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Application of evidential network to model uncertainty in quantitative risk assessment of Natech accidents

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ABSTRACT: Natech is a technological accident which is triggered by a natural disaster. Increasing frequency of natural disasters along with an increasing growth of industrial plants are bound to increase the risk of Natechs in the future. Due to a lack of accurate field observations and empirical data, risk assessment of Natechs has largely been reliant on experts opinion and thus prone to epistemic uncertainty in addition to aleatory uncertainty originating from randomness of natural disasters. Evidential Network (EN) is a directed acyclic graph based on Dempster-Shafer Theory to explicitly model the propagation of epistemic uncertainty in system safety and reliability assessment. In the present study, we have illustrated an application of EN to handling epistemic uncertainty in risk assessment of flood-induced floatation of storage tanks.

1 INTRODUCTION

Technological accidents which are triggered by natural disasters such as earthquakes, lightning, storms, wildfires, tsunamis, and floods are known as Natechs. Natural disasters have reportedly led to the release of significant amounts of oil, chemicals, and radiological substances (Showalter & Myre 1994, Rasmussen 1995, Young et al. 2004).

The occurrence of Natechs in industrial plants, particularly oil terminals, can result in catastrophic consequences in terms of large spillage of petroleum products. In 2005, the floods triggered by the Hurricane Katrina in the U.S. caused a spillage of ~ 8 million gallons of oil into the ground and waterways. In August 2017, the Hurricane Harvey in the U.S. caused damage to storage tanks in refineries and petrochemical plants, leading to a substantial release of pollutants. The structural damage caused by natural events, however, does not compare with the environmental damage and revenue losses due to interruption in production and supply chain: the Hurricane Harvey made oil refineries shut down as for safety precautions, leading to at least a loss of more than 1 million barrels of oil per day in refining capacity (CNBC, 2017).

Natechs has been recognized in quantitative risk assessment of industrial plants by many researchers (Young et al. 2004, Godoy 2007, Cruz & Okada 2008, Antonioni et al. 2009, Haptmanns 2010, Krausmann et al. 2011, Landucci et al. 2012, Necci et al. 2013, Marzo et al. 2015, Mebarki et al. 2016, Khakzad & van Gelder 2017, 2018, Kameshwar & Padgett 2018). The scarcity of historical data, especially data with sufficient resolution and accuracy, has made the majority of previous studies reliant on analytical or simulative techniques (e.g., finite element modeling) in modeling and calculating the probability of failure modes. This mostly has been carried out based on modeling the envisaged failure mechanisms as a function of loads exerted by natural disasters (e.g., impact of tsunami wave) and the resistance of impacted vessels.

The stochastic features of natural disasters as well as randomness of failure mechanisms are naturally modeled via probability density functions. Either the types or the parameters of such density functions are usually estimated based on insufficient (either amount or accuracy) objective data. This lack of objective data is usually tried to be compensated for by experts opinion based upon their experience, knowledge, and even intuition, inevitably introducing degrees of epistemic uncertainty into the analysis.

The Evidence Theory (Dempster-Shafer Theory, DST), originally initiated by Dempster (1967) and further developed by Shafer (1976), is an effective tool to handle imprecise probabilities and reasoning under epistemic uncertainty. According to DST, all the possible states (mutually exclusive and collectively exhaustive) of a system is presented in a set known as *the frame of discernment* $\mathbf{\Omega}$. To each subset of Ω such as **A**, an evidential weight **m(A)** can be assigned to indicate the degree of evidence (based on objective data or subjective opinion) in favor of the claim that a specific state in Ω belongs to A (Rakowsky 2007). Having m(A), which is also known as belief mass, the amounts of *belief* and

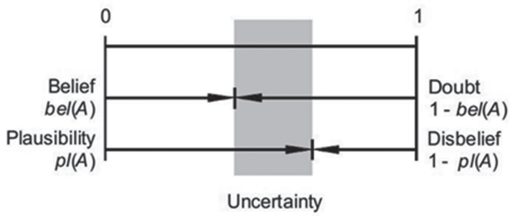

Figure 1. Quantification of epistemic uncertainty through Bel and Pls functions (Rakowsky, 2007).

plausibility of A, equivalent to lower and upper probability bounds of A, respectively, can be determined (Shafer 1976). The difference between plausibility **Pls(A)** and the belief **Bel(A)** represent the epistemic uncertainty of A (Fig. 1).

An Evidential Network (EN) is a directed acyclic graph to propagate uncertainty based on conditional belief functions (Xu & Smets 1996). Simon and Weber (2009) combined DST with Bayesian Network (Pearl, 1988) to take advantage of the junction tree algorithm developed by Jensen (1996) in propagating and computing the marginal belief functions of child nodes based upon those of their parent nodes.

The present study is an attempt to illustrate the potentiality of EN in system safety where due to lack of sufficient accurate data the analysis would be subject to epistemic uncertainty embedded in expert judgement. The application of EN will be demonstrated via safety assessment of oil storage tanks impacted by floods, with the floatation of tanks as the most common failure mode (Cozzani et al. 2010).

2 REASONING UNDER EPISTEMIC UNCERTAINTY

2.1 *Dempster-Shafer theory*

Assume that all the states of a system can be presented in a frame of discernment as $\Omega = \{S1, S2, S3\}$. Accordingly, the set of all the subsets of Ω can be shown as:

$$A_i : \{\{\varnothing\},\{S1\},\{S2\},\{S3\},\\ \{S1,S2\},\{S1,S3\},\{S2,S3\},\Omega\} \quad (1)$$

According to the available evidence (either objective or subjective), an expert may assign a belief mass to each A_i as $0 \le m(A_i) \le 1$. Each A_i for which $m(A_i) > 0$ is called a *focal set*. If all the states of the system are known, then $m(\varnothing) = 0$. Further, it must always hold that:

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

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

$$Bel(A_i) = \sum_{B|B \subseteq A_i} m(B) \quad (3)$$

$$Pls(A_i) = \sum_{B|B \cap A_i \neq \varnothing} m(B) \quad (4)$$

$Bel(A_i)$ and $Pls(A_i)$, which are non-additive, can be taken as lower and upper probability bounds, respectively, of A_i (Simon & Weber 2009):

$$Bel(A_i) \le P(A_i) \le Pls(A_i) \quad (5)$$

$$Bel(A_i^c) = 1 - Pls(A_i) \quad (6)$$

$$Pls(A_i^c) = 1 - Bel(A_i) \quad (7)$$

where A_i^c is the complement of A_i. Having the Bel and Pls functions, the belief mass of a focal set can be determined using the möbius transformation as (Smets 2002):

$$m(A_i) = \sum_{B|B \subseteq A_i} (-1)^{|A_i - B|} Bel(B) \quad (8)$$

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

2.2 *Evidential network*

Simon & Weber (2009) used a Bayesian network (BN) formalism to propagate imprecise probabilities using the belief mass functions assigned to the focal sets. Since the belief masses allocated to the focal sets of each component of the system add up to unity, they can be used as marginal probabilities of the nodes in the BN.

Combination of the mass belief functions of components (nodes) can readily be carried out by means of Boolean algebra. For the sake of exemplification, consider a system Z comprising two components X and Y as shown in Fig. 2.

In Fig. 2, the components and the systems are considered as binary nodes, i.e., being in one of *up* or *down* states. Thus, for instance, the frame of discernment of X and its focal sets can be presented as Ω_X = {up, down} and A_X = {{up}, {down}, {up,down}}, where {up,down} = {up}⊕{down}, respectively. Among the focal sets of X, {up,down} models the uncertainty, indicating that X can be in either up or down states. Now consider a case where

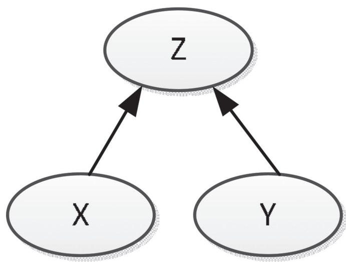

Figure 2. BN for reliability assessment of a two-component system.

Table 1. Truth table used to combine the focal sets of components X and Y via AND and OR gates (Simon & Weber, 2009).

		Z	
X	Y	AND	OR
{up}	{up}	{up}	{up}
{up}	{down}	{down}	{up}
{up}	{up,down}	{up,down}	{up}
{down}	{up}	{down}	{up}
{down}	{down}	{down}	{down}
{down}	{up,down}	{down}	{up,down}
{up,down}	{up}	{up,down}	{up}
{up,down}	{down}	{down}	{up,down}
{up,down}	{up,down}	{up,down}	{up,down}

X = {up} and Y = {up,down} are connected to Z by an AND gate; using Boolean algebra, the state of Z can be identified as $\{up\}\cap\{up,down\} = \{up\}\cap\{up\} \oplus \{up\}\cap\{down\} = \{up\} \oplus \{down\} = \{up,down\}$. Likewise, in case of an OR gate, the state of Z can be identified as $\{up\}\cup\{up,down\} = \{up\}\cup\{up\} \oplus \{up\}\cup\{down\} = \{up\} \oplus \{up\} = \{up\}$. The results of AND and OR gates in the form of a truth table have been presented in Table 1.

For the system shown in Fig. 2, assume that the analyst, based on his degree of belief, has assigned the marginal belief mass distributions to the focal sets of components X and Y as $m(A_X) = \{0.5, 0.4, 0.1\}$ and $m(A_Y) = \{0.4, 0.4, 0.2\}$. We in the next section will demonstrate using a case study how the belief mass distributions can be determined using Equations (2)–(8). Fig. 3 displays the resulting EN in which X and Y are connected to Z via an AND gate.

As can be seen in Fig. 3, the inference algorithm of BN can be used to calculate marginal belief mass distribution of Z based on the marginal mass distributions of X and Y and the truth table (see Table 1) as $m(A_Z) = \{0.2, 0.64, 0.16\}$. Having the belief mass distribution of Z, the belief of Z = {up} can be calculated using Equation (3):

$$Bel(\{up\}) = \sum_{B|B\subseteq up} m(B) = m(\{up\}) = 0.2.$$

This is because among the focal sets of Z, i.e., $A_Z = \{\{up\}, \{down\}, \{up,down\}\}$, only the focal set B = {up} is the subset of {up}. Likewise, the plausibility of Z = {up} can be calculated using Equation (4):

$$Pls(\{up\}) = \sum_{B|B\cap up_{\neq\varnothing}} m(B) = \mathrm{m}(\{up\}) + \mathrm{m}(\{up,down\}) = 0.2 + 0.16 = 0.36.$$

This is because among the focal sets of Z, only the intersections of focal sets {up} and {up,down} with {up} are not null. As a result: $0.2 \le P(Z = up) \le 0.36$.

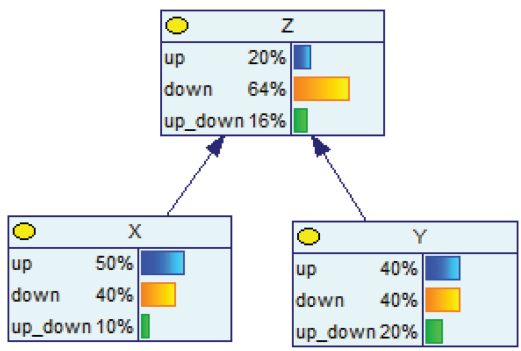

Figure 3. EN for reliability assessment of a two-component system using belief mass distributions.

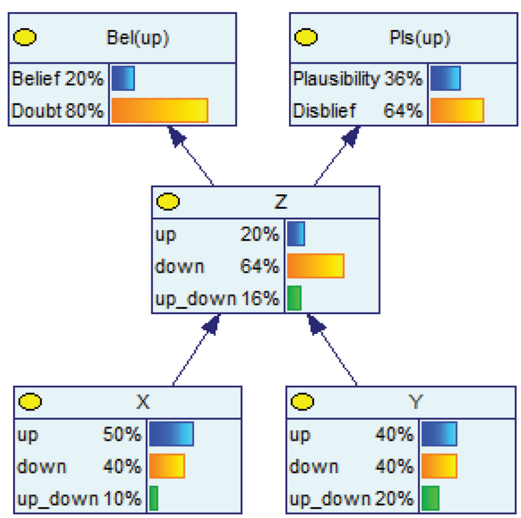

Figure 4. Adding belief (Bel) and plausibility (Pls) nodes in order to calculate epistemic uncertainty of Z = {up}.

Table 2. Conditional belief table used to calculate Bel(up) and Pls(up) of Z in Fig. 4.

Z	Bel(up)	Pls(up)
{up}	1	1
{down}	0	0
{up,down}	0	1

The procedure of calculating belief and plausibility can be carried out using the developed BN (which in fact is an EN) by adding the nodes Bel({up}) and Pls({up}) to the network (Fig. 4). The conditional belief table used to connect these two nodes to node Z is presented in Table 2. It should be noted that since Bel and Pls are non-additive (see Equations (6) & (7)), they have been presented as two separate nodes in the EN.

3 SAFETY ASSESSMENT OF STORAGE TANKS IN CASE OF FLOOD

3.1 *Floatation of storage tanks*

Floatation of storage tanks has reportedly been the most frequent failure mode during floods (Cozzani et al. 2010). Floatation of storage tanks occurs if the upthrust force of flood exceeds the bulk weight of the storage tank (weight of the tank plus the weight of its liquid containment). Fig. 5 presents the loading force (buoyancy) and resisting forces (bulk weight of the tank) contributing to the flotation of the storage tank.

When there is a lack of field or experimental data to relate the characteristics of the natural disaster to the failure modes and failure probabilities of an impacted equipment, one may choose to develop Limit-State Equations (LSE) based on influential loading and resisting forces. Development of LSEs helps the analyst combine his knowledge (though incomplete) of the influential parameters with available objective data to compensate for the inadequacy of objective data required for estimation of failure probabilities.

As for the floatation of storage tanks, the relevant LSE should take into account the weight of the tank W_T, the weight of the contained liquid W_L, and the buoyant force F_B. As can be seen from Fig. 5, we have considered a self-anchored storage tank (not bolted to the foundation) which is a common practice in case of atmospheric storage tanks. As such, the only resisting forces against the tank's floatation comprise the bulk weight of the tank. Considering the direction of the forces in Fig. 5, the LSE can be developed as:

$$LSE = F_B - W_T - W_L \tag{9}$$

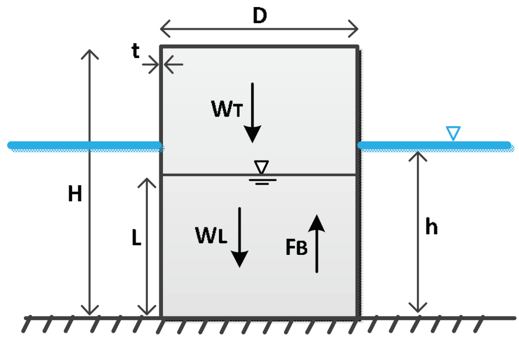

Figure 5. Schematic of the load-resistance forces considered for tank floatation.

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

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

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

where D: tank's diameter, H: tank's height, t: tank shell's thickness, L: height of liquid inside the tank, h: height of flood's inundation, ρ_w: flood water density, ρ_s: tank shell's density, ρ_l: liquid's density, and g: gravitational acceleration. Accordingly, the floatation probability of the tank can be presented as P(LSE > 0).

3.2 *Failure analysis*

For the sake of exemplification, assume that the analyst, based on objective data, would know the amounts of the tank's and flood's parameters as listed in Table 3, except the initial amount of chemical liquid (gasoline in this example).

Floatation of a storage tank due to slow submersion can result in an instantaneous release of liquid should the tank collapse, continuous release of the entire containment in a limited time in case of full disconnection of large pipelines, or a minor release in case of partial disconnection of flanges and pipelines (Cozzani et al 2010). In any of these release scenarios, if the initial inventory of the tank was not known before the floatation, the estimation of a priori inventory of the tank would be subject to uncertainty (epistemic).

Since the analyst would have doubts about the initial inventory of the tank before the flood impacted the plant, he decides to seek the opinion of two experts (e.g., operators working at the storage tank area). The first expert comes up with

Table 3. Parameters used for risk assessment of floatation.

Parameter	Value
H (m)	6
D (m)	10
t (m)	0.01
h (m)[¥]	N ($\mu = 1, \sigma = 0.2$)
ρ_s (kg/m^3)	7900
ρ_w (kg/m^3)	1024
ρ_l (kg/m^3)[§]	850

[¥] due to aleatory uncertainty inherent in flood's forecast.
[§] gasoline has been considered as the chemical liquid.

P(L = 0.5 m, L = 1.0 m, L = 1.5 m) = (0.2, 0.5, 0.3) whereas the second expert with P(L = 0.5 m, L = 1.0 m, L = 1.5 m) = (0.5, 0.3, 0.2). As such, the experts' uncertainty about the initial inventory of the storage tank can be expressed using imprecise probabilities as:

$$\begin{cases} 0.2 \le P(L = 0.5) \le 0.5 \\ 0.3 \le P(L = 1.0) \le 0.5 \\ 0.2 \le P(L = 1.5) \le 0.3 \end{cases} \tag{13}$$

According to the parameters in Table 3, the tank's weight, the weight of liquid containment, and the buoyancy force can be calculated as $W_T = 219$ (KN), $W_L = 655\,L$ (KN), and $F_B = 789\,h$ (KN), respectively. The floatation probability can thus be calculated as:

$$P(LSE > 0) = P(F_B > W_T + W_L) = P(789h > 219 + 655L) = P\left(h > \frac{219 + 655L}{789}\right) \tag{14}$$

3.3 *Uncertainty modeling*

Considering L as an uncertain variable with three states as L1 = 0.5 m, L2 = 1.0 m, and L3 = 1.5 m, its frame of discernment would be:

Ω_L = {L1, L2, L3}.

Consequently, the set of its focal sets would be:

A_L: {{L1}, {L2}, {L3}, {L1, L2}, {L1, L3}, {L2, L3}, {L1, L2, L3}}.

Using the equations in Section 2.1, the belief mass of each focal set can be determined. For example, consider the first focal set, {L1} with the lower and upper bound probabilities as shown in Equation (13). Based on Equation (5), Bel({L1}) = 0.2 and Pls({L1}) = 0.5. Since {L1} is a singleton, using Equation (8), m({L1}) = Bel({L1}) = 0.2. Similarly, m({L2}) = 0.3, and m({L3}) = 0.2.

As another example, consider the focal set {L1, L2}. Since {L1}, {L2}, and {L1, L2} are all the subsets of {L1, L2}, using Equation (8), we will have m({L1, L2}) = Bel({L1, L2}) – Bel({L1}) –Bel({L2}).

Further, based on Equation (6), Bel({L1, L2}) = 1 – Pls({L3}) = 1 – 0.3 = 0.7.

As a result, m({L1, L2}) = 0.7 – 0.2 – 0.3 = 0.2. Following the same procedure, m{{L1}, {L2}, {L3}, {L1, L2}, {L1, L3}, {L2, L3}, {L1, L2, L3}} = (0.2, 0.3, 0.2, 0.2, 0.1, 0, 0). Since m({L1, L3}) = m({L1, L2, L3}) = 0, they would not be considered as focal sets any more.

3.4 *Probability of floatation*

As can be seen from Equation (14), the only influential parameters in estimating the probability of floatation are the flood inundation height h and the liquid containment height L. To facilitate the propagation of uncertainty – aleatory uncertainty in h and epistemic uncertainty in L – the EN in Fig. 6 can be developed. It is worth noting that compared to the EN proposed by Simon & Weber (2009), in our EN both the belief and plausibility of *Floatation* have been modeled using a single node, considering the fact that:

$$Bel(A_i) + Unc(A_i) + Dis(A_i) = 1.0 \tag{15}$$

$$Unc(A_i) = Pls(A_i) - Bel(A_i) \tag{16}$$

$$Dis(A_i) = 1 - Pls(A_i) \tag{17}$$

where $Unc(A_i)$ and $Dis(A_i)$, respectively, refer to the uncertainty and disbelief about the focal set A_i (see Fig. 1).

In the EN shown in Fig. 6, the states of the node L have been represented by its focal sets with the respective belief masses as marginal probabilities (although belief masses are not probabilities, as discussed in Rakowsky (2007)). As opposed to the node L, the states of the node h are the discretized intervals of h with their (real) marginal probabilities calculated based on the normal distribution presented in Table 3. In this regard:

$$h = \begin{cases} h1 & if \quad 0 \le \mathrm{h} < 0.8 \\ h2 & if \quad 0.8 \le \mathrm{h} < 1.2 \\ h3 & if \quad 1.2 \le \mathrm{h} < 1.6 \\ h4 & if \quad 1.6 \le \mathrm{h} < 2.0 \end{cases}$$

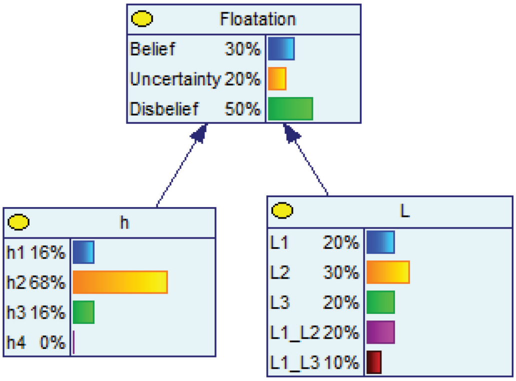

Figure 6. Evidential network to estimate the probability of floatation under aleatory and epistemic uncertainty.

The conditional belief table used to calculate the marginal masses of the node Floatation has been shown in Table 4. The conditional masses can readily be calculated using Equation (14). As an example, consider the combination of h2: $0.8 \leq h < 1.2$ with the states (focal sets) of L:

- Case 1

{L1}: $L = 0.5$

$$P\left(h2 > \frac{219 + 655L1}{789}\right) = P(h2 > 0.69) = 1.0$$

Since h is always greater than 0.69 (note $0.8 \leq h < 1.2$), the belief and plausibility of the floatation, as the lower and upper bounds of probability, are both equal to 1.0. This, in turn, yields a zero uncertainty (see Equation (16)) and a zero disbelief (see Equation (17)). See the 6th row in Table 4.

- Case 2

{L2}: $L = 1.0$

$$P\left(h2 > \frac{219 + 655L2}{789}\right) = P(h2 > 1.11) = P(1.11 < h < 1.2) = 0.133$$

As a result, Bel = Pls = 0.133, Unc = 0.0, and Dis = 0.867 (7th row in Table 4).

- Case 3

{L3}: $L = 1.5$

$$P\left(h2 > \frac{219 + 655L3}{789}\right) = P(h2 > 1.52) = 0.0$$

Since h is always smaller than 1.2 (note $0.8 \leq h < 1.2$), the belief and plausibility of the floatation, as the lower and upper bounds of probability, are both equal to 0.0. This, in turn, yields a zero uncertainty and a disbelief of unity (8th row in Table 4).

- Case 4

{L1, L2}: $L = 0.5$ or 1.0

From Case 1 (L = 0.5) and Case 2 (L = 1.0), the probabilities of floatation were calculated as 1.0 and 0.133, respectively. Accordingly, the lower probability can be taken as Bel = 0.133 whereas the upper probability as Pls = 1.0. This in turn will result in Unc = 0.867 and Dis = 0.0 (9th row in Table 4).

- Case 5

{L1, L3}: $L = 0.5$ or 1.5

From Case 1 (L = 0.5) and Case 3 (L = 1.5), the probabilities of floatation were calculated as 1.0 and 0.0, respectively. Accordingly, the lower probability can be taken as Bel = 0.0 whereas the upper probability as Pls = 1.0. This in turn will result in Unc = 1.0 and Dis = 0.0 (10th row in Table 4).

As can be seen from Fig. 6, given the marginal and conditional probabilities and belief masses, the lower bound probability of floatation has been calculated as Bel = 0.3. Similarly, the amount of uncertainty has been calculated as Unc = 0.2, which together with the amount of belief results in an upper bound probability of floatation as Pls = 0.3 + 0.2 = 0.5.

Modeling the uncertainty of the floatation in a single node instead of two nodes (cf Fig. 4) comes

Table 4. Conditional belief mass distribution for the node Floatation in Fig. 6.

Index	h	L	Bel	Unc	Dis
1	h1	{L1}	0.098	0	0.902
2	h1	{L2}	0	0	1
3	h1	{L3}	0	0	1
4	h1	{L1,L2}	0.098	0	0.902
5	h1	{L1,L3}	0.098	0	0.902
6	h2	{L1}	1	0	0
7	h2	{L2}	0.133	0	0.867
8	h2	{L3}	0	0	1
9	h2	{L1,L2}	0.133	0.867	0
10	h2	{L1,L3}	0	1	0
11	h3	{L1}	1	0	0
12	h3	{L2}	1	0	0
13	h3	{L3}	0.003	0	0.997
14	h3	{L1,L2}	1	0	0
15	h3	{L1,L3}	0.003	0.997	0
16	h4	{L1}	1	0	0
17	h4	{L2}	1	0	0
18	h4	{L3}	1	0	0
19	h4	{L1,L2}	1	0	0
20	h4	{L1,L3}	1	0	0

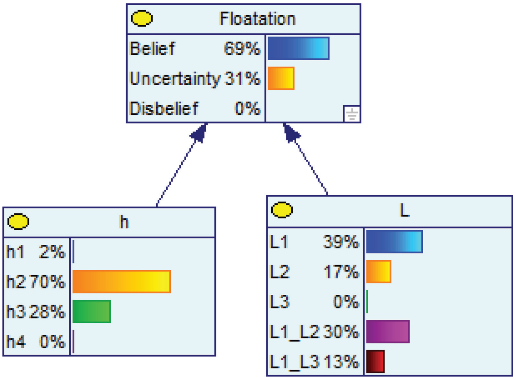

Figure 7. Updated belief masses by means of Disbelief = 0 as soft evidence.

in handy in reasoning about a priori inventory of the storage tank via belief updating. For instance, in case the storage tank is believed to have lost some of its containment as a matter of floatation, the initial belief masses assigned to L can be updated by instantiating the amount of Disbelief to zero (Fig. 7).

The updated belief masses have been depicted in Fig. 7, where L1 (i.e., L = 0.5 m) is believed to be the likeliest amount of initial inventory before the floatation.

4 CONCLUSIONS

In the present study we examined the applicability of evidential networks to system safety under both aleatory and epistemic uncertainties.

Modeling epistemic uncertainty of a parameter in a single node as an aggregation of the degrees of belief, uncertainty, and disbelief, makes it possible to perform belief updating by using a variety hard and soft evidence. We demonstrated the application of evidential networks to assess the vulnerability of storage tanks against flood-induced submersion. However, the methodology, without a loss of generality, can be applied to system safety and reliability assessment in a wide variety of domains.

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