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Human reliability assessment for tank overfilling incident utilizing minimized human performance shaping factors

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Abstract. Human errors are identified as significant contributors to process industry accidents. Human reliability analysis (HRA) has been conducted in previous studies to improve human performance in several industrial operations. However, human error predictions are greatly influenced by various performance-shaping factors (PSFs). Research also demonstrates that PSFs are interdependent, which thereby complicates the modeling and analysis. Therefore, this study performs HRA, for a tank overfilling accident scenario that resulted due to human failure.Fewer independent PSFs through careful classification were used to estimate tank overfilling probability resulting from different human-triggered factors. For HRA, this study uses a combination of the Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) and Bayesian Belief Network (BBN). The failure probability distributions of individual interconnecting tasks were calculated using SPAR-H, and the probabilistic interdependence of each task to the final tank overfilling scenario was modeled using a BBN. From the current analysis, divergent stream identification is determined as the key to lead tank overfilling with 40% probability. This study concludes that BBN can be reliably employed in the Quantitative Risk Analysis (QRA) framework to examine human factors in industrial failure probability estimation for various other human-related industrial accident scenarios.

Introduction

The industrial sector has grown to meet global demand. Chemical process industries (CPIs) must use sophisticated techniques that incorporate human-machine interactions (HMIs) [1]. Despite regulatory action, there has been a continuous increase in accidents at CPIs. Moreover, more than 80% of such accidents in the process industries directly or indirectly correlate to human factors [2]. Legislative bodies are concerned about risk minimization in CPIs and avoid enormous financial and environmental losses [3].

Due to the importance of human factors in safety management, many industries have been conducting human reliability analysis (HRA) [4]. Several HRA approaches have been developed for chemical process industries, including structured probabilistic risk assessment and cognitive theory of control. Fault Tree Analysis (FTA) and Fuzzy Bayesian Network (FBN) are utilized to investigate human factor contribution in flammable storage tanks [5,6]. Standardized Plant Analysis Risk-HRA (SPAR-H) was used to study probabilistic human error in storage and transportation where SPAR-H proved as a simplified method to represent human behavior [6,7]. Human error in Malaysian oil and gas sector has recorded considerable accident rate with 35% as of 2009 (Ministry of Human Resource) [8]. Due to increased oil and gas operations, the risk of accident occurring could further increase [9]. Nonetheless, with the exception of Oktarinandaand Norazahar[10], and Alaw et al.[11], only a few studies have attempted to estimate the probability of human error in the oil and gas sector while taking Malaysia's demographics into account. Hence, there is still a need to accurately identify the human factors, work culture and their interrelationships associated with a chemical plant operation in Malaysia.

QRA is a standardized tool for industrial plant accident analysis and risk mitigation [12]. The current QRA framework also makes use of advanced Computational Fluid Dynamics (CFD) for consequential analysis together with probabilistic modelling [13,14]. Even though QRA is not an exact reflection of reality, it is currently the most widely utilized tool for analyzing the hazardsof complex processes and storage facilities [15]. Although QRA is a consolidated tool, the inclusion of the human factor in its framework is still trivial [16,17].

Humans have contributed to past chemical process industry accidents [18]. The QRA studies in industries could merge in the state-of-the-art human reliability analysis methodologies to quantitatively assess process industries accidents more comprehensively [19]. In this regard, Bayesian Networks (BNs) are effective for analyzing random variable connections, displaying a domain's probabilistic model, and deducing causal probabilities for scenarios given data.Bayesian modeling in QRA framework has been applied in marine research [20–25] and fire- induced domino effect probabilistic modeling [26–31]. Nevertheless, HRA in onshore process industries using Bayesian networking has received less attention. SPAR-H is another second- generation HRA approach that, unlike earlier human error probability (HEP) methods, uses generalizations to represent the spectrum of human behavior. Furthermore, human performanceis influenced by PSF, and their inter-relationship study has only been conducted in regard to the nuclear power plants [32]. Hence, there is also a need to establish an approach to identify the keycorrelating PSFs in oil and gas applications.

This research investigates human error probability for storage tank overfilling in Malaysian process facility demographics and operator culture. Chemical mishaps are common at storage and distribution facilities and the fuel level monitoring is performed by operators and thus necessitates the human reliability analysis [9]. Previous studies on HRA reckon that integratingSPAR-H with BN could deliver enough accuracy with a limited dataset. Hence, in this study, the SPAR-H technique is used to quantify prior human error probability by incorporating modified PSFs (time, stress/stressors, and complexity) and then the Bayesian Belief Network (BBN) model is built to integrate human factors in QRA. The model is validated against a published overfilling storage tank case study.

Methodology

This research aims to improve the QRA framework by including human factors. Figure 1 shows the study's process flow.

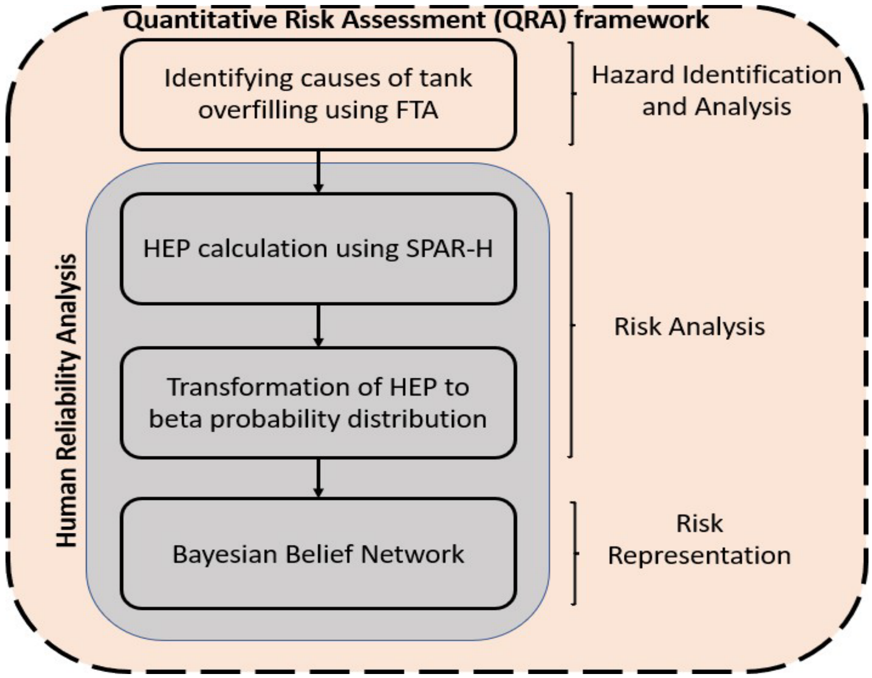

Fig. 1. Process flow of HRA inclusion in QRA framework developed in this study.

Hazard identification:
QRA and risk management frameworks include hazard identification to recognize the causesof any incident. Most of the common hazard identification techniques used in process industriessuch as Hazard and Operability Study (HAZOP), What-If Analysis, Preliminary Hazard Analysis, etc. are qualitative based as summarized by [31]. However, FTA provides a qualitativeand quantitative estimate of hazard and a logical, quantified description of unwanted events, including basic events from human factors as one of the causes of failure to the top event. Therefore, this study adopts the fault tree analysis from Steijn et al. [7] for the estimation of modified human error probability as initial basis or input to BBN model.

Human error probability calculation using SPAR-H:
Studies show that integrating SPAR-H method with BBN delivers enough accuracy with a limited dataset. Based on earlier research, BBN-SPAR-H has the simplest structure and is the most likely method to be included in this extended QRA framework. SPAR-H classifies PSFs that affect human reliability in process industry operations. As illustrated in figure 2, the existingSPAR-H has eight PSFs and can't effectively manage dependencies [32,33]. Liu and Li [34] suggested to deduce a SPAR-H model that comprises of independent set of well-defined PSFs toreduce the overall model complexity. In this respect and relating to the tank overfilling scenario,the present study carefully considers three key independent PSFs, namely, available time, processcomplexity, and mental stress/stressors as suggested by Park et al. [32]. The consensus was reached through careful evaluation by an experienced team of process safety experts and operators that have experienced in handling the same tasks as in this case study.

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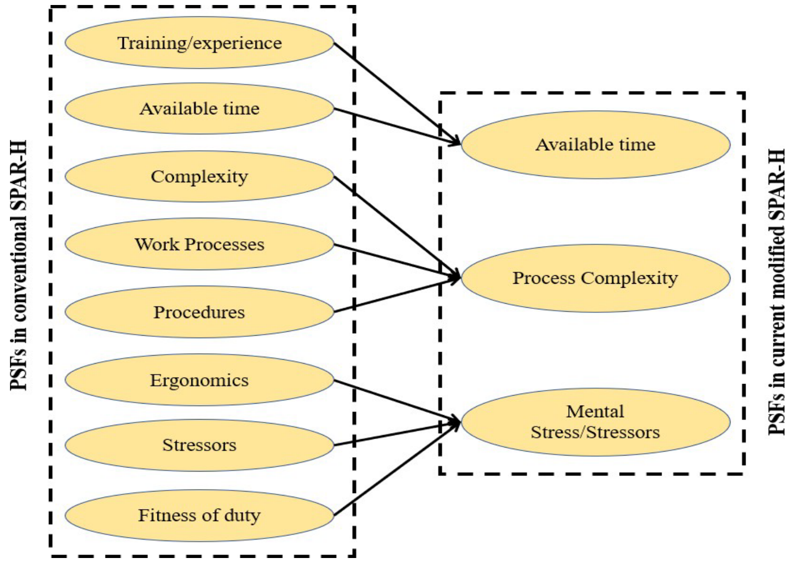

Fig. 2. Modified SPAR-H methodology with less independent PSFs determined in this study.

Expert judgments are needed to identify the appropriate multipliers for each PSF depending on three conditions: worst-case scenario, modal-case scenario, and best-case scenario. Further details on the PSF multiplier definition can be found elsewhere [35]. Multiplier ranges for currentstudy are listed in Table 1.

Table 1. Multiplier Ranges for PSFs considered in current research [35,36].

PSF	Multiplier range
Available time	0.01-10 (less available time corresponds to greater multiplier)
Mental Stress and stressors	1-5 (high stress corresponds to greater multiplier)
Process Complexity	1-5 (high complexity corresponds to greater multiplier)

The corresponding multipliers of each independent PSF are used to estimate the overall Human Error Probability (HEP) given by equation 1[36,37].

$$\mathrm{HEP} = \mathrm{HEP}_{\mathrm{nominal}} \prod_{1}^{3} \mathrm{PSF}_{\mathrm{i}} \mathrm{i} = 1,2,3, \ldots \tag{1}$$

'$\mathrm{HEP}_{\mathrm{nominal}}$' for diagnosis task is 0.01 while for action task is 0.001 [38]. Diagnosis relates to cognition, which includes everything from analyzing information to making decisions whereas pressing a button etc. is referred to as action task. If the calculated product of multipliers and the nominal human error probability yield an illogical value of higher than 1, the adjusted HEP needsto be used as shown in Equation 2 [36,37].

$$\mathrm{HEP}_{\mathrm{adjusted}} = \frac{\mathrm{HEP}_{\ \mathrm{nominal}}\, \Pi_1^3 \mathrm{PSF}_{\mathrm{i}}}{\mathrm{HEP}_{\mathrm{nominal}}\, (\Pi_1^3 \mathrm{PSF}_{\mathrm{i}} - 1) + 1} \tag{2}$$

Single-point HEP transformation to Beta distribution. Uncertainty may develop in the conventional method of calculating human error due to varied thinking styles. The multipliers are necessary because the numerous point inputs must be translated to the Beta distribution (probability distribution), which can decrease the gap by allowing the analyst to express their uncertainty across a large range. This research calculates the beta probability distribution's standard deviation and mean using the three-point estimate approach (equations 3 and 4) [39,40].

$$\text{Mean } (\mu) = \frac{\min + (4\text{mod}) + \max}{6} \tag{3}$$

$$\text{Std, dev } (\sigma) = \frac{(\max - \max)}{6} \tag{4}$$

The lowest realistic case is called the min (best case scenario), normal operation is called the mod (modal case scenario), and the highest realistic case is called the max (worst case scenario). The min number indicates the quickest time to complete a task and vice versa. In this work, an operator with 20 years of experience at one of Malaysia's multinational oil and gas firms determined failure probabilities through expert judgment. The formula to obtain the beta probability distribution is given in equation 5 [7].

$$\mathrm{P(x)} = \frac{(\mathrm{x}-\mathrm{p})^{\alpha-1}(\mathrm{q}-\mathrm{x})^{\beta-1}}{\mathrm{B}(\alpha,\beta)(\mathrm{q}-\mathrm{p})^{\alpha+\beta+1}}; \alpha = \left(\frac{1-\mu}{\sigma^2} - \frac{1}{\mu}\right)\mu^2, \beta = \alpha\left(\frac{1}{\mu} - 1\right) \tag{5}$$

The α and β represent the number of success (α) and failures (β) that have been observed.

Bayesian Belief Network (BBN):
Computing resources have progressed sufficiently to allow probabilistic modeling using Bayesian networks a viable option. Furthermore, BBN modeling is gaining popularity in severalareas of industrial risk management [41] using GeNIe Modeler [42]. Beta Distribution providesnetwork prior probability distributions. The continuous beta distribution model is converted to discrete data. GeNIe Modeler [42] uses Monte-Carlo sampling to generate random variables. This stochastic model will generate random inputs inside the defined boundary. Each run buildsconditional probability. The model has 1,000 samples and discretization. Current scenario statesfail or not fail for conditional probability. The model's maximum and lowest boundaries are basedon each node's starting value. To limit node sensitivity, BBN should have fewer than five layers,but this relies on the topology since asymmetrical intermediary nodes may be deliberate [43]. BBN outputs failure probabilities for each Failure Tree gate. The software employs Bayes Theorem propagation, which incorporates prior node beliefs. The failure probability of storage tank overfilling is predicted with this knowledge.

Modelled Scenario:
Pumping activities from a ship to two land-based atmospheric storage tanks are included in the scenario. Offloaded fuel exceeded the initial (empty) target Tank X's capacity. To compensate, flow is transferred to Tank Y while the ship's pumps remain operating. This resultedin tank overfilling caused by human error.

Results and discussions

The nodes representation and the interdependency between nodes follow the already established fault tree network from the study of Steijn et al. [7]. The well-established fault tree for tank overfilling scenario is shown in figure 3 is then translated into BBN for probabilistic assessmentas shown in figure 4.

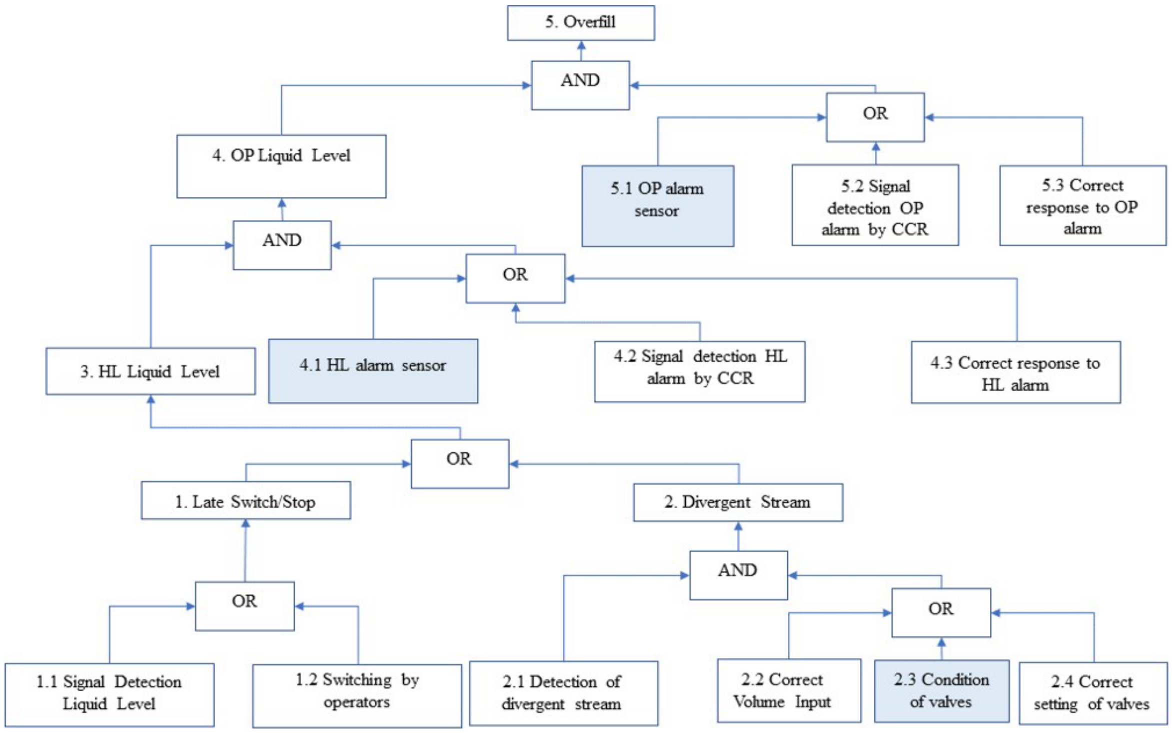

Fig. 3. Fault tree network for tank overfilling scenario established by Steijn et al. [7] where, HL =High Level, OP = Overfill Protection, CCR= Central Control Room.

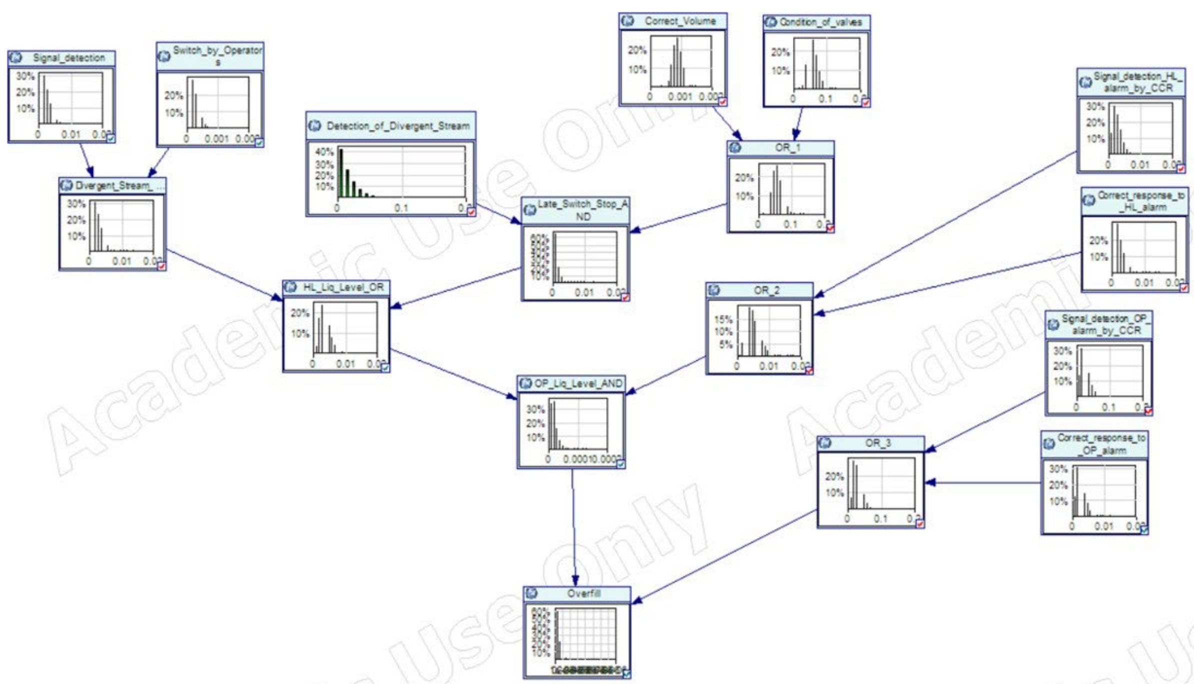

Fig. 4. Probabilistic BBN model for tank overfilling scenario developed based on current PSFs.

Figure 4 of the BBN model shows a 60% possibility of tank overfilling, with Overfill Protection (OP) liquid level failure being more likely (40%) than OP alarm detection and reactionfailure. This is because the high-level liquid valve requires operator intervention to stop the pumpand thus possibly be mishandled. OP liquid level is highly influenced by the failure of high liquidlevel, which is caused by late switch operation (60%) and divergent stream detection failure (40%chance). The reason in this scenario could be that both processes (switch operation and divergent stream detection) are being performed by a human operator in control room, and any delay in valve operation or tank liquid detection leads to undesired overfilling scenario. The operators may not provide continuous monitoring in such operations due to eyestrain and the task is to justswitch the tank back or maintain routing to the tank if it is empty after long durations. The use of autonomous switches could provide on-time response to switching and divergent detection totimely avoid the overfilling without operator straining. The BBN model identified the major factors (nodes) likely to contribute to tank overfilling. This study used fewer separate PSFs thanearlier investigations, which improved failure probability prediction. This discovery lowered thecomplexity of estimating human error probability. The BBN model quantifies the interdependence of several contributing components.

Table 2 shows comparative analysis where Steijn et al. [7] random value distribution resultedin more scattered data than the existing questionnaire datasets. This may be because Steijn et al. [7] had a greater standard deviation. However, the difference in the mean failure probability is only 6% and a lower standard deviation of this study is more reliable because the data is closer to the mean. Moreover, the probability data skewness in present work is less which corresponds to greater accuracy and thus the present work appears to be of greater significance in terms of simplicity and accuracy. Overall, the tank overfilling probability is low because failure probability didn't surpass 1×10^{-3} [44].

Table 2: Comparison of the statistical parameters in failure probability distribution against published work.

Data Source	Mean	Standard Deviation	Skewness
Steijin et al. [7]	4.9e-07	8.8e-04	3.86
Current work	4.6e-07	6.2e-04	3.63

Since the method involves elicitation of prior probability from the expert judgment, the data collection from virtual simulation can also further improve the reliability of the data as it is closely imitating the real digital HMI interface environment. The scarcity of empirical data alongwith uncertainty and variability creates further challenges in the human failures' quantification. Therefore, assessing and identifying suitable prediction tools with limited dataset is essentially required for future research to overcome the current limitation of data availability for human error probability estimation in process industry.

Conclusions

This study reduces model complexity by limiting the number of PSFs from eight to three factors. Instead of a subjective point probability assessment, the SPAR-H point probability is transformed into a beta probability distribution to represent the spectrum of human error probability. This reduces the uncertainty element in the prediction of human error probability. It was discovered that the current model with fewer independent PSFs conforms to the one with all eight PSFs involved. A BBN was developed using a previous study's tank overfilling scenario. The causal components (nodes) of BBN were determined using fault-tree analysis from past research. The risk of tank overfilling was found to be substantially dependent on the fundamental cause of failure in divergent stream identification by operator. According to the study, BN may be utilized effectively in QRA to examine the dependence of human-related factors on the probability of failure associated to the outcome. There is still potential in training of non-technical staff and development of novel assessment methods to further exploit the performance shaping factors as necessitated in high-risk systems. Furthermore, diverse research analyses are plausible in terms of cognitive load of operators in complex dynamic work environments using advancing techniques such as machine learning and Artificial Intelligence (AI) and CFD.

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