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Fuzzy Bayesian network based on an improved similarity aggregation method for risk assessment of storage tank accident

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ABSTRACT

Fuzzy Bayesian network (FBN) has been widely used for risk assessment of accidents in process industries to deal with complex causality and uncertainty arising from complex interdependence among risk factors, insufficient data and complex environments. The similarity aggregation method (SAM) is a method of aggregating fuzzy opinions considering consensus degree. However, SAM does not take into account the impact of individual differences on consistency, which will bring a certain degree of uncertainty. Therefore, this work proposes an improved SAM based FBN model to better deal with various types of uncertainty. This methodology makes the prediction results of the storage tank accident more accurate and reliable. The result analysis indicates that the improved SAM is of significance to improve the reliability of the input data of FBN. Then, the critical analysis of the root node shows the effectiveness and reliability of FBN in identifying the critical events of the storage tank accident. The proposed method can predict the probability of storage tank accidents, determine the proportion of main contributing factors and identify the critical causes of storage tank accidents more reliably and accurately. It can provide important supporting information for decision-makers to optimize risk management strategies.

1. Introduction

Storage tanks are important facilities in the petrochemical industry, which store large volumes of flammable, explosive, toxic and hazardous materials (Ding et al., 2021). With the increase of the strategic and production demands for energy reserves in the petrochemical industry, the volume and quantity of storage tanks are increasing and the scale of tank farms is expanding, showing the characteristics of large-scale integration and the coexistence of multiple tanks. Once a fire, explosion, or toxic dispersion occurs in a storage tank, it may cause much more severe secondary accidents, and even multi-level domino effects (Chen et al., 2018; Cozzani et al., 2014; Khakzad et al., 2013b; Naderpour and Khakzad, 2018). Moreover, in an actual fire scenario, multiple adjacent tank fires may interact (Wan et al., 2020) and produce synergistic effects in domino effects (Ding et al., 2019, 2020a), which can result in a devastating and uncontrollable fire accident (Liu et al., 2020; Wan et al., 2018). Therefore, it is of great significance to carry out effective risk assessment on storage tanks to prevent catastrophic accidents.

Conventional quantitative risk assessment (QRA) methods have been widely used to identify and quantify risks in various fields including, but not limited to, the Bayesian network (BN) (Khakzad et al., 2013a, 2014), dynamic Bayesian network (DBN) (Khakzad, 2015; Rebello et al., 2018), combination of computational fluid dynamics (CFD) and probit model (Yang et al., 2020), Monte-Carlo method (Marseguerra and Zio, 1996), Bow-Tie (Ding et al., 2020b; Khakzad et al., 2012), fault tree analysis (FTA) (Hyun et al., 2015), event tree analysis (ETA) (Hong et al., 2009), analytical hierarchy process (AHP) (Aminbakhsh et al., 2013) and so on. Interested readers can refer to Khan et al. (2015), which reviewed the development of QRA models and presented a more detailed description of these methods and their extension employed in process safety in the last few decades. Some studies and data manuals have given precise probabilities for some basic events. However, in most practical situations, it is difficult to represent the probabilities of events with accurate values due to the lack of historical data and incomplete knowledge. This will inevitably lead to uncertainty when assigning precise probabilities to ambiguous events. In the case of expert judgment when expressing ambiguous events, fuzzy probability is a good way to deal with uncertainty. However, it is a big challenge for traditional QRA methods to process fuzzy failure data under uncertainty.

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Fuzzy set theory (FST) is an effective tool to handle epistemic uncertainty (due to inaccuracy, vagueness and lack of knowledge) of failure probability. The uncertainty can be considered in terms of intervals or fuzzy numbers (Horčík, 2008; Li et al., 2019). For further application, some researchers have incorporated FST into some QRA techniques to improve them, like the newly formed fuzzy Bayesian network (FBN) (Yazdi and Kabir, 2017; Zarei et al., 2019), fuzzy dynamic Bayesian network (FDBN) (Ji et al., 2018), fuzzy Bow-Tie (Ouache and Adham, 2014), fuzzy fault tree analysis (FFTA) (Kabir et al., 2016), fuzzy event tree analysis (FETA) (Ramzali et al., 2015), fuzzy Petri net (Chang et al., 2018), fuzzy failure mode and effects analysis (fuzzy FMEA) (Kumru and Kumru, 2013) and fuzzy hazard and operability analysis (fuzzy HAZOP) (Ahn and Chang, 2016). For the studies of the storage tank accident, Wang et al. (2013) and Shi et al. (2014) introduced FFTA to estimate the probability of fire and explosion accidents for oil storage tanks. Yazdi et al. (2017)(Yazdi et al., 2017b) employed FFTA to conduct failure probability analysis of a storage tank system. Halloul et al. (2019) proposed an adapted FFTA to assess the risk of an oil storage tank fire. These studies of storage tank accidents have listed the risk factors of storage tank accidents, and some accident statistics articles (Chang and Lin, 2006; Zheng and Chen, 2011) have also discussed the risk factors of storage tank accidents. Based on these studies, risk factors can be roughly divided into six categories, including: operational error, maintenance error, equipment failure, piping rupture or leak, tank crack or rupture and natural hazard triggering technological disasters (Natech). However, an FFTA-based method cannot deal with the dependence of risk factors and new evidence for updating under uncertainty.

Bayesian network (BN) is considered a robust technique for risk assessment due to its ability to express dependencies among events, update probability based on new evidence and reason under uncertainty. As a result, the fuzzy Bayesian network (FBN), which combines FST with BN to consider uncertainty, has been effectively applied in reliability and risk analysis. For instance, Zarei et al. (2019) chose a linear opinion pool as a technique of aggregating expert opinions to develop a FBN methodology to deal with uncertainty in chemical process systems. Yazdi and Kabir (2017) proposed a FBN based on a sum-production algorithm for risk assessment of process industries under the conditions of uncertainty and statistical dependency of events. Yan et al. (2016) utilized an improved approach considering expert weighting to aggregate fuzzy numbers and further conducted BN to obtain the occurrence probability of gas leakage. Rostamabadi et al. (2019) integrated FBN into the Human Factors Analysis and Classification System framework to consider interdependencies, uncertainties and insufficient data on human errors and organizational failures in process accidents. Li et al. (2020) proposed an FBN based on the linear opinion pool method to apply in real-time risk analysis of road tankers containing flammable liquids in an uncertain environment. There are also some studies using FBN in other industries (Eleye-Datubo et al., 2008; Li et al., 2012; Wang and Chen, 2017; Zhang et al., 2016). Based on previous studies, the application of FBN has not been widely employed in storage tank farms.

The aggregating process is a vital part of the application of FST, and there are some available techniques such as the arithmetic averaging operation (Detyniecki, 2000), linear opinion pool (Clemen and Winkler, 1999), max-min Delphi method (Ishikawa et al., 1993), Similarity Aggregation Method (SAM) (Hsu and Chen, 1996) and fuzzy analytic hierarchy process (FAHP) (Yazdi and Kabir, 2017). The arithmetic averaging operation is just a simple arithmetic mean of individual opinions. The linear opinion pool combines experts' distributions through a weighted arithmetic average. The Max-min Delphi method considers the maximum degree of uncertainty from experts' judgments to obtain the possible probability intervals. SAM is a straightforward method using the index of consensus and the importance of each expert to aggregate individual fuzzy opinions. FAHP is the extension of conventional AHP, processing the subjective knowledge of each expert with fuzzy numbers to compute their weight more objectively.

Each aggregation method has its own characteristics, in which most of the methods pay more attention to the method of obtaining expert weights. For these methods, experts are usually considered to be academicians or industry personnel specializing in the corresponding field, including technicians, operators, maintenance workers, or managers who have been working in storage tank farms for many years. However, in addition to the weight of experts, the similarities among their estimates are also worth considering when aggregating expert opinions. If most of the experts with low weight have similar estimates, only considering the weights of experts is likely to ignore or greatly reduce these opinions, which will cause the aggregation results to fail to reflect the widely recognized estimates. It is important to realize that the agreement of individual opinions and the importance of individuals are both key parameters of the aggregation process. Among the preceding methods mentioned, SAM is the only approach that takes into account both the weight of experts and the degree of consensus. It combines the two through a simple linear relationship by the proportion coefficient (relaxation factor) β so that they are independent of each other. However, when dealing with the consensus degree, the influence of expert weight on the agreement degree of experts cannot be neglected. Ignoring the differences in individual contributions to the agreement will cause the results to deviate from the experts' true estimates, because the reliability of experts' estimates varies with their individual background and experience. It is difficult for the decision-maker to determine β scientifically because it is hard to balance the effect of agreement degree and expert weight on the results. Therefore, β will inevitably bring uncertainty due to subjective judgment. Ranking the main contributing factors and identifying critical basic events contributing most to the occurrence of the top event are crucial for the decision-maker to allocate limited resources to prevent accidents and mitigate their consequences. The applications of posterior probabilities and importance (critical) measures to FBN are both good attempts to confirm the critical nodes of causes.

Therefore, the purpose of this paper is to propose an improved FBN model for risk assessment of storage tank accidents under uncertainty, in which an improved SAM of aggregating fuzzy opinions is proposed. Firstly, the improved SAM not only considers the consensus degree, but also tackles the consensus difference arising from the different cognitive level of individuals in the process of aggregation, which makes the aggregation results more inclined to the estimation of highly reliable experts. The proposed method also reduces the influence of β, which is difficult to determine scientifically, on the estimation results. Secondly, combining FST and BN can not only deal with epistemic uncertainty arising from lack of data and incomplete knowledge, but also express and infer uncertain knowledge and data, handle the causal relationship and perform probability prediction and updates. In general, this work proposes an improved FBN model to reduce the uncertainty of the input parameters of the BN model to a certain degree. It can be used to predict the probability of storage tank accidents and identify critical root nodes (events) more reliably.

The paper is organized as follows. The procedure of the proposed methodology is described in Section 2. Section 3 employs a case study to demonstrate the risk assessment process of a storage tank accident in a chemical industry park. Results and discussion are presented in Section 4. Conclusions are provided in Section 5.

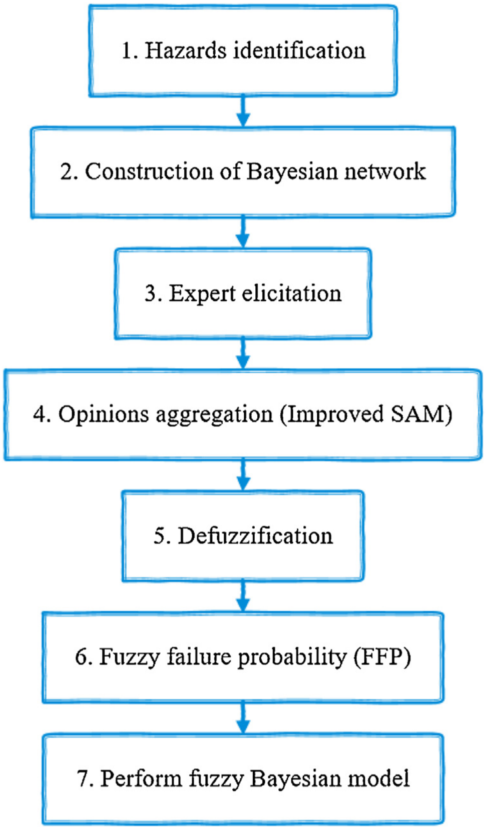

Fig. 1. Procedure of the proposed methodology.

2. Methodology

A methodology is developed to conduct QRA under uncertainty by combining BN and FST. Fuzzy numbers are employed to quantify the fuzzy opinions of experts. An improved SAM is proposed to aggregate the fuzzy opinions of experts considering consensus differences. The whole methodology is presented in seven steps as shown in Fig. 1. Detailed descriptions of these steps are presented in the following subsections.

2.1. Hazards identification

Hazards identification is a key part of risk assessment. Whether the identification is comprehensive or not has a great impact on the results of the risk assessment. Several methodologies have been widely used to identify hazards, such as Preliminary Hazards Analysis (PrHA), Hazards and Operability Analysis (HAZOP) and Failure Mode and Effects Analysis (FMEA) (Hyatt, 2018). Each of them enables a series of subjective judgments from experts. However, the methods are highly dependent on expert experience and experts may not be able to consider all possible failures, which brings great uncertainty to the final risk assessment results. Therefore, it is very important to combine objective data into the process of hazard identification. Analyzing the causes of historical accidents can help us identify more potential hazards that experts may have not noticed, which helps to obtain more complete hazard information and further study the causality and probability. As a result, this work adopts the combination of subjective judgment and objective data to identify potential hazards, which makes risk identification more complete, and further makes the results of risk assessment more reliable.

2.2. Construction of Bayesian network

BN is a probabilistic inference method under uncertainty that has been widely applied in risk assessment. Nodes represent random variables, and directed arcs depict conditional dependencies between the linked nodes (Pearl, 2014). The type and strength of conditional dependencies between two nodes are depicted by conditional probability tables (CPTs) assigned to nodes. After the hazard identification analysis, the root nodes (basic events) in BN are determined. Then all root nodes are classified and the intermediate node of each set of root nodes is determined. Next, the identified intermediate nodes are classified layer by layer. After multiple classifications, the main contributing factors (intermediate nodes) that directly point to the leaf node (top event) are finally determined. Because the assignment of CPTs requires exact causality but is generally difficult to acquire, it is a common practice to build conditional probability tables by using traditional AND / OR logic gates (Zarei et al., 2019).

2.3. Expert elicitation

Expert elicitation is adopted in this study for further calculating the probabilities of fuzzy events, because it is essentially a scientific consensus methodology and is often used to obtain expert opinions (Zarei et al., 2019). In order to obtain fair and reasonable estimates, a questionnaire survey is adopted to obtain the domain expert judgments. However, expert elicitation comes with uncertainty depending on the expert's reliability, which becomes very visible when two or more experts give different answers or even conflicting answers (Pasman and Rogers, 2020). There have been various ways to treat expert estimates considering uncertainty, including even those ending up in probability values to be used in a BN. Pasman and Rogers (2020) reviewed and presented various approaches with detailed explanations and examples to deal with expert judgment. The combination of expert elicitation and FST is one approach which is suitable to estimate probabilities of events when there is uncertainty due to insufficient statistical data and knowledge, because FST (Zadeh, 1965) plays its role in dealing with uncertainties, including imprecision, vagueness and randomness. Linguistic terms play an important role in dealing with events that are too complex or vague to describe with conventional quantitative expressions (Kabir and Papadopoulos, 2018). The values of linguistic terms are words or sentences in nature, such as "very low", "low", "medium", "high" and "very high". According to human memory capacity, the number of language terms for expert scoring is more proper between 5–9, following seven plus-minus two chunks (Nicolis and Tsuda, 1985). For this part, experts need to express their subjective opinions on failure probabilities of BEs using linguistic terms according to their own experience and knowledge. In order to weaken the bias of expert evaluation, heterogeneous expert judgement has been adopted here.

2.4. Opinions aggregation (Improved SAM)

Linguistic terms can be represented as different shapes of membership functions, such as fuzzy numbers and possibility distributions (e.g., uniform, or normal). Compared with the possibility distributions which can translate into probability distributions, fuzzy numbers that can translate into crisp fuzzy probabilities are more conducive to further quantitative analysis and comparative analysis. Triangular and trapezoidal shapes of membership functions are widely used for representing linguistic terms, which have been found to be more effective for risk assessment (Yazdi and Kabir, 2017). In this study, fuzzy triangular numbers and fuzzy trapezoidal numbers are both employed to estimate the probabilities of BEs. Here, subjective opinions expressed by experts with

Table 1
Weighting criteria and score of experts.

Constitution	Classification	Score
Professional position	Senior manager	10
	Junior academic/Professor	8
	Engineer/Vice-professor	6
	Technician	4
	Worker	2
Service time	≥30 years	10
	20–29	8
	10–19	6
	6–9	4
	≤5	2
Education level	PhD (Doctor of Philosophy)	10
	Master	8
	Bachelor	6
	HND (Higher National Diploma)	4
	School level	2
Age	≥50	8
	40–49	6
	30–39	4
	<30	2

linguistic terms need to be transformed into fuzzy numbers first and then aggregated.

Different experts may have different judgments on the same event in terms of their different experience, positions, knowledge background and other factors. Due to these factors, each expert's judgment will have different credibility. In order to obtain more reliable aggregation results, it is vital to determine the method applied to the aggregation process, which could have a great impact on the results of risk assessment. Most aggregation methods use expert weight as the only indicator to show the reliability of estimates. SAM is a more objective and robust aggregation method, not only considering the relative importance of various experts, but also the relative agreement of experts' opinions. However, these two factors are independent of each other. Original SAM only uses a simple linear relationship to integrate these two factors, while in fact, the expert weight and similarity degree are interactive. SAM does not consider the impact of expert weight when considering the degree of agreement, thus it needs to be improved. When considering the agreement degree among experts, their contributions to the absolute agreement of each expert are different due to individual differences. Therefore, this section proposes an improved SAM to integrate expert weight into the calculation of the degree of agreement, which takes into account the differences in the contribution of experts with different weights to the consensus degree. This also helps to weaken the impact of less credible experts on the results, and reduce the errors caused by ignoring the impact of individual differences on agreement. Due to the different levels of heterogeneous experts, the reliability of their estimates varies. It is sloppy to determine expert weights based on a single factor, such as position or education, and it is more reasonable to make multi-criteria decisions. The weighting criteria of experts can be seen in Table 1. Normally, the following four factors are considered: professional position, service time, education level, and age (Ramzali et al., 2015; Senol et al., 2015). Each factor is classified into several levels with different scores. For example, if a 65-year-old expert who is a professor with 40 years' service time and a doctorate, the overall weight score can be calculated as: 8 + 10 + 10 + 8 = 36. Then the weight of this expert is the ratio of his/her overall weight score to the weight scores of all the experts.

Suppose that each expert E_k (k = 1,2,. . ., M) states his/her opinion by using the linguistic terms which are predetermined according to the application background. These linguistic terms can be transformed into corresponding fuzzy numbers, and then the aggregated fuzzy numbers are obtained according to the following improved SAM algorithm:

(1) Calculate the agreement degree (similarity degree) $S(\tilde{R}_u, \tilde{R}_v)$ of the opinions between each pair of experts. $\tilde{R}_u = (a_1, a_2, a_3, a_4)$ and $\tilde{R}_v = (b_1, b_2, b_3, b_4)$ are standard trapezoidal fuzzy numbers corresponding to the opinions of experts E_u and E_v. The similarity function of $S(\tilde{R}_u, \tilde{R}_v)$ is defined as (Hsu and Chen, 1996):

$$S(\tilde{R}_u, \tilde{R}_v) = 1 - 1/4\sum_{i=1}^{4}|a_i - b_i| \tag{1}$$

where $S\left(\tilde{R}_u, \tilde{R}_v\right) \in [0, 1]$. The greater the value of $S\left(\tilde{R}_u, \tilde{R}_v\right)$, the more agreement exists between the two experts' opinions. When $S\left(\tilde{R}_u, \tilde{R}_v\right) = 1$, it means the opinions of the two experts are the same. If $S\left(\tilde{R}_u, \tilde{R}_v\right) = 0$, it means the opinions of the two experts have no intersection. Then, the Delphi method (Linstone and Turoff, 1975) should be used to adjust expert opinions. However, after the second scoring by the experts, the opinions of the experts may still have no intersection. This improved method will aggregate the opinions according to the credibility of the experts in the next step to improve the reliability of the aggregation results.

(2) Calculate the Weighted (Absolute) Agreement (WA) degree $WA(E_u)$ of the experts.

$$WA(E_u) = \frac{\sum_{\substack{v=1 \\ v \neq u}}^{N} W(E_v) \cdot S(\tilde{R}_u, \tilde{R}_v)}{\sum_{\substack{v=1 \\ v \neq u}}^{N} W(E_v)} \tag{2}$$

where $W(E_u)$ is the weight of expert E_u and $W(E_v)$ is the weight of expert E_v. Eq. (2) is the core work of the improved SAM. Unlike the average Agreement (AA) degree of the original SAM, the improved SAM integrates the expert weight into the calculation of absolute agreement degree, which is also named the weight agreement (WA) degree, to further obtain more reasonable and reliable aggregate estimates.

(3) Calculate the Relative Agreement (RA) degree, $RA(E_u)$ of the experts (Hsu and Chen, 1996).

$$RA(E_u) = \frac{WA(E_u)}{\sum_{u=1}^{M} WA(E_u)} \tag{3}$$

(4) Calculate the Consensus Coefficient (CC) degree, $RA(E_u)$ of expert, E_u (u = 1,2,. . ., M) (Hsu and Chen, 1996):

$$CC(E_u) = \beta \cdot W(E_u) + (1 - \beta) \cdot RA(E_u) \tag{4}$$

where β ($0 \leq \beta \leq 1$) is a relaxation factor of this method. Based on the cases of Hsu and Chen (1996), β is a critical factor to balance the RA degree and the degree of importance (weight) W of each expert. Since β indicates which is more critical between the $W(E_u)$ and $RA(E_u)$ assigned by the decision-maker, the value of β need to be predetermined by the decision-maker according to their preferences. The influence of expert agreement increases as β decreases. When β = 1, the CC degree is completely determined by the expert weight W. On the contrary, when β = 0, it is completely determined by expert agreement. The consensus degree coefficient of each expert is a good indicator for evaluating the relative worthiness of each expert's opinion (Ramzali et al., 2015).

(5) Calculate the aggregated result of the experts' opinions, and the "overall" fuzzy number $\tilde{R}$ can be obtained as follows (Hsu and Chen, 1996):

$$\tilde{R} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + CC(E_M) \times \tilde{R}_M \tag{5}$$

2.5. Defuzzification

The aim of defuzzification is to convert the "overall" fuzzy number into the fuzzy possibility score (FPS) after its aggregation. Various techniques are commonly used for defuzzification, such as the center of the area (CoA) (Sugeno, 1999), fuzzy maximizing and minimizing sets (Chen and Hwang, 1992), mean-of-maxima (MOM) (Zhao and Govind, 1991) and the α -weighted valuation (Detyniecki and Yager, 2000). In this study, the CoA defuzzification technique is employed.

$\tilde{R} = (r_1, r_2, r_3, r_4)$ is a standard trapezoidal number, and its membership function is (Banerjee and Roy, 2012):

$$\mu_{\sim R}(x) = \begin{cases} 0 & x < r \\ \dfrac{x - r_1}{r_2 - r_1} & r_1 \le x < r_2 \\ 1 & r_2 \le x < r_3 \\ \dfrac{x - r_4}{r_3 - r_4} & r_3 \le x < r_4 \\ 0 & x \ge r_4 \end{cases} \tag{6}$$

The defuzzification process of trapezoidal fuzzy numbers can be described as follows (Sugeno, 1999):

$$\mathrm{FPS} = \frac{\int_{r_1}^{r_2} \frac{x - r_1}{r_2 - r_1} x dx + \int_{r_2}^{r_3} x dx + \int_{r_3}^{r_4} \frac{r_4 - x}{r_4 - r_3} x dx}{\int_{r_1}^{r_2} \frac{x - r_1}{r_2 - r_1} dx + \int_{r_2}^{r_3} dx + \int_{r_3}^{r_4} \frac{r_4 - x}{r_4 - r_3} dx} = \frac{1}{3} \frac{(r_4 + r_3)^2 - r_4 r_3 - (r_1 + r_2)^2 + r_1 r_2}{(r_4 + r_3 - r_1 - r_2)} \tag{7}$$

Defuzzification has the disadvantage of discarding uncertainty information. The recent studies dealing with fuzzy BN have used defuzzified (crisp) values and have been less concerned about visualizing the uncertainty for decision making (Lavasani et al., 2015; Yan et al., 2016; Zarei et al., 2019). Some advanced versions of BNs can deal with discrete and continuous distributions, and can better handle uncertainty. At present, this work adopts a discrete BN and uses defuzzified fuzzy numbers to obtain a de-fuzzy possibility. It is termed the fuzzy possibility score (FPS) as expressed. As for visualizing the uncertainty to improve QRAs, this can be further studied and considered in future studies.

2.6. Fuzzy failure probability (FFP)

Combined with the process of defuzzification, these two steps are the approach of transforming the fuzzy possibility in the form of fuzzy numbers into FFP. This step is to convert the FPS obtained from the defuzzification process into the corresponding FFP. The function proposed by Onisawa (1988) is widely used to convert the crisp FPS into a crisp FFP by many scholars after the process of defuzzification in fuzzy QRAs. Although Onisawa's function proposed in Onisawa (1988) was first proposed to establish the relationship between error possibility and error rate (probability) for human reliability analysis of complex systems, it has been applied to the failure of equipment in Onisawa (1990). Later, many researchers also tried to extend Onisawa's function to different kinds of failures, including equipment (tank and pipeline, etc.) failure, and further demonstrated its applicability for different kinds of failures (Lavasani et al., 2015; Shi et al., 2014; Wang et al., 2013; Yan et al., 2016; Yazdi and Kabir, 2017; Zarei et al., 2019). Therefore, in this work, this step adopts Onisawa's function to convert the defuzzified FPS into FFP as follows:

$$FFP = \begin{cases} \dfrac{1}{10^K} & \text{if FPS} \neq 0 \\ 0 & \text{if FPS} = 0 \end{cases} \quad K = \left[\left(\frac{\text{1-FPS}}{\text{FPS}}\right)\right]^{\frac{1}{3}} \times 2.301 \tag{8}$$

where K is a constant value, FPS is fuzzy possibility score, and FFP is fuzzy failure probability for each event. Note that the FFP in this article is the result of fuzzy estimates and actually is a defuzzified crisp value derived via FST.

In addition to the method used in this work, many other attempts also have provided reasonable and acceptable mechanisms of transforming possibility into probability (Chanas and Heilpern, 1989; Chanas and Nowakowski, 1988; Dubois et al., 1993). Although a complex conversion will cause the loss of uncertain information, conversion still makes sense. For the approach used in the present study, defuzzifying the fuzzy possibility in the form of fuzzy numbers into an FPS and then into an FFP makes it easier to provide a quantified probability value to facilitate decision-making. Compared with some other complicated methods of obtaining probability distributions, such as the method in Dubois et al. (1993), the approach of obtaining probability values is more convenient for calculation and result analysis of BN. This is why the approach of transforming fuzzy possibility into FFP through defuzzification and Onisawa's function is adopted in the present study.

2.7. Perform fuzzy Bayesian model

The final step is to input the fuzzy probability of each BE into the developed BN. Considering the conditional dependencies of variables, BN represents the joint probability distribution $P(X)$ of variables $X = \{X_1, \ldots, X_n\}$ as (Nielsen and Jensen, 2009):

$$P(X) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \tag{9}$$

where $Pa(X_i)$ is the parent set of X_i for any $i = 1, \ldots,$ n. Accordingly, the probability of X_i is calculated as (Nielsen and Jensen, 2009):

$$P(X_i) = \sum_{X_j, j \neq i} P(X) \tag{10}$$

BN takes advantage of Bayes theorem to update the prior probabilities of variables given new observations, called evidence, E, thus yielding posterior probabilities (Nielsen and Jensen, 2009):

$$P(X|E) = \frac{P(X, E)}{P(E)} = \frac{P(X, E)}{\sum_X P(X, E)} \tag{11}$$

3. Application of the methodology

3.1. Hazards identification of storage tank accident

Abnormal existence of flammable substances is a common situation in storage tank accidents. This situation may involve a wide range of causes, such as pipeline leaks, failures in maintenance operations and so on. The fire triangle is usually used to classify the causes of fire and explosion accidents identified by experts, for which the ignition source is always the emphasis in storage tank accidents (Halloul et al., 2019; Shi et al., 2014; Wang et al., 2013; Yazdi et al., 2017). Although academic research is progressing, knowledge of the actual scene of the accident in the storage tank area is still insufficient. The hazard identification method suggested in Section 2.1 is more suitable for the classification of the causes of

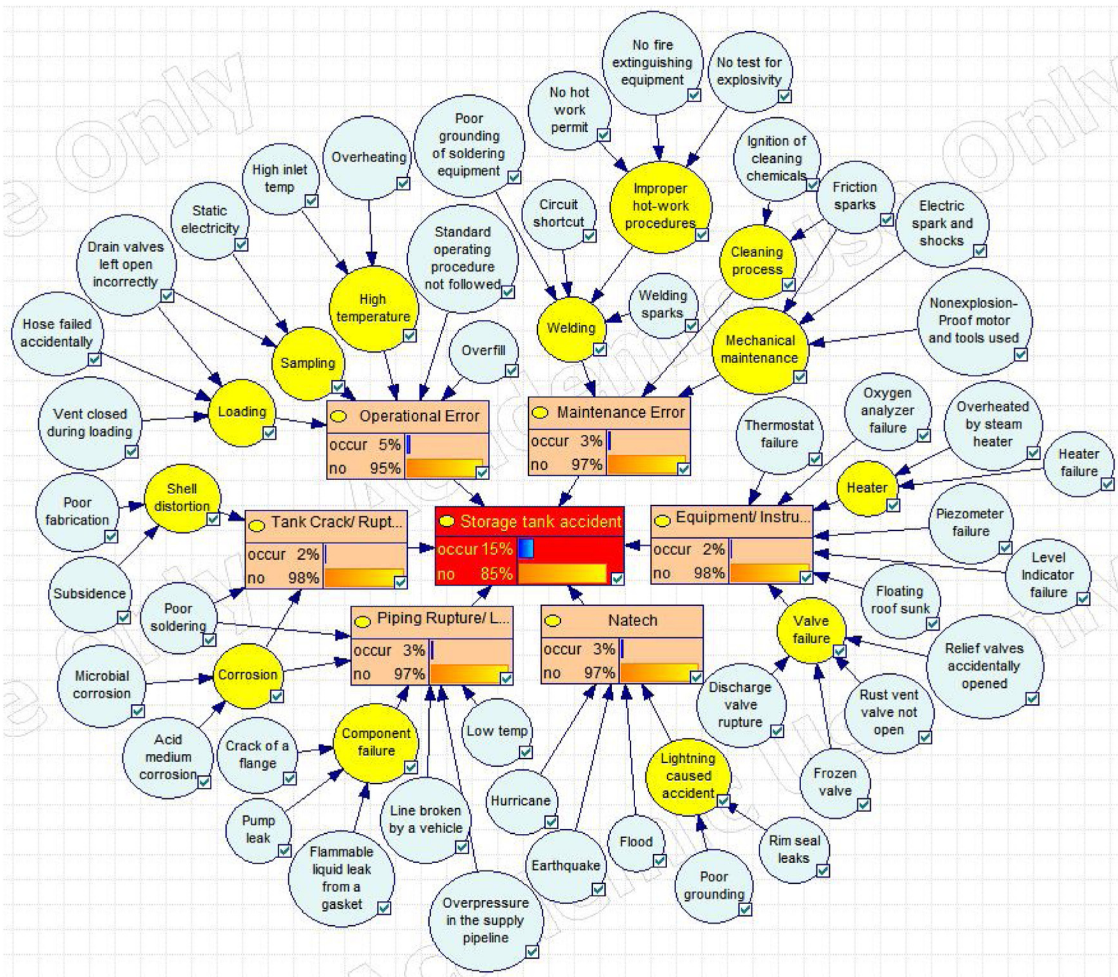

Fig. 2. A general BN for storage tank accident.

storage tank accidents, which are obtained both by expert brainstorming and objective accident cases analysis, so as to conduct a risk assessment of storage tank accidents with a more objective and more comprehensive network structure. Mainly based on expert identification and the analysis of 242 accidents in Chang and Lin (2006), the basic events of storage tank accidents are identified as shown in the blue nodes in Fig. 2. Some risk factors of storage tank accidents mentioned in the Introduction section are also considered.

3.2. Construction of BN for storage tank accident

At the end of the previous step, the root cause of the tank accident is determined. The causes of tank accidents can be classified into six categories, i.e. operational error, maintenance error, equipment failure, piping rupture, tank crack and Natech. This classification could help enterprises to identify the processes or objects that need to be focused on from a large category, and to better allocate safety measures. After determining the basic events, the inductive method is used to determine intermediate events, and finally, six major contributing events are identified. The dependencies among variables are studied through FTA, based on existing research on storage tank accidents, and then FTA is transformed into BN. The fishbone diagram obtained from the statistical analysis of 242 storage tank accidents in Chang and Lin (2006) is the main reference for the dependencies of BN. For the maintenance errors that caused the tank accidents, we reanalyze the causes of the accidents based on the FTA. Also, based on the FTA, an analysis of the causes of Natech is added. In the process of FTA, we ask experts for their opinions on the dependencies and partially consider the causality of the FTA in Wang et al. (2013) and Shi et al. (2014a). Finally, variable dependencies are determined for FTA and BN. The final BN model of the storage tank accident is shown in Fig. 2. It is a general BN model, and the nodes should be properly deleted according to the actual situation when performing risk assessments for different storage tank scenarios. In the present study, we use software Genie to conduct Bayesian reasoning, to avoid a cumbersome calculation of BN with many nodes.

3.3. Aggregate the fuzzy numbers of root nodes

After the BN structure is determined, experts are required to estimate the possibility distribution of basic events. In this study, seven fuzzy linguistic terms were selected for expert elicitation, as shown in Fig. 3. A detailed description of the linguistic terms and the corresponding fuzzy numbers is displayed in Table 2.

In this study, three experts were asked to directly evaluate the possibility distribution of root nodes in linguistic terms and the result is defuzzified into a fuzzy possibility score (FPS) and finally converted into probability through Eq. (8). Table 3 shows the specific information of these experts, and the relative weight of the experts in column 7 is calculated by the following Eq. (12). For

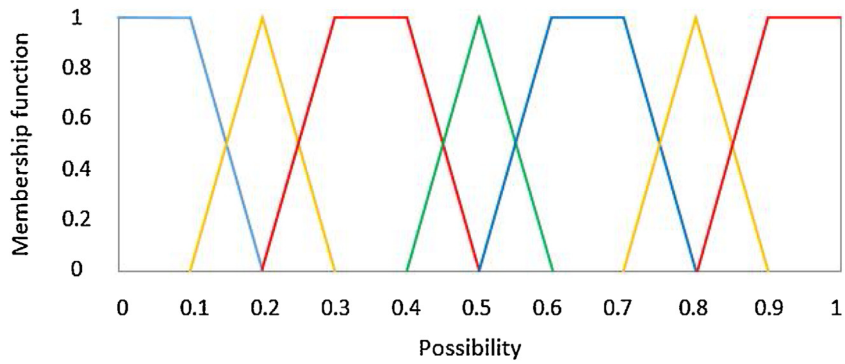

Fig. 3. Fuzzy numbers representing values of linguistic terms.

Table 2
fuzzy number sets of the scale (Ramzali et al., 2015).

Linguistic terms	Fuzzy numbers
Very Low (**VL**)	(0,0,0.1,0.2)
Low (**L**)	(0.1,0.2,0.2,0.3)
Mildly Low (**ML**)	(0.2,0.3,0.4,0.5)
Medium (**M**)	(0.4,0.5,0.5,0.6)
Mildly High (**MH**)	(0.5,0.6,0.7,0.8)
High (**H**)	(0.7,0.8,0.8,0.9)
Very High (**VH**)	(0.8,0.9,1,1)

example, for expert 1, the weight value $W(E_1)$ = 14 / (14 + 26 + 34) = 0.189.

$$\text{Weight value of expert } i = \frac{\text{Weight score of expert } i}{\sum_{i=1}^{M} \text{Weight score of expert } i} \tag{12}$$

An example is shown in Table 4, which shows the detailed process for the improved SAM to aggregate expert opinions into överallf̈uzzy numbers. After obtaining experts' judgments, linguistic terms are converted into corresponding fuzzy numbers, and then the improved SAM is used to aggregate experts' opinions of each root event to obtain the aggregated fuzzy number. Because the relaxation factor is difficult to determine, this article chooses a general number, 0.5.

3.4. Obtain fuzzy failure probability (FFP) of root nodes

BNs require crisp probability, so it is necessary to convert the above-mentioned aggregated fuzzy numbers into crisp values. Firstly, the aggregated fuzzy number obtained in the last section should be defuzzified into the FP, and then it is further transformed into the fuzzy failure probability (FFP) shown in Table 4.

4. Results and discussion

4.1. The impact of individual opinions on the root node

Two sets of cases are given in Table 5. For the first set (cases 1–4), the estimates of the two experts with higher weight are constant while the estimate of the expert with low weight varies from M to VL. For the second set (cases 5–8), the estimates of the two experts with lower weight are constant while the estimate of the expert with high weight varies from M to VH. The variations shown in the row 4 are the probability differences of the aggregate results obtained from the improved SAM and original SAM of the two sets. The values in the row 5 are the probability change percentages of the improved SAM relative to the original SAM.

For cases 1–4, it can be seen that when the expert's estimate of the low weight decreases, the results of the two methods also decrease. The aggregate results of the improved SAM are always greater than those of the original SAM, which demonstrates that the improved SAM can weaken the impact of low-reliability (weight) experts when there are significant gaps among experts' estimations. For cases 5–8, it can be seen that when the expert's estimate with a high weight increases, the results of the two methods also increase. The aggregate results of the improved SAM are always greater than those of the original SAM, which shows that the improved SAM can strengthen the influence of high-reliability experts on the results. Regardless of cases 1–4 or cases 5–8, when the estimation gaps among experts become wider, the variations between the two methods gradually increase, and the percent change in probability also increases, even up to 36.75 % in the worst case. This indicates that the improved SAM tends to weaken the impact of low-reliability experts and increase the impact of high-reliability experts on the aggregation results. In the case where the opinions of experts are quite different, this improved method will have a greater significance.

4.2. The impact of relaxation factor

Table 6 shows the aggregate results of the improved SAM and original SAM for root event 2 when β = 0. The absolute weighted agreement (WA) degree of low-weight expert E1 is unchanged, while the WAs of the other two experts with higher weight are improved. From the comparison of RA in rows 5–7, it can be seen that the RA of expert E1 with the lowest weight is reduced by using the improved SAM, and the RAs of the other two experts increase. As for the CC that reflects the importance and agreement of experts, as shown in rows 8–10, the value of expert E1 is decreased and the value of the highest-weight expert, E3, increases, which means that the improved SAM has changed the individual contribution of experts in agreement degree. It reduces the proportion of experts

Table 3
Expert information and weight.

Expert	Professional position	Service time (year)	Education level	Age	Weight score	Weight value
Expert 1	Technician	6–9	HND	<30	4 + 4+4 + 2 = 14	0.189
Expert 2	Professor	6–9	PhD	30–39	8 + 4+10 + 4=26	0.351
Expert 3	Senior manager	≥30	Master	40–49	10 + 10 + 8 + 6 = 34	0.460
					74	1

Table 4
Detailed aggregation and fuzzy failure probability calculation process of root event 2.

S (E_1 & E_2)	0.55	$S(\tilde{R}_u, \tilde{R}_v) = 1 - 1/4\sum_{i=1}^{4}\lvert a_i - b_i\rvert$
S (E_1 & E_3)	0.55	$S(E1\&E2) = 1 - 1/4(\lvert 0.2 - 0.7\rvert + \lvert 0.3 - 0.8\rvert + \lvert 0.4 - 0.8\rvert + \lvert 0.5 - 0.9\rvert) = 0.55$
S (E_2& E_3)	1	
WA(E_1)	0.5500	$WA(E_u) = \sum_{v=1,v\neq u}^{N} W(E_v)\cdot S(\tilde{R}_u, \tilde{R}_v)/\sum_{v=1,v\neq u}^{N} W(E_v)$
WA(E_2)	0.8690	
WA(E_3)	0.8425	
RA(E_1)	0.2432	$WA(E_2) = \left[W(E_1)\cdot S(\tilde{R}_2, \tilde{R}_1) + W(E_3)\cdot S(\tilde{R}_2, \tilde{R}_3)\right]/[W(E_1) + W(E_3)] = (0.189\times 0.55 + 0.46\times 1)/(0.189 + 0.46) = 0.8690$
RA(E_2)	0.3842	
RA(E_3)	0.3725	
CC(E_1)	0.2161	$CC(E_u) = \beta\cdot W(E_u) + (1-\beta)\cdot RA(E_u)(\beta = 0.5)$
CC(E_2)	0.3676	$CC(E_1) = \beta\cdot W(E_1) + (1-\beta)\cdot RA(E_1) = 0.5\times 0.198 + (1-0.5)\times 0.2432 = 0.2161$
CC(E_3)	0.4163	
Aggregation for Event 2	$\tilde{R} = 0.2161\times(0.2, 0.3, 0.4, 0.5) + 0.3676\times(0.7, 0.8, 0.8, 0.9) + 0.4163\times(0.7, 0.8, 0.8, 0.9) = (0.5919, 0.6919, 0.7136, 0.8136)$	$\tilde{R} = CC(E_1)\times\tilde{R}_1 + CC(E_2)\times\tilde{R}_2 + CC(E_3)\times\tilde{R}_3$
Fuzzy probability score (FPS)	0.7028	
Fuzzy failure probability (FFP)	0.0187	

Table 5
Aggregation results of root nodes under different judgments of experts.

Fuzzy Probability (FP)	Case 1 (M, H, VH)	Case 2 (ML, H,VH)	Case 3 (L, H, VH)	Case 4 (VL, H, VH)	Case 5 (VL, L, M)	Case 6 (VL, L, MH)	Case 7 (VL, L, H)	Case 8 (VL, L,VH)
Improved SAM	2.65e-02	2.30e-02	2.26e-02	2.58e-02	5.03e-04	7.61e-04	9.37e-04	8.55e-04
Original SAM	2.56e-02	2.14e-02	2.01e-02	2.23e-02	4.72e-04	6.74e-04	7.60e-04	6.25e-04
Variation	9.00 e-04	1.60e-03	2.50 e-03	3.60 e-03	3.09e-05	8.74e-05	1.77e-04	2.30e-04
Percent	3.45 %	7.27 %	12.34 %	16.02 %	6.54 %	12.97 %	23.36 %	36.75 %

Table 6
Aggregation process and results of root event 2 when β = 0.

Method	Improved SAM	SAM
WA(E_1)	0.5500	0.5500
WA(E_2)	0.8690	0.7750
WA(E_3)	0.8425	0.7750
RA(E_1)	0.2432	0.2619
RA(E_2)	0.3842	0.3690
RA(E_3)	0.3725	0.3690
CC(E_1)	0.2432	0.2619
CC(E_2)	0.3842	0.3690
CC(E_3)	0.3725	0.3690
$\tilde{R}$	(0.5784,0.6784,0.7027,0.8027)	(0.5690,0.6690,0.9652,0.7952)

with lower weight and increases that of experts with higher weight. The aggregated fuzzy number of the improved SAM is greater than that of the original method, which indicates that the improved SAM does make the aggregation result tend to "H" to a certain extent, that is, reflecting the opinion of the expert with high weight and high credibility.

When β is different, the corresponding change is consistent with the preceding analysis. After calculation, the larger the β, the smaller the difference between the aggregate results of the two methods, as shown in Fig. 4. This is because the influence of agreement on the consensus becomes smaller. Note that when β changes from 0 to 1, the change of the aggregation result of the improved SAM is smaller than that of the original SAM, which can be compared from the adjacent pictures in Fig. 4. Specific values in Fig. 4 can be seen in Table A1 of the Appendix A. That is to say, the improved SAM is less affected by β, regardless of the minimum value, the most likely value range or the maximum value of the fuzzy number, for example, as shown in Fig. 5. As we know, β is difficult to determine by the decision-maker. Compared with the original SAM, the improved SAM reduces the impact of the uncertainty factor β to a certain extent. It is equivalent to reducing the impact of the uncertainty arising from the change of β itself on the aggregated result. When only the agreement degree is considered, that is, β = 0, the improved method can avoid the occurrence of larger errors. When β is specified with other values, such as 0.3, 0.5, 0.7, etc., the improved method can highlight the preference of estimation to a certain extent and increase the reliability of the aggregation results. Hence, β is worth analyzing and the smaller the β, the more obvious the improvement effect.

4.3. Root node analysis of storage tank accident

Fig. 6 graphically shows the difference (ΔFFP) between the fuzzy failure probability obtained by the improved SAM (FFP) and the original SAM (FFP_{SAM}). The detailed probabilities of the root nodes in Fig. 6 are shown in Table A2 of the Appendix A. It can be seen that the value of ΔFFP could be positive, zero or negative. A positive value means that the improved SAM increases the fuzzy failure probability. On the contrary, a negative value means the fuzzy failure probability is reduced. In some cases, the value of ΔFFP is equal to zero, which means that improved SAM has no or negligible influence on the fuzzy failure probability in these cases. Therefore, these events are not listed in Fig. 6. The probability of some events is very small, such as low temperature, hurricane, earthquake, level indicator failure, nonexplosion-proof motor and tools used and no fire extinguishing equipment. The improved SAM actually has a very small effect on their failure probability, and the probability variation is about 10^{-6}–10^{-7}. In the practice of a QRA, failure probabilities of basic events are often larger than 10^{-4}, so the impact of the improved SAM on such events is negligible.

Small changes in probability have been presented here in order to demonstrate the effect of the improved SAM. Table A2 of the Appendix A reveals that for the preceding events with very small probability, experts' estimates are usually less than "M". According to expert weight in Table 3, expert E3 has the largest weight, fol-

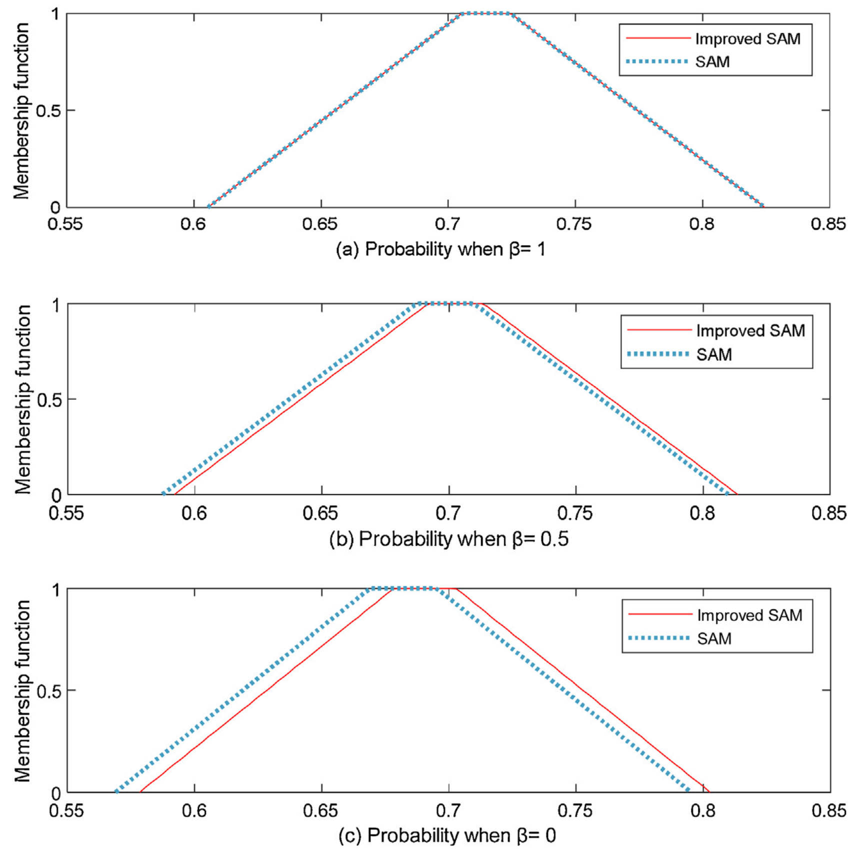

Fig. 4. The probability membership functions under different values of relaxation factor.

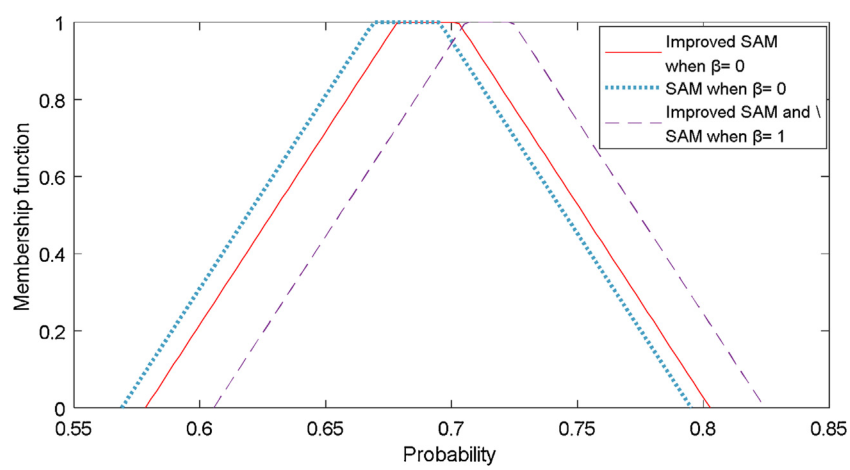

Fig. 5. The probability membership functions when $\beta = 0$ and $\beta = 1$ for different aggregation methods.

lowed by E2 and E1. For this situation, when the estimation result of at least one of the experts, E2 or E3, is greater than that of E1, the value of ΔFFP is positive. This is because the improved SAM itself reduces the impact of low-weight experts on the aggregate results. When the differences among experts' opinions are not large, this reduction effect will become weak. This is the case for some basic events with ΔFFP = 0, in which the gap is small enough. Events 20, 21, 33, 36 and 43 are the root events with negative ΔFFP in this case study. It is found that at least one of the three experts has an estimate of "L". When the estimates of two experts with larger weight are smaller than that of the expert with smaller weight, such as for events 20, 21 and 36, the improved SAM will make the "overall" result smaller, which means that it will tend to be the smaller estimate given by experts with larger weight. For event 33, the highest weight expert's estimate is the largest, but the "overall" estimate of the improved SAM is less than the original SAM. The reason is that the gap among the three experts is very small. The minimum part of expert opinions' intersection is larger than the intersection of the two adjacent membership functions defined in advance. This means that the agreement degree of experts occupies an absolute dominant position, which is higher than the importance of experts. The minimum and maximum weight experts' estimates of event 43 are the same, while the E2's estimate is relatively low. In this situation, the decrease in probability is the result of the combination of weight and agreement. Events 1, 2, 4, 11, 13, 23–25, 28, 37 and 39 are relatively obvious root events that are affected by the improved

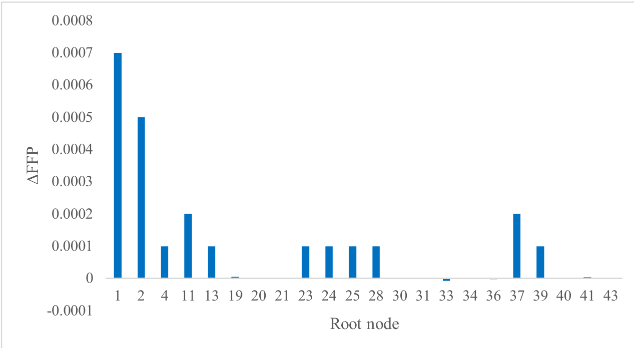

Fig. 6. ΔFFP of root node.

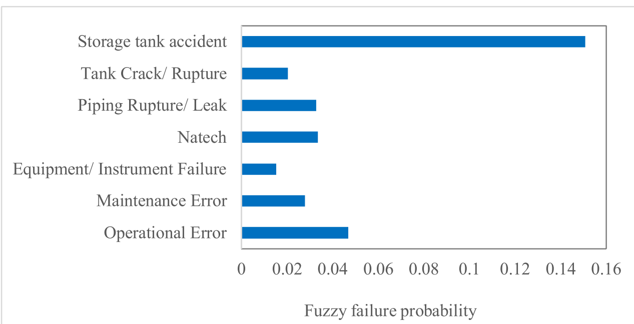

Fig. 7. Fuzzy failure probability of the storage tank accident and its main contributing events.

SAM. In these cases, the low-weight expert has underestimated these events, so the improved SAM makes the final aggregation results higher. Through the comparison of these events, the higher the agreement of the two experts with larger weight and the wider the gap between the two experts with the lower weight, the more obvious the impact of the improved method on the probability improvement is, such as for events 1, 2 and 25. If the agreement degree of the two experts with lower weight is high or the estimation gap between the two experts with larger weight is wide, the impact of the improved SAM on the probability increase is relatively low, such as for events 23 and 28. For cases when the degree of agreement among the three experts is similar, the changes in probability are generally small, such as in events 13 and 39.

4.4. Main contribution analysis of the storage tank accident

Fig. 7 indicates the fuzzy failure probabilities of the storage tank accident and main contribution events in this case study. Specific values in Fig. 7 can be found in Table A3 of the Appendix A. It can be seen that the fuzzy failure probability of the storage tank accident is about 0.15. For the top event, the contribution of operation error (26 %) is the largest, followed by Natech (18.98 %) and pipeline rupture/leak (18.59 %). Some literature (Di Pasquale et al., 2015; Kariuki and Löwe, 2006; Ramos et al., 2020) also emphasized the influence of human factors on the accident in industrial systems. The root cause of operational errors lies in the lack of relevant knowledge and awareness. Additionally, the operational error is most likely to occur due to the different qualifications among the operators. Natech usually produces strong destructive effects in a short period of time, so it is difficult to take appropriate measures in time to mitigate the consequences. For example, many oil tanks that meet the relevant standards of lightning protection for oil storage still incur lightning accidents every year due to the limitations of the existing lightning protection measures (Wu and Chen, 2016). This easily triggers a technological accident, plant equipment damage or a hazardous chemical release. The transportation of oil and gas depends on pipelines (Shahriar et al., 2012), and the failure of the pipelines is likely to cause leakage, fires and explosions, which will tend to cause a series of serious disasters by triggering domino effects (Ji et al., 2020). Based on these potential hazards, the decision-maker can choose a better resource allocation for different specific aspects of the storage tank farm to prevent accidents and mitigate the consequences, rather than generally for the human factor or machine failure.

4.5. Critical analysis

It is crucial to identify the most critical root nodes contributing to the occurrence of the top event for the decision-maker to take appropriate actions to prevent accidents and mitigate consequences. The posterior probability, as shown in Fig. 8 (a), is the corresponding probability of root nodes when the top accident occurs. Although this is a method to identify critical events, in order to further verify the reliability of results, the Fussel-Vesely (FV) (Yan et al., 2016), describing the root events' contribution on the top event, is also utilized to identify the critical nodes, which have more contribution in reducing the probability of the top event, as demonstrated in Fig. 8 (b). For a root event X_i, the FV can be calculated as (Yan et al., 2016):

$$I_{X_i}^{FV} = \frac{P(TE = occur) - P(TE = occur|X_i = 0)}{P(TE = occur)} \tag{13}$$

Specific values in Fig. 8 can be seen in Table A4 of the Appendix A. According to the posterior probabilities shown in Fig. 8 (a), root node 1 (Overfill), 2 (Standard operating procedure not followed), 5 (Static electricity), 11 (Poor soldering), 24 (Rim seal leaks) and 38 (Friction sparks) are the six most critical root nodes for the occurrence of a storage tank accident, so they are most likely to cause a storage tank accident directly. Fig. 8 (b) shows the FV of the probability of each root node, which indicates root node 1 (Overfill), 2 (Standard operating procedure not followed), 5 (Static electricity), 11 (Poor soldering), 24 (Rim seal leaks) and 38 (Friction sparks) have the most contribution to the occurrence of the storage tank accident.

It can be seen that the critical nodes identified by posterior probability and FV are identical. Their mutual verification increases the reliability of the results. Static electricity (Node 5) and friction sparks (Node 38) are considered to be the most critical factors causing tank accidents. This result is consistent with the result estimated by Shi et al. (2014) using FFTA. Overfilling is one of the most common operational errors (Chang and Lin, 2006). Due to rim seal leaks, the rim seal is the place most likely to be ignited by lightning in a thunderstorm (Chang and Lin, 2006). It is indeed a situation that deserves more attention. Meanwhile, non-compliance with the operation process is the human factor most likely to cause accidents. The critical events identified by the two methods have many similarities with the summary of storage tank accidents (Chang and Lin, 2006) and the conclusions of domain literature (Shi et al., 2014). This also verifies that the critical nodes identified by the two methods are the objects that need to be focused on in actual decision-making.

5. Conclusions

In the present study, an improved FBN approach combining an improved SAM and BN is proposed to deal with uncertainty for risk assessment of the storage tank accident. The proposed model can well tackle the epistemic uncertainty caused by insufficient data and incomplete knowledge in risk assessment. An improved SAM is proposed to make the aggregated fuzzy opinions of root nodes better reflect expert judgments. It reduces the proportion of experts

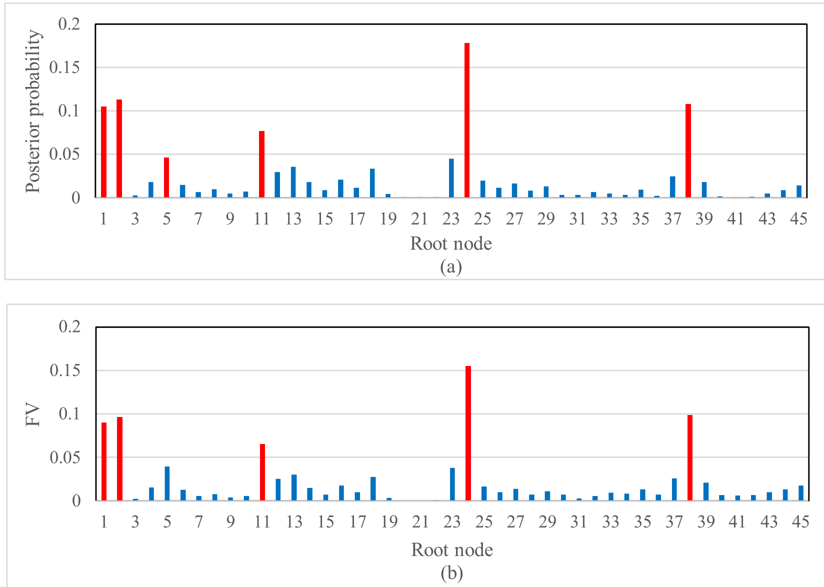

Fig. 8. (a) Posterior probability, (b) FV of the root node using FBN model.

with low weight and increases the proportion of experts with high weight in the "overall" estimation results. Compared with the original SAM, the improved SAM has a lower sensitivity to β, which is difficult to identify scientifically. The analysis of the results in the case study indicates that the improved FBN proposed in this work can provide more realistic, scientific and reliable data in the risk analysis of storage accidents than the FBN using SAM. Therefore, the improved FBN can predict the probability of storage tank accidents and identify the main critical factors more realistically.

Compared with previous studies on quantification of storage tank accidents, this work adopts a new classification for the factors that lead to storage tank accidents, which are divided into six types of contributing factors, including operational error, maintenance error, equipment failure, piping rupture or leak, tank crack or rupture and Natech. Unlike the general classification (people, machines, environment, and management), this study classifies the causes of storage tank accidents from the perspective of risk management promotion, and regards the Natech disaster that has been concerned more frequently in recent years as an independent category. This can help the decision-maker allocate risk management resources in a more reasonable and effective manner by sorting the probability of the six types of contributors. Through critical analysis, static electricity and friction sparks are identified as the most critical root nodes contributing to the storage tank accident. Based on the resource allocation of the main contributing factors, this process further promotes more targeted design or reinforcement of storage tanks. In a comparison among the critical nodes identified by the proposed FBN, historical data and the predicted results from FFTA, the reliability of the critical analysis results of the improved FBN model is confirmed. This facilitates the decision-maker to achieve optimal resource allocation with limited resources.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgements

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Appendix A.

Table A1
Output parameters of comparative analysis of relaxation factor.

The value of β	Improved SAM	SAM
$\beta = 1$	(0.6055,0.7055,0.7244,0.8244)	(0.6055,0.7055,0.7244,0.8244)
$\beta = 0.5$	(0.5919,0.6919,0.7136,0.8136)	(0.5873,0.6873,0.7098,0.8098)
$\beta = 0$	(0.5784,0.6784,0.7027,0.8027)	(0.5690,0.6690,0.9652,0.7952)

Table A2
Description, expert judgment and fuzzy failure probability (FFP/ FFP_{SAM}) of root events.

Number	Description of root Events	Expert judgment			FFP	FFP_{SAM}	$\Delta FP = FFP-FFP_{SAM}$
		E1	E2	E3			
1	Overfill	L	H	H	0.0166	0.0159	0.0007
2	Standard operating procedure not followed	ML	H	H	0.0187	0.0182	0.0005
3	Overheating	L	ML	L	4.80e-04	4.80e-04	0.0000
4	High inlet temp	L	ML	MH	0.0029	0.0028	0.0001
5	Static electricity	ML	M	MH-H	0.0070	0.0070	0.0000
6	Drain valves left open incorrectly	L	ML-M	M	0.0023	0.0023	0.0000
7	Hose failed accidentally	L	L	M	0.0010	0.0010	0.0000
8	Vent closed during loading	L	ML	M	0.0018	0.0018	0.0000
9	Poor fabrication	L	L	M	0.0010	0.0010	0.0000
10	Subsidence	ML	ML	ML	0.0015	0.0015	0.0000
11	Poor soldering	ML	M-MH	H-VH	0.0118	0.0116	0.0002
12	Microbial corrosion	ML	M-MH	M	0.0046	0.0046	0.0000
13	Acid medium corrosion	ML	MH	M	0.0055	0.0054	0.0001
14	Crack of a flange	ML	M	ML-M	0.0030	0.0030	0.0000
15	Pump leak	ML	ML	ML	0.0015	0.0015	0.0000
16	Flammable liquid leak from a gasket	M	ML	M	0.0035	0.0035	0.0000
17	Line broken by a vehicle	L	ML	H	0.0018	0.0018	0.0000
18	Overpressure in the supply pipeline	ML	M	MH	0.0058	0.0058	0.0000
19	Low temperature	L	M	L	8.57e-04	8.52e-04	5e-06
20	Hurricane	L	VL	VL	2.34e-05	2.36e-05	−2e-07
21	Earthquake	L	VL-L	VL	4.82e-05	4.84e-05	−2e-07
22	Flood	L	VL-L	L	1.53e-04	1.53e-04	0.0000
23	Poor grounding	M	M	MH	0.0075	0.0074	0.0001
24	Rim seal leaks	MH	H	H	0.0276	0.0275	0.0001
25	Discharge valve rupture	L	M	M	0.0030	0.0029	0.0001
26	Frozen valve	L	ML	M	0.0018	0.0018	0.0000
27	Rust vent valve not open	ML	ML	M	0.0025	0.0025	0.0000
28	Relief valves accidentally opened	VL	L	MH	0.0013	0.0012	0.0001
29	Floating roof sunk	VL	MH	ML	0.0020	0.0020	0.0000
30	Level Indicator failure	L	L	ML	5.38e-04	5.35e-04	3e-06
31	Piezometer failure	L	L	ML	5.38e-04	5.35e-04	3e-06
32	Heater failure	L	ML	ML	0.0010	0.0010	0.0000
33	Overheated by steam heater	L	L	ML-M	7.55e-04	7.63e-04	−8e-06
34	Oxygen analyzer failure	L	L	ML	5.38e-04	5.35e-04	3e-06
35	Thermostat failure	L	ML	ML-M	0.0014	0.0014	0.0000
36	Nonexplosion-Proof motor and tools used	ML	L	L	4.02e-04	4.05e-04	−3e-06
37	Electric spark and shocks	L	ML	H	0.0043	0.0041	0.0002
38	Friction sparks	MH	M	H-VH	0.0163	0.0163	0.0000
39	Ignition of cleaning chemicals	L	ML	MH	0.0029	0.0028	0.0001
40	No test for explosivity	VL	ML	L	3.10e-04	3.08e-04	2e-06
41	No fire extinguishing equipment	VL	VL	ML	1.61e-04	1.57e-04	4e-06
42	No hot work permit	L	L	L	2.23e-04	2.23e-04	0.0000
43	Circuit shortcut	ML	L	ML	8.87e-04	8.88e-04	−1e-06
44	Poor grounding of soldering equipment	ML	ML	ML	0.0015	0.0015	0.0000
45	Welding sparks	M	L	M	0.0024	0.0024	0.0000

Table A3
Fuzzy failure probability of the storage tank accident and its main contribution events based on an improved FBN.

Main contributing factors and accidents	Probability obtained by the improved FBN
Operational Error	0.046763
Maintenance Error	0.027740
Equipment/ Instrument Failure	0.015266
Natech	0.033460
Piping Rupture/ Leak	0.032779
Tank Crack/ Rupture	0.020317
Storage tank accident	0.150765

Table A4
Posterior probability and FV value of the root node in the improved FBN model.

Number	Description of root Events	Posterior FFP	FV value
1	Overfill	0.1054	0.0903
2	Standard operating procedure not followed	0.1133	0.0964
3	Overheating	0.0030	0.0026
4	High inlet temp	0.0184	0.0156
5	Static electricity	0.0464	0.0397
6	Drain valves left open incorrectly	0.0153	0.0130
7	Hose failed accidentally	0.0069	0.0058
8	Vent closed during loading	0.0099	0.0081

Table A4 (*Continued*)

Number	Description of root Events	Posterior FFP	FV value
9	Poor fabrication	0.0053	0.0043
10	Subsidence	0.0076	0.0061
11	Poor soldering	0.0768	0.0657
12	Microbial corrosion	0.0299	0.0254
13	Acid medium corrosion	0.0358	0.0304
14	Crack of a flange	0.0182	0.0152
15	Pump leak	0.0091	0.0076
16	Flammable liquid leak from a gasket	0.0212	0.0178
17	Line broken by a vehicle	0.0119	0.0102
18	Overpressure in the supply pipeline	0.0336	0.0279
19	Low temperature	0.0047	0.0039
20	Hurricane	0.0001	0.0001
21	Earthquake	0.0003	0.0002
22	Flood	0.0008	0.0007
23	Poor grounding	0.0451	0.0379
24	Rim seal leaks	0.1783	0.1550
25	Discharge valve rupture	0.0199	0.0169
26	Frozen valve	0.0119	0.0102
27	Rust vent valve not open	0.0166	0.0141
28	Relief valves accidentally opened	0.0086	0.0073
29	Floating roof sunk	0.0133	0.0113
30	Level Indicator failure	0.0036	0.0073
31	Piezometer failure	0.0036	0.0030
32	Heater failure	0.0066	0.0056
33	Overheated by steam heater	0.0050	0.0099
34	Oxygen analyzer failure	0.0036	0.0087
35	Thermostat failure	0.0093	0.0135
36	Nonexplosion-Proof motor and tools used	0.0023	0.0076
37	Electric spark and shocks	0.0249	0.0263
38	Friction sparks	0.1081	0.0991
39	Ignition of cleaning chemicals	0.0184	0.0212
40	No test for explosivity	0.0019	0.0072
41	No fire extinguishing equipment	0.0010	0.0065
42	No hot work permit	0.0014	0.0068
43	Circuit shortcut	0.0054	0.0101
44	Poor grounding of soldering equipment	0.0091	0.0133
45	Welding sparks	0.0146	0.0178

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