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Assessment of Dynamic Failure Probabilities for Human Factors

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Abstract: Human factors have been identified as one of the major root causes to most catastrophic incidents in processing industries. However, the estimation of failure probabilities due to human factors with time; in other words, the ability to learn from the process history has received little attention. In this study, a hybrid methodology is developed which combines a conventional Swiss Cheese model with Bayesian theory to predict the failure probabilities by human factors. Accident sequence precursor data within a period of interval time is utilized to generate the dynamic mode. This methodology is then applied to offshore safety assessment study. The result shows that the failure probabilities of human factors can be predicted for the desired time interval. It is proven that the approach has the ability to learn from process history and act as a predictive tool that provide early warnings toward human deficiency. A robust action plan can then be taken to enhance the overall human performance and ultimately to reduce the likelihood of major incidents.

Key words: Bayesian inference, dynamic failure probabilities, human factor, Swiss Cheese model

INTRODUCTION

It has been estimated that up to 99% of accidental losses (except for natural disasters) begin with Human Error (HE) that is supported by data from more than 1500 investigations (Bridges and Tew, 2010). This is not only human unintentionally making errors directly to the process itself but also they are creating deficiencies in the design and management systems. Therefore, there is a need to increase focus on Human Factors (HF). Health and Safety Executive (HSE) has defined HF also known as ergonomics as: The environmental, organizational and job factors and human and individual characteristics which influence behavior at work (HSE, 1999).

To overcome this issue, a Swiss Cheese model proposed by Reason (1990) is among the most recognized tools to deal with HF since other common hazard analysis tools such as FTA and HAZOP are more suited in managing process hazards. The uniqueness of the Swiss Cheese model is the ability to force investigators to address the latent failures within the causal sequence of events. Several hazard analysis methods had utilized the same concept used in the Swiss Cheese model such as Human Factors Analysis and Classification System-HFACS (Wiegman and Shappell, 2003); Incident Cause Analysis Method-ICAM (Gibband and de Landre, 2002) and Safety Through Organizational Learning-SOL (Fahlbruch and Schobel, 2011). However, this model is more valuable if it is integrated with a quantitative analysis tool to enhance its capability.

Bayesian Network (BN) is recognized as the powerful tool to support causal inference in situations where the data for analysis suffered with a high level of uncertainty (Ren *et al*., 2008). In recent years BN had been commonly utilized in the development of a more dynamic failure assessment of processing facilities. Meel and Seider (2006) is the pioneers in implementing this approach to revise the process deviations and failure analysis in chemical process industries. Meel *et al*. (2007) combined Bayesian and joint probability theories to conduct the dynamic failure assessment and to develop a predictive model of a given process. Kalantarnia *et al*. (2008) has used the dynamic failure assessment model to analyze a chemical process unit and joint probability theory as a predictive model. A few researchers such as Kalantarnia *et al*. (2008) and Yun *et al*. (2009) utilized a similar methodology. Nevertheless, few attempts are made to assess HF contribution in failure probabilities using this tool.

Although, most of the methodologies emphasized in estimating failure probabilities of a process or system operation. Therefore, this study reports the proposed method of integrating the Swiss Cheese with BN in order to estimate the dynamic failure probabilities that is

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associated with HF. The proposed methodology can be used by safety or design engineers as a predictive guideline to monitor or enhance human performance in the processing industries.

METHODOLOGY

Step 1: The starting point of this study is to identify all the expected causes and failure factors through literature studies and empirical investigations. Hence, a causal conceptual model proposed by Reason (2008) that used a similar concept with the Reasons's Swiss Cheese model is utilized. This model uses five levels of hierarchical abstraction: Level 1; Consequence, Level 2; Accident, Level 3; Incident, Level 4; Trigger event and Level 5; Root cause, where each level provides a different cause/contributory model.

Step 2: Prior failure distribution represents the knowledge about the system prior to the start of operation and can be formulated as follows:

$$f(X) = X^{a-1}(1-X)^{b-1} \tag{1}$$

where, f(X) is the prior distribution, X is the failure probability of the HF and a,b are the parameter of the prior failure distribution.

The value of a and b are selected using historical information or expert knowledge. An uninformative prior may be used if no knowledge is available. Hence, in this study, Jeffrey's prior distribution is utilized to overcome the above matter, as shown below (Jeffreys, 1946, 1961):

$$\pi^*(X) = x^{-0.5}(1-X)^{-0.5} \tag{2}$$

where, $\pi^*(X)$ is the Jeffrey's prior distribution when $a = b = 0.5$.

Step 3: The likelihood function is estimated through the application of Accident Sequence Precursor (ASP) data that represent the number of near misses and incidents that occur within the process as it operates. The likelihood function is defined as (Johnson and Rasmuson, 1996):

$$f(\text{Data}|X) = \binom{M}{N} X^N (1-X)^{M-N} \tag{3}$$

where, f(Data|X) is the likelihood function, M is the number of "Challenges" and N is the number of "Occurrences/failures".

Step 4: Bayesian inferences are used to calculate the posterior distribution through utilization of the Jeffrey's prior distribution and likelihood functions. The posterior distribution can be formulated as below (Ferson, 2005):

$$f(X|\text{Data}) \alpha \pi^*(X) f(\text{Data}|X) \alpha X^{N-0.5}(1-X)^{M-N-0.5} \tag{4}$$

where, f(X|Data) is the posterior distribution.

If the value above 1.00, the failure probability has to be assumed to be 1.00 and no more, as a total failure probability can never exceed 1.00 (Williams, 1992).

CASE STUDY

A study on offshore safety assessment by Ren *et al.* (2007) is revisited to test the proposed model. The study aimed to analyze the collision risk between a floating Production, Storage and Offload (FPSO) unit and the authorized vessels during a tandem offloading operation. The failure factors are identified using the Swiss Cheese model in a way that the human elements indirectly may cause the collision with the FPSO and thus may cause personal injury/loss, as demonstrated in Fig. 1.

The estimated failure probabilities are called the 'Priors' representing our belief about the system before observing the new data. In the absence of parameter values of the prior distribution function; Jeffrey's prior distribution is used that weights all the parameters equally that providing a relatively flat distribution in the region of interest; that is, a non-informative prior distribution, as

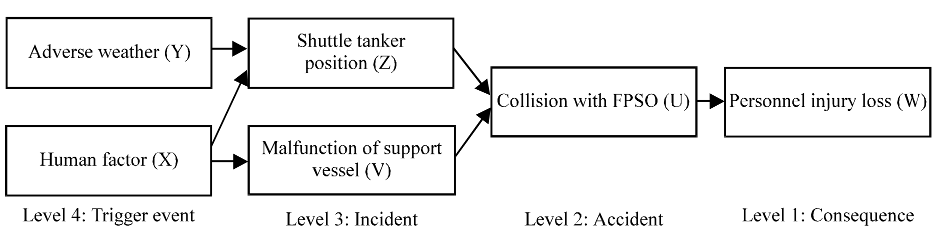

Fig. 1: Failure factors of the collision risk between an FPSO unit and the authorized vessels (Ren *et al.*, 2007)

presented in Eq. 2. As ASP such as wrong procedure used, work pressure, stress and unclear language, is generated during the period of study, Bayesian theory is utilized to update the prior failure probabilities. As an example, Table 1 shows the hypothetical ASP data of HF over 10 time interval. The data is reported cumulatively, showing the total number of occurrences/failures, N_j and number of challenges, M_j through the end of each time interval. The posterior failure probabilities are estimated from the Jeffrey's prior distribution and likelihood function using Bayesian inference, as presented in Eq. 4. The mean value of the posterior failure probabilities is updated from the prior mean a/a+b to (a+N)/(a+b+M) where, a = b = 0.5.

RESULTS

Table 1 illustrates the results of the posterior failure probabilities assessment over the time interval of 10 months. It shows that the posterior failure probabilities of HF change drastically as new data are observed and integrated into the analysis. It is important to note that the proposed model only focuses on the estimation of failure probabilities of HF to show the influence of HF in the overall failure probability profile.

Figure 2 is simulated to clearly signify the above posterior failure probabilities with time. The slope of the trend line represents the hazard rate, which is the failure probability per unit time, associated with HF.

To estimate the average failure probabilities of HF within the next time intervals, the linear hazard model presented in Fig. 2, could be utilized as a predictive tool. As an example, the average failure probability of HF in the 11 months may be estimated by substituting the value in the model:

$$P_{HF}(t = 11) = (0.033\times 11)+0.4755 = 0.8385$$

The above calculation shows that the average failure probability of HF in the 11 months is predicted with the value of 0.8385. The same approach can be used to predict the failure probabilities for the others time interval, as illustrated in Table 2.

Table 2 shows the trend is increasing with time since the failure probabilities are revised once there is increased in cumulative ASP of HF data. This approach is less complex and easy to be used, with the assumption that the HF is equally distributed over the time domain and behaving as normal. However, in reality the occurrence of failure over time is random. To overcome this problem, a Poisson distribution model may be used where it will be considered in a future study.

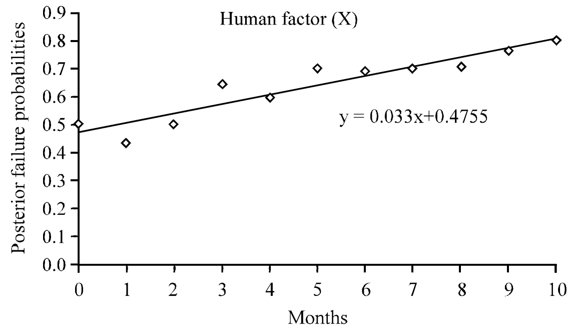

Fig. 2: Posterior failure probabilities with time for HF

Table 1: Posterior failure probabilities of HF over 10 months

	Hypothetical ASP data		
Months	M	N	Posterior failure probabilities
0	0	0	0.5000
1	7	3	0.4375
2	16	8	0.5000
3	23	15	0.6458
4	35	21	0.5972
5	41	29	0.7024
6	49	34	0.6900
7	58	41	0.7034
8	69	49	0.7071
9	81	62	0.7622
10	97	78	0.8010

M: No. of challenges, N: No. of occurrences/failures

Table 2: Predicted posterior failure probabilities for the next 5 months interval

Month	Predicted posterior failure probabilities
11	0.8385
12	0.8715
13	0.9045
14	0.9375
15	0.9705

DISCUSSION

The failure probabilities are validated by comparing the result calculated using the proposed model with the result presented by Ren *et al.* (2007), as shown in Table 3.

For prior failure probabilities of HF, the proposed model used the Jeffrey's prior distribution with the value of 0.5000 while Yun *et al.* (2009) used a collective data from expert's judgment with the value of 0.4050, which slightly different with 19%. It is observed that the proposed model is not relying on human intervention while Ren *et al.* (2007) required experts to justify the fuzzy prior probabilities and once the new data are observed, experts are required to revise the previous fuzzy prior probabilities in order to estimate the updated posterior failure probabilities.

And, for the posterior failure probabilities of HF, the proposed model presented varies value; depending on cumulative ASP data within the interval period of study, as shown in column four of Table 1, while Ren *et al.* (2007)

Table 3: Model comparison

Failure probabilities of HF	Proposed model	Ren *et al*. (2007)
Prior	0.5000	0.4050
Posterior	Range values from 0.5000 until 0.8010 depending on the time interval (As shown in column four of Table 1)	0.4640

only estimated 0.4640 as its posterior failure probabilities at one time. The dynamic mode of the proposed approach is important as part of the management of occupational safety since the level of human performance can be monitored with time. Through the monitoring process, any deficiency of HF may be detected and a robust action plan such as revise the work schedule, simplify the procedure and refresher training can be implemented to prevent incident happen.

CONCLUSION

This study has demonstrated the application of the dynamic failure probabilities assessment using Bayesian theory. Dynamic failure probabilities assessment is heavily dependent on the ASP data that encourages the presence of a strong safety culture for monitoring and recording of incidents. The applicability of this model was presented in a case study that shows the failure probabilities of HF can be predicted for the desired time interval. As a result, a robust action plan can be implemented to enhance the overall human performance in processing industries.

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