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RESEARCH ARTICLE

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Protecting oil storage tanks against floods: Natech risk assessment with imprecise probabilities

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Abstract

Natechs are technological accidents that are triggered by natural disasters. The increase in the frequency and severity of climatic natural disasters along with the growth of industrialization has accelerated the demand for development of dedicated methodologies for risk assessment and management of Natechs. Due to a lack of accurate and sufficient data, risk assessment of Natechs has largely been based on subjective assumptions and imprecise probabilities, making the assessed risks and the subsequent risk management strategies deficient in terms of cost-effectiveness. In the present study, evidence theory, as an effective technique for dealing with imprecise probabilities, and Bayesian network, as an effective tool for reasoning under uncertainty, are combined to develop a methodology for risk analysis of Natechs based on imprecise probabilities with no attempt to increase the precision of the input data but the accuracy and cost-effectiveness of the outcomes. Flotation of oil tanks during floods has been considered to exemplify the methodology. The methodology is demonstrated to outperform conventional approaches where average probabilities or generic probability distributions are used instead of interval probabilities for risk assessment and management.

KEYWORDS

Bayesian network, decision making, evidence theory, interval probability, oil storage tank

1 | INTRODUCTION

Technological accidents that are triggered by natural disasters are known as natural-technological accidents or Natechs.[1] Natechs that occur in chemical and process plants can be catastrophic due to the possibility of damage to process units and subsequent release of hazardous chemicals, which may cause fire and explosions [1–8] or major environmental pollution.[9–12]

Among the various process units, atmospheric storage tanks have reportedly been the most vulnerable type of vessel.[11] This is because such vessels have thin shells and high volume/weight ratios. A thin shell makes the storage tank very susceptible to lateral forces exerted by high winds or floods, whereas a high volume/weight ratio makes the tank susceptible to buoyancy force in the event of floods or heavy rainfalls.[13] Flotation of atmospheric storage tanks (Figure 1) due to the buoyancy force has been identified as the most common failure mode during floods.[10,13,14]

Compared to conventional technological accidents, which are caused by random failures or human error,

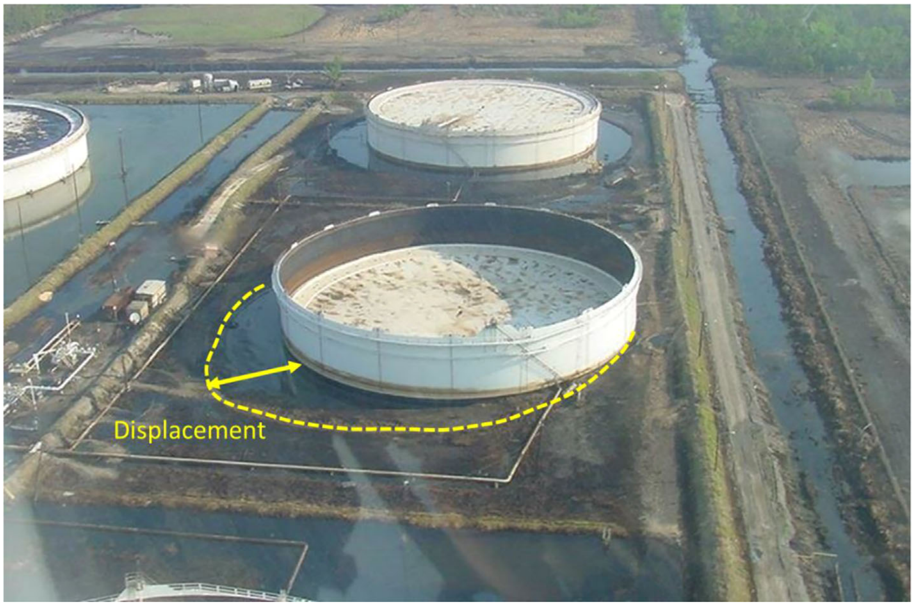


FIGURE 1 Flotation and displacement of a storage tank at Murphy Oil due to Hurricane Katrina.[11]

risk assessment and management of Natechs are prone to more uncertainty and are thus more challenging.[12,15] The foregoing uncertainty consists of aleatory uncertainty that arises from the randomness of natural disasters or failures, and epistemic uncertainty that represents our lack of knowledge due to insufficient or inaccurate objective data for the Natech of interest.

Probability theory has effectively been used to account for uncertainty embedded in the occurrence and severity of natural disasters as well as the extent of damage they may cause to structures and industrial plants.[16–21] However, in the absence of sufficiently large and reliable datasets or accurate field measurements, subject matter experts will inevitably come up with subjective, imprecise probabilities that may influence the accuracy and credibility of the risk analysis if not properly handled.[22–24] Evidence theory[25,26] is an effective tool for handling imprecise probabilities.[27–35] In evidence theory, the propagation of uncertainty is based on belief masses rather than probability masses. Belief masses are the analyst's degrees of belief about a hypothesis and can be derived from imprecise probabilities. Compared with probability theory, the application of evidence theory to the domain of risk assessment and management has not been so widespread, mainly due to a lack of efficient inference algorithms. Simon et al.[33] and Simon and Weber[36] demonstrated that Bayesian network (BN) can be used to handle belief masses the same way it can be used for probabilities. Khakzad[37] later demonstrated that BN can be used for both belief mass propagation (forward analysis) and updating (backward analysis).

The present study aims to demonstrate an application of evidence theory to risk assessment and management of Natechs when, due to a lack of knowledge, the analyst may express their uncertainty in the form of interval probabilities. The developed methodology is not to increase the precision or quality of input data (imprecise probabilities) but to improve the accuracy and cost-effectiveness of the subsequent risk assessment outcomes. Section 2 briefly reviews the concept of evidence theory and how it can be combined with BN. In Section 3, the methodology is applied to risk assessment and management of tank flotation during floods, while in Section 4 the results are discussed in comparison with some other conventional techniques. Section 5 concludes the work.

2 | REASONING UNDER UNCERTAINTY

2.1 | Bayesian network

BN is a probabilistic graphical model for reasoning under uncertainty,[38,39] consisting of a qualitative part and a quantitative part. The qualitative part, or the structure of the graph, consists of several nodes to represent random variables, and arcs to indicate the dependencies among the connected nodes. The quantitative part of BN consists of conditional probabilities of nodes X_i given their parent nodes $pa(X_i)$ in the form of $P(X_i|pa(X_i))$. Such conditional probabilities are the BN parameters and can either be elicited from experts or learned from historical data. The joint probability distribution of nodes $\{X_1, X_2, ..., X_n\}$ can be presented as the product of the conditional probability of each node given its immediate parents as follows:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | \mathrm{pa}(X_i)). \tag{1}$$

Having the joint probability distribution, the marginal probability of random variables can be calculated using a number of inference algorithms. As an example, consider a parallel system with two binary components X and Y in Figure 2A with failure probabilities $P(\mathrm{X} = \mathrm{fail}) = 0.2$ and $P(\mathrm{Y} = \mathrm{fail}) = 0.3$. The system can be modelled using the BN in Figure 2B, resulting in the system's failure probability of $P(\mathrm{System} = \mathrm{fail}) = 0.06$.

During the past two decades, BN has extensively been employed in fault diagnosis, safety assessment, and risk management of process units and operations, mainly based on crisp probabilities (or point probabilities). [40-43] However, there have been some attempts at using imprecise probabilities in BN.[37,44,45]

2.2 | Evidence theory

Using evidence theory,[25,26] all the possible states of a random variable can be presented in a set, named the frame of discernment Ω. To each subset of Ω such as A_i, which is a hypothesis about the state of the variable, a weight $0.0 \leq m(A_i) \leq 1.0$ can be assigned to express the degree of belief, based on objective data or subjective opinion, in the claim that the variable state belongs to A_i.[32] Having $m(A_i)$, which is also known as the belief mass of A_i, the belief $bel(A_i)$ and plausibility $pls(A_i)$ can be determined.

For the sake of clarity, consider component X in Figure 2A with the two states, fail and work, and thus a frame of discernment as $\Omega_X = \{\mathrm{fail}, \mathrm{work}\}$. Therefore, the set of all the subsets of Ω_X would be A: $\{\{\emptyset\}, \{\mathrm{fail}\}, \{\mathrm{work}\}, \{\mathrm{fail}, \mathrm{work}\}\}$, where $A_1 = \{\emptyset\}$, $A_2 = \{\mathrm{fail}\}$, $A_3 = \{\mathrm{work}\}$, and $A_4 = \{\mathrm{fail}, \mathrm{work}\}$. Each member of A for which $m(A_i) > 0$ is called a focal set. If we are certain that all the states of the variable are included in the frame of discernment, then $m(\emptyset) = 0$. It must always hold that:

$$\sum_{A_i} m(A_i) = 1. \tag{2}$$

Having the belief masses determined, the belief and plausibility measures of each focal set can be defined using the following:

$$bel(A_i) = \sum_{A_j | A_j \subseteq A_i} m(A_j), \tag{3}$$

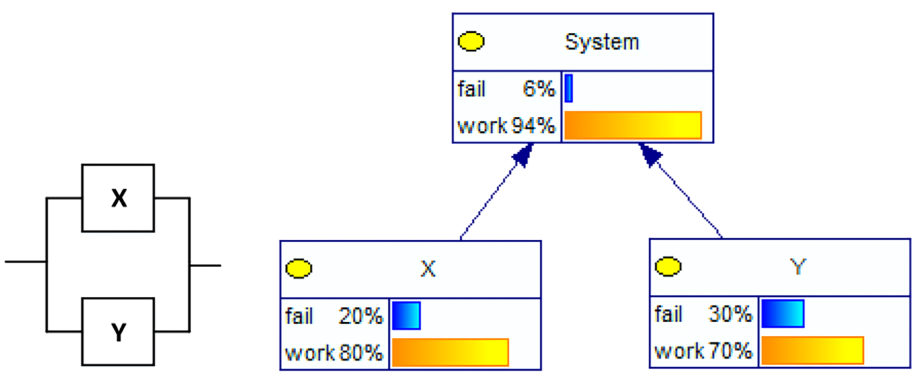
$$pls(A_i) = \sum_{A_j | A_j \cap A_i \neq \emptyset} m(A_j). \tag{4}$$

For instance, an expert may assign the weights $m_X(\{\mathrm{fail}\}, \{\mathrm{work}\}, \{\mathrm{fail}, \mathrm{work}\}) = (0.15, 0.8, 0.05)$, in which $m_X(\{\mathrm{fail}, \mathrm{work}\}) = 0.05$ refers to the expert's uncertainty about the state of X. Using Equations (3) and (4), the belief and plausibility of $\mathrm{X} = \{\mathrm{fail}\}$ can be calculated, respectively, as $bel(\mathrm{X} = \{\mathrm{fail}\}) = m(\{\mathrm{fail}\}) = 0.15$ and $pls(\mathrm{X} = \{\mathrm{fail}\}) = m(\{\mathrm{fail}\}) + m(\{\mathrm{fail}, \mathrm{work}\}) = 0.15 + 0.05 = 0.2$. It should be noted that in calculating the plausibility of $\mathrm{X} = \{\mathrm{fail}\}$ using Equation (4), the mass of {fail, work} should be considered because $\{\mathrm{fail}\} \cap \{\mathrm{fail}, \mathrm{work}\} \neq \emptyset$; however, it should not be considered in calculating the belief of $\mathrm{X} = \{\mathrm{fail}\}$ via Equation (3) because $\{\mathrm{fail}, \mathrm{work}\} \not\subseteq \{\mathrm{fail}\}$.

Further, the amount of uncertainty $Unc\,(A_i)$ of a focal set can be expressed as the difference between $pls(A_i)$ and $bel(A_i)$ [32]:

$$Unc(A_i) = pls(A_i) - bel(A_i). \tag{5}$$

Since $m_X(\{\mathrm{fail}, \mathrm{work}\})$ represents the uncertainty about the state of X, Equation (5) can be used to calculate



(A) (B)

FIGURE 2 (A) A parallel system with two binary components. (B) Modelling the system using a Bayesian network (BN) where nodes X and Y are connected to node System using AND gate.

this parameter as $m_X(\{\text{fail, work}\}) = pls(X = \{\text{fail}\}) - bel(X = \{\text{fail}\}) = 0.05$. Subsequently, $bel(A_i)$ and $pls(A_i)$, which are non-additive (their sum is not necessarily equal to 1.0.), can be taken as lower and upper probability bounds of A_i, respectively[26]:

$$bel(A_i) \leq P(A_i) \leq pls(A_i), \tag{6}$$

$$bel(A_i^c) = 1 - pls(A_i), \tag{7}$$

$$pls(A_i^c) = 1 - bel(A_i), \tag{8}$$

where A_i^c is the complement of A_i in the sense that $A_i^c = \Omega - A_i$.

According to Equation (6), $0.15 \leq P(X = \text{fail}) \leq 0.2$. Moreover, according to Equations (7) and (8), $bel(X = \{\text{work}\}) = 1 - pls(X = \{\text{fail}\}) = 0.8$ and $pls(X = \{\text{work}\}) = 1 - bel(X = \{\text{fail}\}) = 0.85$, and thus $0.8 \leq P(X = \text{work}) \leq 0.85$. Having the *bel* and *pls* functions, the belief mass of a focal set can be determined using the Möbius transformation as follows[31,46]:

$$m(A_i) = \sum_{A_j | A_j \subseteq A_i} (-1)^{|A_i - A_j|} \, bel(A_j), \tag{9}$$

where $|A_i - A_j|$ refers to the difference between the number of elements of A_i and A_j.

2.3 | Using imprecise probabilities in BN

Simon and Weber[36] showed that belief masses can be used in BN the same way as the probabilities, and thus the algorithms developed for BN could be employed to propagate belief masses in a system. Since the belief masses allocated to the focal sets of each random variable must add up to 1.0, they can be treated as marginal probabilities for the root nodes in a BN.

Considering the system in Figure 2, assume that due to a lack of sufficient knowledge, the analyst cannot assign precise probabilities to the states of X and Y and decides to express their uncertainty in the form of interval probabilities as $0.15 \leq P(X = \text{fail}) \leq 0.35$ and $0.2 \leq P(Y = \text{fail}) \leq 0.5$.

Having these interval probabilities, the belief masses of the focal sets of X and Y can be identified. For instance, consider $P(X = \text{fail})$, where its lower and upper bounds can be taken as the *bel* and *pls* functions, respectively:

- $bel(X = \{\text{fail}\}) = 0.15 \rightarrow m_X(\{\text{fail}\}) = 0.15$
- $bel(X = \{\text{work}\}) = 1 - pls(X = \{\text{fail}\}) = 1–0.35 = 0.65 \rightarrow m_X(\{\text{work}\}) = 0.65$
- $m_X(\{\text{fail, work}\}) = 1 - m_X(\{\text{fail}\}) - m_X(\{\text{work}\}) = 1–0.15 - 0.65 = 0.2$
- As a result: $m_X(\{\text{fail}\}, \{\text{work}\}, \{\text{fail, work}\}) = (0.15, 0.65, 0.2)$.

Following the same procedure, $m_Y(\{\text{fail}\}, \{\text{work}\}, \{\text{fail, work}\}) = (0.2, 0.5, 0.3)$. The calculated mass beliefs can now be used in BN to compute the belief masses of the system. In the BN shown in Figure 3, the focal sets of X and Y have been considered as the states of nodes X and Y while the respective belief masses have been considered as their probabilities. The same focal sets have also been considered for node System, which is connected to nodes X and Y via AND gate. The truth table shown in Table 1 can be used to populate the conditional belief table of node system.[36]

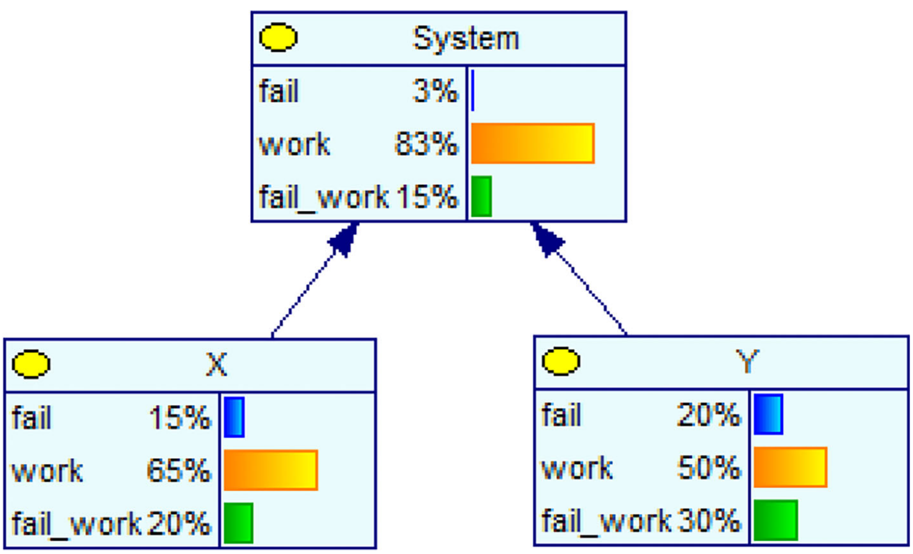


FIGURE 3 Bayesian network (BN) for failure assessment of system using belief masses of X and Y. Nodes X and Y are connected to node system by AND agte.

TABLE 1 Truth table used to populate the conditional belief table of node system in Figure 3 in case of AND gate and OR gate.[36]

		System: AND gate			System: OR gate		
X	Y	{fail}	{work}	{fail, work}	{fail}	{work}	{fail, work}
{fail}	{fail}	1	0	0	1	0	0
{fail}	{work}	0	1	0	1	0	0
{fail}	{fail, work}	0	0	1	1	0	0
{work}	{fail}	0	1	0	1	0	0
{work}	{work}	0	1	0	0	1	0
{work}	{fail, work}	0	1	0	0	0	1
{fail, work}	{fail}	0	0	1	1	0	0
{fail, work}	{work}	0	1	0	0	0	1
{fail, work}	{fail, work}	0	0	1	0	0	1

The developed BN can accordingly be used to calculate the belief masses of node System. Having the belief masses of System as $m_{\text{System}}(\{\text{fail}\}, \{\text{work}\}, \{\text{fail, work}\}) = (0.03, 0.825, 0.145)$, the *bel* and *pls* functions or the lower and upper bound probabilities of (System = fail) can be calculated as $bel(\text{System} = \{\text{fail}\}) = 0.03$ and $pls(\text{System} = \{\text{fail}\}) = 0.03 + 0.145 = 0.175$, resulting in $0.03 \leq P(\text{System} = \text{fail}) \leq 0.175$.

3 | RISK ANALYSIS WITH INTERVAL PROBABILITIES

3.1 | Flotation of storage tanks

Flotation of oil storage tanks has reportedly been the most frequent failure mode during floods.[14] Flotation of storage tanks occurs if the upthrust force of the flood (buoyancy force F_B) exceeds the bulk weight of the storage tank (weight of the tank W_T plus the weight of its containment W_L). Considering that such tanks are usually unanchored and thus no resisting force is exerted on them from their foundation, F_B, W_T, and W_L are the only forces considered for the flotation of the tank in Figure 4. Given the tank's dimension and the flood's inundation depth, the foregoing forces can be modelled as follows:

$$F_B = \rho_w g \frac{\pi d^2}{4} h, \tag{10}$$

$$W_T = \rho_s g \left(\pi d H + 2 \frac{\pi d^2}{4} \right) t, \tag{11}$$

$$W_L = \rho_l g \frac{\pi d^2}{4} L. \tag{12}$$

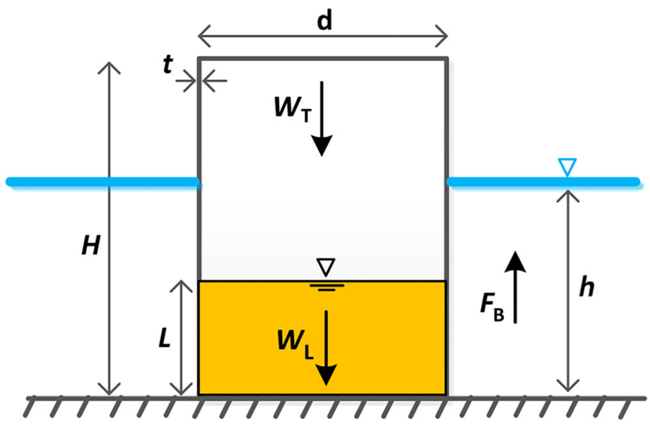


FIGURE 4 Schematic of flotation-related loading and resisting forces acting on an oil storage tank.

The parameters and the random variables used in Equations (10)–(12) as well as their values and their probability distributions are listed in Table 2.

Given the foregoing forces, the limit-state equation (LSE) for the flotation of the tank can be developed as follows[20,47]:

$$\text{LSE} = F_B - W_T - W_L. \tag{13}$$

As such, the flotation probability of the tank can be presented as the probability that LSE >0.

For the sake of illustration, consider the possibility of an imminent flood that may hit the storage tank in the next coming hours (in the United States, the National Weather Service issues flood warnings when flooding is possible or expected within 12–48 h). Based on historical data, the inundation height of the flood is expected to follow a normal distribution (Table 2). Further, assume

TABLE 2 Parameters used to develop the limit state equation for flotation of the storage tank.

Parameters	Symbols	Values
Tank height	H (m)	6
Tank diameter	d (m)	10
Tank shell thickness	t (m)	0.01
Chemical inventory height	L (m)	(0.5, 1.0, 1.5)
Tank material density (steel)	ρ_s (kg/m^3)	7900
Flood water density	ρ_w (kg/m^3)	1024
Chemical inventory density (gasoline)	ρ_l (kg/m^3)	850
Flood inundation height	h (m)	$N(\mu = 1, \sigma = 0.2)$

that although the specific values of the tank dimensions are known (Table 2), the initial amount of crude oil inside the tank is unknown as the mechanical and automatic level indicators each shows a different value: the mechanical level indicator, which is likely to malfunction and is thus not reliable, shows the crude level as $L = 1.0$ m but the automatic gauge shows the level as $L = 0.5$ m. Therefore, the operator decides to take a glance at the crude level via the top manhole, estimating the crude level as $L = 1.5$ m. As such, the operator's uncertainty about the level of crude oil can be modelled as a tertiary random variable L with three states, as $L_1 = 0.5$ m, $L_2 = 1$ m, and $L_3 = 1.5$ m, with the following interval probabilities based on their confidence in the mechanical and automatic gauges and his own estimate:

- $0.2 \leq P(L_1) \leq 0.5$
- $0.3 \leq P(L_2) \leq 0.5$
- $0.2 \leq P(L_3) \leq 0.3$.

3.2 | Flotation risk assessment

According to the parameters in Table 2, the magnitudes of the three forces can be calculated as $W_T = 268$ (kN), $W_L = 655 \times L$ (kN), and $F_B = 789 \times h$ (kN). The probability that the storage tank floats due to the buoyancy force can be calculated as follows:

$$\begin{aligned} P(\text{flotation} = \text{yes}) &= P(F_B > W_T + W_L) \\ &= P(789\,h > 268 + 655\,L) \\ &= P\left(h > \frac{268 + 655\,L}{789}\right). \end{aligned} \tag{14}$$

Considering L as an uncertain variable with three states as L_1, L_2, and L_3, its frame of discernment is $\Omega_L = \{L_1, L_2, L_3\}$. Consequently, its focal sets would be A_L: $\{\{L_1\}, \{L_2\}, \{L_3\}, \{L_1, L_2\}, \{L_1, L_3\}, \{L_2, L_3\}, \{L_1, L_2, L_3\}\}$. The belief mass of each focal set can subsequently be determined. For example, for the first focal set $\{L_1\}$ with the lower and upper bound probabilities as $0.2 < P(L_1) < 0.5$, the belief and plausibility functions can be determined as $bel(\{L_1\}) = 0.2$ and $pls(\{L_1\}) = 0.5$. Since $\{L_1\}$ is a singleton, $m(\{L_1\}) = bel(\{L_1\}) = 0.2$. Similarly, $m(\{L_2\}) = 0.3$ and $m(\{L_3\}) = 0.2$.

Further, consider the focal set $\{L_1, L_2\}$. Since $\{L_1\}$, $\{L_2\}$, and $\{L_1, L_2\}$ are all the subsets of $\{L_1, L_2\}$, we will have $m(\{L_1, L_2\}) = bel(\{L_1, L_2\}) - bel(\{L_1\}) - bel(\{L_2\})$. Furthermore, $bel(\{L_1, L_2\}) = 1 - pls(\{L_3\}) = 1–0.3 = 0.7$. As a result, $m(\{L_1, L_2\}) = 0.7–0.2 - 0.3 = 0.2$. Following the same procedure, $m\{\{L_1\}, \{L_2\}, \{L_3\}, \{L_1, L_2\}, \{L_1, L_3\}, \{L_2, L_3\}, \{L_1, L_2, L_3\}\} = (0.2, 0.3, 0.2, 0.2, 0.1, 0.0, 0.0)$. Since $m(\{L_1, L_3\}) = m(\{L_1, L_2, L_3\}) = 0$, they would not be considered as focal sets any more.

As can be seen from Equation (14), the only influential parameters in estimating the probability of tank flotation are the flood inundation height (h) and the chemical height (L). To facilitate the propagation of uncertainty—aleatory uncertainty in h and epistemic uncertainty in L–the BN in Figure 5 is developed.

It should be noted that in Figure 5, the focal sets of L have been considered as the states of node L, and the respective belief masses have been considered as their marginal probabilities. Moreover, since h is a continuous variable, it has been discretized into three intervals while the marginal probability of each interval has been calculated using the normal distribution in Table 2. The discretized intervals for h are as follows:

- h_1: $0.0 \leq h < 0.8$
- h_2: $0.8 \leq h < 1.2$
- h_3: $1.2 \leq h < 2.0$.

Using Equation (14), the conditional belief table of node 'Flotation' can be developed as shown in Table 3.

As an example, consider $h = h_2$ (i.e., $0.8 \leq h < 1.2$) and $L = \{L_1, L_2\}$:

- If $L = L_1 = 0.5$, then $P(\text{flotation} = \text{yes}) = P\left(h > \frac{268+655\,L}{789}\right) = P(h > 0.75) = 1.0$. Note that since $0.8 \leq h < 1.2$, the probability of $h > 0.75$ is equal to 1.0.
- If $L = L_2 = 1.0$, then $P(\text{flotation} = \text{yes}) = P\left(h > \frac{268+655\,L}{789}\right) = P(h > 1.17)$. Since $0.8 \leq h < 1.2$, the probability of $h > 1.17$ should be modified to $P(1.17 < h < 1.2)$, which is equal to 0.04.
- As such, for $L = \{L_1, L_2\}$, the lowest and highest probabilities of flotation would be 0.04 and 1.0, respectively, which in turn can be taken as $bel(\text{flotation} = \{\text{yes}\}) = 0.04$ and $pls(\text{flotation} = \{\text{yes}\}) = 1.0$. As a result:

THE CANADIAN JOURNAL OF CHEMICAL ENGINEERING

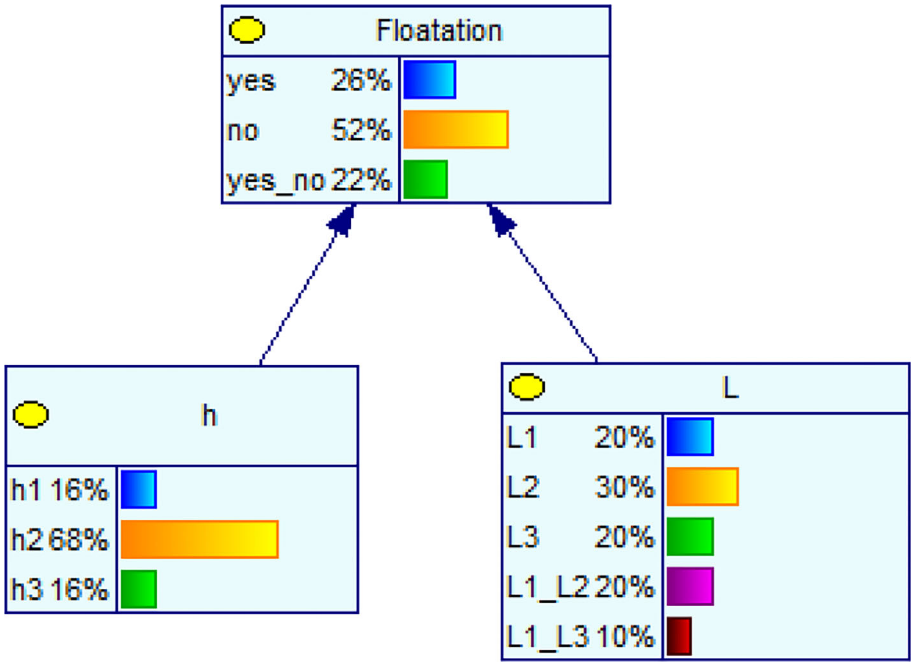


FIGURE 5 Bayesian network (BN) to estimate the probability of tank flotation.

TABLE 3 Conditional belief mass distribution for the node 'Flotation' in Figure 5.

		Flotation		
h	***L***	**{yes}**	**{no}**	**{yes, no}**
h_1	$\{L_1\}$	0.05	0.95	0
h_1	$\{L_2\}$	0	1	0
h_1	$\{L_3\}$	0	1	0
h_1	$\{L_1, L_2\}$	0	0.95	0.05
h_1	$\{L_1, L_3\}$	0	0.95	0.05
h_2	$\{L_1\}$	1	0	0
h_2	$\{L_2\}$	0.04	0.96	0
h_2	$\{L_3\}$	0	1	0
h_2	$\{L_1, L_2\}$	0.04	0	0.96
h_2	$\{L_1, L_3\}$	0	0	1
h_3	$\{L_1\}$	1	0	0
h_3	$\{L_2\}$	1	0	0
h_3	$\{L_3\}$	0.002	0.998	0
h_3	$\{L_1, L_2\}$	1	0	0
h_3	$\{L_1, L_3\}$	0.002	0	0.998

$m_{\text{Flotation}}$ ({yes}) = *bel*(flotation = {yes}) = 0.04; $m_{\text{Flotation}}$ ({no}) = *bel*(flotation = {no}) = 1 − *pls*(flotation = {yes}) = 1–1 = 0; and $m_{\text{Flotation}}$ ({yes, no}) = 1 − $m_{\text{Flotation}}$ ({yes}) – $m_{\text{Flotation}}$ ({no}) = 1–0.04 = 0.96.

Quantifying the BN, the belief masses of the focal sets of 'Flotation' can be calculated as $m_{\text{Flotation}}$ ({yes}) = 0.26, $m_{\text{Flotation}}$ ({no}) = 0.52, and $m_{\text{Flotation}}$ ({yes, no}) = 0.22. Consequently, the belief and plausibility functions or the lower and upper bound probabilities of (flotation = yes) can be calculated as: $0.26 \le P(\text{flotation} = \text{yes}) \le 0.48$. Likewise, $0.52 \le P(\text{flotation} = \text{no}) \le 0.74$.

3.3 | Flotation risk management

Flotation of the storage tank can result in instantaneous release of oil in the case of tank collapse or a major release of oil in the case of disconnection of flanges and pipelines.[11,14] In chemical plants and tank terminals, it is a common risk management strategy to add water to empty tanks or tanks of low inventory to increase their resistance to flotation. This would also increase the resistance against sliding and shell buckling. Assume that the analyst determines the probability of flotation $0.26 \le P$ (flotation = yes) ≤ 0.48 is too high and decides to add water to the tank to decrease the probability. Figure 6 presents the storage tank with added water, under the simplifying assumption that the mixing of oil with water is negligible, and all the oil stands above the added water. The added weight of the water can be calculated as follows:

$$W_w = \rho_w g \frac{\pi d^2}{4} L_w \tag{15}$$

where L_w is the depth of the added water, and ρ_w is its density, which is taken the same as the density of flood water for the sake of simplicity.

By adding water to the storage tank, the LSE in Equation (13) would be modified as follows:

$$\mathrm{LSE} = F_\mathrm{B} - W_\mathrm{T} - W_\mathrm{L} - W_\mathrm{w}. \tag{16}$$

The revised probability of flotation can thus be calculated as follows:

$$\begin{aligned} \mathrm{P}(\text{flotation} = \text{yes}) &= P(F_\mathrm{B} > W_\mathrm{T} + W_\mathrm{L} + W_\mathrm{w}) \\ &= P(789\,h > 268 + 655\,L + 789\,L_\mathrm{w}) \\ &= P\left(h > \frac{268 + 655\,\mathrm{L} + 789\,L_\mathrm{w}}{789}\right) \end{aligned} \tag{17}$$

To decide how much water to add to the tank, more information would be required regarding the cost of tank failure (i.e., tank flotation) and the cost of water removal from the tank after the flood passes and risk of flotation diminishes. In this regard, assume that flotation of the tank would result in a major release of oil with a total cost $1M for the tank repair and environmental remediation. On the other hand, if water is added to the tank to prevent its flotation, the removal of water from the tank would cost $10k for each 0.25 m of added water (given the tank dimensions 0.25 m of water equals about 20 m^3 of water). However, if the tank floats in spite of adding water to it, the total cost would still be $1M. It is because a floating tank is assumed to be damaged beyond redemption and having its content released due to rupture or disconnection of connected pipeline. As such, removing the water from the damaged tank would be pointless, leaving the total cost unchanged as $1M. Having this information, the analyst can determine the cost-effective amount of added water.

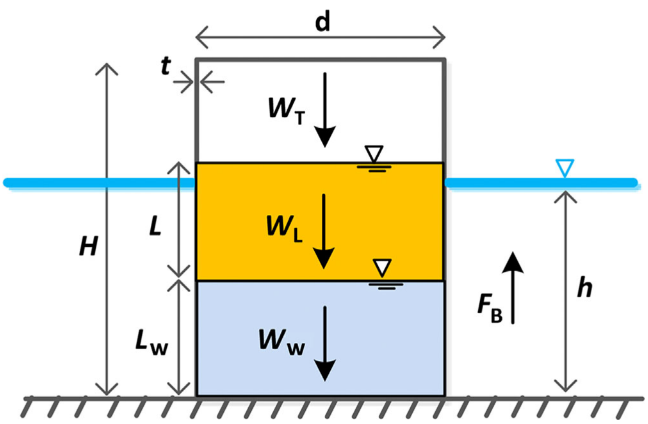


FIGURE 6 Schematic of flotation-related loading and resisting forces acting on a chemical storage tank after adding water.

To do so, four decision alternatives are considered for adding water as $L_{W1} = 0$ m (i.e., add no water); $L_{W2} = 0.25$ m, $L_{W3} = 0.50$ m, and $L_{W4} = 0.75$ m. Following the same procedure described in Section 3.2, the interval probabilities for the tank flotation under each decision alternative can be calculated, as listed in Table 4. Having the cost of the tank flotation ($1M) and the cost of adding water to the tank ($10k for each 0.25 m of water), the expected cost for each decision alternative can be calculated as the multiplication of the interval probabilities and the costs. For instance, given $L_{W2} = 0.25$ m, the probability of flotation and no flotation are calculated as $0.08 < P(\text{flotation} = \text{yes}) < 0.20$ and $0.80 < P(\text{flotation} = \text{no}) < 0.92$. Subsequently, the lower and upper expected costs can be calculated as follows:

- Lower expected cost $(L_{W2}) = 0.08 \times \$1\mathrm{M} + 0.92 \times \$10\mathrm{K} = \$89.2\mathrm{K}$
- Upper expected cost $(L_{W2}) = 0.2 \times \$1\mathrm{M} + 0.8 \times \$10\mathrm{K} = \$208\mathrm{K}$

Therefore, the expected cost for L_{W2} would be [$89.2K, $208K].

As can be seen from the expected costs in Table 4, $L_{W3} = 0.5$ m can be selected as the best decision alternative as, compared with the other alternatives, it has both the lowest minimum expected cost ($22.9 K) and the lowest maximum expected cost ($27.8 K). Considering flotation, sliding, and shell buckling as the feasible failure modes for atmospheric tanks during floods, flotation is the likeliest failure mode.[14,47] As such, if adding 0.5 m of water could lower the probability of flotation to [0.003, 0.008], it would also reduce the likelihood of sliding (due to an increase in the weight of the tank and the friction force exerted on its bottom from the ground) and shell buckling (due to an increase in the internal pressure of the tank which can withstand the buckling).[17,47]

TABLE 4 Interval probabilities of flotation given different amounts of added water.

How much water to add?	P(flotation = yes)	P(flotation = no)	Expected cost (× $1000)
$L_{W1} = 0$ m	[0.26, 0.48]	[0.52, 0.74]	[260, 480]
$L_{W2} = 0.25$ m	[0.08, 0.20]	[0.80, 0.92]	[89.2, 208]
$L_{W3} = 0.50$ m	[0.003, 0.008]	[0.992, 0.997]	**[22.9, 27.8]**
$L_{W4} = 0.75$ m	[0.0002, 0.0005]	[0.9995, 0.9998]	[30.2, 30.5]

Note: The bold values show the least expected cost, indicating L_{w3} as the most cost-effective decision alternative.

4 | DISCUSSION

To evaluate the effectiveness of the developed methodology, two common approaches to dealing with interval probabilities are considered in this section for risk assessment and management of the tank. In the first approach, each probability interval is replaced with an average probability, whereas in the second approach, the probability intervals are replaced with a normal distribution to consider the uncertainty in L (depth of crude oil in the tank).

4.1 | Average probabilities instead of interval probabilities

Regarding the probability intervals for L, each probability interval may be replaced with an average probability. One formula for calculating the average probability has been proposed by Yager and Kreinovich.[48] If a probability interval is presented with a lower probability p_j^- and an upper probability p_j^+ as $p_j = \left[p_j^-, p_j^+\right]$, the average probability that may be used as a surrogate for the interval can be calculated as follows[48]:

$$p_j^{\sim} = \frac{\Sigma^+ - 1}{\Sigma^+ - \Sigma^-} \cdot p_j^- + \frac{1 - \Sigma^-}{\Sigma^+ - \Sigma^-} \cdot p_j^+, \tag{18}$$

where:

$$\Sigma^+ = \sum_{i=1}^{n} p_i^+, \tag{19}$$

$$\Sigma^- = \sum_{i=1}^{n} p_i^-. \tag{20}$$

Therefore, given the probability intervals for L as $0.2 \le P(L_1) \le 0.5$, $0.3 \le P(L_2) \le 0.5$, and $0.2 \le P(L_3) \le 0.3$, the values of Σ^+ and Σ^- can be calculated as follows:

$$\Sigma^+ = \sum_{i=1}^{3} p_i^+ = p_1^+ + p_2^+ + p_3^+ = 0.5 + 0.5 + 0.3 = 1.3,$$

$$\Sigma^- = \sum_{i=1}^{3} p_i^- = p_1^- + p_2^- + p_3^- = 0.2 + 0.3 + 0.2 = 0.7.$$

Subsequently, the average probabilities for L_1, L_2, and L_3 can be calculated as $p_1^{\sim} = 0.35$, $p_2^{\sim} = 0.4$, and $p_3^{\sim} = 0.25$, which are actually the arithmetic mean values of the intervals. Now, L can be considered as a discrete variable with a discrete distribution as $P(L_1, L_2, L_3) = (0.35, 0.4, 0.25)$. Having h as a normal variable (Table 2) with a normal distribution as $h \sim \mathrm{N}(1, 0.2)$, Monte Carlo simulation can be employed to estimate the probability of flotation via Equation (14). Conducting the simulation for 10,000 iterations, part of which is presented in Table 5, the probability of flotation can be estimated as $P(\text{flotation} = \text{yes}) = 0.384$, and subsequently $P(\text{flotation} = \text{no}) = 1 - 0.384 = 0.616$. Using the same approach, the probability of flotation after adding certain amounts of water to the tank (i.e., $L_w = 0.25$, 0.5, and 0.75 m) can be estimated by applying the Monte Carlo simulation to Equation (16). The results have been summarized in Table 6 under columns 3 and 4.

As can be seen from Table 6, for both $L_{W1} = 0$ m and $L_{W2} = 0.25$ m, the flotation probabilities calculated using the discrete distribution for L are consistent with those calculated using the interval probabilities as they lie within the range:

- For $L_{W1} = 0$ m $\rightarrow P(\text{flotation} = \text{yes}) = 0.384 \in [0.26, 0.48]$
- For $L_{W2} = 0.25$ m $\rightarrow P(\text{flotation} = \text{yes}) = 0.184 \in [0.08, 0.20]$

However, for $L_{W3} = 0.50$ m and $L_{W4} = 0.75$ m, the point probabilities calculated under the discrete distribution are one order of magnitude larger than those calculated using the interval probabilities:

- For $L_{W3} = 0.50$ m $\rightarrow P(\text{flotation} = \text{yes}) = 0.042 \notin [0.003, 0.008]$
- For $L_{W4} = 0.75$ m $\rightarrow P(\text{flotation} = \text{yes}) = 0.003 \notin [0.0002, 0.0005]$

Given the point probabilities of the flotation, only one expected cost (instead of expected cost interval) can be calculated for each decision alternative. For instance, for $L_{W2} = 0.25$ m, the expected cost can be calculated as follows:

- Expected cost (L_{W2}) = 0.184 × \$1M + 0.816 × \$10K = \$192.2 K

Calculating the expected costs for the other decision variables, $L_{W4} = 0.75$ m with the lowest expected cost of \$32.9 K should be selected as the best decision, which is different from the best decision selected under the probability intervals—that is, $L_{W3} = 0.50$ m with the lowest expected cost [\$22.9 K, \$27.8 K].

4.2 | Normal distribution instead of interval probabilities

Given three values for L as $L_1 = 0.5$ m, $L_2 = 1.0$ m, and $L_3 = 1.5$ m, the analyst may decide to model L as a

TABLE 5 Monte Carlo simulation to estimate P(flotation = yes) given a discrete distribution for L.

Iteration No.	Generate random numbers for h: $h \sim N$ ($\mu = 1, \sigma = 0.2$)	Generate random numbers for L: $L \sim D$ (0.35, 0.4, 0.25)	Calculate: $\frac{268+655L}{789}$	$\begin{cases} 1 \text{ if } h > \frac{268+655L}{789} \\ 0 \text{ if } h < \frac{268+655L}{789} \end{cases}$
1	0.883888904	1	1.169835234	0
2	1.016611466	1	1.169835234	0
3	0.894045686	1.5	1.584917617	0
4	0.785400632	0.5	0.754752852	1
5	1.041193289	0.5	0.754752852	1
⋮	⋮	⋮	⋮	⋮
10,000	0.726801434	0.5	0.754752852	0
				P(flotation = yes) = $\frac{\text{SUM}}{10{,}000}$

TABLE 6 Flotation probabilities and expected costs under different probability distributions.

	Interval probabilities for L		$L \sim D$ (0.35, 0.4, 0.25)		$L \sim N$ (1, 0.5)		Expected cost (×\$1000)		
	1	2	3	4	5	6	7	8	9
How much water to add (m)?	Float = Yes	Float = No	Float = Yes	Float = No	Float = Yes	Float = No	Interval probabilities	$L \sim$ Discrete dist.	$L \sim$ Normal dist.
$L_{W1} = 0$	[0.26, 0.48]	[0.52, 0.74]	0.384	0.616	0.329	0.671	[260, 480]	384	329
$L_{W2} = 0.25$	[0.08, 0.20]	[0.80, 0.92]	0.184	0.816	0.155	0.845	[89.2, 208]	192.2	163.5
$L_{W3} = 0.5$	[0.003, 0.008]	[0.992, 0.997]	0.042	0.958	0.052	0.948	**[22.9, 27.8]**	61.2	71
$L_{W4} = 0.75$	[0.0002, 0.0005]	[0.9995, 0.9998]	0.003	0.997	0.013	0.987	[30.2, 30.5]	**32.9**	**42.6**

Note: The bold values show the least expected costs and respective decision alternatives under different probabilistic approaches. Using the method of interval probabilities, L_{w3} can be selected as the most cost-effective decision alternative.

normal variable with a mean value 1.0 and standard deviation 0.5 as $L \sim N(1, 0.5)$. Compared with the assumption of a discrete distribution for L in the previous section, the assumption of a normal distribution for L in this section seems to be more arbitrary and thus less credible. However, it is considered in the present study as an ad hoc approach commonly practiced when insufficient data is available to support other probability distributions. [10]

Knowing that h is also a normal variable as $h \sim N$ (1, 0.2), Monte Carlo simulation can be used to estimate the probability of flotation. Conducting the simulation for 10,000 iterations, the probability of flotation can be estimated as P(flotation = yes) = 0.329, and subsequently P(flotation = no) = 1–0.329 = 0.671. Using the same approach, the probability of flotation after adding certain amounts of water to the tank can be estimated by applying Monte Carlo simulation, as listed in Table 6 under columns 5 and 6. The results obtained via the normal distribution for L are consistent with those obtained via the interval probabilities for $L_{W1} = 0$ m and $L_{W2} = 0.25$ m:

- For $L_{W1} = 0$ m $\rightarrow P$(flotation = yes) = 0.329 $\in$ [0.26, 0.48]
- For $L_{W2} = 0.25$ m $\rightarrow P$(flotation = yes) = 0.155 $\in$ [0.08, 0.20]

However, the flotation probabilities for $L_{W3} = 0.50$ m and $L_{W4} = 0.75$ m are larger by one and two orders of magnitude, respectively, than those obtained via the probability intervals:

- For $L_{W3} = 0.50$ m $\rightarrow P$(flotation = yes) = 0.052 $\notin$ [0.003, 0.008]
- For $L_{W4} = 0.75$ m $\rightarrow P$(flotation = yes) = 0.013 $\notin$ [0.0002, 0.0005]

Calculating the expected costs for the decision variables, $L_{W4} = 0.75$ m with the lowest expected cost of \$42.6K should be selected as the best decision, which is the same as the best decision under the discrete distribution but different from the one under the probability intervals, that is, $L_{W3} = 0.50$ m with the lowest expected cost [\$22.9K, \$27.8K].

5 | CONCLUSION

In the present study, we presented an innovative application of evidence networks to risk assessment and management of oil storage tanks during floods. The methodology developed in the present study can be summarized in four steps: (i) employing evidence theory for identifying beliefs from subjective data, (ii) propagating beliefs through BN, (iii) converting the propagated beliefs back into interval probabilities, and (iv) using interval probabilities for decision making.

It was demonstrated that risk assessment and decision making with interval probabilities may result in different outcomes than would replacing them with average probabilities or presumptive probability distributions. It was shown that replacing interval probabilities with the respective average probabilities may increase the precision of the probability estimates but not necessarily the accuracy of risk assessment outcomes or the cost-effectiveness of risk management strategies. However, in the absence of required resources (time, expertise, etc.) for dealing with interval probabilities, the analyst may decide to replace them with average probabilities as the results in that case seem to be more consistent with the results obtained from the interval probabilities. However, more applications and comparisons are required to determine if the average probabilities could efficiently substitute the interval probabilities for risk assessment and decision making under uncertainty.

Although we applied the methodology to the domain of Natechs, it is applicable to other domains where, due to a lack of accurate and sufficient data, subject matter experts are unable to determine precise probabilities and may rather express their uncertainty in the form of imprecise or interval probabilities. It is also worthwhile to note that the methodology developed in the present study aims to enable the analysts to consider and handle imprecise probabilities rather than improve the precision of such probabilities. That said, application of the developed methodology alongside techniques for increasing data precision and accuracy (e.g., by increasing the precision and reliability of measuring techniques and devices) could further improve the creditability of risk analysis outcomes.

AUTHOR CONTRIBUTIONS

Alireza Dehghanisanij: Writing – original draft; formal analysis; methodology. **Nima Khakzad:** Supervision; funding acquisition; writing – review and editing; validation. **Ernesto Salzano:** Writing – review and editing; validation. **Paul Amyotte:** Validation; writing – review and editing.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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