Analytic Hierarchy Process for the Estimation of the Probability of Failures of Safety Barriers in Oil and Gas Installations

F. DI MAIO[1], O. SCAPINELLO[1], E. ZIO[1,2,3], C. CIARAPICA[4], L. DECARLI [4], L. LA ROSA[4]

[1] *Energy Department, Politecnico di Milano, Via La Masa 34, 20156 Milano, Italy, francesco.dimaio@polimi.it, oscarscapinello@gmail.com, enrico.zio@polimi.it*

[2] *Mines ParisTech, PSL Research University, Sophia Antipolis, France*

[3] *Eminent Scholar, Department of Nuclear Engineering, Kyung Hee University, Republic of Korea*

[4] *Eni E&P division, via Emilia 1, 20097 San Donato Milanese, Italy, costanza.ciarapicaalunni@eni.com, luca.decarli@eni.com, laura.larosa@eni.com*

The Analytical Hierarchy Process (AHP) is a decision-making method capable of handling qualitative and quantitative elements. In this work, it is used to estimate the Failure Probabilities (FPs) of safety barriers (technical, procedural and organizational), within the framework of risk assessment of an oil and gas upstream plant. The barriers are modelled by a multistate Bayesian Network (BN) and FPs are defined for each barrier relative to their Health States (HSs). Expert elicitation procedures are adopted for feeding the AHP and a practical illustration is provided with regards to the safety barriers of the slug catcher of the upstream plant.

Keywords: Risk Assessment, Safety Barriers, Multistate Variables, Bayesian Networks, Failure Probability, Analytic Hierarchy Process, Expert Elicitation, Operating Integrity, Slug Catcher.

1. Introduction

Safety barriers are designed and implemented to reduce the probability of accidents and mitigate their consequences (ISO 17776). Various approaches have been proposed to model their contribution to risk, including by simplified risk indexes (Cozzani et al., 2009), and within Monte Carlo simulations (Abdolhamidzadeh et al., 2010) and Quantitative Risk Assessments (QRAs) based on Bow-Tie (BT) diagrams (Cherubin et al., 2011). However, the influence of the safety barriers current health state on their safety function performance is usually neglected (Landucci et al., 2016).

In the companion paper (Di Maio et al., 2020a), a multistate Bayesian Network (BN) has been introduced to allow Bayesian updating of the risk assessment, accounting for modelling the safety barriers health state, as inferred from Knowledge, Information and Data (KID) (Zio, 2016) that becomes available from different sources, e.g., from monitoring the system and component parameters, collecting field data, reporting inspection and maintenance information, etc. In such framework, safety barriers are described by their current Health State (HS) and Failure Probability (FP). The probability P(·) of the uncertain barrier performance when in a given HS (i.e., High (H), Medium (M), Low (L)) is related to specific Key Performance Indicators (KPIs) measured on the basis of field data collected at the plant. The barrier FP is typically estimated resorting to different techniques, depending on the barrier type.

We consider a practical case in which there is no data available for calculating the FP of a barrier. On the other hand, the available expert knowledge and information are structured within an Analytic Hierarchy Process (AHP) (Saaty, 1980). A case study is presented related to the preventive barriers of the slug catcher of the upstream plant.

The rest of the paper is organized as follows: Section 2 introduces the context of the case study and Section 3 presents the BN and the techniques used for the risk assessment; in Section 4 an application of the proposed methodology is shown and, finally, in Section 5 some conclusions are drawn.

2. Case Study

The case study regards the slug catcher unit of the onshore upstream plant and is presented in the companion paper (Di Maio et al., 2020a). The slug catcher receives the incoming multiphase flow from the offshore platforms and performs a preliminary gas liquid separation, thus representing the first process bottleneck of the onshore facility. Several hazards (e.g., human error, equipment failure and deviation from operating conditions) could lead to the Loss of

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Primary Containment (LOPC) of the slug catcher, from which different consequences, namely Flash Fire (FF), Jet Fire (JF), Pool Fire (PF) and Explosion (EX), can arise. Some preventive safety barriers (e.g., Process Safety Management System (PSMS), Task Management (TM), Design Integrity (DI), Operating Integrity (OI), Process Control (PC) and Pressure Protection System (PPS)) are considered to reduce the LOPC probability, and some recovery barriers (e.g., Isolation & Depressurization (I&D), Fire Management (FM), Emergency Response System (ERS) and Spill Containment System (SCS)) are considered to mitigate the effects of the accident consequences.

3. Safety Barriers Characterization

The safety barriers are modelled in the BN of Figure 1 by a corresponding safety node, characterized by Health States (HS) and the corresponding Failure Probability (FP). As mentioned earlier, different approaches are used to evaluate HSs and FPs with respect to the kind of barrier and depending on the data available (see also the accompanying papers (Di Maio et al., 2020a) and (Di Maio et al., 2020c) for further details).

3.1 *FP Evaluation*

The FP, the probability that the barrier fails to perform its safety function in a considered period of time when its HS is H, M or L, is indicated as p_H, p_M, p_L, respectively. Depending on the type of barrier (technical, procedural or organizational) a different procedure has been developed for estimating these probabilities:

- Technical barriers: estimation of failure rates from existing databases, such as (OREDA, 2002);
- Procedural barriers: estimation of failure rates by Human Reliability Analysis (HRA);
- Organizational barriers: estimation of failure rates by Organizational and Human Reliability Analysis (OHRA).

Finally, when the data relative to some specific barriers is missing, but expert knowledge and information is available, FP estimation can be done by expert elicitation, as proposed in (Ramzali et al., 2015). The procedure adopted is described in what follows.

3.1.1 *Expert weight evaluation*

When data are not available, we resort to an expert elicitation procedure to quantify p_H, p_M and p_L (Ramzali et al., 2015). In practice, Q experts are questioned in order to collect their educated assignment to the FP values $p_{HS,q}$of a safety barrier for the different HS {H,M,L} and then the expert values are weight-aggregated as:

$$p_{HS} = \sum_{q=1}^{Q} p_{HS,q} w_q \tag{1}$$

where w_q is the weight assigned to the q-th expert, q=1,2,…,Q, which accounts for various factors influencing his/her credibility (i.e., education level, professional position and years of experience, in Table 1) (Zio, 1996; Zarei et al.,2017). The expert relative weights can be obtained by an AHP (Figure 2), with pairwise comparisons of the trustworthiness of the experts using the factors as decision criteria (Yazdi et al., 2017).

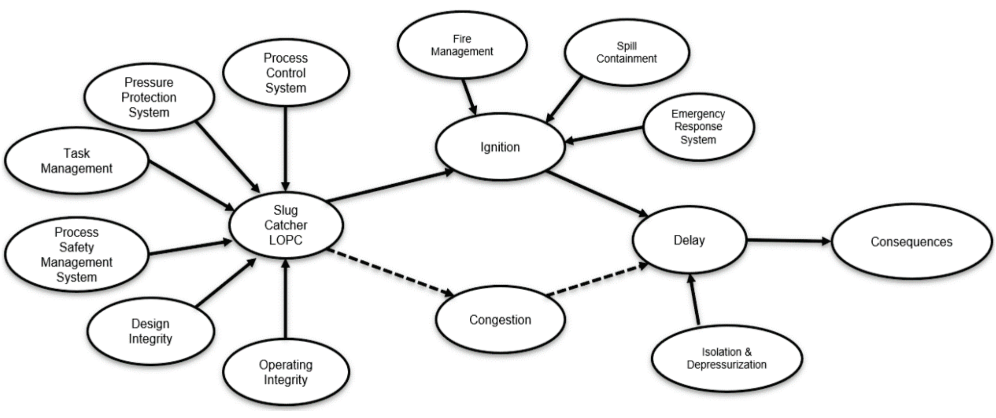

Fig. 1. BN of the slug catcher LOPC.

Table 1. Example of scoring table for the expert factors

Factor	Classification	Score
Experience	>29	5
	20-29	4
	10-19	3
	6-9	2
	<6	1
Job Position	Director/Manager	5
	Safety Officer	4
	Process Designer	3
	Engineer	2
	Technician	1
Education	PhD	5
	MSc	4
	BSc	3
	Diploma	2
	School Level	1

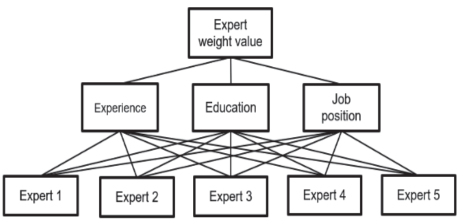

Fig. 2. AHP model for the expert weight evaluation

Comparison data are collected into comparison matrices. Each element c_{ij} of a comparison matrix C should satisfy the constraint $c_{ij} \cdot c_{ji} = 1$ .The weights relative to the importance for each entry (expert or criterion) can be determined by solving an eigenvector problem. More precisely, it can be shown that given the matrix of pairwise comparisons for the element of interest, the principal eigenvector provides the vector of weights, when normalized, and the maximum eigenvalue is a measure of consistency of the comparisons entered in the matrix (Zio et al., 2003). For complete consistency, the maximum eigenvalue, λ_{max}, should be equal to the order of the matrix, *m.* The level of consistency of a given pairwise comparison matrix can be measured by a parameter called Consistency Ratio (CR), defined as the ratio between the Consistency Index, CI = $(\lambda_{max} - m)/(m-1)$, and the random index (RI), which is the statistically averaged consistency index of randomly generated matrices of order *m* with entries artificially forced to be consistent. A consistency ratio of 0.10 or less is considered acceptable in many practical applications (Saaty, 1980).

4. Application

An application of the proposed methodology is shown with respect to the Operating Integrity (OI) safety barrier of the slug catcher unit presented in Section 2. As few data are available, an expert elicitation procedure has been devised in order to obtain as much knowledge and information as possible in order to evaluate the FP of the barrier.

4.1 *Expert Elicitation Application*

As scarce data is available for OI, the corresponding FPs, p_H, p_M and p_L are evaluated resorting to an expert elicitation procedure. In line with (Hemming, 2017), the following question is asked to Q experts in order to evaluate the $\lambda_{LOPC,q}$ (i.e., the LOPC frequency estimated by the q-th expert):

- "W*hat is your best estimate for the frequency of a LOPC event in an onshore plant when no safety barrier is applied?"*

Then, a pair of questions are asked to the q-th expert in order to evaluate $\lambda_{LOPC,H,OI,q}$ and $\lambda_{LOPC,M,OI,q}$ ($i.e.,$ the frequency of LOPC when the barrier *OI* is implemented in HS equal to H and equal to M, respectively):

- *H: "What do you think is the most plausible frequency of a LOPC event when OI is optimal?"*
- *M:* **"***What do you think is the most plausible frequency of a LOPC event when OI is degraded?"*

Answering to these questions, experts provide their estimation about the effect of the barrier *OI* on the frequency of a LOPC. In order to do this, we must find a correlation between frequency and FP $\{p_H, p_M, p_L\}$. We can write:

$$p_{H,OI} = \frac{P_{LOPC}(T|HS_{OI} = H)}{P_{LOPC}(T)} \quad (2)$$

$$p_{M,OI} = \frac{P_{LOPC}(T|HS_{OI} = M)}{P_{LOPC}(T)} \quad (3)$$

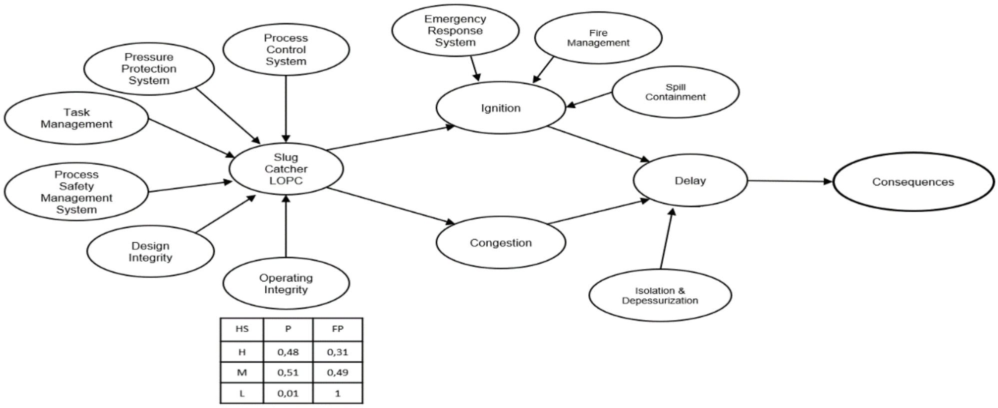

Fig. 3. BN with the CPT of the OI.

Assuming exponential probability distributions $P_i(T) = 1 - e^{-\lambda_i T}$, if $\lambda_{LOPC}T \ll 1$, $\lambda_{LOPC,H,OI}T \ll 1$ and $\lambda_{LOPC,M,OI}T \ll 1$ and if we consider T=1 year, we can rewrite Eqs. (2) and Eq. (3) as:

$$p_{H,OI} \approx \frac{\lambda_{LOPC,H,OI}}{\lambda_{LOPC}} \tag{4}$$

$$p_{M,OI} \approx \frac{\lambda_{LOPC,M,OI}}{\lambda_{LOPC}} \tag{5}$$

Resorting to Eqs. (4) and (5), we are able to compute the value of $p_{H,B,q}$ and $p_{M,B,q}$ for each expert $q = 1, 2, \ldots, Q$ and, applying Eq. (1), we can evaluate FP $\{p_H, p_M, p_L\}$ for barrier *OI*. It is always assumed that $p_L = 1$.

4.2 *Expert Elicitation Results*

A group of Q=11 experts has been surveyed: their personal factors (education level, professional position and years of experience) are scored and are used to evaluate their w_q (see Table 2).

Table 2. Expert scores and weights

Expert	Job	Experience	Education	w_q
Expert 1	3	3	4	0.20
Expert 2	2	1	4	0.06
Expert 3	2	1	4	0.06
Expert 4	2	2	4	0.10
Expert 5	2	1	5	0.08
Expert 6	2	2	4	0.10
Expert 7	2	1	4	0.06
Expert 8	2	1	4	0.06
Expert 9	2	2	4	0.10
Expert 10	2	1	5	0.08
Expert 11	2	2	4	0.10

Table 3. Expert answers

Expert	$\lambda_{LOPC,q}$	$\lambda_{LOPC,H,OI,q}$	$\lambda_{LOPC,M,OI,q}$
Expert 1	5	1	4
Expert 2	100	30	70
Expert 3	100	80	90
Expert 4	100	80	90
Expert 5	0.14	0,12	0,13
Expert 6	10000	0,0001	0,01
Expert 7	20	9	11
Expert 8	100	25	75
Expert 9	50000	5000	0,01
Expert 10	10000	0,0001	0,001
Expert 11	100000	0,0001	0,01

Applying Eqs. (4) and (5), we compute the values of $p_{H,OI,q}$ and $p_{M,OI,q}$ for each expert $q = 1, 2, \ldots, Q$ from the answers listed in Table 3. Applying the w_q shown in Table 2 and Eq. (1), we calculate $p_{H,OI} = 0.311$ and $p_{M,OI} = 0.492$, whereas it is assumed that $p_{L,OI} = 1$. The CPT of the OI safety barrier can now be filled, as shown in Figure 3.

In a similar fashion, it is possible to elicit the FP values for the remaining non-technical safety barriers (namely TM, PSMS and DI), for which no data are available, in order to fill their corresponding CPTs. The results of the elicitation process for these barriers are shown in Figure 4, where the BN is complete with the CPTs for each preventive safety barrier and their effects on the system are considered in the consequence node risk assessment.

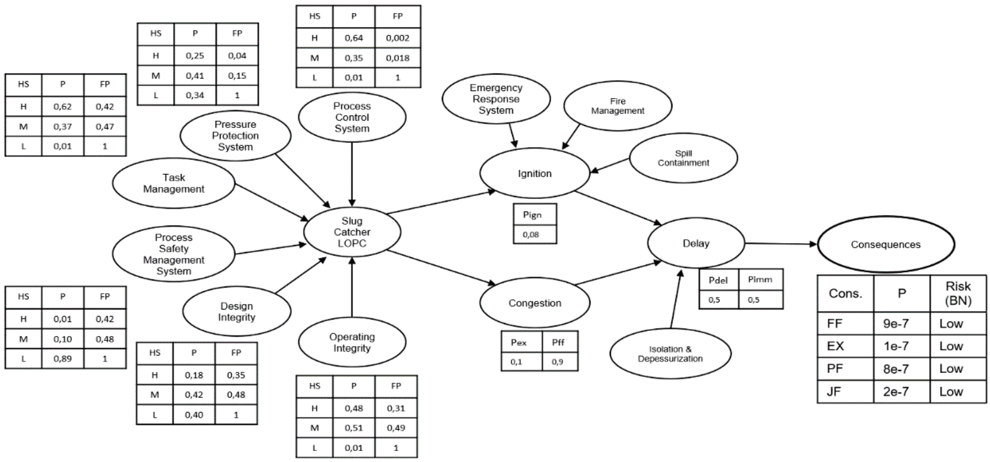

Fig. 4. BN complete with the CPTs for each preventive safety barrier

5. Conclusions

Barriers FP estimation is difficult as data are often not available. This work has shown one possible approach to FP estimation, based on expert elicitation which is typical in risk assessment. The subjectivity of the elicitation procedure has been mitigated by the use of AHP to evaluate the expert weights for the aggregation of the expert estimates. In the specific case study considered, the FP values $\{p_H, p_M, p_L\}$ of the preventive safety barrier OI have been estimated and used into the BN model for the risk assessment (see the companion paper (Di Maio et al., 2020a) for further details).

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