A Multistate Bayesian Network for accounting the degradation of safety Barriers in the Living Risk Assessment of Oil and Gas Plants

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The BAseline Risk assessment Tool (BART) is currently used by the Eni oil and gas company for the living risk assessment of oil and gas upstream plants. BART combines a simplified Quantitative Risk Assessment (QRA) with a Bow-Tie (BT) approach. In this work, we implemented in BART the capabilities for considering the degradation of the barriers, which affects the safety performance. For this, we resort to a multistate Bayesian Network (BN), which maps the BT of BART and whose nodes correspond to the safety barriers, each one characterized by a Health State (HS) and by a Failure Probability (FP). HS is assessed on the basis of specific Key Performance Indicators (KPIs), whereas FP is quantified from failure datasets (for technical barriers), Human Reliability Analysis (HRA) (for operational and organizational barriers) or the Analytic Hierarchy Process (AHP) based on expert elicitation (for barriers for which data are lacking). The proposed BN approach is applied to the barriers designed for limiting the consequences of a release in the slug catcher (i.e., Flash Fire (FF), Jet Fire (JF), Pool Fire (PF), Explosion (EX) or Toxic Dispersion (TX)) of the upstream onshore plant. The results of the assessment are benchmarked with those obtained with the original BART and show that the BN approach adds the capability of providing an accurate and updatable description of the barrier conditions in the risk assessment of the plant during its life.

Keywords: Risk Assessment, Safety Barriers, Degradation, Bayesian Networks, Multistate Variables, Slug Catcher, Upstream Onshore Plant

1. Introduction

An oil and gas company must ensure the safety of plants operations for environmental preservation, workers and public protection, economics and reputation. Safety by design is pursued with the implementation of preventive and mitigative safety barriers, for reducing the probability of accident initiating events and mitigating the consequences, respectively (ISO 17776). Various approaches have been proposed to model the performance of safety barriers, including simplified risk indexes (Cozzani et al., 2009), Monte Carlo simulation (Abdolhamidzadeh et al., 2010) and Quantitative Risk Assessment (QRA) based on Bow-Tie (BT) diagrams (Cherubin et al., 2011). However, influence of the safety barriers current health state on their performance has been so far neglected (Landucci et al., 2016).

To overcome this limitation, in this work, we resort to a multistate Bayesian Network (BN) modelling approach (Pearl, 1986; Botje, 2006; Khakzad et al., 2013; John et al., 2016) to handle the information on the barriers health state.

The novelty of the BN framework here proposed is that the multistate variables values are inferred from whatever Knowledge, Information and Data (KID) (Zio, 2016) is available related to the safety barriers health state, as gathered from different sources, e.g., by monitoring system and component parameters, collecting field data, reporting inspection and maintenance information, etc. Indeed, in what follows, the safety barriers are described by multistate variables characterizing the current Health State (HS) and the Failure Probability (FP). The probability P(·) of the barrier performance in a given HS (i.e., High (H), Medium (M), Low (L)) is estimated on the basis of specific Key Performance Indicators (KPIs) related to field data collected at the plant for a specific time, whereas the barrier FP is estimated resorting to

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different techniques, depending on the following barrier types:

- Technical: equipment and hardware systems;
- Procedural: actions and activities that the personnel has to perform, in order to ensure safety;
- Organizational: personnel with defined roles or functions, and specific competence.

In this work, we consider a specific case related to the preventive barriers of the slug catcher of the upstream onshore plant. We compare the results provided by the multistate BN model with those of the BAseline Risk assessment Tool (BART), that is the reference methodology for risk assessment in Eni, and show the advantages of a proper multistate characterization of the safety barriers (i.e., introducing the HS and FP evaluation for all types of barriers).

The remainder of the paper is arranged as follows: Section 2 presents the main features of the BART methodology, Section 3 introduces the implementation of BNs into the BART methodology, Section 4 describes the process of characterization of the safety barriers and Section 5 shows the application to the case study of the upstream onshore plant; finally, in Section 6 some conclusions are drawn.

2. BART

BART combines a simplified QRA methodology with a BT model approach to identify the potential hazards and the associated risks that may arise from a process or activity carried out in onshore/offshore oil and gas installations (Cherubin et al., 2011). The analysis by BART involves:

(i) Modelling the plant and dividing it into functional units according to the process flow, the operative conditions, and the equipment layout;
(ii) For each functional unit, identifying the consequences foreseeable from an accident (e.g., Flash Fire (FF), Jet Fire (JF), Pool Fire (PF), Explosion (EX) or Toxic Dispersion (TX));
(iii) Evaluating the baseline risk (i.e., the risk which the installation would be exposed to without considering any preventive/recovery barrier in place), in terms of accident frequency and consequence severity, using the simplified QRA;
(iv) Evaluating the actual risk, in terms of accident frequency and consequence severity, considering the effectiveness of the preventive and recovery barriers in place, using the BT (see Section 2.1).
(v) Reducing the exposure to actual risks by suggesting the implementation of proper corrective actions aimed at improving the reliability and the performance of the preventive and recovery barriers in place, or adding new preventive and/or recovery barriers.

2.1 *Bow-Tie*

BT is a graphical approach to model accident scenarios, from causes to consequences (ISO 17776). A BT comprises a Fault Tree (FT) representing the possible events causing the accident, whose top event becomes the initial event of an Event Tree (ET) delineating the scenarios that can arise depending on the failure or success of the devised safety barriers, some of which may lead to undesirable consequences (Delvosalle et al., 2005; Bellamy et al., 2007; De Ruijter & Guldenmund, 2016).

The BT methodology is implemented in BART to evaluate the actual risk for the accident scenarios screened out by the simplified QRA, explicitly modelling the contribution of the preventive/recovery barriers actually in place in each functional unit for preventing/mitigating accident escalation. The specific barrier contribution to safety can be inferred from the available documentation, plant personnel interviews and survey administration. In particular, surveys are aimed at qualitatively estimating the reliability of each barrier by filling checklists (CLs). The CL survey is inevitably subjective and needs, thus, to be performed in a structured and controlled way. Furthermore, the BT framework has difficulty in accounting for the actual health/degradation state (HS) of the barriers, so that eventually BART reduces the baseline risk by the same amount irrespectively of the actual HS of the barriers. Furthermore, the static nature of the FTs and ETs in the BT is such that it does not easily allow for adaptive, updated estimates of the risk due to the HSs of the barriers changing along with time.

3. Bayesian Networks

BNs are here proposed to implement specific capabilities to BART that can overcome the BT limitations. BN is a graphical, analytical approach widely used in risk analysis (Abimbola et al., 2015; Cai et al., 2013; Mancuso et al., 2017; Trucco et al., 2008; Wu et al., 2015). Formally, a BN is a directed acyclic graph consisting in (Jensen, 2001):

- Nodes $V = \{1, 2, \dots, N\}$, which represent events whose combinations can lead to an accident, so each node i represents a random event that encodes a set of discrete states $S^i = \{s_1^i, s_2^i, \dots, s_m^i\}$ (multistate variables);
- Directed arcs $E \subseteq \{(i,j) | i,j \in V, i \neq j\}$, which indicate conditional dependencies among nodes. Specifically, the arc $(j,i) \in E$, which connects node $j \in V$ to node $i \in V$, indicates that the event at node i is conditionally dependent on the event at node j. A path is a sequence of nodes $(i_1, i_2, \dots, i_\eta), \eta > 1$, such that $(i_j, i_{j+1}) \in E, j < \eta$. since the BN is acyclic, there is no path $(i_1, i_2, \dots, i_\eta), \eta > 1$ such that $(i_j, i_{j+1}) \in E$, $j < \eta$ and $i_1 = i_\eta$. The immediate follower nodes of i ∈ V form the set $V_+^i = \{j | (i,j) \in E\}$ and their sets of states form the family $S_+^i = \{S^j | j \in V_+^i\}$, whereas its immediate predecessor nodes are in the set $V_-^i = \{j | (j,i) \in E\}$, whose set of states is the family $S_-^i = \{S^j | j \in V_-^i\}$;
- Conditional Probability Tables (CPTs) assigned to the nodes, which quantify the conditional dependencies among nodes in terms of the conditional probability $P_i(S^i | S_-^i)$ that node i will be in a particular state, given the states of its parent nodes.

In the specific application to risk assessment, the quantification of the accident consequences probability is calculated by the joint probability multiplication rule:

$$P(S^1, S^2, \dots, S^\eta) = \prod_{j=1}^{\eta} P_j\left(S^j \middle| S_-^j\right) \qquad (1)$$

where $(S^1, S^2, \dots, S^\eta)$ is the family of states of the path $(i_1, i_2, \dots, i_\eta)$, leading to the consequence node i_η.

3.1 *Mapping a BT into a BN*

A BT may be converted into a BN following a specific mapping procedure, as described in (Bobbio et al. 2001), (Bearfield and Marsh, 2005) and (Khakzad et al., 2013). The structure of the BN is developed from the FT of the BT, in such a way that primary events, intermediate events and the top event of the FT are represented as root nodes, intermediate nodes and the leaf node in the equivalent BN, respectively. Then, each safety barrier in the ET of the BT is represented by a safety node and the consequences of the ET become a consequence node having as many states as the number of the ET consequences. After the BNs equivalent to the FT and ET are developed, they are connected to each other via the top event as a pivot node. Figure 1 provides a scheme of the mapping procedure adopted.

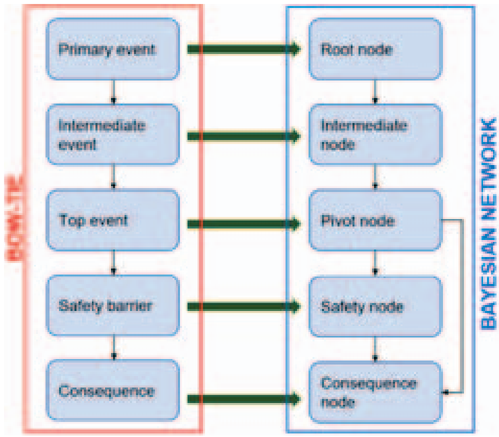

Fig. 1. Bow-Tie to Bayesian Network mapping procedure

4. Safety Barriers Characterization

The novelty of the BN model here proposed is that each safety barrier is considered in the BN by placing a safety node, each one characterized by Health States (HS) and Failure Probability (FP). The different approaches adopted in order to evaluate HSs and FPs differ depending on the kind of barriers and data available, as we shall see in what follows.

4.1 *HS evaluation*

The HS reflects the health condition of the barrier, which is defined as High (H), Medium (M) and Low (L), corresponding to optimal, acceptable and poor performances respectively. The probability that the HS of a barrier is H, M or L is quantified on the basis of specific Key Performance Indicators (KPIs), for each barrier. To model the relationship between KPIs and HS {H,M,L} we resort to a probabilistic relationship, where prototypical conditions are used as anchor points. Anchors provide the analysts with examples for which the assessment is somewhat "natural" and which can be used for assessing, by comparison, situations which deviate from anchors, thus reducing subjectivity. In line with (Zio et al., 2009), a KPI is described by continuous input variables X_{KPI} with values x_{KPI} in the range [0,1]. For a specific KPI value x_{KPI} of X_{KPI}, there can be uncertainty with respect to the HS {H,M,L} of the barrier, though, typically, the higher the x_{KPI}, the better the overall barrier performance. Then, the HS of a safety barrier is represented by a random variable X_{HS} whose possible states are {H,M,L}. The probabilities

$P(x_{HS}|x_{KPI})$ of being in state x_{HS} given the assessed KPI value x_{KPI} are obtained with the anchor points listed in Table 1, and result in the distributions shown in Figure 2. Depending on the kind of information available for the barrier of interest, several KPIs can be defined.

Table 1. Anchor points.

x_{HS}	x_{KPI}	$P(x_{HS}|x_{KPI})$
H	0	0.01
	0.4	0.01
	1	0.89
M	0	0.10
	1	0.10
L	0	0.89
	0.7	0.01
	1	0.01

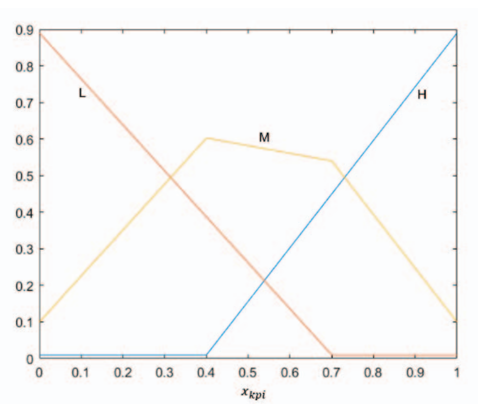

Fig. 2. Probability distributions $P(x_{HS}|x_{KPI})$ for the HSs H, M and L.

4.2 *FP Evaluation*

The FP, the probability that the barrier fails to perform its 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 devised for estimating these probabilities:

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

When data relative to some specific barriers are missing, the FP estimation is done by expert elicitation, as proposed in (Ramzali et al., 2015) and in the accompanying paper (Di Maio et al., 2020c).

5. Case study: Onshore Plant

An application of the proposed methodology is shown regarding the slug catcher unit of the onshore upstream plant. 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. The results are benchmarked with those obtained by BART, whose top event is defined as the Loss of Primary Containment (LOPC) of the slug catcher, which can lead to different consequences, namely FF, JF, PF and EX. BART builds a BT for the LOPC of the slug catcher (shown in Figure 3): several hazards (e.g., human error, equipment failure and deviation from operating conditions) are modelled to lead to the top event "Slug Catcher LOPC" (circle in the middle); 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.,

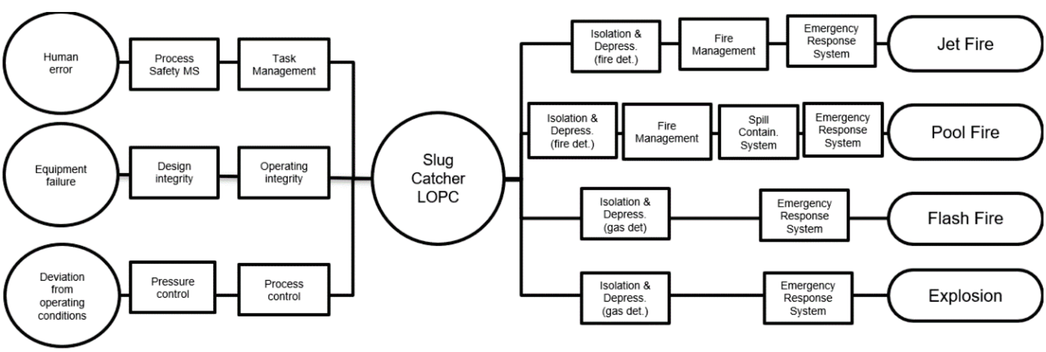

Fig. 3. BT of the slug catcher LOPC.

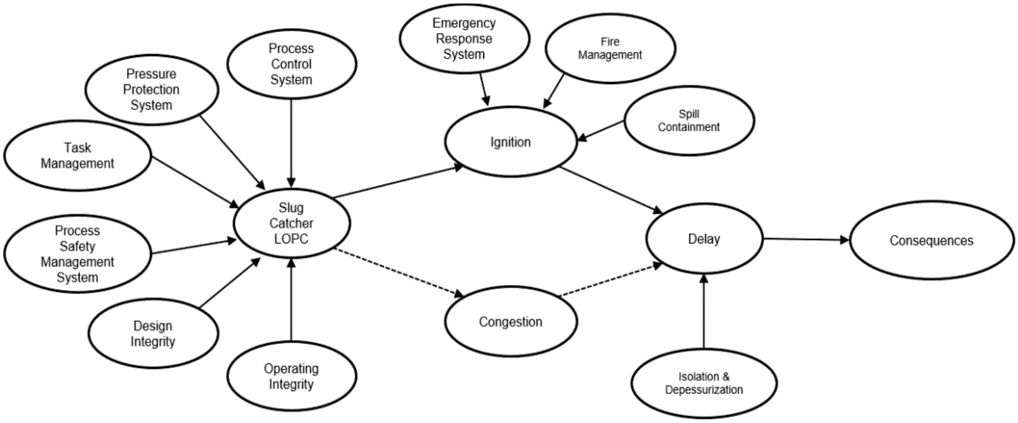

Fig. 4. BN of the slug catcher LOPC.

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 (final leaves).

Following the BT-BN mapping procedure of Section 3.1, the BN shown in Figure 4 is built. The pivot node "Slug catcher LOPC", fed by the preventive safety barriers nodes, leads to the intermediate nodes describing the ignition escalation, fed by the recovery barriers, and ultimately to the consequence node. Once the barriers have been fully characterized with respect to the values of HS and FP (see also the accompanying papers (Di Maio et al., 2020b) and (Di Maio et al., 2020c) for further details), on the basis of the KID collected during a specific monitoring period (e.g., one year), the probability of the consequences, $P_{Cons}(\cdot)$, can be evaluated, following the BN rules. The results provided by the multistate BN-based approach with the CPTs shown in Figure 5 are compared with those of the BT-based approach of BART and shown in Table 2. Both approaches provide coherent risk results (i.e., low risk).

Table 2. Risk of each consequence evaluated by both BT-based and BN-based approaches.

Consequence	Risk (BT)	Risk (BN)
FF	LOW	LOW
EX	LOW	LOW
JF	LOW	LOW
PF	LOW	LOW

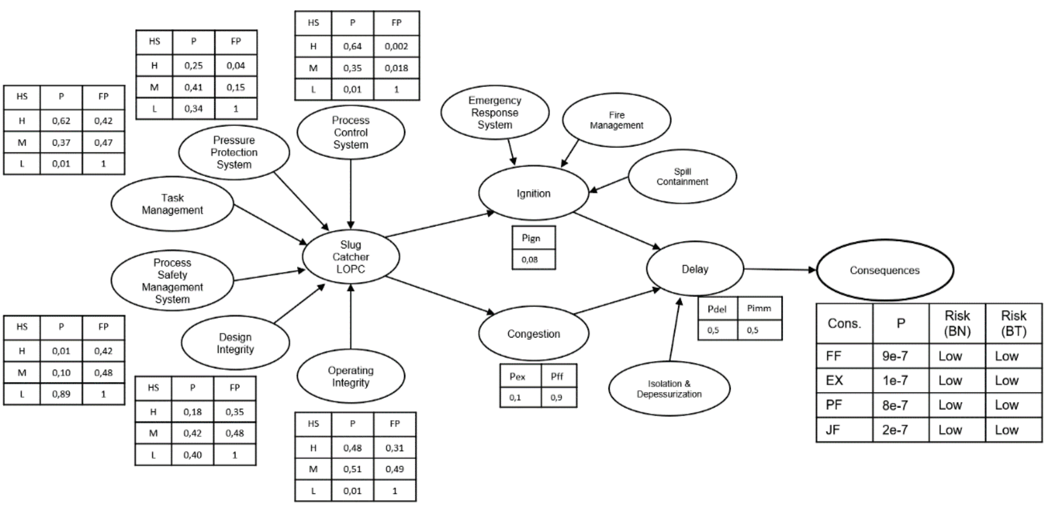

Fig. 5. BN with complete CPTs for the preventive barriers.

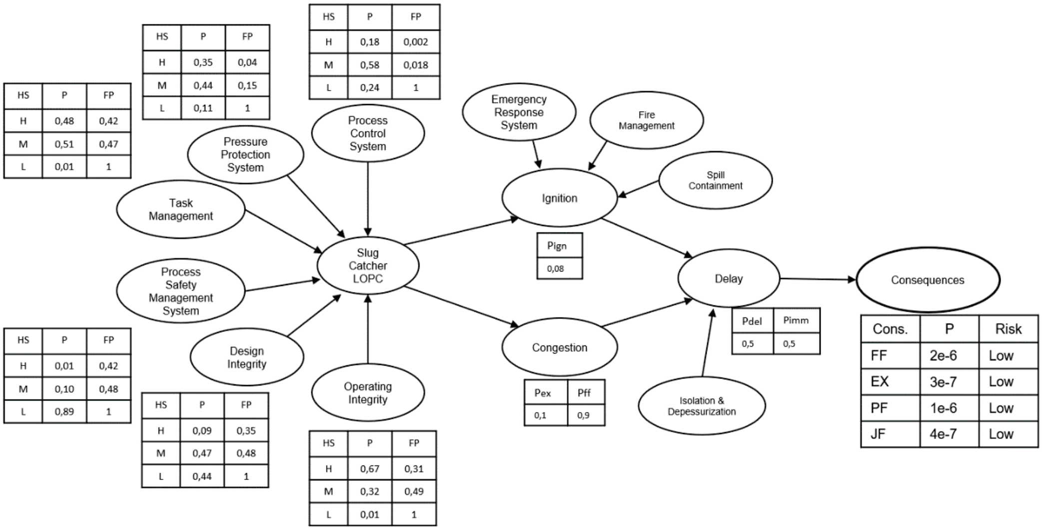

Fig. 6. Updated BN of the slug catcher LOPC.

Assuming that it is possible to collect new KID for the following monitoring period (e.g., one year), in Figure 6 we show that it is possible to update the KPI evaluation for each safety barrier and, correspondingly, HS probabilities, allowing to constantly monitor barrier conditions and performances as they affect the risk matrix values. Thus, assuming new KID is available for the slug catcher, a BN with updated CPTs can be built in order to produce a Dynamic risk assessment (see the accompanying paper (Di Maio et al., 2020b) for a detailed example of a CPT update). Figure 6 shows the BN for the slug catcher LOPC, whose preventive safety barrier CPTs and resulting risk assessment have been updated.

6. Conclusions

In this paper, a multistate BN-based approach for the risk assessment of an oil and gas plant is developed. From an existing BT-based approach (BART), we added the capabilities for considering the degradation of barriers within a multistate modelling scheme. The advantages of adopting a multistate BN-based approach instead of the consolidated BT-based approach for risk assessment in upstream plants have been shown, allowing for a deeper and more realistic analysis of the degradation processes undergoing in an oil and gas plant.

References

Abdolhamidzadeh, B., Abbasi, T., Rashtchian, D., Abbasi, S.A. (2010). A new method for assessing domino effect in chemical process industry. J. Hazard. Mater. 182.

Abimbola, M., Khan, F., Khakzad, N., Butt, S. (2015). Safety and risk analysis of managed pressure drilling operation using Bayesian network. Saf. Sci. 76, 133–144.

Bearfield, G., & Marsh, W. (2005). Generalising Event Trees Using Bayesian Networks with a Case Study of Train Derailment. Computer Safety, Reliability, and Security, 52–66.

Bellamy, L.J., Ale, B.J.M., Geyer, T., Goossens, L.H., Hale, A.R., Oh, J., Mud, M.L., Bloemhof, A., Papazoglou, I.A., Whiston, J. (2007). Storybuilder – a tool for the analysis of accident reports. Reliab. Eng. Syst. Saf. 92 (6), 735–744.

Bobbio, A., Portinale, L., Minichino, M., & Ciancamerla, E. (2001). Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. Reliability Engineering & System Safety, 71(3), 249–260.

Botje, M. (2006). Introduction to Bayesian Inference.

Cai, B., Liu, Y., Zhang, Y., Fan, Q., Liu, Z., & Tian, X. (2013). A dynamic Bayesian networks modeling of human factors on offshore blowouts. Journal of Loss Prevention in the Process Industries, 26(4), 639–649.

Cherubin, P., Pellino, S., & Petrone, A. (2011). Baseline risk assessment tool: A comprehensive risk management tool for process safety. Process Safety Progress, 30(3), 251–260.

Cozzani, V., Tugnoli, A., Salzano, E. (2009). The development of an inherent safety approach to the prevention of domino accidents. Accid. Anal. Prev. 41.

De Ruijter, A., & Guldenmund, F. (2016). The bowtie method: A review. Safety Science, 88, 211–218.

Delvosalle, C., Fievez, C., Pipart, A., Fabrega, J.C., Planas, E., Christou, M., Mushtaq, F. (2005). Identification of reference accident scenarios in Seveso establishments. Reliab. Eng. Syst. Saf. 90, 238–246.

Di Maio, F., Scapinello, O., Zio, E., Ciarapica Alunni, C., Decarli, L., La Rosa, L. (2020b). A Novel KPI for Continuously Monitored Safety Barriers based on Probabilistic Safety Margins. Proceedings of the ESREL2020 PSAM15 Conference, 21-26 June 2020, Venice, Italy.

Di Maio, F., Scapinello, O., Zio, E., Ciarapica Alunni, C., Decarli, L., La Rosa, L. (2020c). Analytic Hierarchy Process for the Estimation of the Probability of Failures of Safety Barriers in Oil and Gas Installations. Proceedings of the ESREL2020 PSAM15 Conference, 21-26 June 2020, Venice, Italy.

ISO 17776 (2016), Petroleum and natural gas industries - Offshore production installations – Major accident hazard management during the design of new installations.

Jensen F. (2001), Bayesian networks and decision graphs. New York: Springer-Verlag.

John, A., Yang, Z., Riahi, R., Wang, J., (2016). A risk assessment approach to improve the resilience of a seaport system using Bayesian networks. Ocean Eng. 111, 136–147.

Khakzad, N., Khan, F., & Amyotte, P. (2013). Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network. Process Safety and Environmental Protection, 91(1-2), 46–53.

Landucci, G., Argenti, F., Spadoni, G., & Cozzani, V. (2016). Domino effect frequency assessment: The role of safety barriers. Journal of Loss Prevention in the Process Industries, 44, 706–717.

Mancuso, A., Compare, M., Salo, A., & Zio, E. (2017). Portfolio optimization of safety measures for reducing risks in nuclear systems. Reliability Engineering & System Safety, 167, 20–29.

Mkrtchyan, L., Podofillini, L., & Dang, V. N. (2015). Bayesian belief networks for human reliability analysis: A review of applications and gaps. Reliability Engineering & System Safety, 139, 1–16.

OREDA (2002). Offshore Reliability Data Handbook. DNV, Trondheim, Norway.

Pearl, J. (1986). Fusion, propagation, and structuring in belief networks. Artificial Intelligence, 29(3), 241–288.

Ramzali, N., Lavasani, M. R. M., & Ghodousi, J. (2015). Safety barriers analysis of offshore drilling system by employing Fuzzy Event Tree Analysis. Safety Science, 78, 49–59.

Trucco, P., Cagno, E., Ruggeri, F., Grande, O., 2008. A Bayesian belief network modelling of organisational factors in risk analysis: A case study in maritime transportation. Reliab. Eng. Syst. Saf.93, 823–834

Wu, W.-S., Yang, C.-F., Chang, J.-C., Château, P.-A., Chang, Y.-C. (2015). Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. Reliab. Eng. Syst. Saf. 142, 515–524.

Zio, E., Podofillini, L., Baraldi, P., Dang, V., Librizzi, M., & Conti, M. (2009). A Bayesian network model for dependence assessment in human reliability analysis. Reliability, Risk, and Safety.

Zio, E. (2016). Some Challenges and Opportunities in Reliability Engineering. IEEE Transactions on Reliability, 65(4), 1769–1782.