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An integration of human factors into quantitative risk analysis using Bayesian Belief Networks towards developing a 'QRA+'

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ABSTRACT

Quantitative Risk Analysis (QRA) is a standard tool in some high-risk industries (such as the on- and offshore exploration and production and chemical industry). Presently, existing knowledge concerning human error likelihood and human reliability assessment is insufficiently represented in QRAs. In this paper we attempt to implement the quantification of the human factors in a QRA, which we call QRA+.

We analysed a specific incident scenario: the risk of overfilling chemical storage tanks that operate at atmospheric pressure. This scenario was chosen because it is a relevant example of a high-risk scenario in the chemical industry. We identified relevant technological and human parameters within this scenario through on-site visits and interviews with site-experts. The quantitative knowledge concerning the technological parameters was obtained from officially documented SIL statistics, whereas the Standardized Plant Analysis Risk-Human Reliability analysis (SPAR-H) was used to quantify the human factors. Beta distributions were used to model failure probability distributions to account for the uncertainty inherent in dealing with human reliability.

For seamless integration of existing qualitative and quantitative knowledge, we made use of a Bayesian Belief Network. The resulting model provides an integrated and more accurate estimation of the failure probabilities for both technological and human factors and the uncertainty surrounding such probability estimates. Furthermore, it gives insight in where these failure probabilities originate and how they interact. This will allow companies to identify those parameters they need to influence to get optimal results concerning their management of risk.

1. Introduction

The Quantitative Risk Analysis (QRA) is a widely used tool for risk management since late 1970 (Swuste et al., 2019). For some high-risk industries (such as the on- and offshore exploration and production, and chemical industry), the QRA is even considered standard and mandatory to receive a license to operate and standards exist that describe requirements of a QRA (Haugen, 2018). Even though (occupational) accidents occur with decreasing frequency over the past few years in many front-running companies (iOGP, 2019), accidents and incidents still cause considerable personal harm on a broader societal scale (Takala et al., 2014). Therefore, continued research to help organisation improve their risk management, such as innovations surrounding the QRA, are therefore still a necessity.

The goal of a QRA is to calculate the probability for the occurrence of specific risks given an activity or process (Van Gelder and Vrijling, 2008) and to ultimately develop a QRA model to determine the numerical risk to different groups (see Pasman and Reniers, 2014 for a more elaborate overview of the arrival of the method). A QRA generally consists of four stages:

1. *Hazard identification*: The identification of factors and scenarios which may pose a relevant hazard.
2. *Hazard analysis*: Recognition of hazards that may arise from a system or its environment, documenting their unwanted consequences and analysing their potential causes.
3. *Consequence analysis* Creating a model of the system response to a particular fault or hazard.
4. *Risk analysis and summation*: Fault and event trees analysis and summation of all risks concerning all consequence categories.

Although, during a QRA the technical, human and organizational factors should be considered, in practice the assessment of human and organisational factors is generally superficial (Torres et al., 2016; Zhen et al., 2018). This is the conclusion Skogdalen and Vinnem (2010) derived after systematically reviewing 15 Norwegian QRAs. While human factors play an important role in most incident scenarios (e.g. Reason, 1997; Groeneweg, 2002), their influence in QRAs are often estimated heuristically based on expert judgement or seemingly arbitrary rules. Even in technical standards, the inclusion of human factors is dealt with by artificially inflating the failure probability of related safety functions

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without substantive justification (NEN-EN-61511; NEN-EN-61518).

In this paper we address the resulting methodological gap between the extensive methods of estimating technological failure probabilities and the rather limited methods used to estimate human failure probabilities (Pasman et al., 2018). The existence of this gap is not due to a lack of methods available to estimated human error probability or human reliability assessments (HRA). Numerous methods exist to understand human error probability in qualitative (e.g., Tripod, HFACS) or in a quantitative predictive fashion (e.g., HEART; Williams, 1986 or SPAR-H; Gertman et al., 2005). Rather, we consider it more likely that (perceived) difficulties in application of these techniques is the cause of their underuse in QRAs. Ideally, QRA are based on technological, human, and organisational factors as a coherent whole.

In this paper we expand upon a model in which we attempt to integrate human factors into a QRA (Steijn et al., 2017). As such, we work towards a QRA which is capable of coherently modelling technological, human and organisation factors, resulting in a proof of principle of a QRA that could be considered a 'QRA+'. We will describe a method to apply a more substantiated human reliability assessment in a QRA to bridge the aforementioned gap. This description will be based upon a case study that was done concerning an overfill scenario for chemical storage tanks which work at atmospheric pressure (PGS-29 tanks according to the Dutch 'Guideline for above-ground storage of flammable liquids in vertical cylindrical tanks'). We elaborate on our earlier work by going into more detail concerning the chosen methodology of beta distributions and Bayesian Belief Networks, and by also implementing the estimates for the technical barriers in the discussed model.

This paper addresses the scope of this special issue concerning 'safety analytics' in several ways. In particular this paper focuses on the development of a prediction model, i.e., the a QRA. This QRA integrates leading and lagging indicators of human and technological factors. This way the QRA+ will better support safety related decision making my major hazard companies.

In the remainder of this paper we will first present the chosen human reliability assessment (HRA) tool and the chosen methodology to model the QRA+. Next, the qualitative analysis of our case study is reported, through which the relevant components were selected for our model. Then, we describe the result of quantifying the human and technical components in our model. The paper ends with a discussion of the resulting model and reflection on the employed methodology.

1.1. Human reliability assessments and QRA

In the nuclear industry human reliability assessment has been applied starting as early as 1975 (Forester et al., 2009). In other industries human factors have received less attention in QRAs - with some notable recent exceptions (e.g., Gould et al., 2012; Skogdalen and Vinnem, 2010). This despite the fact that several HRA methods have been developed. Examples are the Human Error Assessment and Reduction Technique (HEART; Williams, 1986), Cognitive Reliability and Error Analysis Method (CREAM; He et al., 2008; Hollnagel, 1998), Technique for Human Error Rate Prediction (THERP, Swain and Guttman, 1974, 1983), Accident Sequence Evaluation Program (ASEP; Swain, 1987), Systematic Human Action Reliability Procedure (SHARP1; Wakefield et al., 1990) and the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H; Gertman et al., 2005). Groth extensively reviewed and compared different human performance models deriving a combined set of Performance Shaping Factors PSFs (Groth, 2009). However, this derived set is not yet as consistently quantified as the individual methods. Therefore, for this study it was decided to make use the SPAR-H model as the main method to estimate human error probability.

SPAR-H, originally created in 1999 by the U.S. Nuclear Regulatory Commission (NRC) in cooperation with Idaho National Laboratory (INL), was chosen as it is already commonly used in the nuclear industry and has been implemented in the oil and gas industry as well

Table 1
PSFs and the range for the associated multiplier as defined in SPAR-H (Gertman et al., 2005).

PSF	Multiplier range
Available time	0.01–10*
Stress and stressors	1–5
Complexity	0.1–5
Experience and training	0.1–10
Procedures	0.5–50
Ergonomics	0.5–50
Fitness for duty	1–5*
Work processes	0.8–2

Note. When multiple PSFs have a strong influence on a certain task, an 'adjustment factor' avoids obtaining a failure probability of more than 1 (see Table 4, note 2).

* In cases with inadequate time or when personnel are unfit for the task, SPAR-H assumes a probability of 1 (100%) for failure.

(Gould et al., 2012; Paltrinieri et al., 2016). Furthermore, SPAR-H was considered the most practical method for evaluation and quantification of human reliability by the authors. Gould and colleagues (2012) also made note that SPAR-H was less cumbersome to apply compared to other HRA methods like HEART. However, Paltrinieri and colleagues (2016) concluded that the application of SPAR-H in its current form does require a thorough qualitative analysis of the tasks performed by the operator and crew in the chosen scenario.

According to the initiating author, SPAR H "… decomposes probability into contributions from diagnosis failures and action failures, accounts for the context associated with human failure events by using performance-shaping factors (PSFs), and dependency assignment to adjust a base-case Human Error Probability (HEP), guidance on how to assign the appropriate value of the PSF and offers an adjustment factor to reduce double counting of influencing factors shared by PSFs." (Gertman et al., 2004, p.1). The SPAR-H model contains eight Performance Shaping Factors (PSFs) which are representative of the relevant area (see Table 1).

To determine a failure probability, the SPAR-H model takes task properties and several PSFs that affect the execution of the task. SPAR-H distinguishes diagnosis (e.g., determining appropriate course of action) and action (e.g., operating equipment) tasks and in total eight PSFs (see Table 1). The distinction between diagnosis and action tasks is relevant as both types of task have a different nominal failure probability (Blackman et al., 2008). Diagnosis tasks are estimated to fail more often than action tasks when evaluated in the same local conditions (PSFs).

Human reliability for both action and diagnosis tasks is influenced by the conditions under which the work is done, these conditions are modelled using PSFs. For each task all PSFs need to be rated on an individual PSF specific scale (e.g. below nominal, nominal or above nominal). The rating of the PSFs needs to be done based on a qualitative analysis of the task. For each level a multiplier value is available to modify the nominal failure probability associated with the task. The PSF multipliers therefore also define the relative amount of influence a PSF can have on the failure probability of a task (i.e. the multiplier range; see Table 1).

As such, SPAR-H provides a framework to analyse a specific task and obtain a point estimate for human reliability given that task. A point estimate is a single value assigned to, in this case, the probability of an event occurring without taking uncertainty into account. However, due to the uncertainty inherent in estimates of human reliability, as mean estimates are used to make predictions over groups of individuals, single point estimations are bound to be inaccurate. Estimating a range or distribution in which the human reliability probability lies should be preferred. In the following section we describe how we transformed point estimates to probability distributions.

1.2. From point estimate to probability distribution

The estimates made with SPAR-H or the other HRA methods are focused on obtaining a point estimate to describe the probability of human reliability. The uncertainty inherent when making point estimates can be considered by making use of probability distributions instead. Here we will do so by integrating three techniques: Beta distributions, three-point estimation and non-parametric Bayesian Belief Networks (BBN).

1.2.1. Beta distributions

Beta distributions are commonly used to describe failure probability density functions (PDFs) on a scale of 0 to 1, as discussed by van Erp et al. (2015). The formula to calculate a Beta distribution is given as follows:

$$f(x) = \frac{(x-p)^{\alpha-1}(q-x)^{\beta-1}}{B(\alpha,\beta)(q-p)^{\alpha+\beta+1}}$$

In this formula p and q are given and indicate the range of the distribution, x can therefore only be equal or larger than p (i.e., 0) and equal or smaller than q (i.e., 1). The shape of the distribution is determined by α and β. The α and β represent the number of success (α) and failures (β) that have been observed. As the number of observation increases (i.e., higher α and β) the distribution will be narrower (i.e., more certainity in the estimation of the error probability). In order to plot a beta distribution, knowledge surrounding α and β are required.

The formula allows updating a beta distribution as new data becomes available. Updating is the process of combining existing information (prior knowledge) with new data to calculate an updated estimate (posterior knowledge). The knowledge concerning the prior distribution for each barrier is based on literature, the site-visit and expert judgement. As more data becomes available (e.g., through observations or measurements over time), the uncertainty concerning the can be reduced. This is visually represented by the distribution becoming narrower and covering a smaller range of possible probabilities. The Beta distribution describes the range the failure probability is estimated to have based on the given available information.

Fig. 1 gives an example of a Beta distribution based on minimal estimation of 0.04%, a modal estimation of 0.4% and maximal estimation of 89%. These estimations are indicated in the figure by the vertical red dotted lines. A point estimate of the failure rate using the model estimation of 0.4% would suggest an accuracy that is not justified given the high level of uncertainty. The peak and most likely failure probability is at the modal estimation, but the tail runs up to 89% which is unlikely, but technically possible. The wide range indicates a level of high uncertainty surrounding the true reliability estimate. Knowing the shape of the distribution also allows organisations to take specific actions aimed at the long tail of the Beta distribution.

1.2.2. Three-point estimations

To implement the Beta distribution in QRA+ requires a transformation from (multiple) point estimates obtained from SPAR-H to the α and β required to plot a beta distribution. This is possible through the three-point estimation method (van Dorp and Kotz, 2002; Stein and Keblis, 2009). This method estimates a distribution based on the minimal, the maximal and the modal failure probability. With the help of the PSFs defined by SPAR-H and input obtained during the qualitative analysis on site, maximum, minimal and modal failure probabilities were estimated:

- The lowest realistic failure probability estimation (minimum estimation; min)
- The modal failure probability estimation (modal estimation; mod)
- The highest realistic failure probability estimation (maximum estimation; max)

With these three point estimates, a mean and standard deviation can be derived:

$$\mu = \frac{min + (4 * mod) + max}{6}$$

$$\sigma = (max - min)/6$$

Given that the modal estimation is based on observations, whereas the minimum and maximum estimations are derivations, the modal estimation is given more weight in determining the (weighted) average. With the estimated (weighted) average and standard deviation, the associated α and β can be inferred for a beta distribution:

$$\alpha = \left(\frac{1-\mu}{\sigma^2} - \frac{1}{\mu}\right)\mu^2$$

$$\beta = \alpha\left(\frac{1}{\mu} - 1\right)$$

This α and β can be interpreted as the number of success and failures that need to be observed in order to obtain the beta distribution that approximates the established three-point distribution. This is not an exact methodology, however, this a-priori information serve only as a starting point and should ideally be updated with additional data

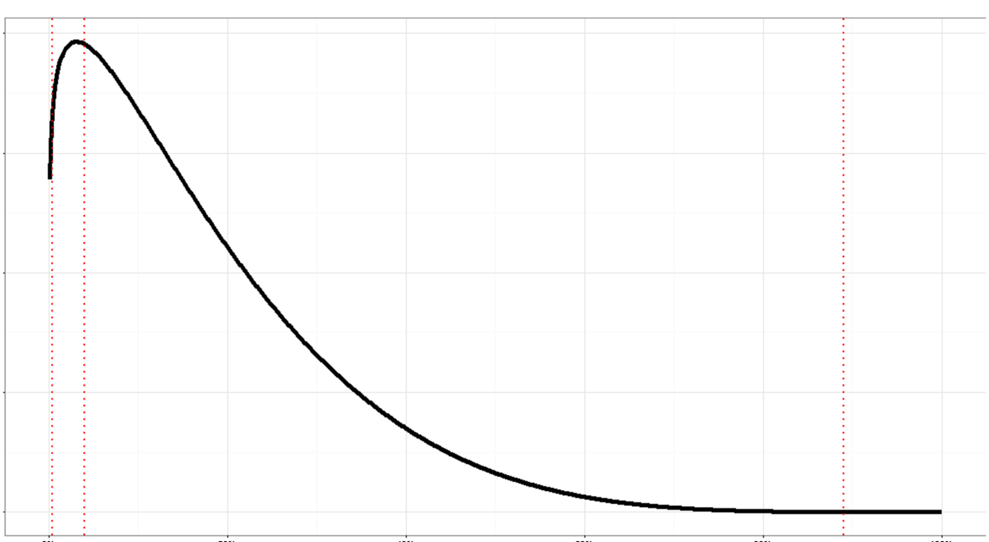

Fig. 1. A Beta distribution based on a best-case estimation of 0.04%, a nominal estimation of 0.4% and a worst-case estimation of 89%.

achieved from real life over time (e.g, through observations or through simulations).

1.2.3. Bayesian Belief networks

Bayesian Belief Network (BBN) modelling is enjoying increased interest in many fields of risk management (e.g., Weber et al., 2010; Zarei et al., 2019). Computing resources have advanced sufficiently to make modelling through expansive Bayesian networks a realistic possibility. Correspondingly a sharp increase in the use of Bayesian networks in risk management applications is seen (Weber et al., 2010) and several examples are available of its application in the field of safety and risk management (Gran et al., 2012; Hänninen et al., 2014; Vinnem et al., 2012; Phillipson et al., 2014). Example applications are a BBN model for maritime safety management (Hänninen et al., 2014), the investigation of risks during maintenance of offshore installations including both technical and human factors (Gran et al., 2012; Vinnem et al., 2012), and the Causal Model for Air Transport Safety (CATS; Ale et al., 2008; Khakzad et al., 2013a; 2013b).

BBN was chosen as framework for QRA+ based on several inherent properties. First of all, fault trees are based on Boolean logic and therefore do not allow to incorporate probabilistic cause consequence relationships, in contrast to BBN's. Secondly, BBN's allow expression and seamless integration of 'certainty' via probability distributions or conditional probability tables. This makes them suitable for predictive modelling of technological, human and organisational factors together to assess a specific (safety) outcome. The model is not based on single probabilities (e.g., the chance of a technical failure in the compressor is 1 in 10.000 h on average), but instead works with a distribution or table of probabilities given certain conditions (e.g., most compressors work up to 30.000 h but some fail within days). Thirdly, different types of information can be combined including statistics obtained from observed data as well systematic estimates made by subject matter experts. Finally, the visual representation is intuitive and relatively easy to communicate with both expert and non-expert audiences.

In sum, BBNs provide a framework in which a family of Beta distributions (Van Erp et al., 2015) can be modelled. Non-parametric Bayesian belief networks (Hanea, 2008; Ale et al., 2008) make it possible to include Beta distributions directly as a prior for specific node in a Bayesian network which represents a failure tree. Combining different tools and techniques potentially allow for more substantiated assessments of human reliability in the context of QRAs.

Here we will investigate the possibility to transform point estimates of human reliability obtained with SPAR-H into Beta distributions by applying the three-point estimation method. These Beta distributions will subsequently be used as input in the Bayesian Belief Network. Fig. 2 illustrates these steps. In theory this methodology has the potential to integrate distributions of estimations of human, organizational, and technological reliability. In this paper we focus on establishing a proof of principle for the methodology by modelling substantiated human reliability distributions as a QRA+. We illustrate the techniques on a case study of chemical storage tanks for which a fault tree has been constructed and which will be remodeled as a Bayesian belief network, allowing for more realistic probabilistic cause – consequence relationships and allowing for probability density functions of the human error probabilities.

2. Case study

To develop the proof of principle of the QRA+ a relevant incident scenario was chosen to serve as a case study: the overfill scenario for chemical storage tanks which work at atmospheric pressure (PGS-29 tanks). Tank farming is a high-risk industry in which overfilling is considered a negative outcome with potentially severe consequences.

The most serious European incident concerning an overfill occurred in Buncefield on 11 December 2005. Another notable overfill event occurred on Oct. 23, 2009, At the Cataño oil refinery in Bayamón, Puerto Rico (CSB, 2009). Analysis of these incident revealed that the human factor (e.g., fatigue) played an important role (Wilkinson and Bell, 2015). Operator error has been identified as most frequent cause for an overfill (Chang and Lin, 2006).

Techniques that can help with improved modelling of the safety and risks concerning this scenario are desirable. Especially considering that filling and emptying operations are conducted frequently and overfills do still occur. Additional advantage of this scenario is that it concerns a process with clear boundaries (i.e., an independent process with relatively little impact from other on-site processes) which makes it a relatively straightforward case to study. In the next section we provide further details concerning the specific case.

2.1. Case description

A major Dutch oil storage company cooperated in the case study. An extensive qualitative study was performed which included: a bowtie sessions workshop, multiple interviews, document study and data analysis. To guide the qualitative study a specific scenario was selected. The specific scenario was aimed at pump operations from a ship towards two land-based atmospheric storage tanks. In these operations, the ship pumps are used, level sensing is available in a central control room and most of the physical changes to valves are done by personnel working outside. In the scenario the total quantity being offloaded exceeded the remaining space in the first (empty) target tank. To accommodate the scenario calls for a so called 'flying switch' procedure towards a second empty tank. With this procedure the flow is redirected while the ship's pumps are not shut down during the switch from target tank A to target tank B. These situations arise when for example an ocean tanker moors at the pier and two tanks are needed to process the content.

The qualitative study resulted in data from various sources, such as the alarm system log of the company and expert judgements on barriers that are in place in scenario. With this data, we identified relevant barriers and modelled them in a failure tree (described below). In addition, we estimated presence and strength of PSFs concerning these barriers in order to establish human-reliability estimates with the SPAR-H methodology.

2.2. Qualitative analysis: creating the failure tree and the BBN

Based on the information and data gathered through interviews and onsite visits a failure tree was modelled describing the process of the selected scenario. A distinction was made between the primary process, a control process, and the 'critical response'. Below we describe these processes in more detail. Fig. 3 illustrates the resulting failure tree and Table 2 provides the summary of all gates and barriers in the accident scenario model for a tank overfill scenario.

2.2.1. Failures in the primary process

Two pathways were identified in the primary process where deviations could lead to an undesired liquid level: (1) during the operation the switch or stop is too late'[1] *(e.g., because an alarm is missed),* or (2) a diverging product stream is created *(e.g., when a valve is not fully sealed)*. Two barriers were considered important to avoid initiating a switch or stop too late. First of all, the liquid level needs to be properly monitored during the filling operation in the central control room to be able to detect in time when the goal liquid level is reached. Second, the switch or stop needs to be performed correctly and in time by operators. If one of these two barriers fail, the switch or stop will be initiated too late. Four barriers were found to be important to avoid creating a

[1] For our model we do not distinguish a failure to switch to another tank or to stop pumping altogether. For both situations, similar factors apply with timely action being the most important.

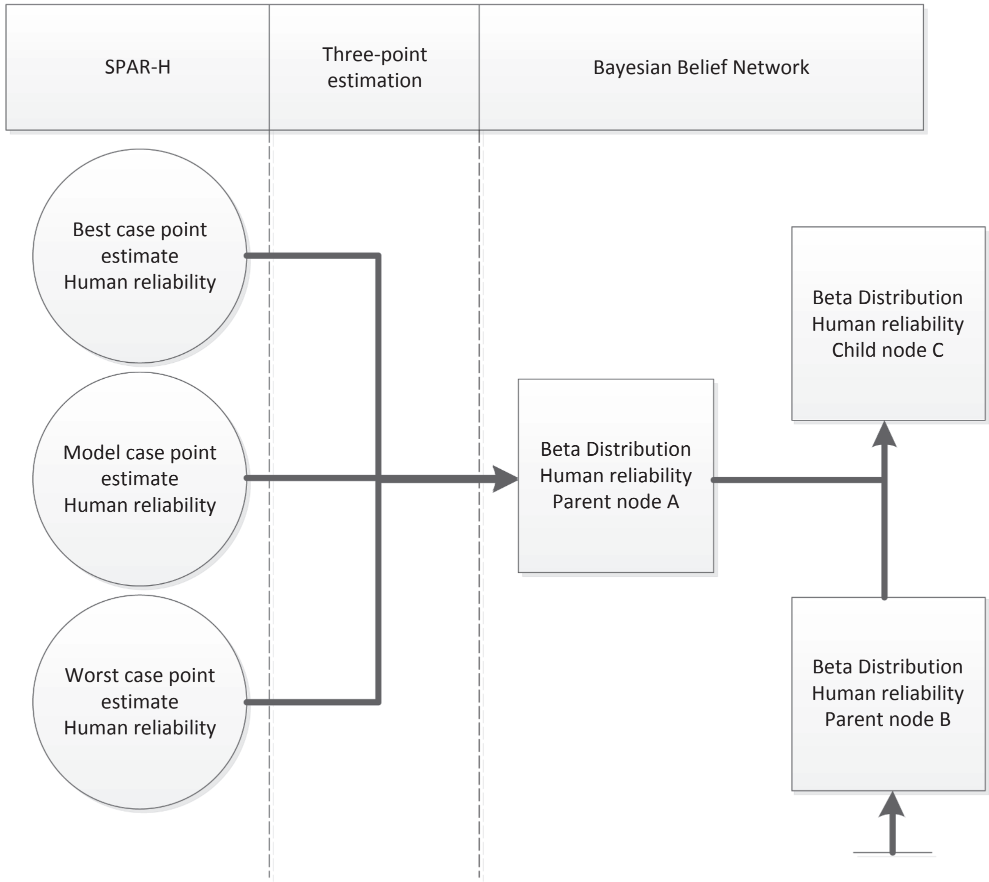

Fig. 2. Beta distributions were calculated by making a three-point estimation with three single-point estimates obtained through SPAR-H.

divergent product stream. First, all valves need to be set correctly for a proper flow of the product. Second, the condition of the valves needs to be undamaged to avoid leakages. Third, the correct volume needs to have been calculated before initiating the pumping operation (to prevent a situation wherein more product is pumped then was expected). Fourth, once a diverging stream is created, this stream should be detected in time. If the last barrier fails in combination with one of the former three, a (undetected) diverging product stream will be created. If the switch or stop is initiated too late or a (undetected) diverging product stream is created, the high-level alarm (HL alarm) liquid level will be reached. This alarm is generated by the main level sensor and presented through the digital control system.

2.2.2. *Control and operational response*

Once the first undesired liquid level is reached, triggering the HL alarm, control over the primary process is considered lost. The scenario then shifts from an operational (primary) process towards a control and response process. This process is oriented towards taking action to avoid further increase of the liquid level. Three barriers were identified that are important towards initiating a proper response to the HL alarm. First of all, the HL alarm needs to function correctly. Second, the HL alarm signal needs to be observed and interpreted correctly in the central control room. Thirdly, operators need to react swiftly and correctly once a signal is detected. When the undesired liquid level is reached and one of these barriers fail, the liquid level will reach a critical level. This level triggers an overfill protection alarm (OP alarm) which is generated by sensing equipment which is technically independent from the HL alarm though it is reported through the same digital control system.

2.2.3. *Critical response*

The processes which occur when the critical liquid level is reached is very similar to the control process described above. The main difference is that a lack of a proper response in this phase will lead to an overfill. Again, three barriers were identified that are important towards initiating a proper response to the OP alarm. First of all, the OP alarm needs to function correctly. Second, the OP alarm signal needs to be observed and interpreted correctly in the central control room. Thirdly, operators need to react quickly and correctly once the signal is detected. When the critical level is reached and either one of these barriers fail, an overfill will occur.

The failure tree can be modelled as a Bayesian belief network as shown in Fig. 4. The nodes in the BBN are the same nodes which are used in the fault tree of Fig. 3, but now they are modelled as a probabilistic cause consequence relationship. The arrows show the conditional dependence from the parent node to its child node. The possible addition of red nodes in the above network will be discussed in Section 4, where the advantages of representing the human factors related to the overfill scenario in a BBN will become visible.

3. Results

The failure tree presented in Fig. 3 and explained in the preceding chapter presents the main causal logic which is present in the overfill scenario that was studied. To quantify a failure tree, probabilities are needed for each of the input nodes. Quantification is thus needed for ‘failures’ of each of the relevant barriers. In Table 2 a detailed specification is given for the nodes and gates which are present in the model and the connections between the different nodes. For each barrier node a prior distribution needs to be developed that models questions like: *What is the probability that the HL level sensor will fail when called upon?*

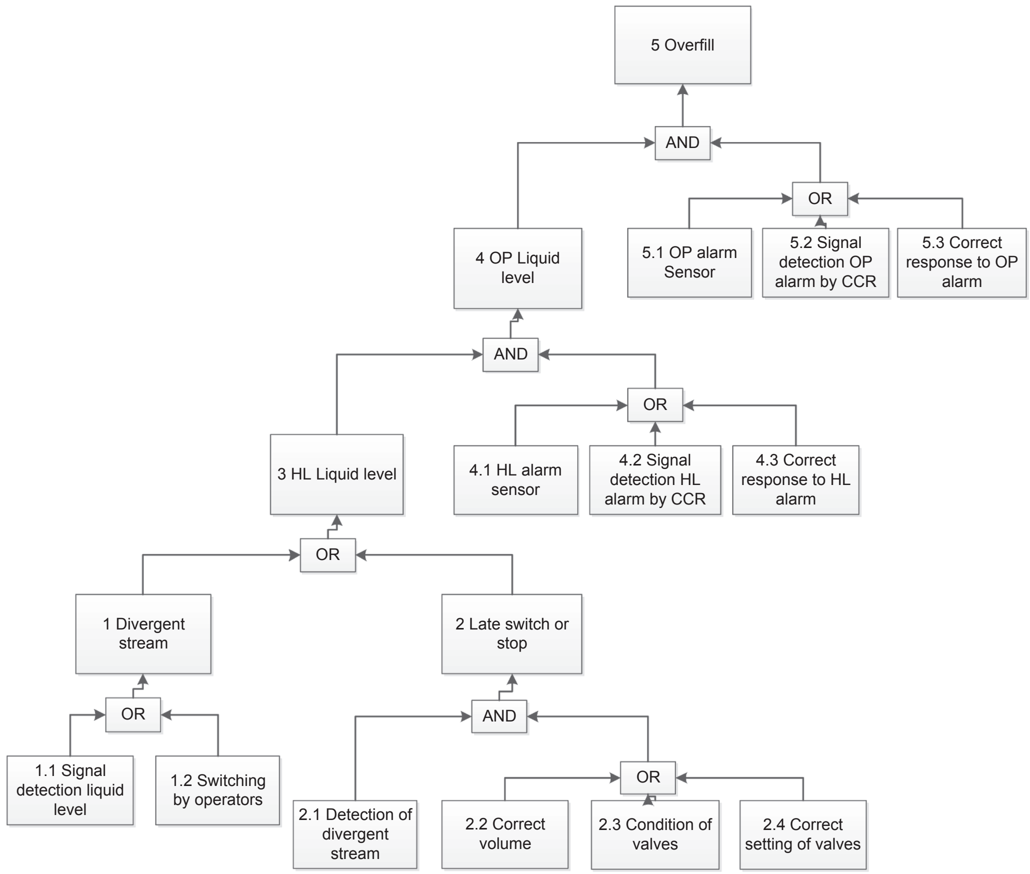

Fig. 3. Failure tree for the risk of overfilling during a flying switch procedure, in which first the HL a (high-level) alarm is reached, followed by the OP (overfill protection) alarm before an Overfill occurs.

Table 2
Identified gates and barriers in the accident scenario model for a tank overfill scenario.

Node	Type	Name	Description	Parent Node[1]	Child Node
1	Gate	*Late switch or stop*	The switch or stop is initiated too late	*1.1 OR 1.2*	*3*
1.1	Barrier	*Signal detection liquid level*	The liquid level needs to be monitored to be able to initiate a stop or switch in time.	–	*1*
1.2	Barrier	*Switching by operators*	Performing the stop or switch correctly and in time.	–	*1*
2	Gate	*Diverging stream*	A diverging product stream is created	*2.1 AND 2.2 OR 2.3 OR 2.4*	*3*
2.1	Barrier	*Detection divergent stream*	*Detection of divergent stream in time.*	–	*2*
2.2	Barrier	*Correct setting of valves*	*Making sure all valves are set correctly*	–	*2*
2.3	Barrier	*Condition of valves*	*Prevention of damage to the valves causing leakages.*	–	*2*
2.4	Barrier	*Correct volume*	*Determining the correct volume to be pumped.*	–	*2*
3	Gate	*Undesired liquid level*	*The liquid level has increased beyond the desired level.*	*1; 2*	*4*
4	Gate	*Critical liquid level*	*The liquid level has increased to a critical level.*	*3 AND 4.1 OR 4.2 OR 4.3*	*5*
4.1	Barrier	*High level sensor*	*Functioning of the HL alarm*	–	*4*
4.2	Barrier	*Signal detection HL alarm by CCR*	*Detection and proper interpretation of the HL alarm signal*	–	*4*
4.3	Barrier	*Correct response to HL alarm*	*Fast and proper response once the HL alarm signal is detected*	–	*4*
5	Gate	*Overfill*	*Liquid level has increased beyond the capacity of the storage tank.*	*4 AND 5.1 OR 5.2 OR 5.3*	–
5.1	Barrier	*Overfill protection sensor*	*Functioning of the OP alarm*	–	5
5.2	Barrier	*Signal detection OP alarm by CCR*	*Detection and proper interpretation of the OP alarm signal*	–	5
5.3	Barrier	*Correct response to OP alarm*	*Fast and proper response once the OP alarm signal is detected*	–	5

Note 1: Although the barriers do not have parent nodes at this stage of model development, indicator nodes to measure the current state of the barriers are introduced in chapter 3.
HL = High Level, OP = Overfill Protection, CCR = Central Control Room

(node 4.1) or *What is the probability that the operations team will fail to detect an HL alarm if it should sound?* (node 4.2). For each gate node a formula needs to be established to integrate the probability distributions which are present in the influencing nodes.

The model primarily consists of barriers concerning human reliability and contains only three technical barriers: *Condition of valves with respect to leakage* (node 2.3)*, High level sensor functioning on demand* (4.1), and *Overfill protection sensor functioning on demand* (node 5.1). In this paper we focus primarily on the modelling of the human reliability distributions as a QRA+. In the next section a brief description is given on how the technical barriers were handled. Next, we will describe how the barrier and gate nodes were quantified.

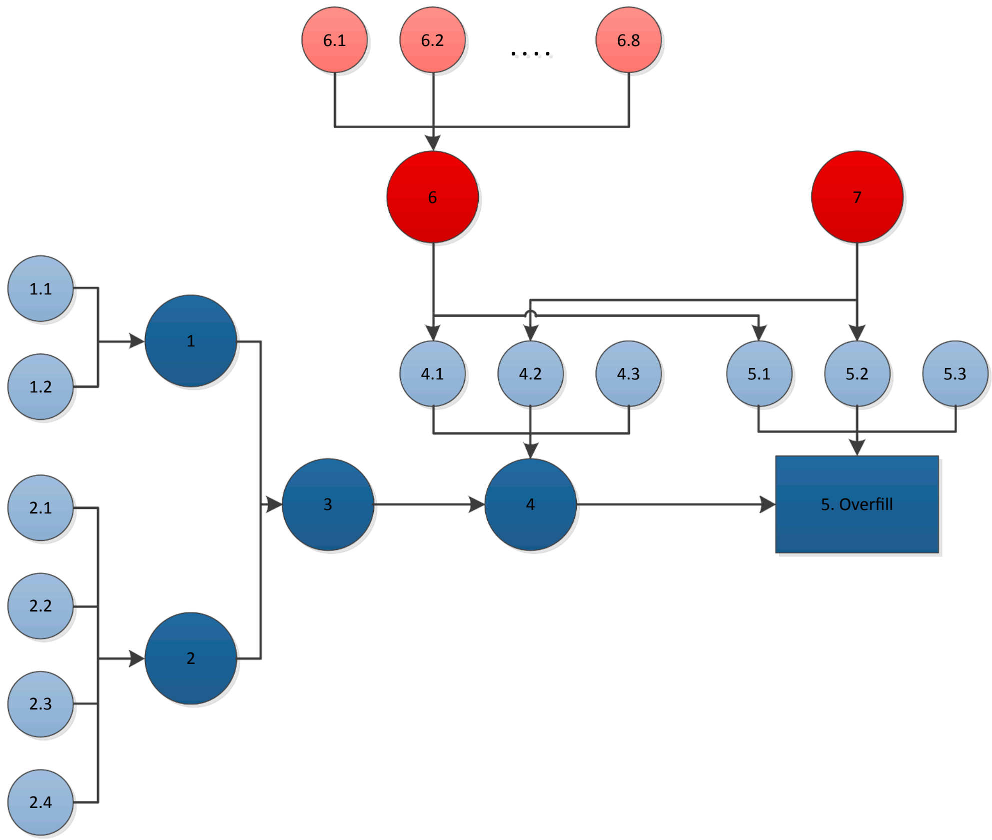

Fig. 4. Bayesian belief network of overfill scenario shown in Fig. 3.

3.1. Quantifying the technical barrier nodes

The prior failure probability density function (PDF) used to model barriers with a technical element were based on a variety of technical documents, including the norms NEN-EN-IEC 61511 (2005) and NEN-EN-IEC 61508 (2010), an alarm systems guide (EEMUA, 2013), and the safety manual for the sensor used.

The norms NEN-EN-IEC 61511 (2005) and NEN-EN-IEC 61508 (2010) define the Safety Integrity Level (SIL) the safety functions of a technical systems need to comply with. To determine the SIL level for a barrier, the existing safety level needs to be compared to the desired safety level concerning a risk. The required reduction determines the required SIL level for the barrier. There are four SIL levels which describe the maximal acceptable probability that a safety function could fail on demand. Table 3 shows that at SIL 1. the safety function is expected to reduce the risk for failure by a factor of 10–100, whereas at SIL 4, the safety function needs to reduce the risk by a factor of 10,000–100,000 (NEN-EN-IEC 61511, Table 3). A safety function's SIL level is determined based on the necessary risk reduction to make the risk in a given context acceptable based on the current values of society (NEN-EN-IEC 61508-4).

Two of the technical barriers concern a sensor for an alarm. In the current scenario, these sensors are not connected to an automatic trip system and require the intervention of an operator. Therefore, they are considered to be safety related alarms (EEMUA, 2013), which require an operator action. In this case the equipment delivering the alarm and the operator response are both part of the safety related system. EEMUA (2013) states that in this case no average probability of failure on demand should be claimed of better than 0.01.

Table 3
Description of SIL levels (NEN-EN-IEC 61511-1).

Safety Integrity Level (SIL)	Target average probability of failure on demand	Target risk reduction
4	$\geq 10^{-5}$ to $< 10^{-4}$	> 10,000 to ≤ 100,000
3	$\geq 10^{-4}$ to $< 10^{-3}$	> 1000 to ≤ 10,000
2	$\geq 10^{-3}$ to $< 10^{-2}$	> 100 to ≤ 1000
1	$\geq 10^{-2}$ to $< 10^{-1}$	> 10 to ≤ 100

However, in this case study scenario the required actions of the operators are modelled separately to the functionality of the technical sensors. This allows for a more detailed and structured assessment of the probability that the operator will fail in response to the alarm, compared to the method described in the technical documents discussed above. The exact method of quantification of the human factor is described in the next section.

To determine the failure probability of the first sensor concerning the high level (HL) alarm, independent of the operator action, the safety manual published by the manufacturer was consulted. This document states that probability of failure per hour is 9.71E − 08. In other words, the expected mean time between failures is 1173 years. This probability is considerably small and could be considered inconsequential for the current model. No such information is available for the sensor concerning the overfill protection (OP) alarm. However, during the qualitative analyse (site visits and interviews) it was established that this sensor is of simple design and that errors could be detected swiftly. As such, for both sensors it was determined that their failure probability was considerably small and therefore could be considered negligible in the scope of the current model. It was therefore opted to remove these barriers from the model and work with the assumption that the alarms would work on demand.

The remaining technical barrier: *Condition of valves* (node 2.3), was based on the SIL levels out of convenience. No data or information was known to the authors concerning a-priori failure rates of valves. Therefore, it was decided to use SIL 1 as base to establish a conservative

Table 4
Example on how to obtain the point estimates for the failure probability distribution for barrier 1.1 *Signal detection liquid level.*

PSF	Modal Level	Modal multiplier	Explanation[1]	Best Case Multiplier	Worst case Multiplier
Available Time*	Nominal	1	–	1	1
Stress and Stressors	Nominal	1	This task is a routine task. Stress might be experienced if workload is high.	1	2
Complexity	Nominal	1		1	1
Experience and Training	Nominal	1	The task is rather straightforward, experience and training are not required for performance, but would make it easier.	0.1	1
Procedures	Nominal	1	The task does not require explicit procedures, but could be helpful if formulated.	0.5	1
Ergonomics	Nominal	1	–	1	1
Fitness for Duty*	Nominal	1	–	1	1
Work Processes	Nominal	1	Work processes surrounding this task are in order and could be improved but also worsen due to circumstances.	0.8	2
Failure probability[2]		,01		,0004	0,04

Note. This example concerns a diagnosis task type with a nominal failure probaility of .01. PSF = Performance Shaping Factor.
1. Explanation is only provided when the PSF deviates from nominal in one or more cases.
2. In the case of the multipliers resulting in a nonsensical probability higher than 1, SPAR-H prescribes the following adjustment formula: $AFP = \frac{NFP * PSF_{composite}}{NFP * (PSF_{composite} - 1) + 1}$, Where AFP is Adjusted Failure Probability and NFP is Nominal Failure Probability.

prior failure probability distribution for this technical barrier. The first SIL level prescribes a fixed value failure probability between 1 in 10 and 1 in 100. Using the three-point estimation method, 0.1 as maximum and 0.01 as minimum, and 0.055 (0.1 + 0.01/2) as modal failure probability, results in a Beta distribution with $\alpha = 12.7$ and $\beta = 218.25$ as a priori PDF (see Table 5, 2.2).

3.2. Quantifying the human factor barrier nodes

Spar-H attributes a nominal failure probability (NFP) of 0.01 to diagnosis tasks and a NFP of 0.001 for action tasks. We identified the following barriers in our model as diagnosis tasks: *Signal detection liquid level* (node 1.1), *Detection diverging streams* (node 2.1), *Signal detection HL alarm by CCR* (node 4.2) and *Signal detection OP alarm by CCR* (node 5.2). The following barriers were identified as action tasks: *Switching by operators* (node 1.2), *Correct settings valves* (node 2.2), *Correct volume* (node 2.4), and *Correct response* (node 4.3)

With the help of the PSFs defined by SPAR-H and input obtained during the qualitative analysis on site, three failure probabilities were estimated for each barrier. The nominal failure probability estimation was based on the qualitative study on site. The main goal in this process was to obtain substantiated priors for each barrier through expert judgement. The best-case estimation was based on a scenario where human factors were optimized to a degree that was considered realistically possible. The worst-case estimation was based on a scenario where human factors were assumed to have deteriorated to a state that would realistically allow a company to remain functional. The resulting three values could then be used for a three-point estimation to obtain α and β values for each barrier (see Section 1.2.2).

In Table 4 we provide an example of this process for barrier 1.1 *Signal detection liquid level.* This example assumes (based on on-site observations) that in the modal scenario all PSFs for this barrier are nominal. However, the worst and best case vary from the modal scenario based on the PSFs ‘Stress and stressors’, ‘Experience and training’, ‘Procedures’, and ‘Work progress’. For example, since this task (i.e., detecting the signal indicating the liquid level reaches its target) is part of the primary process, little stress is generally involved. However, an operator could be under some stress if the workload is especially high.

SPAR-H proposes a lower bound of $1.0E^{-5}$ for a single error probability to still be meaningful in a scenario (Gertman et al., 2005). Proponents with a lower error probablity should be considered to be dropped. No barrier fell below this lower bound. See Table 5 for a complete overview of all values obtained for the barriers.

3.3. Quantifying the gate nodes

The core of the model consists of a failure tree describing the paths that could lead from the primary process to an overfill. At each level an ‘And’, ‘Or’, or ‘Combined gate’ is included indicating the condition that needs to be met before advancing in the tree. In our model, these gates represent the probability that a specific critical result is not met. In table 6 the gates are listed together with a description of the path leading to the gate and the mathematical formula representing this path. This allows us to take the inherent uncertainty of these sort of calculations into account. Software is available that allows such formulas to work with distributions rather than fixed values, for example Uninet (Hanea, 2008).

4. Conclusion and discussion

In this paper we provide further proof of principle for the integration of both human and technical factors in the development towards QRA+ for a high-risk activity. Currently, the assessment of the human factors in Quantitative Risk Assessments generally could be considered superficial. The application of HRA in QRA could be stimulated by facilitating the application of HRA methods in a practical way. Here we presented a methodology that allows the implementation of HRA through SPAR-H while compensating for uncertainty inherent in working with (human) failure probabilities by using Beta distributions. By implementing the HRA-method SPAR-H qualitative information gathered on site and through interviews, can be transformed into quantitative information in a structured way. This paper expands on a previous publication (Steijn et al., 2017) providing information on how to implement the technical factors in this model and by providing more insight in the exact numbers in the model that were obtained through the described methodology.

The QRA+ has been applied for a very specific case: the risk for an overfill during a flying switch from tank A to tank B of 30.000 m^3 K1-liquid (petrol/light naphtha). This case was chosen because overfill is an example of a very relevant high consequence low occurrence scenario. At the same time, it concerns a relative simple procedure from which the relevant factors can be successfully identified, modelled and

Table 5
Overview quantification of all barriers.

Node	Name	*a*	*b*	*M*	*SD*	*5%*	*95%*
1.1	*Signal detection liquid level*	3.96	292.77	1.3%	*0.7%*	*0.4%*	*2.6%*
1.2	*Switching by operators*	0.97	28.07	3.3%	*3.2%*	*1.6%*	*9.9%*
2.1	*Detection divergent stream*	3.42.	6.59.	34.2%.	*14.3%.*	*12.6%*	*59.5%*
2.2	*Correct setting of valves*	1.01	73.98	1.3%.	*1.3%.*	*0.1%*	*4.0%*
2.3	*Condition of valves*	12.70.	*218.25.*	*5.5%.*	*1.5%*	*3.3%*	*8.2%*
2.4	*Correct volume*	1.09.	125.70.	0.9%.	*0.8%.*	*0.1%*	*2.5%*
4.1	*High level sensor*	–	–	*negligible*			
4.2	*Signal detection HL alarm by CCR*	1.26	12.99	0.9%	*0.7%*	*0.8%*	*23.3%*
4.3	*Correct response to HL alarm*	1.1	313.52	0.3%	*0.3%*	*0.0%*	*1.0%*
5.1	*Overfill protection sensor*	–	–	*negligible*			
5.2	*Signal detection OP alarm by CCR*	1.26	12.99	0.9%	*0.7%*	*0.8%*	*23.3%*
5.3	*Correct response to OP alarm*	1.09	124.09	0.9%	*0.8%*	*0.1%*	*2.5%*

quantified. The resulting model gives with relative little computational effort insight in the process of the flying switch and would allow for sensitivity analysis concerning which barriers contribute most to the modelled risk.

The current methodology allows both quantitative and qualitative data to be combined in a single model. This way information from all available sources is utilized. SPAR-H provides the means to translate qualitative information into failure probabilities for human tasks.

The use of Beta distributions within a Bayesian Belief Network adds complexity compared to simpler conditional probability tables (CPT). However, this added complexity is justified since being able to use Beta distributions takes the uncertainty surrounding (human) error probabilities into account. The use of distributions rather than single values to model failure probability distributions, avoid putting too much value in a single number. The single point estimates obtained through SPAR-H were transformed into beta distributions with the help of the three-point estimation technique.

Furthermore, beta distributions allow updating with new information to provide more accurate combined technical and human factor failure rate estimations. For the presented model this requires the identification of influential indicators for each barrier. This would allow organizations to update the model to their situation through an assessment or measurement of the relevant indicators. This could subsequently allow comparisons with benchmarks when data is gathered from sufficient organizations. The potential of the described method to establish pre-developed models for certain high-risk scenarios and relevant indicators, addresses an important barrier in the application of these method. Paltrinieri and colleagues (2016) concluded that the application of requires a thorough qualitative analysis of the tasks performed by the operator and crew in the chosen scenario.

The use of a Bayesian Belief Network also adds complexity when the number of random variables and the number of different states of these variables, becomes large. These large numbers would lead to very time intensive specifications of the probabilistic relationships. In order to reduce the model building effort, the CPTs can be approximated to Noisy-OR and Noisy-AND gates. These gates require fewer conditional probability estimates in approximating the CPTs, as shown for instance in Chockalingam et al. (in preparation) while eliciting probabilities in BBNs to distinguish between intentional attacks and accidental technical failures in critical infrastructures.

The proof of principle presented in this paper is but the first step in the development of a QRA +, ultimately leading to QRA + applications with substantive HRA foundation. The methodology described here can serve as a foundation for future applications on different scenarios. Through multiple applications of this approach, the method can be optimized. For example, this will show whether the model can be considered generic for this particular scenario or whether this will be different for each company. By including other companies, additional data can be accumulated which can be used to improve a priori assumptions currently in the model and therefor can lead to better estimations of failure probabilities. This may lead in turn to a benchmark given a particular scenario to which companies can compare based on the status of for example their PSFs. Alternatively, the method could be applied to other high-risk low probability scenarios. It can be used to create models for other high-risk/low probability scenarios. This acquired knowledge can subsequently be applied to other scenarios, to allow the establishment of benchmarks for QRA + given a variety of risks.

Although the integration of the human and technical factor has been successful, the current methodology has several limitations that need to be addressed in the future. First of all, the current model does not yet take interdependencies into account. The failure probability distribution for each barrier has been defined in isolation while it can be expected that the failure probability of certain barriers is not completely independent. For example, if the H-H alarm is missed, it is likely that the same operator will also miss the H-H-H alarm because the same factors that caused the operator to miss the first alarm are still present. In other words, if it is established that the barrier *signal detection has* failed at the H-H alarm, this increases the chance that the barrier *signal detection* will also fail at the H-H-H alarm. This can be incorporated in the BBN by adding a human factor node 7, which influences 4.2 and 5.2 (see the red nodes in Fig. 4). Similarly, technical independence rarely takes place in practice. For example, even though activation of the H-H alarm and the H-H-H alarm are independent systems, their display in the Central Control Room takes place through a similar system. If this display system fails, both the H-H alarm and the H-H-H alarm are likely

Table 6
Formulas used in the model.

Gate	Formula	Formula description
1	$P(1) = 1 - ((1 - P(1.1)) * (1 - P(1.2)))$	*Barrier 1.1 or 1.2 fails.*
2	$P(2) = (1 - ((1 - P(2.2)) * (1 - P(2.3)) * (1 - P(2.4)))) * P(2.1)$	*Barrier 2.2, 2.3, or 2.4 fails and barrier 2.1 fails.*
3	$P(3)=1 - ((1 - P(1)) * (1 - P(2))$	*Gate (1) or (2) is reached.*
4	$P(4) = (1 - ((1 - P(4.1)) * (1 - P(4.2)) * (1 - P(4.3)))) * P(3)$	*Gate (3) is reached and barrier 4.1, 4.2, or 4.3 fails.*
5	$P(5) = (1 - ((1 - P(5.1)) * (1 - P(5.2)) * (1 - P(5.3)))) * P(4)$	Gate (4) is reached and barrier 3.1, 0.3.2, or 3.3 fails.

to fail to alert the operator in charge of monitoring the alarms. This can be incorporated in the BBN by adding a technical factor node 6, which influences 4.1 and 5.1 (see Fig. 4).

A second limitation is that the presented model has not yet integrated organization factors in the current model as well. The current proof of principle shows the successful integration of the human and technical factor. This still leaves organization factors which also play an important role in most incidents. This could be addressed in future work. There are tools available to quantify the organizational factors (e.g. van Kampen et al., 2016). Here they are mostly addressed as the PSFs or influential factors that affect the error probability of the human or technical elements. Integrating these organizational factors in a similar fashion as above can be incorporated in the BBN by adding PSF nodes 6.1–6.8 (in Fig. 4), influencing the human factor node 6, for each of the 8 PSFs listed in Table 3. Secondly,

A third limitation, is that the model is based on numerous assumptions and estimations. SPAR-H is but one of many possible theories to determine human error. Other models might result in different values. This is also why this model benefits from the use of Beta distribution; these distributions take these forms of uncertainty by providing a distribution rather than a single value. In theory, the used a-priori estimations will become more accurate as more data is accumulated. However, the current case-study, a tank overfill, is a high risk, low probability scenario. This scenario was specifically chosen. As a result, the opportunities to gather additional observations at the undesired top-level event will be limited. It is therefore important that the a priori estimations are established as accurately as possible. We note however that failure data of valves and sensors at lower levels may also be helpful to feed our models.

To conclude, integration of substantiated estimations of human failure probabilities will have substantial implications for quantitative risks assessments. Although further research is required, the development of QRA+ will allow companies to make more detailed risk assessments and allows them to identify a wider range of interventions to reduce the risk of failures in activities and thereby improve their safety performance.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssci.2019.104514.

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