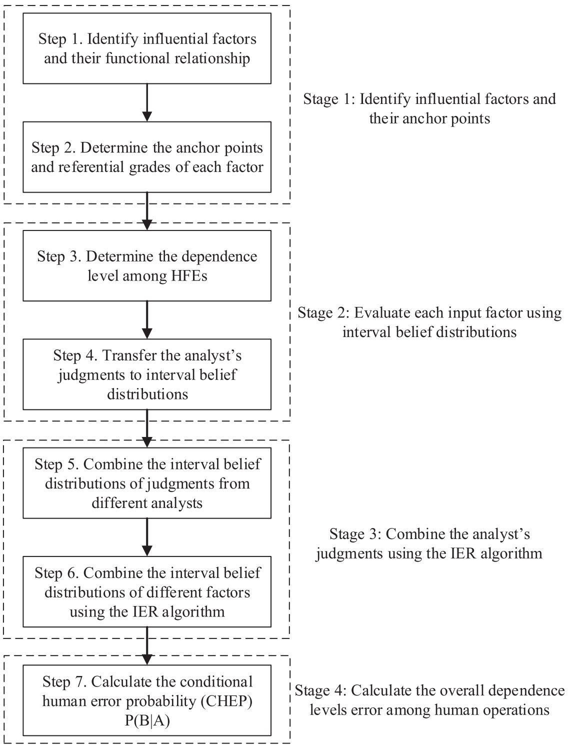

FIGURE 1. Framework of the proposed method.

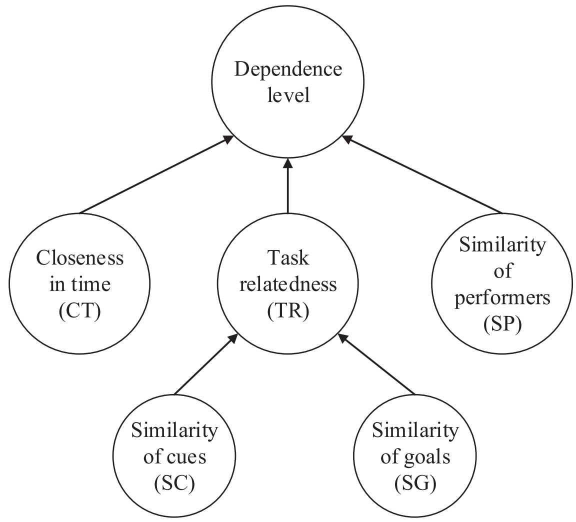

FIGURE 2. Functional relationship among factors.

In order to conduct human dependence assessment, the first step is to determine the factors that have influences on the dependence of human actions. For example, five influential factors are identified in the THERP model for nuclear power plants, namely, "closeness in time", "task relatedness", "similarity of cues", "similarity of goals", and "similarity of performers" [12]. However, it should be noted that the identification of the influential factors is based on the specific situation and application, and the influential factors may change according to the changes in the assessment situation.

Furthermore, once the influential factors are identified, the relationship among these factors should be determined for assessment. For example, the functional relationship among the influential factors of a working model for post-initiator HFEs of a nuclear power plant is shown in Fig 2. It is shown that there are four independent factors and one intermediate factor, hence, the influential factors could be further distinguished. Normally, it is assumed that only judgments on independent factors can be provided, and the assessment on intermediate factors is determined based on the assessment of its sub-factors.

Step 2: Determine the anchor points and referential grades of each factor

After identifying the influential factors and their relationships, the anchor points and the corresponding referential grades of each factor should be provided as the guidance for analyst's judgment to support the dependence assessment based on prior knowledge obtained from experts. The anchor points of a factor represent possible situations of the factor, and the corresponding referential grades qualitatively provide the impact of this factor on the dependence of human actions. For example, the "closeness in time" between two actions can be different, which would have different effects on the dependence between these two actions, such as anchor point "5 min" indicates referential grade "Complete Dependence", "30 min" indicated "Moderate Dependence", and "8 h" indicates "Zero Dependence".

Step 3: Determine the dependence level among HFEs with respect to each factor

Based on the anchor points and referential grades obtained in Step 2, the analysts could provide judgments of the input factors by referring to the anchor points and corresponding grades, where the anchor points are critical to reduce the subjectively of the judgment. However, due to the complexity of the real world, the judgment provided by the analyst may not be straightforward, as the analyst may not be able to incorporate all the belief on a specific dependence level, especially when ambiguity and uncertainty occur. In the proposed method, the ambiguity of the analyst's judgment can be expressed by dividing into sets of possible dependence levels, i.e., grade intervals, and uncertainty can be represented using the interval belief distribution. Furthermore, ratios can be provided by the analyst to indicate the relative probabilities of different grade intervals.

An example of analyst's judgments is shown in Table 1. Case 1 indicates that the analyst is totally confident that the dependence level is High Dependence (HD). Case 2 shows that the analyst is confident that the dependence level lies within Moderate Dependence (MD) and HD, but has no idea which dependence level is more likely. Case 3 indicates that the analyst believes that HD is 2 times more likely than MD. Case 4 shows that the analyst provides the judgment within levels Low Dependence (LD), MD, and HD.

Step 4: Construct interval belief distributions

After obtaining the analyst's judgments on the dependence level of each factor, these judgments should be transformed into interval belief distributions for combination. Since the

TABLE 1. Examples of analyst's judgments for a specific factor.

Case	Dependence level
Case 1	{MD}
Case 2	{MD,HD}
Case 3	{MD}:{HD}=1:2
Case 4	{LD}:{MD}:{HD}=1:3:2

model is based on five dependence levels, the frame of discernment would be $\Theta = \{ZD, LD, MD, HD, CD\}$, and the number of grade intervals is $5 \times 6 \div 2 = 15$.

For cases where the analyst fails to provide the ratio of different grade intervals, the belief would be assigned to the entire grade interval, for example, the interval belief distribution of Case 2 in Table 1 can be calculated as:

$$S = \{([MD, HD], 1)\}$$

For cases where the ratios of different grades are provided, their belief degrees can be calculated by dividing total belief into different grades according to the ratio. For example, the belief degrees of Case 3 in Table 1 can be calculated as:

$$\beta_{MD} = \frac{1}{1+2} = 0.3333, \quad \beta_{HD} = \frac{2}{1+2} = 0.6667$$

and the interval belief distribution is obtained as:

$$S = \{(MD, 0.3333), (HD, 0.6667)\}$$

Step 5: Combine the interval belief distributions of judgments from different analysts for a specific factor

In actual assessment practice, it is normally the case that not only one but several analysts are asked to provide their judgment on a factor, and a corresponding interval belief distribution can be constructed based on each judgment. Then, the judgments from different analysts for specific factors should be combined.

It should be noted that since different analysts may provide different judgments, and these judgments may vary quite hugely, it is necessary to determine the credibility of each judgment. Therefore, the weight of the analysts' judgments are determined based on their credibility degrees, shown in (7)-(10).

Suppose there are four analysts that provide judgments on a specific factor independently, and the interval belief distributions are constructed based on their judgments, shown in Table 2. As shown in the table, Analyst 1 and 2 suggest that the dependence level lies between LD and MD, while Analyst 3 shows more belief in the level MD, HD or CD, and Analyst 4 supports dependence levels MD and HD.

Hence, the weights of the judgments are calculated using (7)-(10), and can be obtained as:

$$\omega_1 = 0.2571, \ \omega_2 = 0.2558, \omega_3 = 0.2558, \ \omega_4 = 0.2313$$

Then, the interval belief distributions can be combined using (16)-(20), and the combination result can be obtained as:

$$S = \{(LD, 0.1949), (MD, 0.4468), (HD, 0.2898), (CD, 0.0685)\}$$

TABLE 2. Interval belief distributions of judgments from different analysts for a specific factor.

Analyst	Interval belief distribution
Analyst 1	{(LD,0.3),(MD,0.7)}
Analyst 2	{(LD,0.5),(MD,0.5)}
Analyst 3	{(MD,0.2),(HD,0.5),(CD,0.3)}
Analyst 4	{(MD,0.25),(HD,0.75)}

Step 6: Combine the interval belief distributions of different factors

After determining the interval belief distributions of different factors, the interval belief distributions should be fused. It should be noted that only the judgments of the factors from the same level in the functional relationship can be combined, and the interval belief distribution of a factor in the upper level is obtained by the combination of interval belief distributions of its corresponding sub-factors. For example, in Fig 1, the interval belief distributions of factors "Similarity of Cues" and "Similarity of Goals" can be combined to get the BBA of factor "Task Relatedness". Moreover, if the judgments for "Task Relatedness" are also directly provided, they should be used to combine with the combined result, and the weight of each interval belief distribution should be determined based on its credibility degree as well. Through this step, it is clearly displayed that how the fused interval belief distributions constructed and how the input factors influence on the dependence level, and the fused interval belief distribution represents the combined result that is calculated by the input factors.

Step 7: Calculate the CHEP $p(B|A)$

Once the final interval belief distribution is obtained by combining the interval belief distributions of different factors, the CHEP can be calculated to draw a final conclusion, and the conditional human error probability CHEP $p(B|A)$ can be calculated as [48]:

$$p(B|A) = \sum_{i=1}^{N} \beta_i \times p_i(B|A) \tag{24}$$

with

$$p_i(B|A) = \frac{1 + K \times p_B}{K + 1} \tag{25}$$

where $i = ZD$, LD, MD, HD and CD. $p_i(B|A)$ can be regarded as the utility value of dependence level i, p_B is the basic human error probability of task B, $K = 0,\ 1,\ 6,\ 19,\ \infty$ for dependence levels CD, HD, MD, LD and ZD, respectively.

However, it should be noted that for cases where interval uncertainty is involved, i.e., the judgments from the analysts lie in several dependence levels without specific preference, grade intervals would be involved in the final interval belief distribution, and the CHEP would be an interval as well. Hence, in this case, when the belief degree β_{ij} is assigned to the highest grade θ_{jj} in the grade interval θ_{ij}, the upper value of the CHEP can be obtained as:

$$p^{+}(B|A) = \sum_{i=1}^{N}\sum_{j=i}^{N} \beta_{ij} \times p_j(B|A) \tag{26}$$

Similarly, if the uncertainty turns out to be against the assessment, i.e., the belief degree β_{ij} is assigned to θ_{ii}, the lowest grade in the interval θ_{ij}, the lower value of the CHEP can be obtained as:

$$p^{-}(B|A) = \sum_{i=1}^{N}\sum_{j=i}^{N} \beta_{ij} \times p_i(B|A) \tag{27}$$

Therefore, the CHEP can be represented as $p(B|A) \in [p^{-}(B|A), p^{+}(B|A)]$, and the average expected utility value $p_{avg}(B|A)$ can be calculated using (23).

IV. CASE STUDY

In order to demonstrate the process and the effectiveness of the proposed method, two case studies on post-initiator human failure events of a nuclear power plant [2], [10] are used.

This case study refers to a set of required operator actions to avoid excessive boron dilution in the reactor cooling system in case of an anticipated transient without scram (ATWS) at a boiling water reactor (BWR). It is assumed that the standby liquid control system (SLCS) has been successfully initiated by the operators to shut the reactor down. The operators are required to increase the voiding and inhibit the actuation of the automatic depressurization system (ADS) to facilitate the reactor shutdown. The operator tasks include the prevention of the ADS (Action A) and the control of the reactor vessel level (Action B) to prevent diluting boron concentration after the ADS failure. The probability of human failure in controlling the reactor vessel level is used as the output.

Two examples are considered, the first example considers the case where the analysts' judgments are precise judgments without interval uncertainty, while the case where interval uncertainty exists in the analysts' judgments is considered in the second example.

A. EXAMPLE 1: ASSESSMENT WITHOUT INTERVAL UNCERTAINTY

1) CASE SETTING

In order to conduct the dependence assessment, the influential factors that influence the dependence of B and A should be determined first. In this case, three factors that directly influence the dependence level are identified, namely, CT, TR, and SP. Moreover, TR is believed to be affected by two factors: SC and SG. Hence, there are five influential factors in this problem, four of which are input factors and one is the intermediate factor, and the functional relationship is shown in Fig 2.

Hence, when conducting the assessment, the interval belief distribution of SC and SG is firstly calculated by transferring the analysts' judgments on SC and SG to interval belief distributions. Then, the interval belief distribution of TR is calculated by combining the interval belief distributions of SC and SG. Finally, the fused interval belief distribution that represents the assessment results is obtained by combining all the input factors.

For each influential factor, anchor points and linguistic judgments corresponding to five dependence levels are provided by experts. The anchor points and corresponding linguistic judgments for CT are shown in Table 3, and the anchor points and corresponding linguistic judgments for SC, SG, and SP are shown in Table 4, Table 5 and Table 6, respectively.

TABLE 3. Anchor points and referential grades for input factor CT.

Anchor points	Grades	Linguistic judgment
24 h	ZD	Two tasks are very widely separated in time
8 h	ZD	Two tasks are widely separated in time
1 h	LD	The time difference between tasks is less than wide
30 min	MD	It is not relevant in the dependence assessment
20 min	HD	The tasks are in a short time window, but not close enough
5 min	CD	The two tasks are close in time

TABLE 4. Anchor points and referential grades for input factor SC.

Anchor points	Grades	Linguistic judgment
Different sets of indicators for different parameters	ZD	No similarity of cues is present between tasks
Different sets of indicators for the same parameters	LD-MD	An intermediate level of cues similarity exists although not fully moderate
Single indicator for the same parameter	MD-HD	The level of cues similarity is more than moderate
Different sets of indicators for the same physical quantity	HD-CD	Slightly more than high level of similarity of cues is present between the tasks
Same sets of indicators for the same sets of parameters	CD	The tasks present complete similarity of cues

TABLE 5. Anchor points and referential grades for input factor SG.

Anchor points	Grades	Linguistic judgment
Different functions by different systems	ZD	No similarity of cues is present between tasks
Different functions by same system	LD	A low level of goals similarity exists
Same function by different systems	HD	The level of goals similarity is high
Same function by same system	CD	A complete level of similarity of goals is present between tasks

TABLE 6. Anchor points and referential grades for input factor SP.

Anchor points	Grades	Linguistic judgment
TSC vs control shift room	ZD	No similarity of performers is present between tasks
Different steam	LD	A low level of performer similarity exists
Different individual with same qualification	MD	The level of performer similarity is moderate
Same team	HD	High level of performer similarity is present between tasks
Same person	CD	The tasks are accomplished by the same individual. In this case, the similarity of performer is complete.

The weights of the influential factors are determined using the AHP method, where the hierarchical relationship of the influential factors is shown in Fig 2. For assessing the dependence level of TR, the hierarchical level consists of two factors SC and SG, and the weight can be directly obtained by pairwise comparison. Suppose that the judgment concerning the relative importance of factor SC over factor SG is:

$$m_{CG} = \frac{1}{m_{GC}} = 2$$

Hence, the weights of factors SC ω_{SC} and SG ω_{SG} can be calculated as:

$$\omega_{SC} = \frac{2}{3}, \quad \omega_{SG} = \frac{1}{3}$$

Similarly, the weights of factors TR ω_{TR}, SP ω_{SP} and CT ω_{CT} can be obtained as:

$$\omega_{TR} = 0.6483, \quad \omega_{SP} = 0.2297, \quad \omega_{CT} = 0.1220$$

2) ANALYSTS' JUDGMENT

Based on the anchor points and linguistic judgments suggested by experts in Table 3, 4, 5 and 6, the analyst can provide judgments of the dependence level between two tasks with respect to each of the input factors by referring to this information. Assume that there are three analysts to provide their judgments on the dependence level of each input factor, and the judgments are shown in Table 7.

TABLE 7. Analysts' judgments on input factors for Example 1.

Factor	Analyst	Dependence level
Closeness in time	Analyst 1	{LD}:{MD}=3:2
	Analyst 2	{LD}
	Analyst 3	{MD}:{HD}=5:1
Similarity of cues	Analyst 1	{MD}
	Analyst 2	{LD}:{MD}=1:1
	Analyst 3	{LD}:{MD}:{HD}=1:2:1
Similarity of goals	Analyst 1	{HD}:{CD}=3:1
	Analyst 2	{HD}
	Analyst 3	{MD}:{HD}=1:3
Similarity of performers	Analyst 1	{LD}
	Analyst 2	{ZD}:{LD}=1:4
	Analyst 3	{ZD}:{LD}:{MD}=2:3:1

For example, for factor "closeness in time", Analyst 3 suggests that the dependence level MD is 5 times more likely than HD. For factor "similarity of cues", Analyst 1 has full confidence that the dependence level is LD. For factor "similarity of goals", all analysts have more confidence that the dependence level is HD. For "similarity of performers", the judgments given by the analysts show more belief in dependence level LD.

3) IER PROCESS

Based on the analysts' judgments shown in Table 7, the interval belief distributions can be constructed, shown in Table 8.

TABLE 8. Interval belief distributions based on analysts' judgments for Example 1.

Factor	Analyst	Interval belief distribution
Closeness in time	Analyst 1	{(LD,0.6),(MD,0.4)}
	Analyst 2	{(LD,1)}
	Analyst 3	{(MD,0.8333),(HD,0.1667)}
Similarity of cues	Analyst 1	{(MD,1)}
	Analyst 2	{(LD,0.5),(MD,0.5)}
	Analyst 3	{(LD,0.25),(MD,0.5),(HD,0.25)}
Similarity of goals	Analyst 1	{(HD,0.75),(CD,0.25)}
	Analyst 2	{(HD,1)}
	Analyst 3	{(MD,0.25),(HD,0.75)}
Similarity of performers	Analyst 1	{(LD,1)}
	Analyst 2	{(ZD,0.2),(LD,0.8)}
	Analyst 3	{(ZD,0.3333),(LD,0.5),(MD,0.1667)}

Then, the interval belief distributions constructed based on the analysts' judgments are combined to obtain a more comprehensive and reliable assessment of the input factors using the IER algorithm. First, the weights of these interval belief distributions can be obtained by calculating the credibility of each judgment using (7)-(10). Then, the BPAs are combined to obtain the assessment of different factors. The combined interval belief distributions of the input factors are shown in Table 9.

TABLE 9. Combined interval belief distributions of the influential factors for Example 1.

Factor	Combined interval belief distribution
Closeness in time	{(LD,0.5219),(MD,0.4293),(HD,0.0488)}
Similarity of cues	{(LD,0.2098),(MD,0.7619),(HD,0.0283)}
Similarity of goals	{(MD,0.0599),(HD,0.8801),(CD,0.0599)}
Similarity of performers	{(ZD,0.1370),(LD,0.8078),(MD,0.0552)}

The combined interval belief distributions of input factors are then fused using the IER algorithm. Since it is a two-level hierarchy in the functional relationship, the combination should also consist of two steps. First, the interval belief distributions of factors SC and SG should be combined to calculate the interval belief distribution of factor TR. According to (16), the weighted BPAs of the two interval belief distributions can be obtained as:

$$\begin{aligned} m_{SC}(LD) &= \omega_{SC}\beta_{LD}^{SC} = 0.1399, \\ m_{SC}(MD) &= \omega_{SC}\beta_{MD}^{SC} = 0.5079, \\ m_{SC}(HD) &= \omega_{SC}\beta_{HD}^{SC} = 0.0189, \\ m_{SC}(\Theta) &= 1 - \omega_{SC} = 0.3333 \\ m_{SG}(MD) &= \omega_{SG}\beta_{MD}^{SG} = 0.0200, \\ m_{SG}(HD) &= \omega_{SG}\beta_{HD}^{SG} = 0.2933, \\ m_{SG}(CD) &= \omega_{SG}\beta_{CD}^{SG} = 0.0200, \\ m_{SG}(\Theta) &= 1 - \omega_{SG} = 0.6667 \end{aligned}$$

Then, by combining the weighted BPAs using the IER algorithm, the interval belief distribution for factor TR can be obtained as:

$$S_{TR} = \{(LD, 0.1632), (MD, 0.6222), (HD, 0.2028), (CD, 0.0116)\}$$

Secondly, the interval belief distributions of factors CT, TR and SP are combined using the same process to calculate the final interval belief distribution of CHEP $p(B|A)$, and the combined interval belief distribution is:

$$S_{CHEP} = \{(ZD, 0.0164), (LD, 0.2937), (MD, 0.5272), (HD, 0.1539), (CD, 0.0086)\}$$

Assume the basic human error probability of the task B is $p_B = 0.01$, then the conditional human error probability

$p(B|A)$ can be calculated as:

$$
\begin{aligned}
p(B|A) &= \sum_{i=1}^{5} \beta_i \times p_i(B|A) \\
&= 0.0164 \times 0 + 0.2937 \times \frac{1+19\times 0.01}{20} + 0.5272 \\
&\quad \times \frac{1+6\times 0.01}{7} + 0.1539 \times \frac{1+1\times 0.01}{2} \\
&\quad +0.0086 \times 1 = 0.1836
\end{aligned}
$$

Hence, the conditional human error probability CHEP $p(B|A)$ given the failure of task A is 0.1836.

4) COMPARATIVE ANALYSIS

In order to further illustrate the effectiveness and efficiency of the proposed method, the result is compared to the assessment results using the dependence assessment method based on evidence theory and AHP [28] and the evidential AHP dependence assessment method [49], and the comparison results are shown in Table 10.

TABLE 10. Comparison results of different dependence assessment methods for Example 1.

Method	CHEP value
Su et al. [28]	0.1404
Chen et al. [49]	0.1936
Proposed method	0.1836

As shown in Table 10, the CHEP value of the dependence assessment based on evidence theory and AHP [28] is $p(B|A) = 0.1404$, and the CHEP value of the evidential AHP dependence assessment method [49] is $p(B|A) = 0.1936$, both are relatively close to the result of the proposed method. Hence, it can be concluded that the proposed method can provide reliable dependence assessment results when interval uncertainty is not involved.

B. EXAMPLE 2: ASSESSMENT UNDER INTERVAL UNCERTAINTY

1) ANALYSTS' JUDGMENTS

In this section, a case of interval uncertainty in the analysts' judgments is considered to show the effectiveness and efficiency of the proposed method to deal with interval uncertainty in the inputs.

By referring to the anchor points and linguistic judgments shown in Table 3, 4, 5 and 6, the judgments of the dependence level between two tasks are provided by the analysts. Similarly to Example 1, it is assumed that there are three analysts to provide their judgments, and the judgments are shown in Table 11.

2) IER PROCESS

Based on the analysts' judgments, the interval belief distributions of the input factors can be constructed, and are shown in Table 12.

TABLE 11. Analysts' judgments on input factors for Example 2.

Factor	Analyst	Dependence level
Closeness in time	Analyst 1	{LD,MD}:{MD}=2:1
	Analyst 2	{MD}
	Analyst 3	{MD,HD}
Similarity of cues	Analyst 1	{LD,MD}
	Analyst 2	{LD,MD}:{MD}:{MD,HD}=1:1:2
	Analyst 3	{MD}:{MD,HD}=1:1
Similarity of goals	Analyst 1	{LD}:{LD,MD}=1:1
	Analyst 2	{MD}
	Analyst 3	{LD}:{MD}:{MD,HD}=1:2:1
Similarity of performers	Analyst 1	{LD}:{LD,MD}:{HD}=1:3:1
	Analyst 2	{ZD,LD}:{LD}:{LD,MD}=1:2:1
	Analyst 3	{ZD}:{LD,MD}:{MD}=2:1:2

TABLE 12. Interval belief distributions based on analysts' judgments for Example 2.

Factor	Analyst	Interval belief distribution
Closeness in time	Analyst 1	{([LD,MD],0.6667),(MD,0.3333)}
	Analyst 2	{(MD,1)}
	Analyst 3	{([MD,HD],1)}
Similarity of cues	Analyst 1	{([LD,MD],1)}
	Analyst 2	{([LD,MD],0.25),(MD,0.25),([MD,HD],0.5)}
	Analyst 3	{(MD,0.5),([MD,HD],0.5)}
Similarity of goals	Analyst 1	{(LD,0.5),([LD,MD],0.5)}
	Analyst 2	{(MD,1)}
	Analyst 3	{(LD,0.25),(MD,0.5),([MD,HD],0.25)}
Similarity of performers	Analyst 1	{(LD,0.2),([LD,MD],0.6),(HD,0.2)}
	Analyst 2	{([ZD,LD],0.25),(LD,0.5),([LD,MD],0.25)}
	Analyst 3	{(ZD,0.4),([LD,MD],0.2),(MD,0.4)}

Then, the interval belief distributions constructed based on the analysts' judgments are combined using the IER algorithm to obtain the assessment of the input factors, and the combined interval belief distributions of the input factors are shown in Table 13.

TABLE 13. Combined interval belief distributions of the influential factors for Example 2.

Factor	Combined interval belief distribution
Closeness in time	{([LD.MD],0.1620),(MD,0.6896),([MD,HD],0.1484)}
Similarity of cues	{([LD,MD],0.2253),(MD,0.4857),([MD,HD],0.2889)}
Similarity of goals	{(LD,0.2006),([LD,MD],0.0831),(MD,0.6292),([MD,HD],0.0871)}
Similarity of performers	{(ZD,0.0950),([ZD,LD],0.0657),(LD,0.3200),([LD,MD],0.3315),(MD,0.1282),(HD,0.0595)}

For the two-level hierarchical functional relationship, the interval belief distributions of factors SC and SG are firstly combined to obtain the interval belief distribution of factor TR, and is calculated as:

$$
\begin{aligned}
S_{TR} = \{&(LD, 0.0435), ([LD, MD], 0.1528), (MD, 0.6104), \\
&([MD, HD], 0.1933)\}
\end{aligned}
$$

Then, by combining the interval belief distributions of factors CT, TR and SP using the IER algorithm, the final interval belief distribution of the conditional human error probability CHEP can be obtained as:

$$
\begin{aligned}
S_{CHEP} = \{&(ZD, 0.0098), ([ZD, LD], 0.0068), (LD, 0.0800), \\
&([LD, MD], 0.1527), (MD, 0.6087), \\
&([MD, HD], 0.1334), (HD, 0.0085)\}
\end{aligned}
$$

Similarly to Example 1, assume the basic human error probability of the task B is $p_B = 0.01$. Since interval uncertainty exists in this problem and the obtained interval belief distribution includes grade intervals, the conditional human error probability $p(B|A)$ would also be in the form of interval data. The upper and lower value of the CHEP can be calculated using (21)-(22), when the belief degree is assigned to the highest grade of the grade interval, the upper value of the CHEP can be obtained as:

$$\begin{aligned} p^{+}(B|A) &= \sum_{i=1}^{5}\sum_{j=i}^{N}\beta_{ij}\times p_j(B|A) \\ &= 0.0098\times 0+(0.0068+0.0800) \\ &\quad \times\frac{1+19\times 0.01}{20}+(0.1527+0.6087) \\ &\quad \times\frac{1+6\times 0.01}{7}+(0.1334+0.0085) \\ &\quad \times\frac{1+1\times 0.01}{2}=0.1921 \end{aligned}$$

When the belief degree is assigned to the lowest grade of the grade interval, the lower value of the CHEP could be calculated as:

$$\begin{aligned} p^{-}(B|A) &= \sum_{i=1}^{5}\sum_{j=i}^{N}\beta_{ij}\times p_i(B|A) \\ &= (0.0098+0.0068)\times 0+(0.0800+0.1527) \\ &\quad \times\frac{1+19\times 0.01}{20}+(0.6087+0.1334) \\ &\quad \times\frac{1+6\times 0.01}{7}+0.0085\times\frac{1+1\times 0.01}{2} \\ &= 0.1305 \end{aligned}$$

Thus, the CHEP given the task A's failure is $p(B|A) = [0.1305, 0.1921]$, and the uncertainty degree of this interval can be calculated as $p^{+}(B|A) - p^{-}(B|A) = 0.1921 - 0.1305 = 0.0616$. The average utility value of the CHEP can be obtained as $p_{avg}(B|A) = \frac{1}{2}\left[p^{+}(B|A)+p^{-}(B|A)\right] = 0.1613$, which equals to the average utility obtained using the betting probability [50], and that is because since only grade intervals with two grades are involved, (23) is exactly the utility calculation equation using the betting probability. Furthermore, it should be noted that the confidence in the analysts' judgment is not considered in this case, hence, the confidence of the CHEP result is not considered.

3) COMPARATIVE ANALYSIS

In order to further demonstrate the effectiveness of the proposed method in dealing with interval uncertainty, the results are further compared to the assessment results using the dependence assessment method based on evidence theory and AHP [28] and the evidential AHP dependence assessment method [49], and the comparison results are shown in Table 14.

It is clear in Table 14 that the result of the proposed method is different from the results using the dependence assessment method based on evidence theory and AHP [28] and the evidential AHP dependence assessment method [49] since the result of the proposed method is a interval value while the results of other methods are simply expected utilities. That is because by using grade intervals to represent interval uncertainty in the analysts' judgment and using maximum and minimum utility rather than the pignistic probability function to calculate the CHEP value, the proposed method could more effectively reflect the interval uncertainty in the assessment. Furthermore, it can be noted that the CHEP values of other methods both lie between the CHEP interval obtained using the proposed method, which confirms the effectiveness and accuracy of the proposed method. Therefore, it can be concluded that the proposed method could effectively deal with interval uncertainty and reflect the interval uncertainty in the assessment results.

TABLE 14. Comparison results of different dependence assessment methods for Example 2.

Method	CHEP value
Su et al. [28]	0.1503
Chen et al. [49]	0.1880
Proposed method	[0.1305,0.1921]

C. DISCUSSION

As shown in Example 1 and Example 2, the result of the proposed method can be in the form of precise data and interval data, depending on the kinds of judgments given by the analysts. As can be seen from the results, by giving the analysts' judgments different weights based on their credibility, the proposed method is able to combine different judgments while considering their credibility, which allows the more credible information to provide more influence toward the final result. In other words, by combining the evidence credibility with the IER algorithm, the uncertainty in the analysts' judgments is reduced.

More importantly, as shown in Example 2, for assessment under interval uncertainty, the result of the proposed method is in the form of interval data, while the results of other methods are simply precise data. As the interval uncertainty is generally difficult to reduce or eliminate, using interval value provides a more comprehensive and reliable way to properly reflect the interval uncertainty in the assessment without degeneration. Hence, the proposed method is shown to be able to provide reliable results for dependence assessment under interval uncertainty.

V. CONCLUSION

In this article, a dependence assessment for human reliability analysis based on the interval evidential reasoning algorithm is proposed. First, the interval belief distribution is applied to represent the analysts' judgments, where both probabilistic and interval uncertainty are captured using grade intervals and belief degrees. Then, the weight of each interval belief distribution is determined based on the credibility of the analysts' judgments. Next, the interval evidential reasoning algorithm is applied to aggregate interval belief distributions of different factors and obtain the final interval belief distribution. Finally, the upper and lower values of the CHEP interval are calculated by assigning the belief degree to the highest and lowest grade of its corresponding grade interval, respectively. By using the interval belief distribution and the IER algorithm to represent and aggregate the analysts' judgments, the proposed method enhances the ability to deal with interval uncertainty of the dependence assessment method. To validate the effectiveness of the proposed method, two numerical examples are examined, the results show that the proposed method not only can deal with cases under interval uncertainty, but also could provide reliable results for cases without interval uncertainty. It can be concluded that the proposed method provides a novel and promising way for dependence assessment in HRA under interval uncertainty.

For future researches, how to use real-world data to more precisely determine the relationship between the parameter and the dependence level of the corresponding factor will be further studied. Furthermore, we will also seek more practical applications for the proposed method and study the potential of integrating the confidence of the analysts' judgments into this method.

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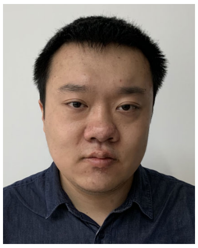
WENHAO BI (Member, IEEE) was born in Weihai, China, in 1986. He received the Ph.D. degree in system engineering from Northwestern Polytechnical University, Xi'an, China, in 2018. He is currently an Assistant Researcher with Northwestern Polytechnical University. His research interests include system engineering and evidence theory.



FEI GAO was born in Jining, China, in 1995. He received the B.S. degree in control engineering from Northwestern Polytechnical University, Xi'an, China, in 2016, where he is currently pursuing the Ph.D. degree in system engineering. His research interests include dependence analysis and evidence theory.

AN ZHANG (Member, IEEE) was born in Baoji, China, in 1962. He received the M.S. degree in systems engineering and the Ph.D. degree in control theory and control engineering from Northwestern Polytechnical University, Xi'an, China, in 1986 and 1999, respectively. He is currently a Professor with Northwestern Polytechnical University. He has authored or coauthored 31 refereed papers in journals and international conference proceedings. His current research interests include evidence theory, decision theory, and UAV control.

MI YANG was born in Tongchuan, China, in 1995. She received the B.S. degree in safety engineering from Northwestern Polytechnical University, Xi'an, China, in 2017, where she is currently pursuing the Ph.D. degree in control theory. Her current research interest includes reliability analysis.