

An Integrated Approach to Support the Dynamic Risk Assessment of Complex Industrial Accidents

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Recent major accidents in the offshore oil and gas (O&G) industry have showed inadequate assessment of system risk and demonstrated the need to improve risk analysis. While direct causes often differ, the failure to update risk evaluation based on the evolution of external conditions has been a recurring problem. Risk is traditionally defined as a measure of the accident likelihood and the magnitude of loss, usually assessed as damage to people, to the environment, and/or economic loss. Recent revisions of such definition include also aspects of uncertainty. However, Quantitative Risk Assessment (QRA) in the offshore O&G industry is based on consolidated procedures and methods, where periodic evaluation and update of risk is not frequently carried out. Dynamic risk assessment methods were recently developed for the O&G offshore industry with the purpose of evaluating risk on a real-time basis, either implementing the periodic frequency update or providing a dynamic estimate of the consequences with specific tools. Periodic update is possible through collection and process of specific indicators. However, its effectiveness relies on continuous monitoring activity and real-time data capturing. For this reason, this contribution focuses on the coupling of such methods with sensors of different nature located in (or around) an offshore O&G system; in particular, the specific application of sensor networks is described. Examples of coupling real-time data acquisition and dynamic risk assessment, with particular reference to evaluation of safety barriers performance, are shown with specific cases. The analysed cases demonstrate that this risk and impact assessment approach may provide effective support to safety-critical decisions.

1. Introduction

Since the occurrence of a series of serious accidents within the oil and gas (O&G) industry, several efforts have been dedicated to the improvement of risk assessment techniques. For instance, the blowouts at Snorre Alpha in 2004 (Petroleum Safety Authority, 2004), Montara in 2009 (Borthwick, 2010), Macondo in 2010 (The National Academies, 2010) and the loss of well control at Gullfaks C in 2010 (Statoil, 2011) led to the development of structured approaches for periodic safety evaluation within the Norwegian O&G sector (Petroleum Safety Authority, 2013).

However, periodic evaluation and update of quantitative risk assessment is not yet carried out in a systematic fashion, leading to static risk pictures at a frozen instant of the system life (Paltrinieri et al., 2015). To overcome this limitation, Paltrinieri and Khan (2016) suggested novel methods focusing on time-varying risk factors, linking the facility equipment and management current condition to the overall risk indexes. Such methodologies allow supporting periodic update of QRA by collecting and aggregating sets of indicators, defined in agreement with the company owning the facility. The effectiveness of such dynamic methods, in terms of application and verification, relies on continuous monitoring activity and real-time data capturing (Paltrinieri et al., 2014a). It implies collection of early warnings, near misses, incidents, accident data, and indicators. Possible difficulties in gathering field data strongly affect the methodologies for frequency and consequences update in QRA studies. Moreover, data-driven approaches to risk assessment are largely unexplored, but have undeniable potential to provide valid support for risk management. For this reason, this

work promotes coupling of dynamic risk analysis (DRA) with sensor networks located in or around O&G systems, in order to support the way forward of O&G risk assessment.

2. Sensors and their input to risk-informed decisions

The “Internet of Things” (IoT), i.e. the presence of network-enabled sensing devices deployed at several locations, has pervaded many industrial scenarios allowing for real-time monitoring of large-scale (physical or man-made) phenomena. More specifically, one of the key elements for the Industry 4.0 revolution is the integration of IoT with cybernetics, machine learning and cloud technology. Wireless sensor networks (WSNs) are common solutions for data collection and decision in IoT-based monitoring applications: information extraction by data processing is employed at a fusion center and the spatial extent within some industrial environments makes wireless technology preferable for the communication phase.

Recent approaches in WSN-design exploit the spatial diversity provided by the sensors for robust decision and multi-antenna processing for energy-efficient transmission and effective data fusion (Ciuonzo et al., 2012). Multi-antenna data fusion techniques for WSNs have been shown practical while exhibiting near-optimal performance both in radio land /maritime scenarios (Salvo Rossi et al., 2016) and in underwater acoustic scenarios (Salvo Rossi et al., 2015), for potential application to various industrial cases. Massive MIMO technology (i.e. the use of very-large antenna arrays at the fusion center) is one of the major components in energy-efficient next-generation wireless systems and has been recently (theoretically) investigated for detection/estimation purposes (Ciuonzo et al., 2015). WSNs are also used in complex environments where an accurate mathematical model is unavailable and learning-by-examples exploiting large data sets is a more robust approach.

In industrial engineering, failure detection is one of the main inputs to risk estimation. In fact, risk is traditionally defined as a measure of the accident likelihood and loss magnitude, assessed as damage to people, damage to the environment, economic loss. However, recent studies suggest that expressing the level of knowledge used for risk assessment should be an intrinsic feature of the calculated value of risk (Aven and Krohn, 2014). The novel framework of Industry 4.0 pushes towards important improvements of such risk knowledge. In fact, it enables technologies for data collection coupled with increased capacity in the communication infrastructure and processing of data from heterogeneous sources. Moreover, it supports the overall goal of risk analysis of providing necessary and comprehensive risk information for decision-making. Risk-informed decisions are used in a number of circumstances where something of value is at stake (Kongsvik et al., 2015). For instance, risk evaluation allows setting a priority scale and allocating appropriate resources for risk management.

For this reason, one of the key objectives in the implementation of safe and efficient O&G 4.0 systems is the development of a digital twin. Such tool implies coherent interaction of digital models describing different aspects of the physical asset, availability of real-time real-world data from the physical asset, capability of remote control on the physical asset, and possibility to use machine-learning tools for monitoring, prediction, optimization procedures (Paltrinieri et al., 2019).

3. Sensor-based Risk Analysis

Risk analysis based on real-time data needs both an appropriate framework for dynamic evaluation and reliable equipment for data collection (Paltrinieri and Khan, 2016). A logic tree may be used to visualize the generic scenario, as depicted by figures 1 and 2. In particular, the bow-tie technique may be appropriate, because its visual form improves understanding of the accident scenario and show safety measures against initiating causes (green boxes in figures 1 and 2) and loss event consequences (red boxes in figures 1 and 2) (CCPS - Center for Chemical Process Safety, 2008). Moreover, the Bow-Tie diagram allows defining quantitative models for risk assessment, integrating information from sensor readings. Both the Risk Influencing Factor (RIF) (Øien, 2001a, 2001b) and the DRA methods (Paltrinieri and Khan, 2016) may be taken as references for a sensor-based approach. Three main elements should be considered:

1. *Assessment of status of causes.* Cause status may be defined by a set of indicators. In this case, these indicators correspond to detection results from the mentioned sensors. Other types of indicators can be also considered, but they should be measurable and indicate the presence and/or extent of the cause.
2. *Performance of safety measures.* Safety measures are effected based on the status of causes, provided by continuous sensor monitoring. In fact, safety measures may be the result of a synergy of various activities, such as detection and procedure activities, and their effectiveness is essential. Safety measures can be technical or operational and may have a different relative importance on the overall risk. For this reason, such safety measures are often modeled themselves and broken down

into subsystems. Measureable indicators may be also defined to assess their performance. This type of indicators aims to report whether the measure can deliver the desired outcome.

3. *Collection of indicators from sensors.* Available information collected through heterogeneous sensors is used as indicators to assess status of causes. In such scenarios, data fusion, i.e. collective processing of possibly-heterogeneous information from sensors for final assessment, represents a key technique for effective system design. The interplay of a space-time correlated process and a space-time-frequency correlated communication channel should be explored by developing suitable source models that exhibit the desired correlation properties for samples while being tractable for analysis. A space-time band-limited process model needs to be defined while a realistic and tractable channel model must be found as the basis for performance analysis. It is apparent how instantaneous channel state information may be inefficient to acquire while focusing on scenarios such as anomaly detection, which is paramount in O&G. In such cases, the use of incoherent modulation represents a valid solution, which results near-optimum from an energy point of view. Within this framework, energy detection has been analyzed in underwater scenarios (Salvo Rossi et al., 2015) and in arbitrary wireless channels (Salvo Rossi et al., 2016).

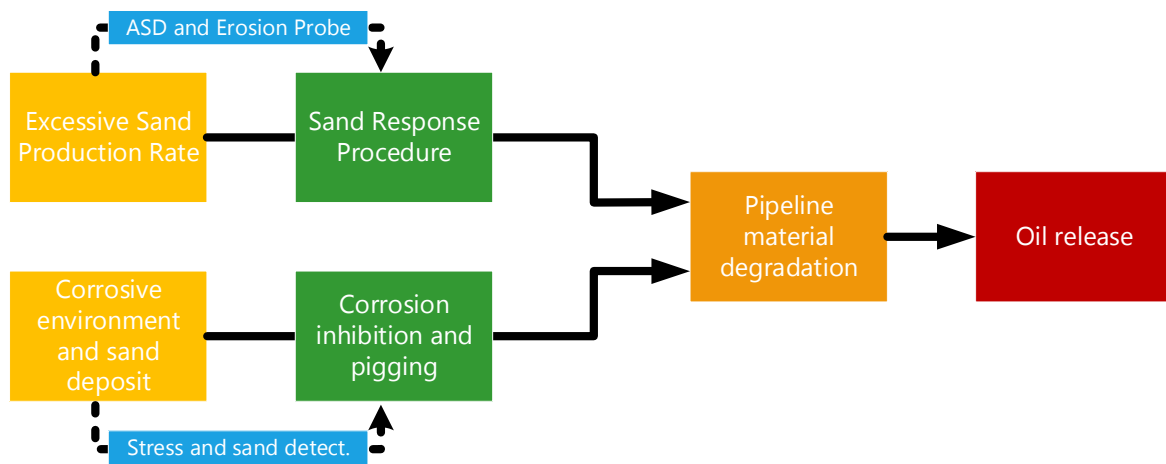


Figure 1: Release scenario due to oil sand, from causes (yellow) to consequence (red). Safety measures (green) stop scenario development and are supported by information from sensors (blue).

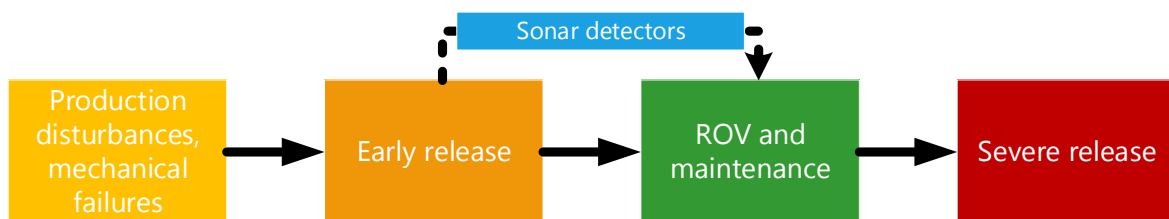


Figure 2: Severe release scenario, from causes (yellow) to consequence (red). A safety measure (green) stops scenario development and is supported by information from sensors (blue).

4. O&G cases for sensor-based risk approach

O&G risk assessment can benefit from the aforementioned sensor-based approach in several cases. Two of the most representative cases are reported in the following to demonstrate the need of such approach and the way forward of O&G risk assessment.

4.1 Sand control

Creation of oil wells in soft formations commonly appropriate control of sand or fines with fluids (White et al., 2008). Sand production is unwanted because it can plug wells, erode equipment, and reduce well productivity. It also has no economic value. In certain producing regions, sand control completions result in considerable operational expenses. For this reason, several strategies are employed to control the consequences of oil sands (Figure 1), as shown by Paltrinieri et al. (2014b).

Excessive sand production rate, i.e. increase in both sand production and flow velocity exceeding a critical threshold, leads to pipeline material degradation. The use of sensors to detect sand allows assessing the extent of sand production. Paltrinieri et al. (2017) indicates two types of sensor-based devices:

- Acoustic Sand Detector (ASD) that performs on line monitoring and gives immediate information. It records the noise produced by sand carried in the process flow. The detectors are placed on the outside of the flow line bends and detect the noise made when sand collides with the pipeline wall.
- Erosion probe, i.e. a metallic surface inserted in the well stream, which is physically eroded by sand particles passing. This detector only reports accumulated effects over a longer time period.

One of the main safety measures used to prevent sand erosion at the root of the problem is the gravel pack. A gravel pack is a downhole filter, which is held in place with a properly-sized screen. In case the gravel pack is not enough, and excessive sand production is detected, a specific sand response procedure should be carried out.

Contrary to the gravel pack, the sand response procedure is heavily based on sensor-based monitoring (Paltrinieri et al., 2014b). In fact, the sand response procedure implies that if sand is detected and its rate exceeds a specific threshold, the flow line should be choked back until the sand production rate is acceptable. Generally, the acoustic sand detector is used for dynamic monitoring and the erosion probe represents a later confirmation of the result obtained.

Corrosive environment and sand deposit may be also cause of pipeline material degradation due to corrosion. As shown by Mayer-Schönberger and Cukier (2013), oil corrosiveness (extent of the cause) can be monitored through multiple wireless sensors measuring level stress on pipes, whose main role is to monitor stress corrosion cracking.

The gravel pack is a safety measure also for this scenario, because it can prevent sand production and sand deposit where the flow is slowed down by line bends. Injection of appropriate chemicals into the fluids in order to inhibit corrosion (chemical treatment) is another safety measure defined to prevent corrosive environment, which may be itself based on sensor detection of oil corrosiveness. Moreover, "Pigs" can be used inside the pipe and traverse the pipeline if sand deposit is expected from the results of sand detectors.

4.2 Environmentally sensitive areas

The recent proposal of installing offshore oil platforms in environmentally sensitive areas, such as the Arctic, have raised general concern within the society. For instance, a Floating Production Storage and Off-loading units (FPSOs) was recently installed in the Barents Sea (Eni Norge, 2016). Its waters are relatively shallow and free from ice during the year, due to high salt level and warm Gulf Stream currents from the Atlantic Ocean. This improves the biodiversity of its ecosystem. In fact, the Barents Sea and the Kara Sea belong to one of the Marine Ecoregions included in the WWF Global 200 (Olson and Dinerstein, 2002). The ecoregion supports abundant fish stocks as well as high concentration of nesting seabirds and a diverse community of sea mammals (Larsen et al., 2004).

O&G production in this area may hide the emergence of unexpected risks due to the intertwining of new technologies and fragile environment. Hasle et al. (2009) warn about a series of environmental and safety challenges related to oil and gas exploration in the Barents Sea, such as the risk of oil spills. Extreme environmental conditions, such as low temperatures, long periods of darkness and scarce onshore infrastructure, represent operational challenges potentially increasing the frequency of accidents. These events may lead to consequences for the environment and subsistence of economy activities. Moreover, they may represent important economic and reputation losses (Kyaw and Paltrinieri, 2015), due to the increased costs of remedial action, the media coverage and the possibility of a moratorium on petroleum activities in that area.

The subsea template of a FPSO is a critical section of the facility where valves and joint points are located. These connections may be potential sources of oil leakage due to pressure increments during production disturbances and/or mechanical failures (Figure 2). For this reason, different types of sensors may be used for oil detection, such as acoustic multibeam sonars for detection of leakage from subsea infrastructures, hydro carbonate suspended in the water, under ice or on the seabed. In fact, Eriksen (2013) states that such sonars have achieved a major breakthrough in terms of performance, physical size, power consumption, uplink flexibility, processing, and price.

Early detection of releases allows appropriate actions to improve system integrity, consequently limiting the environmental impact. Remotely Operating Vehicle (ROV) interventions are also used to verify the presence of oil release before starting important maintenance activities. However, ROV inspections are extremely expensive and especially dedicated expert personnel is required. A reliable sensor network able to identify releases due to mechanical failures would also limit unnecessary ROV inspections.

5. Discussion

The described cases are clear examples of how sensor-based risk management can be employed in O&G. Sets of heterogeneous data can be collected by the mentioned sensors and used to support the realization of the defined safety measures. This would lead to not only safer systems, but also cost-efficient risk management. However, despite the attested need for improved sensor-based risk assessment, its real-time monitoring includes several challenges. For instance, the definition of a probabilistic approach for handling uncertainty, or a graph-based representation of interdependencies to integrate logic trees (Figures 1 and 2) are still open questions. Approaches based on hybrid (model-based and data-driven) structures should be combined with massive data fusion, while integrated within the modern framework of DRA, and tailored for use in O&G digital twin.

Dataset generation and utilization play also a relevant role in such framework. Synthetic datasets for training data-driven models would be necessary in the start-up phase of a digital twin, when real-world data are not available yet. In fact, one crucial point is to assess, understand and minimize the loss in performance of risk models. Successively, when real-world operational data become available through networked devices distributed along the production chain, effective update of the data-driven models must be properly carried out. Finally, it is worth mentioning that the availability of real-time data may be beneficial for the improvement of sub-models aimed at the evaluation of specific components of risk, such as the impact of loss of containment events resulting from process failures. In particular, dynamic process simulators, normally providing detailed results for the design of process equipment, may be extended to the analysis of industrial accidents and may exploit the sensors feedback for real-time adjustment and/or validation. In fact, the capability of dynamic process simulators to deal with equipment and process response to control actions, interlocks or different control logics, etc. provide accurate source term estimation (Pannocchia and Landucci, 2014) and post-release scenarios evolution (Landucci et al., 2018). Hence, this approach may provide a more realistic estimation of the risk associated with critical equipment items.

6. Conclusions

The contribution has suggested a specific approach for dynamic risk analysis for the offshore O&G industry. Such approach may be beneficial for several cases in which (quasi) real-time risk evaluation may support critical operations. Two representative cases have been described: i) sand control in O&G FPSO unit; and ii) oil production in environmental sensitive areas. In both the cases, dynamic risk analysis may employ real-time data provided by sensor networks. Despite its attested need, sensor-based risk assessment presents several challenges, related to the definition of a probabilistic approach handling uncertainty, graph-based representation of interdependencies, and dataset generation and utilization. In particular, the latter would not only affect the approach start-up phase, but also its calibration during use. In fact, this risk assessment approach would have not only the capability to continuously iterate and outline improved system risk pictures, but also the opportunity to compare its results with sensor-measured data and allow for adjustments. This can potentially guarantee progressive improvement of the method reliability for appropriate support to safety-critical decisions.

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